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An Intelligent Mobile Decision Support Framework for Assessing Personal Well-Being among Women IT Employees

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Abstract

Due to the growing complexity of work-related requirements, psychological pressure, and lifestyle challenges faced by women information technology professionals, there is a requirement for intelligent systems that can assess personal well-being continuously and intelligently. The current approaches deal with the well-being components in isolation and offer little help regarding adaptive decision-making. This research presents an Intelligent Mobile Decision Support Framework for Assessing Personal Well-Being of Women IT Professionals by considering multiple well-being factors, machine learning-based classification, risk assessment, and providing personalized recommendations. The proposed framework considers psychological, occupational, social, and lifestyle factors, which include work-life balance, occupational stress, emotional well-being, job satisfaction, workload management, social support, psychological resilience, and lifestyle behaviors. The survey-based dataset was collected from 300 women information technology professionals and pre-processed through the use of data cleaning, data encoding, normalization, and feature selection methods. The developed framework categorizes users based on their well-being level into high, medium, and low well-being groups, and provides recommendations accordingly. The experimental results revealed that the proposed framework provided 94.5% accuracy, 93.8% precision, 94.1%

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recall rate, and 93.9% F1-score performance, better than the conventional machine learning techniques. In the mobile application usability testing, a total satisfaction score of 4.47/5 was recorded, showing successful user interface interaction and utility of recommendations provided. The results show that the framework suggested is indeed personalized, adaptable, and based on the analysis of data, and can be used as an effective way to monitor and enhance the personal well-being of women IT workers.

Keywords: Personal Well-Being Assessment, Intelligent Mobile Decision Support System, Women IT Employees, Machine Learning Classification, Risk Scoring, Personalized Recommendations, Workplace Wellness Management.

1 Introduction

The significance of AI-based approaches for assessing well-being from a human-oriented perspective has been increasing as the personalized monitoring, prediction, and decision-making become possible through intelligent systems. Recently, much attention has been given to the application of artificial intelligence in assessing digital well-being through user-centered approaches, adaptive technologies, and personalized interventions (Shin, 2025). The development of employee well-being frameworks using machine learning and artificial intelligence techniques has been discussed for analyzing the workplace-related aspects and making human-oriented decisions in the framework of Industry 5.0 (Rosca & Stancu, 2024). The application of AI-driven health and risk assessment frameworks has been successful in detecting employee health issues and enhancing well-being holistically, especially in technology-driven workplaces (Poudapally & Swamy, 2026). Intelligent prediction systems together with mobile applications have been used for analyzing the work-life balance of women and providing personalized support for daily life management (Teya & Chowdhury, 2023). Workplace stress, psychosocial risks, and quality of life aspects have been recognized as important contributors to employee well-being (De Sio et al., 2017).

It is known that the psychological well-being of women workers is linked to work support structures, family help, and gender-sensitive organizational approaches (Verma et al., 2018). The influence of professional duties on the personal well-being of women was studied as well, thus indicating the connection between professional needs and personal experience (Campione, 2008). The issue of workload and occupational pressure is seen as an influential element regarding psychological well-being and well-being in general among workers (Lindfors et al., 2006). The workplace environment and issues related to personalization have also been found to be correlated with the comfort, satisfaction, and well-being results of workers (Wells, 2000). Moreover, the availability of organizational resources and continuous support at all life stages has been identified as an important factor affecting the workplace well-being of women (Gervais & Millear, 2014). Hence, a framework of intelligent mobile decision support that involves several well-being indicators, machine learning, and personalized suggestions can serve as an efficient strategy to assess the personal well-being of women IT workers.

Key Contribution

- A mobile-based assessment framework is presented for measuring the personal well-being of women IT professionals by using a combination of demographics, working environment, lifestyle factors, and psychological measures to design a decision support system.
- A well-being assessment process is created by using various measures such as work-life balance, occupational stress, emotional well-being, job satisfaction, managing workloads, social support,

mental hardiness, and lifestyle behavior to categorize well-being level and determine risk conditions.

- The suggested assessment process presents personalized guidelines by analyzing individual well-being level and producing appropriate advice about managing stress, improving lifestyle, maintaining work-life balance, practicing self-care, and accessing professional assistance.
- A monitoring process is provided through the integration of user feedback in order to improve the performance of the recommendation process.

