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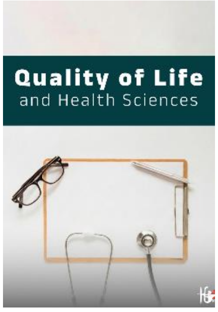

Predicting Quality of Life Among Married Adults Using Family Cohesion, Work–Family Conflict, and Emotion Regulation: A Machine Learning Study

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ABSTRACT

Objective: This study aimed to predict quality of life among married adults in Tehran using family cohesion, work–family conflict, and emotion-regulation strategies through comparative and interpretable machine learning models.

Methods and Materials: This cross-sectional predictive-correlational study was conducted among 420 married and employed adults residing in Tehran, Iran. Participants were recruited through multistage sampling from community centers, healthcare centers, public organizations, private companies, and self-employment settings across different geographical regions of the city. Data were collected using the World Health Organization Quality of Life–Brief Version, the cohesion subscale of the Family Adaptability and Cohesion Evaluation Scales III, the Multidimensional Work–Family Conflict Scale, and the Emotion Regulation Questionnaire. The dataset was divided into an 80% training set and a 20% independent test set. Elastic net regression, support vector regression, random forest regression, gradient boosting regression, extreme gradient boosting, and a multilayer perceptron were developed and compared using repeated 10-fold cross-validation. Model performance was evaluated through the coefficient of determination, root mean squared error, and mean absolute error. Permutation importance and Shapley additive explanations were used to interpret the best-performing model.

Findings: Extreme gradient boosting achieved the highest predictive accuracy, explaining 61% of the variance in quality of life in the independent test set, with an RMSE of 7.32 and an MAE of 5.67. Family cohesion was the strongest positive predictor, followed by cognitive reappraisal and perceived economic status. Strain-based and time-based work interference with family were the strongest negative predictors, while expressive suppression also reduced predicted quality of life. Removing family cohesion or work–family conflict dimensions produced the largest declines in model performance. The nonlinear model outperformed elastic net regression, indicating the presence of interaction and threshold effects among the predictors.

Conclusion: Quality of life among married adults can be predicted with substantial accuracy by integrating family cohesion, work–family conflict, and emotion regulation, with relational support and occupational-family strain emerging as the most influential factors.

Keywords: *Quality of life; family cohesion; work–family conflict; emotion regulation; machine learning; married adults.*

1. Introduction

Quality of life is a multidimensional construct that reflects individuals' evaluations of their physical health, psychological functioning, interpersonal relationships, environmental conditions, and overall satisfaction with life. Among married adults, quality of life is shaped not only by personal resources and socioeconomic circumstances but also by the quality of family relationships, the compatibility of occupational and domestic responsibilities, and the capacity to regulate emotions in demanding situations. Marriage places individuals within an interdependent relational system in which emotional experiences, role expectations, work pressures, and patterns of communication continually influence one another. Accordingly, the well-being of married adults cannot be adequately explained through isolated individual characteristics. It must instead be understood within the broader family and occupational contexts in which adults manage intimacy, parenting, employment, financial responsibilities, and everyday stress. Research on family functioning has consistently shown that relational security and constructive interaction are associated with healthier psychological adjustment, whereas recurrent conflict, emotional disconnection, and sustained stress can undermine the well-being of both adults and children. Longitudinal evidence indicates that hostile child–parent conflict may develop through the cumulative influence of maternal, child, and family conditions across childhood and adolescence, illustrating the enduring significance of relational processes within the family system (Harries et al., 2025). Developmental findings have likewise shown that parent–child conflict changes across adolescence and young adulthood and remains embedded in broader patterns of family adaptation (Son et al., 2024). Although these studies have primarily examined parenting and intergenerational relationships, their findings support a family-systems perspective in which the quality of adult life is inseparable from the emotional climate, cohesion, and conflict patterns of the household.

Family cohesion represents one of the most important relational resources available to married adults. It refers to the emotional bonding, mutual support, shared involvement, sense of belonging, and balanced connectedness experienced among family members. A cohesive family provides members with a stable relational base from which they can respond to occupational strain, financial pressures, parenting demands, illness, and unexpected life transitions. Within such families, individuals are more likely to perceive that their needs are recognized, that responsibilities are shared, and that emotional support is available when difficulties arise. These conditions may enhance psychological security, reduce loneliness, and strengthen perceived control over daily life. Conversely, weak family cohesion may be characterized by emotional distance, limited communication, inconsistent support, and reduced participation in shared decisions, all of which can intensify the effects of external stressors. Research focusing on parental interaction has demonstrated that constructive parenting styles are associated with children's self-management and emotional self-regulation, suggesting that cohesive relational environments foster regulatory capacities and reciprocal adjustment across family members (Ghasemi Tousi, 2025). Similarly, findings from families with elementary-school children during home quarantine showed that mothers' mindfulness and self-efficacy were associated with the quality of parent–child interactions, indicating that relational functioning depends partly on adults' psychological resources and confidence in managing family demands (Hashemi et al., 2022). During the COVID-19 pandemic, parents also played a central role in addressing children's educational and developmental difficulties in virtual learning contexts, further demonstrating how family connectedness and coordinated parental involvement can protect adaptation under conditions of disruption (Amirkhani Dehkordi et al., 2024).

The importance of family cohesion becomes particularly evident when families encounter persistent stress or special caregiving demands. Research among mothers of children with autism has shown that parenting stress and perceived social stigma are associated with the quality of parent–child interactions, indicating that external social pressures and internal family strain can weaken relational responsiveness (Nikbakht & Haghaegh, 2020). A systematic review and meta-analysis similarly demonstrated that parenting stress is elevated across different clinical groups and is closely connected to the difficulties families experience when managing complex behavioral, emotional, or health-related needs (Barroso et al., 2018). In families of children with type 1 diabetes, parental stress, anxiety, and mindfulness were associated with parent–child mealtime interactions, showing that adults' emotional conditions can influence routine relational exchanges in clinically meaningful ways (Van Gampelaere et al., 2020). These findings are relevant to married adults more broadly because they illustrate how chronic stress can become embedded in everyday family interactions and reduce the quality of relational life. At the same time, supportive interventions can strengthen interactional skills and restore more adaptive family processes. Trauma-informed parenting interventions, for example, have been found to improve parental interaction skills in adoptive families while addressing the effects of childhood trauma (Parchami & Bahramipour, 2025). Mindful parenting education has likewise been associated with improvements in the parent–child relationship, parenting stress, and loneliness, suggesting that increasing awareness, emotional presence, and nonreactive communication can benefit both relational functioning and adult psychological well-being (Attar et al., 2023). Together, this literature suggests that cohesive and supportive family relationships may operate as a protective factor for quality of life by reducing the subjective burden of family demands and strengthening emotional security.

Despite the protective role of family cohesion, married adults frequently experience competing pressures from work and family roles. Work–family conflict occurs when the demands of employment and family life are mutually incompatible, such that participation in one role makes effective participation in the other more difficult. This conflict may be time-based, when working hours reduce opportunities for family involvement; strain-based, when occupational fatigue or anxiety carries over into the home; or behavior-based, when attitudes and behaviors required at work are inconsistent with those expected in intimate and family relationships. Work–family conflict may also operate in the reverse direction when family demands interfere with concentration, attendance, or performance at work. Such conflicts can decrease perceived control, increase emotional exhaustion, and limit opportunities for rest, intimacy, social participation, and self-care. Moreira and colleagues found that work–family conflict was associated with mindful parenting through emotional distress and parenting stress, indicating that occupational-family interference can disrupt adults' capacity to remain attentive, accepting, and emotionally available in family interactions (Moreira et al., 2019). This finding is especially relevant to the quality of life of married adults because it demonstrates that work-related strain can affect well-being indirectly by altering the emotional quality of family relationships. When occupational stress repeatedly intrudes into family life, adults may experience lower satisfaction with marriage, reduced family involvement, greater conflict, and poorer psychological functioning.