The remaining sections of this paper are structured as follows. Section II reviews the literature and discusses the approaches that have been proposed for the assessment of employee well-being, decision support systems using artificial intelligence, and personalized recommendations. Section III explains the methodology used for this study, which includes population details, data gathering method, personal well-being measures, data preprocessing, and ethical issues. Section IV talks about the proposed Intelligent Mobile Decision Support Framework, including its architecture, well-being classification model, risk score system, and personalized recommendation system. Section V talks about experimental results and discussions of the experiments that include analysis of participants, comparison of different classification models, and evaluation of the usability of the mobile application. Lastly, Section VI provides the conclusions of this paper.

2 Literature Review

Insecurity at work is considered a key factor affecting employees' well-being, since uncertainty about working conditions affects psychological stability, satisfaction, and quality of life of employees (Mauno & Kinnunen, 1999). Hostility at work and a negative social environment have been shown to affect occupational well-being negatively, stressing the significance of favorable and inclusive workplace conditions (Miner-Rubino & Cortina, 2004). The interaction between the need for caregiving, career stressors, and individual satisfaction has been researched, showing the difficulties that women face when trying to balance work and family life at various stages of life (Gervais & Millear, 2026). Emotional labor, workplace stress, and personal self-control have been shown to be important aspects affecting the well-being of women (Ayradilli & Ustunel, 2026). Financial literacy and decision-making skills have been connected to good financial well-being, proving the significance of personal factors for the general well-being of employees (Chauhan et al., 2026).

Gender-specific disparities in professional environments have been explored, indicating that professional environment, individual characteristics, and organizational resources are factors that lead to disparities in well-being outcomes of employees (Stewart et al., 2026). Family-oriented human resource management approaches have been emphasized as important to sustain women’s professional development and ensure their well-being by managing their personal and professional duties (Li et al., 2026). Participation of women in varied professional areas has been found to enhance workplace efficiency, while the organizational environment continues to shape their occupational experience and well-being (Issah et al., 2026). Workplace environment, gender inclusiveness, and organizational culture have been established as crucial factors influencing the perception of well-being of women professionals working in difficult environments (Borja di Filippo et al., 2026). Data quality, governance, and traceability have become essential elements of intelligent systems, especially when dealing with large and heterogeneous sets of data for making sound decisions. Data lineage-aware engineering helps to efficiently track data sources, data transformation processes, and data processing pipelines.

Data quality, integrity, and provenance are important concerns in mobile health and decision support systems to make sure that the responses provided and inputs generated result in accurate risk scores. Implementation of data governance principles allows for transparency and trust in processing personal well-being information for classification (Valetta et al., 2026). In this regard, used the discussed requirements to develop our framework, which includes multi-dimensional well-being features, reliable data pre-processing, and intelligent classification of female IT workers.

Research Gap

Earlier research has examined various aspects of employee well-being related to individual characteristics, including workplace stress, job satisfaction, work-life balance, psychological well-being, and organizational support. Nevertheless, existing methodologies consider only one aspect of employee well-being and lack an integrated approach that accounts for psychological, occupational, social, and lifestyle aspects related to women IT employees. Despite the use of artificial intelligence and machine learning algorithms for predicting health outcomes and creating support systems for employees, few research studies have considered the creation of mobile-based decision support systems that would enable continuous monitoring of individual well-being statuses and offer corresponding recommendations. Moreover, existing approaches offer general wellness advice and do not take into account individual risks, personal characteristics of users, and feedback mechanisms. Hence, it is necessary to create an intelligent and adaptive mobile decision support system that incorporate multiple well-being measures, classification, risk assessment, and personalized recommendations.

3 Research Methodology

3.1 Study Population, Sampling, and Data Collection

The study participants include women workers who are employed in the information technology (IT) industry, divided into three main categories of job roles: software developers, testers and technical support, and management and other technology-based job roles (such as data analysts, project managers, etc.). The reason behind choosing women IT employees as the population under study lies in the necessity to examine personal well-being determinants affected by work requirements, professional responsibilities, and lifestyle.

In the present study, a cross-sectional, survey-based research methodology was used to collect empirical data from female IT professionals. Data collection was done through a structured questionnaire aimed at capturing demographic features, work-related experiences, mental disorders, lifestyle, and individuals' well-being measures. Purposive sampling was used in order to get individuals who have the required professional exposure in the field of IT. The inclusion criteria consisted of female workers having active involvement in IT firms, more than 21 years old, and a minimum of six months of professional experience.