The consequences of role disruption became particularly visible during the COVID-19 pandemic, when employment, education, childcare, and domestic responsibilities were often concentrated within the same physical environment. Studies conducted during school suspension and home confinement showed that daily routines and parent–child relationships were closely associated with children's adjustment. Children's daily living routines mediated the relationship between parent–child relationships and adjustment problems during school suspension, emphasizing that predictable family organization can translate relational quality into better adaptation (Wu et al., 2025). Similarly, disrupted routines and increased parent–child conflict were associated with psychological maladjustment among children and adolescents during the pandemic (Liu et al., 2021). Although these studies examined child outcomes, they also reflect the pressures experienced by employed and married adults responsible for organizing work, education, caregiving, and household routines. Under such conditions, conflict between roles can become a major determinant of adult quality of life because it simultaneously affects occupational functioning, family relationships, emotional health, and opportunities for recovery. Research further indicates that parental conflict and parenting styles are associated with behavioral problems in preschool children through anxiety, demonstrating how conflict within the adult and parenting system may spread across family relationships (Tabe Bordbar & Koraei, 2025). Such spillover processes reinforce the assumption that work–family conflict should not be considered merely an employment-related inconvenience; rather, it is a systemic stressor capable of influencing multiple dimensions of family and personal well-being.

Emotion regulation constitutes another major psychological mechanism through which married adults respond to family and occupational pressures. Emotion regulation refers to the processes individuals use to monitor, interpret, modify, express, or inhibit emotional reactions. Two commonly examined strategies are cognitive reappraisal and expressive suppression. Cognitive reappraisal involves changing the interpretation of a situation before the emotional response becomes fully activated, whereas expressive suppression involves inhibiting the outward expression of an already-generated emotion. Reappraisal is generally associated with greater flexibility, more constructive communication, and better psychological adaptation, while frequent suppression may contribute to emotional disconnection, physiological strain, and reduced authenticity in close relationships. Difficulties in emotion regulation have been associated with maladaptive conflict-resolution tactics between adolescents and parents, indicating that poor emotional control can intensify negative thoughts, impulsive responses, and ineffective interpersonal behavior (Hosseini et al., 2018). In contrast, parental mindfulness appears to support more adaptive parenting behavior and lower levels of child psychopathology by promoting awareness and nonreactivity in emotionally challenging interactions (Han et al., 2021). These findings imply that emotion regulation may influence married adults' quality of life both directly, through its effects on psychological health, and indirectly, through its effects on marital communication, parenting behavior, and the management of work–family strain.

Mindfulness-based research provides additional evidence regarding the role of regulatory processes in family well-being. Mindful parenting refers to maintaining present-centered, nonjudgmental awareness during interactions with children and responding to family stress with greater emotional balance. A systematic review and meta-analysis found that mindfulness interventions for parents reduced parenting stress and improved selected psychological outcomes among young people, supporting the broader value of regulatory awareness within family systems (Bergdorf et al., 2019). Mindfulness-based parenting training has also been shown to reduce anxiety and parent–child conflict while enhancing parenting self-efficacy among mothers of children with attention-deficit/hyperactivity disorder (Sharifi Rigi et al., 2018). Among parents of preschool children in Tehran, mindfulness-based parenting education improved parent–child relationship quality and reduced parenting stress, suggesting that these approaches are relevant within the Iranian sociocultural context (Hosseini Sahi, 2024). Similar benefits have been reported among mothers of children with hearing loss, for whom mindfulness-based parenting reduced parenting stress despite the continuing demands associated with disability and caregiving (Kabirifard et al., 2024). These intervention findings indicate that the ability to regulate attention and emotion may buffer the negative effects of family strain and strengthen perceived well-being even when external stressors cannot be entirely removed.

The relationship between mindfulness, emotional regulation, and family adaptation is nevertheless complex rather than uniformly protective. A diary study found that mindful parenting could function as both a buffer and a sensitizer in the association between parent–child conflict and parental stress, indicating that heightened awareness may reduce stress in some contexts while increasing sensitivity to relational difficulties in others (Fang et al., 2026). This complexity is important because it suggests that adaptive regulation does not simply eliminate negative emotions; instead, it changes how individuals process and respond to them. Park demonstrated that mindful parenting was related to recurrent conflict and adolescents' externalizing and internalizing problems, reinforcing the role of parental emotional awareness in interrupting cycles of conflict and maladjustment (Park, 2020). During the COVID-19 period, mindful parenting also mediated the relationship between mothers' perceived stress and child adjustment, suggesting that stress affects family outcomes partly through changes in adults' emotional availability and parenting behavior (Cheung & Chao, 2022). Among new mothers, positive mental health was linked to mindful parenting through parenting stress, further indicating that adult well-being, regulatory awareness, and family interaction are reciprocally connected (Oliveira et al., 2024). Thus, emotion regulation may not only predict individual quality of life but may also determine whether occupational and family stressors are translated into chronic conflict, withdrawal, or constructive adaptation.

The combined examination of family cohesion, work–family conflict, and emotion regulation is theoretically important because these constructs represent relational, contextual, and intrapersonal levels of functioning. Family cohesion reflects the availability of emotional support and connectedness; work–family conflict captures pressure arising from incompatible social roles; and emotion regulation reflects the individual's capacity to manage the affective consequences of those pressures. These variables are likely to interact in nonlinear ways. Strong family cohesion may reduce the impact of occupational strain by providing emotional support and shared problem solving, yet its protective influence may weaken when work demands become chronically overwhelming. Cognitive reappraisal may help adults reinterpret temporary family disagreements or job pressures, but it may not fully compensate for severe and persistent role overload. Expressive suppression may appear functional in the short term by preventing overt conflict, while repeated suppression may gradually reduce intimacy and psychological well-being. The available literature supports each of these mechanisms separately, but fewer studies have integrated them within a single predictive framework focused specifically on married adults' quality of life. Existing research has more often emphasized parenting stress, child adjustment, parent–child conflict, or intervention outcomes than the broader life quality of adults occupying simultaneous marital, occupational, and family roles.

Conventional statistical models are valuable for estimating linear associations and testing theoretically specified relationships, but they may be less effective when predictors operate through thresholds, interactions, and nonlinear patterns. Machine learning methods provide an alternative approach by comparing multiple algorithms, evaluating performance in unseen data, and identifying complex combinations of variables that contribute to prediction. In the present context, machine learning can determine whether quality of life is predicted more accurately by linear combinations of family cohesion, work–family conflict, and emotion-regulation strategies or by nonlinear models capable of detecting conditional effects. It can also estimate the relative contribution of each predictor and clarify whether, for example, family cohesion becomes especially protective at high levels of work–family conflict or whether expressive suppression becomes particularly detrimental when cognitive reappraisal is limited. Interpretable machine learning techniques can further translate predictive models into psychologically meaningful patterns by showing the direction and magnitude of each variable’s contribution to individual predictions. This approach is especially suitable for married adults in Tehran, whose quality of life may be shaped by the simultaneous influence of employment pressures, household responsibilities, economic conditions, cultural expectations regarding marriage and parenting, and patterns of emotional expression.

Accordingly, the aim of the present study was to predict quality of life among married adults in Tehran using family cohesion, work–family conflict, and emotion regulation through comparative and interpretable machine learning models.