A total of 300 valid responses were gathered from women IT professionals who worked in various designations and had different organizational backgrounds. The gathered samples comprised of diversity in demographic variables like age category, education level, experience, designation, and working style (site, hybrid, and remote). Responses with incomplete data or lacking critical variables were deleted through the data screening process.

The above-mentioned collected dataset was used in order to develop the proposed mobile decision support framework. The dataset was split into training and testing data sets in order to help with the

development of the model and its evaluation. Training data sets were used to learn the patterns of well-being classification, whereas testing data sets were used in order to assess the performance and effectiveness of the personal recommendations. The collected data helped the framework to recognize the conditions of well-being of individuals and offer appropriate decisions to improve it.

3.2 Personal Well-Being Indicators and Measurement

The well-being assessment was developed to account for several factors that affect the professional and personal quality of life of women workers in the information technology industry. Due to the multidimensionality of well-being, it is necessary to assess psychological, occupational, social, and lifestyle factors that make it possible to evaluate the state of well-being of individuals. The metrics framework comprises the important metrics of well-being, such as work-life balance, occupational stress, emotional well-being, job satisfaction, workload management, social support, mental resilience, and lifestyle behavior. The work-life balance metric measures how well employees can balance their professional duties and personal obligations. The occupational stress metric measures the level of stress that one feels concerning workload, deadlines, and other workplace pressures.

Job satisfaction is the level of contentment felt by employees concerning the work environment, career prospects, and organizational support. Workload management looks at how task demands and time pressure affect personal well-being. Social support is the consideration of the effect of family, coworkers, and organizational relationships on psychological well-being. Mental resilience is the state of individuals' adaptation and recovery from stress and professional challenges, while lifestyle behavior is the consideration of individuals' everyday activities affecting physical and personal well-being.

The indicators were collected using a survey that was designed on the basis of a five-point Likert scale, where 1 stood for strongly disagree, and 5 stood for strongly agree. Each of the indicators contained several questions in order to reliably reflect the particular aspect of well-being. Responses received from individuals were summed up in order to get indicator scores, which were then used to calculate the personal well-being score. The participants were grouped into different well-being categories based on the scored results, where there were low, medium, and high well-being categories. These grouped results were used as targets for designing the intelligent decision support system. This measuring strategy helps the suggested framework detect differences in well-being among female IT workers and offer personalized suggestions for enhancing their well-being.

3.3 Data Preprocessing and Ethical Considerations

The data gathered through the surveys was processed in a systematic manner to enhance the quality of the data, as well as its suitability for building the intelligent mobile decision support system. The data was initially analyzed in terms of completeness, consistency, and reliability. Incomplete, duplicate, and invalid data was eliminated to reduce any possible bias during data analysis. The categorical variables like job designation, working modes, and demographics were coded into numerical format.

The numbers that were extracted using the questionnaire on well-being have been normalized in order to ensure consistency across different levels of features. Normalizing data decreased the effect of differences in scale and increased the efficiency of machine learning analysis. Feature relevance was assessed, and important factors of well-being were chosen for classifying individuals based on their well-being status. The final dataset, which consists of 300 valid answers, was used for analysis.

As far as the ethical aspects go, the study adhered to appropriate standards applicable for conducting human-participant-based research. Participation in the study was voluntary, and informed consent was

secured from all the respondents prior to the collection of the survey data. The participants were informed of the purpose of the study, data collection and processing procedures, and confidentiality of the study.

The collected data was used only for educational and research purposes. Strict data security practices were applied at each stage of the research process to protect the collected data from any inappropriate use or access. The study ensured transparency and confidentiality when handling employees' well-being data in the course of development of the proposed intelligent mobile decision support system framework.

4 Proposed Intelligent Mobile Decision Support Framework

4.1 Overall Architecture of Proposed Framework

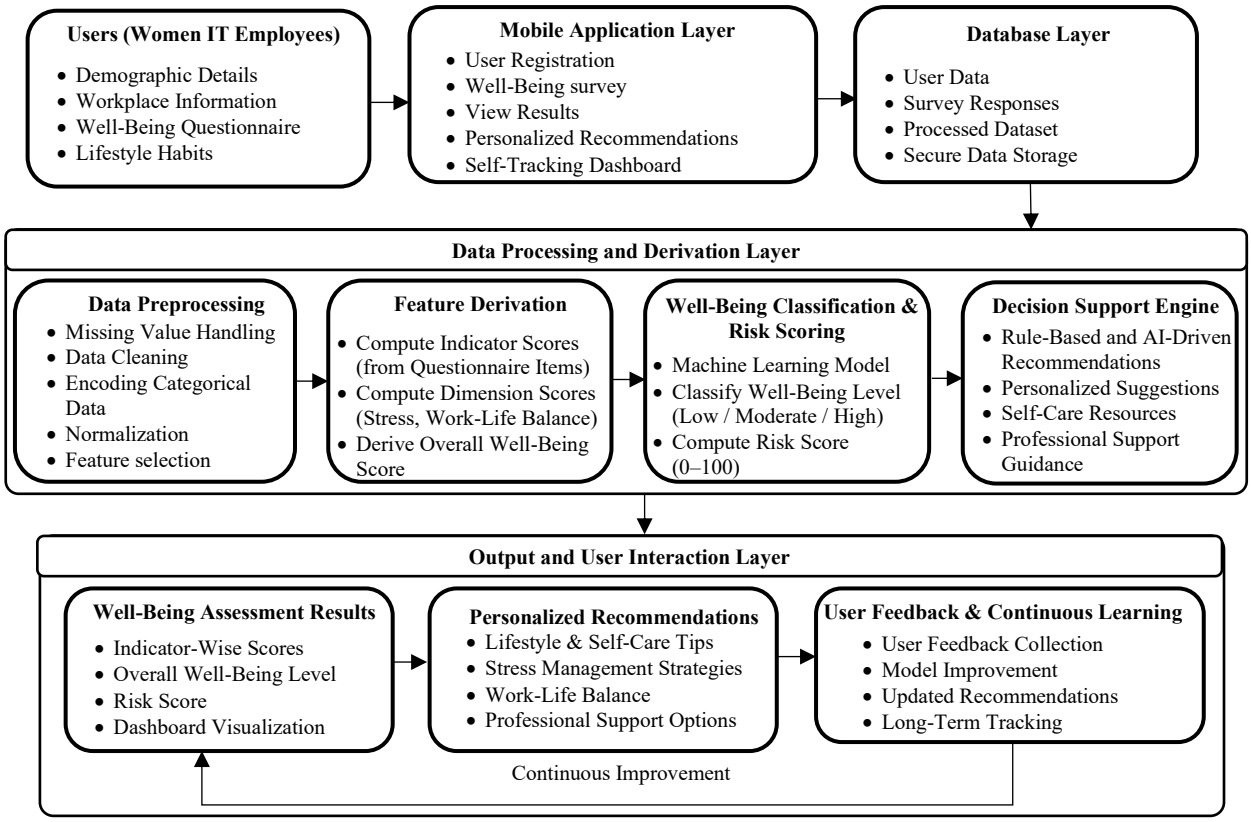


Figure 1: Overall architecture of proposed framework

The architecture of the developed Intelligent Mobile Decision Support Framework for evaluating the personal well-being of female IT employees is shown in figure 1. It includes a series of layers such as the user input, mobile application, data management, processing and derivation, and output interaction layers. First, demographic information, workplace information, answers to a well-being questionnaire, and other relevant information are gathered using the mobile application interface and saved in the database layer. The collected information goes through several preprocessing techniques that include data cleaning, handling of missing values, encoding, normalization, and feature selection. Then, well-being indicators are extracted from the responses to the questionnaire to calculate scores on a dimension level and an overall well-being score. The intelligent classification and risk scoring module categorizes the users depending on their well-being level and calculates the risk conditions. As a result,

the decision support engine provides personalized recommendations about improving lifestyle, managing stress, balancing work and personal life, and professional assistance.

4.2 Well-Being Classification and Risk-Scoring Model

The suggested intelligent mobile decision support system uses the well-being categorization and risk scoring model to detect the well-being condition of the female IT workers and deliver the required intervention to them. This made possible by using the well-being indicators generated from the questionnaire responses, which include work-life balance, occupational stress, emotional well-being, job satisfaction, workload management, social support, mental toughness, and lifestyle behavior. Initially, the extracted feature vector is presented to the classification unit that uses a Stacked Ensemble Learning Approach (where Random Forest and Support Vector Machine are taken as base learners while Gradient Boosting is used as a meta-classifier). The classification unit is responsible for finding the non-linear dependencies between multi-dimensional input vectors and the conditions of well-being and classifying employees on the basis of their well-being into three classes, namely high, moderate, and low.