2. Methods and Materials

2.1. Study Design and Participants

The present study employed a cross-sectional, predictive-correlational design and used supervised machine learning techniques to predict quality of life among married adults based on family cohesion, work–family conflict, and emotion regulation. The statistical population consisted of married and employed adults residing in Tehran, Iran. Participants were recruited from municipal community centers, healthcare centers, educational organizations, private companies, and public-sector workplaces located in the northern, southern, eastern, western, and central areas of Tehran. A multistage sampling procedure was used to obtain a sample representing different geographical and socioeconomic areas of the city. In the first stage, several municipal districts were selected from the five geographical regions of Tehran. In the second stage, community centers and workplaces within the selected districts were identified. In the final stage, eligible married adults were invited to participate in the study through announcements distributed by the cooperating organizations. A total of 456 individuals initially agreed to participate and received the research questionnaires. Of these, 436 participants returned the questionnaires. Sixteen questionnaires were excluded because of substantial missing data, uniform response patterns, or failure to meet the eligibility criteria. Consequently, the final sample consisted of exactly 420 married adults, including 213 women and 207 men. The participants ranged in age from 22 to 59 years, with a mean age of 38.27 years and a standard deviation of 7.91 years.

The inclusion criteria were being legally married, living with one’s spouse at the time of data collection, having been married for at least one year, residing in Tehran, being between 20 and 60 years of age, being employed for at least 20 hours per week, and providing informed consent to participate. Employment was included as an eligibility requirement because meaningful assessment of work–family conflict requires active involvement in both occupational and family roles. Participants were excluded when they reported separation from their spouse, incomplete cohabitation because of an ongoing marital separation, unemployment at the time of the study, a severe neurological or psychiatric condition that substantially interfered with their ability to complete the questionnaires, or submission of a questionnaire with more than 10% unanswered items. Questionnaires containing repetitive or evidently careless response patterns were also excluded before data analysis.

The required sample size was determined by considering both conventional predictive analysis requirements and the need to divide the dataset into independent training and testing subsets. A sample of 420 participants provided sufficient observations for model training, hyperparameter optimization, cross-validation, and evaluation on an untouched test dataset. It also ensured an adequate ratio of participants to predictor variables and reduced the likelihood of unstable estimates or excessive model variance. Before completing the questionnaires, participants received a written explanation of the purpose and procedures of the study. They were informed that participation was voluntary, that they could discontinue participation at any stage without penalty, and that their responses would be analyzed anonymously. No personally identifying information was recorded in the analytical dataset. The questionnaires were completed individually in either paper-and-pencil or secure electronic format, depending on the facilities available at each recruitment site. The average completion time was approximately 25 to 30 minutes.

2.2. Measures

A demographic information form developed for the present study was used to collect participants' background characteristics. The form included age, sex, educational attainment, occupational status, average weekly working hours, duration of marriage, number of children, perceived economic status, and whether both spouses were employed. These variables were collected to describe the sample and to examine whether the predictive performance of the machine learning models improved when basic demographic and occupational characteristics were added to the primary psychological and family-related predictors. The main machine learning analyses emphasized family cohesion, work–family conflict, and emotion regulation, whereas demographic variables were treated as supplementary predictors in the extended models.

Quality of life was assessed using the World Health Organization Quality of Life–Brief Version. This 26-item instrument evaluates individuals' perceived quality of life during the preceding two weeks. It contains two general items assessing overall quality of life and satisfaction with health, as well as 24 items covering four principal domains: physical health, psychological health, social relationships, and environmental conditions. The physical health domain assesses areas such as energy, fatigue, pain, sleep, mobility, daily activities, dependence on medical treatment, and work capacity. The psychological domain examines positive and negative feelings, self-esteem, body image, personal beliefs, concentration, and perceived meaning in life. The social relationships domain assesses personal relationships, perceived social support, and satisfaction with intimate life. The environmental domain includes financial resources, safety, access to healthcare, opportunities for acquiring information and skills, participation in recreational activities, housing conditions, transportation, and the physical environment. Items are rated on a five-point Likert scale, with response anchors varying according to the content of each item. Negatively worded items are reverse-scored before calculation of the domain scores. Raw domain scores are transformed to a scale ranging from 0 to 100, with higher scores indicating better perceived quality of life. For the present study, an overall quality-of-life index was calculated by averaging the four transformed domain scores. This overall index was used as the continuous outcome variable in the machine learning models, while domain-specific scores were retained for supplementary analyses.

Family cohesion was measured using the cohesion subscale of the Family Adaptability and Cohesion Evaluation Scales III developed within Olson's Circumplex Model of marital and family systems. The cohesion subscale contains 10 items designed to assess the degree of emotional bonding, closeness, support, shared activities, family involvement, and perceived connectedness among family members. The items examine the extent to which family members seek assistance from one another, participate in activities together, consult each other when making decisions, feel emotionally close, and maintain a balance between individual independence and family involvement. Participants respond to each item on a five-point Likert scale ranging from 1, indicating almost never, to 5, indicating almost always. The total family cohesion score is calculated by summing the responses to the 10 items and can range from 10 to 50. Higher scores indicate stronger emotional connection, greater family participation, and a more cohesive family system. In the machine learning analyses, the total family cohesion score was entered as one of the primary predictor variables.

Work–family conflict was assessed using the Multidimensional Work–Family Conflict Scale developed by Carlson, Kacmar, and Williams. The instrument consists of 18 items and evaluates conflict in both directions between occupational and family roles. It includes work interference with family and family interference with work and distinguishes among time-based, strain-based, and behavior-based forms of conflict. Time-based conflict occurs when the time devoted to one role restricts the time available for the other role. Strain-based conflict refers to stress, fatigue, tension, or emotional pressure arising in one role and negatively affecting performance in another role. Behavior-based conflict occurs when behaviors that are effective or expected in one domain are incompatible with behavioral expectations in the other domain. The scale therefore contains six dimensions: time-based work interference with family, strain-based work interference with family, behavior-based work interference with family, time-based family interference with work, strain-based family interference with work, and behavior-based family interference with work. Each dimension is represented by three items. Responses are recorded on a five-point Likert scale ranging from 1, strongly disagree, to 5, strongly agree. Total scores range from 18 to 90, with higher scores indicating greater conflict between occupational and family responsibilities. The total score was used as the principal work–family conflict predictor, while the six dimensional scores were included in expanded machine learning models to determine which particular forms and directions of conflict contributed most strongly to quality-of-life prediction.

Emotion regulation was measured using the Emotion Regulation Questionnaire developed by Gross and John. This 10-item self-report instrument assesses two commonly used emotion-regulation strategies: cognitive reappraisal and expressive suppression. Cognitive reappraisal refers to changing the interpretation of an emotional situation in a manner that modifies its emotional impact. This dimension is measured using six items. Expressive suppression refers to inhibiting or concealing the outward expression of an emotion after the emotional response has already been activated and is assessed using four items. Participants rate each statement on a seven-point Likert scale ranging from 1, strongly disagree, to 7, strongly agree. Cognitive reappraisal scores range from 6 to 42, whereas expressive suppression scores range from 4 to 28. Higher scores on each subscale indicate more frequent use of the corresponding strategy. Because cognitive reappraisal and expressive suppression represent theoretically distinct regulatory strategies, they were not combined into a single total score. Instead, the two subscale scores were entered separately into the machine learning models. Cognitive reappraisal was conceptualized as a generally adaptive strategy associated with flexible modification of emotional experiences, whereas expressive suppression represented an inhibition-oriented strategy whose relationship with quality of life could vary according to personal, relational, and cultural conditions.