The general well-being score is determined through the aggregation of various indicator scores using a weighted evaluation method. It can be expressed as,

$$\mathrm{WB}_{\mathrm{score}} = \sum_{i=1}^{n} w_i \, I_i \qquad (1)$$

Equation (1) describes $\mathrm{WB}_{\mathrm{score}}$ = overall well-being score, I_i = individual well-being indicator scores for indicator i, w_i = weight assigned to indicator i and n = total number of indicators.

According to the computed well-being index score, the risk assessment model identifies the probability of lowered well-being levels. It produces a normalized risk score ranging from 0 to 100, where high scores reflect high risk. The risk score is computed based on the difference between individual indicator scores and predetermined well-being threshold levels,

$$R_{\mathrm{score}} = 100 - \left(\frac{\mathrm{WB}_{\mathrm{score}} - \mathrm{WB}_{\mathrm{min}}}{\mathrm{WB}_{\mathrm{max}} - \mathrm{WB}_{\mathrm{min}}} \times 100 \right) \qquad (2)$$

Equation (2) describes the R_{score} = risk score, $\mathrm{WB}_{\mathrm{score}}$ = overall well-being score, $\mathrm{WB}_{\mathrm{max}}$ = maximum possible well-being score and $\mathrm{WB}_{\mathrm{min}}$ = minimum possible well-being score.

The outcomes from the classification and risk-scoring process are then combined with the decision support engine in order to provide personalized advice. Users who score poorly on the well-being scale are given advice concerning stress reduction, workload balancing, and improvements to lifestyles and professionals' well-being. Users with stable well-being status, on the other hand, are advised on preventive health measures. The dynamic process allows the monitoring of the well-being patterns of individuals and makes decision-making timely.

4.3 Personalized Decision Support and Recommendations

The customized recommendation module translates the results of the well-being evaluation into recommendations for women IT workers. The recommendations are based on the classified level of well-being, the risk score, and values of particular indicators. Recommendations that correspond to the identified state of affairs concern the improvement of psychological well-being, work-life balance, lifestyle, and professional well-being.

The decision-making engine evaluates changes in the measures of well-being and makes appropriate suggestions for the needs of the user. Employees who experience stress due to their high stress levels

are given advice regarding stress management and emotional wellness, while people with an imbalance in work and life receive tips about managing their workload, time management, and maintaining a proper balance between their work and personal lives. These recommendations are shown via the mobile application interface, enabling users to check their current condition and take into account the recommendations provided on how to improve it. Another advantage is that the framework is based on constant interaction by receiving feedback from users, which can help improve the recommendations made in the future. The personalized decision support approach proposed above gives a tool to turn assessment outcomes into recommendations. Using individual assessment, risk identification, and adaptation of recommendations, the framework helps in managing well-being proactively for women IT workers.

5 Results and Discussion

5.1 Participant Profile and Well-Being Analysis

The proposed framework was tested using data gathered from 300 women IT employees who had diverse profiles and worked in various environments. In the case of the analysis of participants, it involved demographic factors including the age range, education level, years of experience, professional position, and employment pattern. Through diverse participants, the framework was able to capture differences in the personal well-being status of women professionals in technology-based environments.

Table 1: Demographic profile of participants

Category	Sub-category	Number of Participants	Percentage (%)
Age	21–30 years	128	42.67
	31–40 years	112	37.33
	Above 40 years	60	20.00
Work Experience	<3 years	96	32.00
	3–7 years	132	44.00
	>7 years	72	24.00
Working Mode	On-site	126	42.00
	Hybrid	118	39.33
	Remote	56	18.67
Job Role	Software Development	112	37.33
	Testing and Support	84	28.00
	Management/Other Roles	104	34.67