Before model development, the internal consistency of all instruments was examined in the present sample using Cronbach's alpha and McDonald's omega coefficients. Reliability coefficients of .70 or higher were considered acceptable for research purposes. Item-level distributions were also examined to identify impossible values, substantial floor or ceiling effects, and unusual response patterns. The construct scores were calculated only after completion of data screening and reverse scoring of the relevant items. Higher scores consistently represented higher levels of the construct identified by each scale, namely better quality of life, stronger family cohesion, greater work–family conflict, more frequent cognitive reappraisal, or more frequent expressive suppression.

2.3. Data Analysis

Data analysis was conducted using IBM SPSS Statistics and the Python programming environment with established packages for data management, machine learning, statistical evaluation, and model interpretation. Descriptive statistics, including frequency, percentage, mean, standard deviation, minimum, maximum, skewness, and kurtosis, were first calculated to characterize the sample and study variables. Pearson correlation coefficients were calculated to examine the preliminary relationships among quality of life, family cohesion, work–family conflict, cognitive reappraisal, and expressive suppression. Relationships between demographic characteristics and quality of life were also examined to identify potentially relevant supplementary predictors. Multicollinearity was evaluated using tolerance and variance inflation factor indices. Variance inflation factor values below 5 were considered indicative of an acceptable degree of overlap among predictor variables. Extreme values were examined by reviewing standardized scores, boxplots, and the original response patterns. Values were retained when they represented plausible participant responses and were removed or corrected only when they resulted from demonstrable data-entry errors.

The primary analytical objective was to predict the continuous overall quality-of-life score. The dataset was randomly divided into a training set containing 80% of the participants and an independent test set containing the remaining 20%. Accordingly, the training set included 336 participants, and the test set included 84 participants. The random division was performed using a fixed random seed to ensure reproducibility, and the distribution of the quality-of-life outcome was preserved across the two subsets by grouping the outcome into quantile-based strata before sampling. The test set remained completely separate from model selection, preprocessing decisions, and hyperparameter optimization and was used only for the final evaluation of model performance. This procedure reduced the risk of optimistic performance estimates and provided a more realistic assessment of how the trained models would perform with previously unseen cases.

Remaining missing values were handled within the analytical pipeline to prevent information leakage. Continuous variables were imputed using the median calculated exclusively from the training data, while categorical variables were imputed using the most frequent category in the training set. Continuous predictors were standardized to a mean of zero and a standard deviation of one for algorithms sensitive to differences in measurement scales, including elastic net regression, support vector regression, and the multilayer perceptron neural network. Standardization was not required for tree-based algorithms, although the same data-partitioning procedure was maintained across all models. Categorical demographic variables were transformed using one-hot encoding. All imputation, scaling, and encoding procedures were fitted to the training data and subsequently applied to the test data through integrated preprocessing pipelines.

Two predictor configurations were examined. The primary configuration included the theoretically central variables of family cohesion, overall work–family conflict, cognitive reappraisal, and expressive suppression. The expanded configuration included family cohesion, the six dimensions of work–family conflict, the two emotion-regulation strategies, age, sex, education, marriage duration, number of children, weekly working hours, perceived economic status, and dual-earner family status. Comparing these configurations made it possible to determine whether detailed subdimensions and demographic information provided meaningful incremental predictive value beyond the principal family and psychological variables identified in the study title.

Several supervised regression algorithms were developed and compared. Elastic net regression was included as a regularized linear baseline capable of managing correlated predictors and reducing the influence of less informative variables. Support vector regression with a radial basis function kernel was used to model nonlinear relationships in the predictor space. Random forest regression was applied to capture complex interactions and nonlinear associations through an ensemble of decision trees. Gradient boosting regression and extreme gradient boosting were used to construct sequential tree-based models in which each new tree attempted to correct prediction errors made by preceding trees. A multilayer perceptron neural network was also examined to assess whether a flexible nonlinear architecture could improve prediction accuracy. Including algorithms with different mathematical structures allowed the study to compare linear, kernel-based, ensemble, boosting, and neural-network approaches rather than relying on a single modeling assumption.

Hyperparameters were optimized using repeated 10-fold cross-validation within the training set. In each cross-validation cycle, the training data were divided into 10 folds, nine folds were used to train the model, and the remaining fold was used for validation. This process was repeated until each fold had served as the validation subset, and the complete procedure was repeated five times using different fold assignments. Hyperparameter combinations were evaluated through randomized or grid-based searches, depending on the size of the parameter space. The optimized parameters included the regularization strengths and mixing parameter for elastic net regression; the penalty parameter, kernel coefficient, and epsilon value for support vector regression; the number of trees, maximum tree depth, minimum observations required for node division, and number of predictors sampled at each split for random forest regression; the learning rate, number of estimators, maximum depth, subsampling rate, and regularization parameters for the boosting models; and the number of hidden layers, neurons per layer, activation function, regularization strength, and learning rate for the neural network. Early stopping was used for the neural network and boosting models when applicable to reduce overfitting.

Model performance was evaluated using the coefficient of determination, root mean squared error, and mean absolute error. The coefficient of determination indicated the proportion of variance in quality of life explained by the model, with higher values reflecting stronger predictive performance. Root mean squared error quantified the average magnitude of prediction errors while assigning greater weight to larger errors. Mean absolute error represented the average absolute difference between the observed and predicted quality-of-life scores and provided an interpretable measure of typical prediction error. The optimal model was selected based on the combined criteria of the highest test-set coefficient of determination, the lowest root mean squared error, the lowest mean absolute error, and consistency between cross-validation and test-set performance. A large discrepancy between training and test performance was interpreted as evidence of possible overfitting. Confidence intervals for final test-set performance indices were estimated using 2,000 bootstrap resamples of the independent test dataset.

The best-performing machine learning model was interpreted using permutation-based feature importance and Shapley additive explanation values. Permutation importance assessed the reduction in predictive performance produced by randomly rearranging each predictor while holding the other variables constant. Shapley additive explanations were used to estimate the contribution of each predictor to the predicted quality-of-life score for both the entire sample and individual participants. Positive Shapley values indicated that a variable increased the predicted quality-of-life score, whereas negative values indicated that it reduced the predicted score. Summary and dependence analyses were used to determine the relative importance, direction, and possible nonlinear effects of family cohesion, work–family conflict, cognitive reappraisal, and expressive suppression. Partial dependence analyses were additionally conducted for the most influential predictors to examine whether their associations with predicted quality of life were linear, nonlinear, or characterized by threshold effects. All conventional statistical tests were evaluated using a two-sided significance level of .05, while model selection was based primarily on out-of-sample predictive performance rather than statistical significance alone.

3. Findings and Results

The final analytical sample consisted of 420 married and employed adults residing in Tehran. Participants included 213 women (50.7%) and 207 men (49.3%). Their ages ranged from 22 to 59 years, with a mean age of 38.27 years and a standard deviation of 7.91 years. Regarding educational attainment, 64 participants (15.2%) had a high-school diploma or lower qualification, 51 participants (12.1%) held an associate degree, 188 participants (44.8%) held a bachelor’s degree, 96 participants (22.9%) held a master’s degree, and 21 participants (5.0%) held a doctoral degree. In terms of occupational sector, 158 participants (37.6%) were employed in public-sector organizations, 191 participants (45.5%) worked in private-sector organizations, and 71 participants (16.9%) were self-employed. The participants reported an average of 43.68 working hours per week, with a standard deviation of 8.74 hours. The duration of marriage ranged from 1 to 36 years, with a mean of 12.46 years and a standard deviation of 8.13 years. Eighty-four participants (20.0%) had no children, 136 participants (32.4%) had one child, 157 participants (37.4%) had two children, and 43 participants (10.2%) had three or more children. A total of 278 participants (66.2%) belonged to dual-earner families in which both spouses were employed, whereas 142 participants (33.8%) were the only employed spouse or had a spouse who was not employed at the time of the study. Regarding perceived economic status, 92 participants (21.9%) described their household economic condition as below average, 244 participants (58.1%) described it as average, and 84 participants (20.0%) described it as above average. Geographical representation was maintained across Tehran, with 79 participants (18.8%) recruited from northern districts, 89 participants (21.2%) from southern districts, 86 participants (20.5%) from eastern districts, 82 participants (19.5%) from western districts, and 84 participants (20.0%) from central districts.

Preliminary screening indicated that the retained dataset contained no impossible values or duplicate records. The proportion of missing values for individual variables was below 2.0%, and the remaining missing observations were imputed within the training pipeline without using information from the test dataset. Examination of standardized values and response distributions did not reveal influential data-entry errors. Several participants had relatively high or low scores on the study variables; however, these values were retained because they fell within the theoretically possible ranges of the instruments and represented plausible individual differences. Skewness and kurtosis coefficients were within acceptable limits for all principal variables. Variance inflation factor values ranged from 1.18 to 2.41, indicating that multicollinearity was not sufficiently high to compromise conventional analyses or machine learning model estimation. The training dataset contained 336 participants, and the independent test dataset contained 84 participants. Comparisons between the two subsets showed no statistically significant differences in age, sex distribution, quality of life, family cohesion, work–family conflict, cognitive reappraisal, or expressive suppression, demonstrating that the random partitioning procedure produced comparable training and test samples.

Table 1

Descriptive Statistics, Reliability Coefficients, and Correlations Among the Principal Study Variables

Var.	Mean	SD	Minimum	Maximum	Skewness	Kurtosis	Cronbach's α	McDonald's ω	1	2	3	4	5
1	66.84	11.72	32.50	94.25	−0.21	−0.35	.91	.92	—				
2	36.91	6.48	16.00	50.00	−0.32	−0.18	.88	.89	.58**	—			
3	48.63	12.07	20.00	82.00	0.17	−0.44	.93	.93	−.56**	−.41**	—		
4	29.74	6.31	11.00	42.00	−0.28	−0.21	.86	.87	.43**	.32**	−.26**	—	
5	15.88	5.21	4.00	28.00	0.23	−0.36	.79	.80	−.29**	−.18**	.30**	−.12*	—

1. Quality of life; 2. Family cohesion; 3. Work–family conflict; 4. Cognitive reappraisal; 5. Expressive suppression

As presented in Table 1, participants reported a moderate-to-high average level of quality of life, although the observed range demonstrated substantial individual variation. Family cohesion scores were also generally above the midpoint of the scale, suggesting that most participants perceived a relatively connected and supportive family environment. The mean work–family conflict score was close to the scale midpoint, indicating that incompatibility between work and family responsibilities was common but varied considerably across participants. Cognitive reappraisal was used more frequently than expressive suppression. All scales demonstrated acceptable to excellent internal consistency, with Cronbach's alpha coefficients ranging from .79 to .93 and McDonald's omega coefficients ranging from .80 to .93. Quality of life was positively and strongly correlated with family cohesion, indicating that participants who experienced greater emotional closeness, shared involvement, and support within their families tended to report better quality of life. Quality of life was negatively and strongly correlated with work–family conflict, demonstrating that greater interference between occupational and family responsibilities was associated with lower physical, psychological, social, and environmental well-being. Cognitive reappraisal showed a moderate positive correlation with quality of life, whereas expressive suppression showed a smaller but statistically significant negative correlation with quality of life. Family cohesion was negatively associated with work–family conflict and expressive suppression and positively associated with cognitive reappraisal. Work–family conflict was negatively related to cognitive reappraisal and positively related to expressive suppression. Although these correlations established meaningful bivariate relationships, none approached a level suggestive of predictor redundancy, supporting the simultaneous inclusion of the variables in the predictive models.

Table 2

Cross-Validated and Independent Test-Set Performance of the Machine Learning Models

Model	Cross-Validated R^2, Mean (SD)	Cross-Validated RMSE	Cross-Validated MAE	Test R^2	Test RMSE	Test MAE
Elastic net regression	.47 (.05)	8.48	6.75	.46	8.61	6.84
Support vector regression	.54 (.04)	7.94	6.18	.53	8.04	6.24
Random forest regression	.56 (.04)	7.77	6.00	.55	7.86	6.04
Gradient boosting regression	.58 (.04)	7.59	5.84	.58	7.59	5.88
Extreme gradient boosting	.61 (.03)	7.31	5.61	.61	7.32	5.67
Multilayer perceptron	.55 (.06)	7.86	6.05	.52	8.12	6.30

Table 2 compares the predictive performance of the six supervised regression algorithms. All nonlinear models outperformed elastic net regression, indicating that the relationships between the predictors and quality of life were not entirely linear and additive. Elastic net regression explained 46% of the variance in quality of life in the independent test dataset and produced an RMSE of 8.61 and an MAE of 6.84. Support vector regression improved test-set performance to an R^2 of .53, while random forest regression explained 55% of the variance. Gradient boosting regression achieved a test R^2 of .58 and reduced the typical absolute prediction error to 5.88 quality-of-life points. Extreme gradient boosting demonstrated the best overall performance, explaining 61% of the variance in quality of life in the independent test sample. Its RMSE of 7.32 indicated that the square root of the average squared prediction error was slightly more than seven points on the 0-to-100 quality-of-life scale, whereas its MAE of 5.67 indicated that the average absolute difference between observed and predicted scores was fewer than six points. The close agreement between the cross-validated performance and independent test performance of the extreme gradient boosting model suggested good generalizability and limited overfitting. By contrast, the multilayer perceptron showed somewhat greater variability across validation folds and a reduction from the cross-validated R^2 of .55 to the test R^2 of .52, suggesting that the available sample size did not provide a consistent advantage for the neural-network architecture. The optimized extreme gradient boosting model used 420 estimators, a maximum tree depth of 3, a learning rate of .035, a subsampling ratio of .85, a predictor-column sampling ratio of .80, a minimum child weight of 3, an L1 regularization parameter of .05, and an L2 regularization parameter of 1.20. This relatively shallow, regularized architecture enabled the model to capture nonlinearities and interactions while limiting unnecessary complexity.