Table 1 gives an overview of demographic details of the 300 women IT employees included in this study. The age group distribution reveals that the majority of participants fall in the age range of 21-30 years (128 participants, 42.67%), followed by the age range of 31-40 years (112 participants, 37.33%) with employees above 40 years being 20% (60 participants) of the total. As far as work experience is concerned, most of the participants have experience between 3-7 years (132 participants, 44%), then followed by participants who have less than 3 years of experience (96 participants, 32%) and those who have experience greater than 7 years (72 participants, 24%). On the basis of work mode, the highest percentage is for on-site employees (126 participants, 42%), followed by hybrid employees (118 participants, 39.33%), while remote employees are 18.67% (56 participants). When talking about the role in which employees are working, software development professionals are the highest percentage at 37.33% (112 participants), followed by management and other technical professionals at 34.67% (104 participants), and testing and support professionals at 28% (84 participants). In general, it can be concluded that the participant profile is a good example of diversified representation of women IT

workers of various ages, experiences, working schedules, and occupations to ensure thorough evaluation of personal well-being in a technological environment.

Table 2: Distribution of well-being levels

Well-Being Category	Number of Participants	Percentage (%)
High Well-Being	104	34.67
Moderate Well-Being	142	47.33
Low Well-Being	54	18.00

Table 2 shows the distribution of well-being levels of the 300 women IT employees assessed through the proposed assessment tool. The distribution indicates that most of the respondents were found to be in the moderate well-being level, totaling 142 employees (47.33%), implying that most people have well-being levels that are balanced but can still improve further. In addition, 104 participants (34.67%) of the sample size had high well-being levels. This implies that such respondents are effectively handling their responsibilities professionally and personally. Moreover, 54 employees (18.00%) are classified as having low well-being levels, implying that these employees might need more assistance and personalized solutions concerning their stress levels, workload, or other factors. In conclusion, the distribution shows that there is variation in the well-being conditions of women IT employees and the need for intelligent assessment systems to assess such specific needs.

5.2 Model Performance and Comparative Evaluation

The performance of the suggested intelligent decision support model is assessed by evaluating the classification ability of the suggested model with existing models in machine learning. The evaluation was carried out using significant criteria for prediction to assess the efficiency of well-being classification. The suggested model showed better performance since the model combines various well-being indicators with decision support.

Accuracy

Accuracy is the ratio of all correct classifications among the total number of samples used in testing. This is used to determine the capability of the proposed model to classify various well-being categories.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{3}$$

In equation (3) describes TP as true positive classifications, TN as true negative classifications, FP as false positive classifications, and FN as False Negative classifications.

Precision

This measure represents the number of correctly classified positive samples relative to the total number of positive samples. It shows how trustworthy the predictions of the model.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{4}$$

Equation (4) describes TP = true positive classifications and FP as False Positive classifications.

Higher Precision Value Indicates Lower Number of False Positive Classifications by Framework during Well-being Evaluation.

Recall

Recall evaluates the model's ability to correctly identify actual positive cases. It is particularly important for identifying employees experiencing reduced well-being conditions that require additional support.

$$Recall = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5}$$

A higher recall value indicates improved detection capability for individuals requiring personalized interventions in equation (5).

F1-Score

The F1-Score balances Precision and Recall by evaluating both measures at once.

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

F1-Score helps measure model performance when the distribution of samples across well-being categories varies, as shown in equation (6).

Table 3: Comparative performance evaluation of classification models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Logistic Regression	84.6	82.9	83.5	83.2
Decision Tree	86.8	85.4	85.9	85.6
Random Forest	90.2	89.6	89.8	89.7
Support Vector Machine	88.7	87.9	88.2	88.0
Proposed Intelligent Framework	94.5	93.8	94.1	93.9