Table 3

Incremental and Ablation Analysis of Predictor Configurations Using Extreme Gradient Boosting

Predictor Configuration	Test R^2	Test RMSE	Test MAE	Change in R^2 Relative to Full Model
Demographic and occupational variables only	.16	10.74	8.52	−.45
Family cohesion only	.34	9.51	7.47	−.27
Work–family conflict dimensions only	.36	9.37	7.34	−.25
Emotion-regulation strategies only	.23	10.28	8.05	−.38
Primary theoretical predictors	.57	7.69	6.01	−.04
Full expanded predictor set	.61	7.32	5.67	—
Full model excluding family cohesion	.48	8.45	6.67	−.13
Full model excluding work–family conflict dimensions	.50	8.29	6.53	−.11
Full model excluding emotion-regulation variables	.56	7.78	6.08	−.05
Full model excluding demographic and occupational variables	.59	7.50	5.81	−.02

The incremental and ablation results presented in Table 3 clarified the relative predictive contribution of different variable groups. Demographic and occupational variables alone explained only 16% of the variance in quality of life, demonstrating that background characteristics were insufficient for accurate prediction when used without family and psychological variables. Family cohesion alone explained 34% of the variance, and the six dimensions of work–family conflict alone explained 36%, identifying both constructs as substantial independent predictors. Emotion-regulation strategies alone explained 23% of the variance. When the four principal theoretical variables were entered together, predictive accuracy increased markedly, with the model explaining 57% of the variance and producing an MAE of 6.01. Adding detailed work–family conflict dimensions and demographic and occupational information increased the explained variance from 57% to 61%, indicating a modest but meaningful incremental improvement. The ablation analyses further demonstrated that removing family cohesion from the full model produced the largest decline in performance, reducing the test R^2 from .61 to .48. Removing the work–family conflict dimensions reduced the R^2 to .50, whereas excluding cognitive reappraisal and expressive suppression reduced it to .56. Removing demographic and occupational variables produced only a small decline from .61 to .59. These findings indicate that family cohesion and work–family conflict carried the greatest predictive information, while emotion-regulation strategies made an additional contribution beyond family and occupational conditions. Demographic variables improved prediction slightly but did not account for the central predictive capacity of the model. The difference between the family-cohesion-only and full-model performance also showed that strong family cohesion could not completely offset the adverse predictive influence of occupational-family interference, emotion-regulation patterns, and socioeconomic conditions.

Table 4

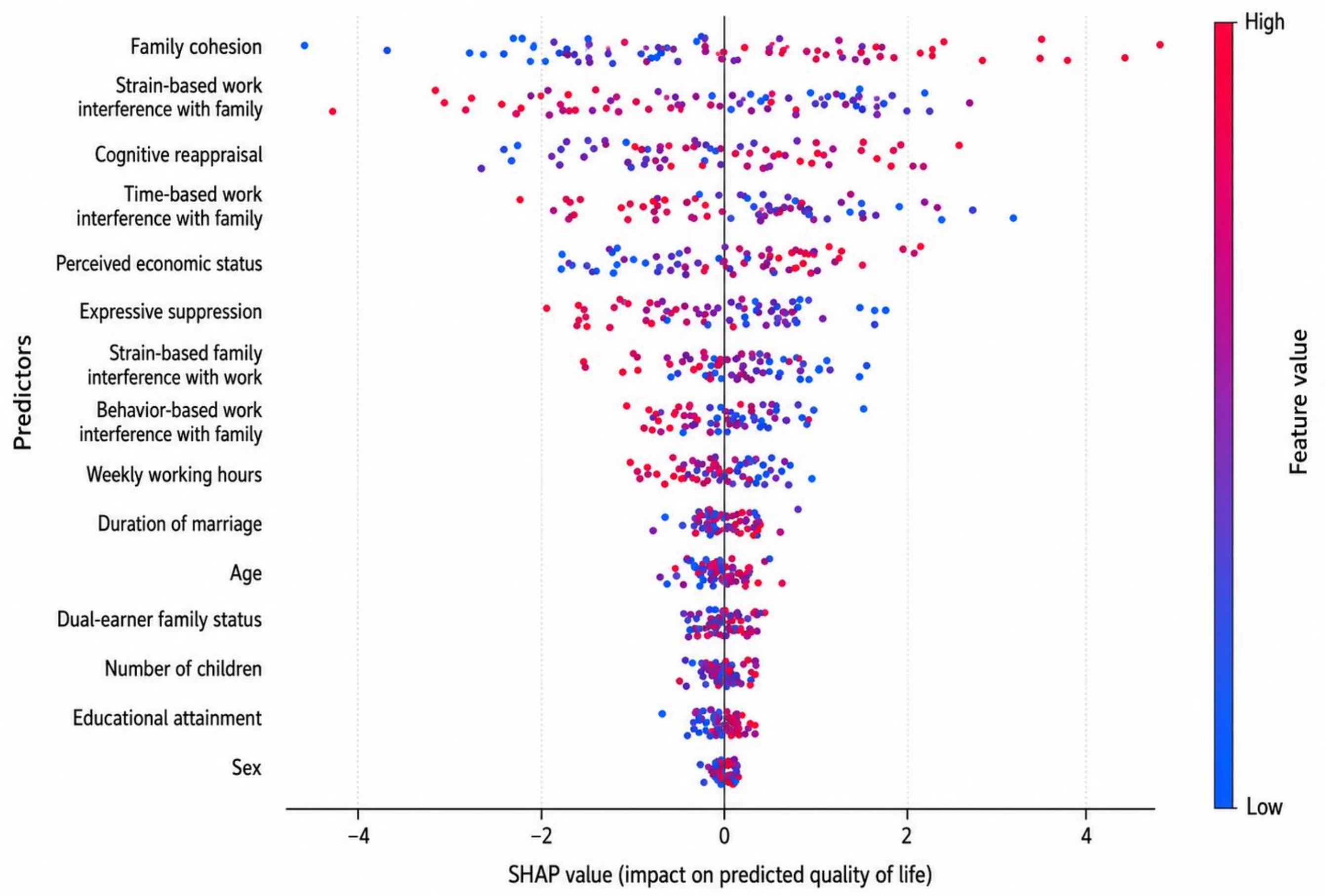
Permutation Importance and Mean Absolute SHAP Values for the Best-Performing Model

Predictor	Increase in RMSE After Permutation	Mean Absolute SHAP Value	Predominant Direction of Association With Predicted Quality of Life	Importance Rank
Family cohesion	2.18	3.46	Positive	1
Strain-based work interference with family	1.87	2.87	Negative	2
Cognitive reappraisal	1.42	2.21	Positive	3
Time-based work interference with family	1.25	1.94	Negative	4
Perceived economic status	1.01	1.61	Positive	5
Expressive suppression	0.86	1.37	Negative	6
Strain-based family interference with work	0.78	1.24	Negative	7
Behavior-based work interference with family	0.62	1.03	Negative	8
Weekly working hours	0.49	0.74	Predominantly negative	9
Duration of marriage	0.42	0.68	Nonlinear	10
Age	0.37	0.61	Nonlinear	11
Dual-earner family status	0.31	0.52	Context-dependent	12
Number of children	0.25	0.44	Context-dependent	13
Educational attainment	0.21	0.38	Predominantly positive	14
Sex	0.09	0.17	Minimal	15

As shown in Table 4, family cohesion was the most influential predictor according to both model-interpretation methods. Randomly permuting family cohesion increased the test RMSE by 2.18 points, and its mean absolute SHAP value indicated that it changed individual quality-of-life predictions by an average of 3.46 points. Higher family cohesion generally shifted predicted quality of life upward, whereas low cohesion shifted predictions downward. Strain-based work interference with family was the second most influential predictor and demonstrated a consistently negative association with predicted quality of life. Participants who reported that occupational tension, exhaustion, or stress interfered with their family roles received substantially lower predicted quality-of-life scores. Cognitive reappraisal ranked third and generally increased predicted quality of life, particularly among participants reporting moderate or high use of reinterpretation when responding to emotionally demanding circumstances. Time-based work interference with family was the fourth most influential predictor, showing that insufficient time for family activities because of occupational demands was associated with lower predictions. Perceived economic status also contributed meaningfully, although its importance was lower than that of family cohesion, work-related strain, and cognitive reappraisal. Expressive suppression shifted predictions downward, especially when high suppression occurred together with elevated work–family conflict. Strain-based family interference with work and behavior-based work interference with family also made independent negative contributions. Weekly working hours had a predominantly negative influence, but this association was weaker than participants' subjective experiences of time-based and strain-based conflict, suggesting that the psychological interference between roles was more informative than the number of working hours alone. Age and marriage duration showed nonlinear rather than uniformly positive or negative patterns. Sex had minimal predictive importance after the family, occupational, emotional, and socioeconomic variables were considered, indicating that the final model's predictions were not primarily determined by whether a participant was male or female.

Figure 1

SHAP Summary Plot Showing the Direction and Magnitude of Predictor Contributions to Quality-of-Life Predictions



The SHAP summary pattern demonstrated substantial heterogeneity in the contribution of individual predictors across participants. High family-cohesion scores were concentrated on the positive side of the SHAP distribution, meaning that stronger emotional bonding and family connectedness consistently increased predicted quality-of-life scores. The effect was nonlinear: improvements in cohesion from low to moderate levels produced relatively large positive shifts, whereas increases among participants who already reported very high cohesion produced smaller additional gains. This pattern suggested diminishing predictive returns at the upper end of the cohesion scale. High strain-based and time-based work interference with family were concentrated on the negative side of the distribution. The negative influence became especially pronounced when strain-based work interference scores exceeded approximately one standard deviation above the sample mean. Cognitive reappraisal displayed an opposite pattern, with higher scores generally producing positive SHAP values. However, its beneficial predictive contribution was most evident when work–family conflict was low or moderate. Under conditions of very high occupational-family strain, cognitive reappraisal remained positively associated with prediction but did not entirely neutralize the negative contribution of work–family conflict.

The SHAP interaction patterns also indicated that the predictors did not operate independently. Low family cohesion intensified the negative contribution of strain-based work interference with family, whereas high cohesion partially reduced the magnitude of this adverse effect. Participants with both low cohesion and high strain-based work interference received the lowest predicted quality-of-life scores in the sample. Conversely, participants with high cohesion, high cognitive reappraisal, and low work–family conflict received the highest predictions. Expressive suppression had a modest negative contribution at low and moderate levels but became more strongly negative at high levels, particularly among participants who simultaneously reported limited family cohesion. Perceived economic status primarily influenced environmental and physical aspects of the predicted outcome, but its contribution remained smaller than the combined influence of relational and occupational variables. Overall, the SHAP distribution supported the conclusion that quality of life was best predicted through an integrated pattern involving supportive family relationships, manageable boundaries between work and family roles, and adaptive regulation of emotional experiences rather than through any single demographic characteristic.

To further evaluate the accuracy of the selected model, observed and predicted quality-of-life scores were examined across the independent test sample. Predictions were closely aligned with observed values throughout the middle and upper portions of the quality-of-life distribution. Errors were somewhat larger for a limited number of participants with exceptionally low quality-of-life scores, indicating that the model showed mild regression toward the sample mean at the lower extreme. The mean prediction residual was close to zero, and visual examination of residuals did not indicate a systematic tendency to overpredict or underpredict across most of the outcome range. Residual dispersion was generally stable, although slightly greater variability was observed among participants with quality-of-life scores below 45. The bootstrap 95% confidence interval for the selected model's test R^2 ranged from .48 to .70, the confidence interval for RMSE ranged from 6.41 to 8.29, and the confidence interval for MAE ranged from 4.89 to 6.43. These intervals indicated that the model's predictive advantage was robust despite the comparatively limited size of the independent test sample.

Taken together, the findings demonstrated that quality of life among married adults could be predicted with substantial accuracy from family cohesion, work–family conflict, and emotion-regulation strategies. Family cohesion emerged as the most important positive predictor, while strain-based and time-based interference of work with family were the most influential negative predictors. Cognitive reappraisal contributed positively to prediction, whereas expressive suppression contributed negatively. The superior performance of the extreme gradient boosting model relative to elastic net regression indicated the presence of nonlinear effects and interactions. Nevertheless, the strong performance of the primary four-predictor configuration showed that a relatively parsimonious model based on the central theoretical variables retained most of the predictive capacity of the expanded model. The final model explained 61% of the variance in previously unseen quality-of-life scores, supporting the usefulness of machine learning for integrating family, occupational, and emotional factors in the prediction of well-being among married adults.

4. Discussion

The present study examined the predictive contribution of family cohesion, work–family conflict, and emotion regulation to quality of life among married adults in Tehran through a comparative machine learning framework. The findings showed that the selected extreme gradient boosting model provided the most accurate out-of-sample predictions and explained 61% of the variance in quality of life. This performance exceeded that of elastic net regression, support vector regression, random forest regression, gradient boosting regression, and the multilayer perceptron model. The superiority of the nonlinear boosting model indicated that quality of life was not determined by a simple additive combination of family, occupational, and emotional variables. Instead, the predictors appeared to operate through nonlinear associations, threshold effects, and interactions. Family cohesion emerged as the most influential positive predictor, whereas strain-based and time-based work interference with family were the most influential negative predictors. Cognitive reappraisal contributed positively to quality-of-life predictions, while expressive suppression contributed negatively. Demographic and occupational variables produced only a limited incremental improvement after the main relational and psychological variables had been entered. Overall, the findings suggest that the quality of life of married adults is primarily associated with the emotional functioning of the family, the extent to which work pressures intrude upon family life, and the strategies individuals use to manage emotional experiences.

The most important finding was the strong positive contribution of family cohesion to quality of life. Participants who reported greater emotional closeness, mutual support, shared involvement, and a stronger sense of family belonging were predicted to have higher quality-of-life scores. Family cohesion was not only the highest-ranking predictor in the final model but was also the variable whose removal caused the largest decline in predictive performance. This finding can be explained through the protective function of cohesive family systems. When family members perceive that they are emotionally connected and can rely on one another, stressful experiences may be interpreted as shared challenges rather than isolated personal burdens. Family cohesion may therefore support psychological security, reduce loneliness, facilitate cooperative problem solving, and increase the availability of emotional and instrumental support. The finding is consistent with evidence showing that constructive parent–child interactions are related to self-management and emotional self-regulation, suggesting that supportive family environments foster reciprocal adaptation and psychological competence (Ghasemi Tousi, 2025). It is also aligned with research indicating that mothers' mindfulness and self-efficacy are associated with more positive parent–child interactions, particularly during periods of disruption and home confinement (Hashemi et al., 2022). The role of parents in managing children's educational and developmental difficulties during virtual learning further demonstrates that coordinated, responsive, and cohesive family functioning can protect members against environmental stressors (Amirkhani Dehkordi et al., 2024).

The positive association between cohesion and quality of life may also be understood in relation to the cumulative effects of family interaction over time. Longitudinal research has shown that hostile child–parent conflict in late adolescence is associated with earlier maternal, child, and family factors, indicating that relational patterns develop gradually and may have enduring consequences for family well-being (Harries et al., 2025). Similarly, parent–child conflict has been found to follow distinct developmental patterns from adolescence into young adulthood, emphasizing that family relationships continue to influence adjustment beyond childhood (Son et al., 2024). In the current study, high family cohesion appeared to increase quality-of-life predictions most strongly among individuals with low or moderate initial cohesion, whereas additional increases at very high levels produced smaller gains. This nonlinear pattern suggests that moving from emotional disconnection to adequate family support may be more consequential than moving from already-high cohesion to exceptionally high cohesion. In practical terms, the absence of cohesion may represent a substantial vulnerability, while a sufficient level of connectedness may provide a stabilizing foundation for adult well-being.