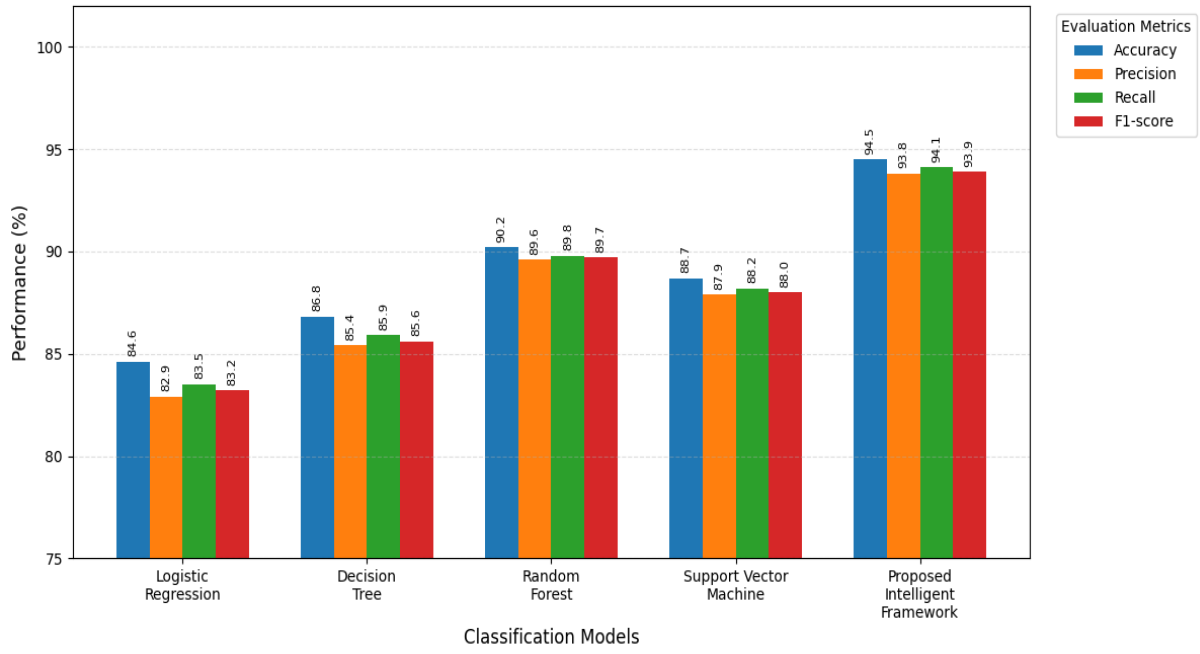


Figure 2: Comparative performance evaluation of classification models

The performance evaluation for different classification models used for the analysis of well-being conditions of women in the IT sector is shown in table 3 and figure 2. It is evident that all models under study have performed well; however, the Intelligent Framework that has been developed by the researcher has performed better than others in all aspects. The Logistic Regression model has performed with 84.6% accuracy, 82.9% precision, 83.5% recall and 83.2% F1-score, while Decision Tree Model has performed better with an accuracy of 86.8% and F1-score of 85.6%. Among the conventional methods of classification, the Random Forest method has performed better with 90.2% accuracy, 89.6% precision, 89.8% recall, and 89.7% F1-score, while the Support Vector Machine has performed with 88.7% accuracy and 88.0% F1-score. The improved performance is because of the use of multi-dimensional well-being factors, the feature derivation process, and decision-making approaches, which help in accurately identifying the well-being status of an individual. The outcomes indicate the success of the developed approach in categorizing different levels of well-being and making customized recommendations for women IT employees.

5.3 Mobile Application Usability Evaluation

The usability of the proposed decision support system application for mobile devices was tested based on the following factors: user interaction, accessibility, utility of recommendations, and general satisfaction. These tests were conducted using test subjects who evaluated various features of the app after interacting with its wellness assessment and recommendation modules.

Table 4: Mobile application usability evaluation

Evaluation Parameter	Mean Score (5-point Scale)
Ease of Use	4.42
Interface Design	4.35
Response Time	4.38
Assessment Understanding	4.46
Recommendation Relevance	4.51
Overall User Satisfaction	4.47

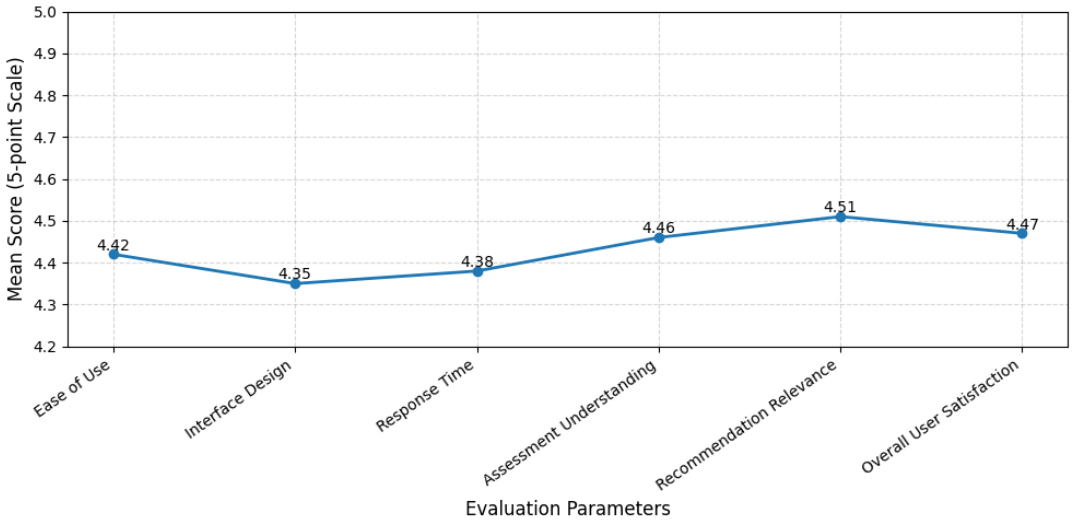


Figure 3: Mobile application usability evaluation scores across different assessment parameters

Table 4 and figure 3 demonstrate the usability evaluation results of the designed intelligent mobile decision support application according to different user experience parameters. The usability assessment

was based on a five-point scale for the application's effectiveness, accessibility, and usability. According to the data obtained during the evaluation, the developed application demonstrated positive user acceptance concerning all the considered parameters. The maximum result was gained in terms of the parameter of recommendation relevancy (4.51/5) as the users considered the personal recommendations provided by the system relevant and useful for resolving their well-being issues. The result obtained for the parameter of assessment understanding (4.46/5) shows that users were able to understand the results of their well-being assessment. Also, a relatively high result was obtained for the parameter of ease of use (4.42/5), response time (4.38/5), and interface (4.35/5). All this proves the effectiveness of the mobile application concerning well-being assessment and personalized decision support. Thus, it can be said that the proposed framework is an effective platform for continuous well-being monitoring and recommendation delivery for women IT employees.

5.4 Implications and Limitations

In conclusion, the Intelligent Mobile Decision Support Framework suggested is expected to have great practical importance in the enhancement of personal well-being management for female IT employees through the implementation of multi-dimensional evaluation, classification using machine learning techniques, scoring of risks, and personalized advice. This framework allows for the detection of well-being issues that arise due to the influence of psychological, occupational, social, and lifestyle factors and helps with making proactive decisions through adaptive decision-making. Nevertheless, there are some limitations of the study that must be taken into account. The assessment was made through the use of information received in questionnaires from 300 IT employees who are women. This may affect the generality of the results in other industries and in other geographical areas as well as in other groups of people. Moreover, the framework is based on self-reporting questionnaire answers that may include subjectivity in people's answers. At the moment, the model does not make use of real-time physiological and behavioral data of the users received via sensors of the wearables. These limitations can be addressed in future studies through large-scale validation, use of real-time sensor data, use of explainable AI methods, and adaptive learning algorithms.

6 Conclusion

The present research suggests a framework for Intelligent Mobile Decision Support for Assessing Personal Well-Being among Women IT Employees to address the problems of existing approaches where only the well-being factors are analyzed in isolation, and there is no personalized decision support. The novelty of the present framework is associated with the inclusion of multidimensional factors of well-being, classification through machine learning, risk scoring, and personalized recommendation generation in the mobile decision support setting. Psychological, occupational, social, and behavioral aspects such as work-life balance, occupational stress, emotional well-being, job satisfaction, workload, social support, mental toughness, and lifestyle are taken into account to assess personal well-being conditions. The evaluation of the suggested framework is based on the dataset of 300 women IT employees. In addition, the proposed model had 94.5% accuracy, 93.8% precision, 94.1% recall, and 93.9% F1-score, thus showing better performance than traditional machine learning models. Finally, the mobile app usability test was successful as the overall score reached 4.47/5, which proves that the designed interface and recommendations system were efficient. The proposed solution presents a pro-active system for continuous monitoring of well-being through assessing the user, identifying risks, making personalized recommendations, and improving them. Future research in this area may include using real-time data from wearables regarding users' physiological and behavioral features, generalizing

the model in different organizational contexts, applying explainable artificial intelligence to increase transparency, creating adaptive learning models, and improving the recommendation accuracy. Also, a broader implementation of the framework is possible via cloud-based services.

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