The second major finding was that work–family conflict, particularly strain-based and time-based work interference with family, substantially reduced predicted quality of life. Strain-based interference was the second most important predictor in the final model, demonstrating that fatigue, tension, and emotional pressure originating in the workplace may be especially harmful when carried into family life. Time-based interference also had a pronounced negative contribution, suggesting that quality of life declines when employment restricts opportunities for family involvement, rest, leisure, and marital interaction. These results correspond with findings showing that work–family conflict is associated with lower mindful parenting through increased emotional distress and parenting stress (Moreira et al., 2019). When occupational strain depletes emotional resources, married adults may have less patience, attention, and psychological availability for their spouses and children. Consequently, the effect of work–family conflict may extend beyond job dissatisfaction and contribute to conflict, withdrawal, reduced intimacy, and poorer functioning across multiple life domains.

The importance of work–family conflict can also be interpreted through the organization of everyday family routines. Research conducted during periods of school suspension showed that children's daily routines mediated the association between parent–child relationships and adjustment problems, illustrating the importance of predictable family organization for psychological adaptation (Wu et al., 2025). Disrupted routines and increased parent–child conflict were similarly associated with psychological maladjustment during the COVID-19 pandemic (Liu et al., 2021). Although these studies focused on children, they illuminate the burden placed on married adults who must coordinate employment, caregiving, household management, and educational responsibilities. When work demands disrupt family routines, adults may experience reduced control over time, more frequent interpersonal tension, and fewer opportunities for psychological recovery. The present finding that subjective work–family interference was more influential than weekly working hours alone is especially important. It suggests that the harmful effect of employment is not determined merely by the number of hours worked but by whether those hours and associated pressures are experienced as incompatible with family responsibilities.

The negative role of work–family conflict may also be intensified by conflict within the broader family environment. Parental conflict and parenting styles have been associated with behavioral problems in preschool children through the mediating role of anxiety, demonstrating how tension within the family system may be transmitted across relationships (Tabe Bordbar & Koraei, 2025). Likewise, parenting stress and social stigma have been linked to less favorable parent–child interactions among mothers of children with autism (Nikbakht & Haghaegh, 2020). A systematic review and meta-analysis further identified elevated parenting stress across different clinical groups, confirming that persistent caregiving and relational demands can undermine family functioning (Barroso et al., 2018). These findings help explain why strain-based work interference was a particularly powerful predictor in the present study. Occupational stress may combine with preexisting family demands, producing cumulative emotional overload that affects psychological health, interpersonal satisfaction, and environmental quality of life.

The third principal finding concerned emotion regulation. Cognitive reappraisal increased predicted quality of life, whereas expressive suppression reduced it. Cognitive reappraisal involves altering the interpretation of an emotionally demanding event before the emotional reaction becomes fully established. This strategy may help married adults interpret disagreements, occupational pressure, and family obligations in more flexible and less threatening ways. Reappraisal may also facilitate constructive communication by reducing impulsive reactions and allowing individuals to consider the intentions and needs of other family members. In contrast, expressive suppression involves inhibiting the visible expression of emotion after it has already been activated. Although suppression may temporarily prevent open confrontation, its repeated use may increase internal tension, reduce emotional authenticity, and limit the communication of needs within intimate relationships. The present results are consistent with evidence that difficulties in emotion regulation and negative automatic thoughts are associated with maladaptive conflict-resolution tactics between adolescents and parents (Hosseini et al., 2018). They also accord with research showing that parental mindfulness is associated with parenting behavior and child psychopathology, suggesting that emotional awareness and nonreactivity support healthier family interactions (Han et al., 2021).

The positive predictive effect of cognitive reappraisal is also compatible with evidence from mindfulness-based parenting studies. Mindfulness interventions for parents have been shown to reduce parenting stress and improve psychological outcomes, indicating that the capacity to observe emotional experiences without immediate reaction can strengthen family adaptation (Bergdorf et al., 2019). Mindfulness-based parenting training has reduced anxiety and parent–child conflict while increasing parenting self-efficacy among mothers of children with attention-deficit/hyperactivity disorder (Sharifi Rigi et al., 2018). Similar programs have improved parent–child relationship quality and reduced parenting stress among parents of preschool children in Tehran (Hosseini Sahi, 2024), and have decreased parenting stress among mothers of children with hearing loss (Kabirifard et al., 2024). Mindful parenting education has also improved parent–child relationships and reduced both parenting stress and loneliness (Attar et al., 2023). These findings support the interpretation that adaptive regulation contributes to quality of life by helping adults remain emotionally available and behaviorally flexible in stressful family situations.

Nevertheless, the current results also indicated that emotion regulation did not operate independently of family and occupational conditions. Cognitive reappraisal had a positive contribution, but it did not completely eliminate the negative influence of very high work–family conflict. This finding suggests that adaptive regulation may buffer stress without fully compensating for chronic structural pressures. A diary study similarly demonstrated that mindful parenting can function as both a buffer and a sensitizer in the association between parent–child conflict and parental stress, showing that greater awareness does not necessarily remove the effects of relational difficulty under all circumstances (Fang et al., 2026). Mindful parenting has also been associated with recurrent conflict and adolescents' internalizing and externalizing problems, indicating that emotional awareness may influence how conflict develops and is maintained within families (Park, 2020). During the pandemic, mindful parenting mediated the association between mothers' perceived stress and child adjustment, suggesting that adult stress influences family outcomes partly through changes in emotional availability and parenting behavior (Cheung & Chao, 2022). Among new mothers, positive mental health was associated with mindful parenting through parenting stress, further supporting the interdependence of adult well-being, emotional regulation, and family interaction (Oliveira et al., 2024).

The model also showed that high family cohesion partially reduced the negative contribution of work–family conflict. Participants with low cohesion and high strain-based interference received the lowest quality-of-life predictions, whereas those with high cohesion, high cognitive reappraisal, and low work–family conflict received the highest predictions. This interaction is theoretically meaningful because it demonstrates that family support may moderate the psychological consequences of occupational pressure. A cohesive family may provide opportunities for shared problem solving, redistribution of responsibilities, emotional validation, and recovery from workplace stress. However, cohesion may become less protective when occupational strain is severe and persistent. Findings from families managing chronic health conditions similarly show that parental stress, anxiety, and mindfulness are associated with routine parent–child interactions, suggesting that relational quality reflects the combined influence of situational demands and psychological resources (Van Gampelaere et al., 2020). Trauma-informed parenting interventions have also improved parental interaction skills in adoptive families, indicating that relational patterns remain modifiable even under conditions of previous adversity (Parchami & Bahramipour, 2025). Therefore, the present results support an integrated explanation in which quality of life is maximized when relational support, manageable role demands, and adaptive emotional regulation occur together.

5. Conclusion

The relatively small contribution of demographic variables is another noteworthy result. Age, sex, education, number of children, marriage duration, weekly working hours, and dual-earner status added only a limited amount of predictive accuracy after the central family and psychological variables were considered. Perceived economic status was more influential than most other background characteristics, but it remained less important than family cohesion, work-related strain, and cognitive reappraisal. This pattern suggests that the subjective and relational quality of adults' experiences may be more important than demographic status alone. Two individuals with similar work hours, educational levels, or family sizes may have very different levels of quality of life depending on whether family relationships are supportive, occupational demands are experienced as intrusive, and emotional responses are managed adaptively. The superiority of extreme gradient boosting over linear regression further indicated that these differences are best understood as configurations of interacting factors rather than isolated main effects.

6. Limitations & Suggestions

A principal limitation of this study was its cross-sectional design, which prevented causal conclusions regarding the direction of the relationships. Higher family cohesion may contribute to better quality of life, but individuals with better psychological functioning may also perceive their families more positively and manage work–family demands more effectively. The study relied on self-report instruments, which may have been influenced by social desirability, common-method variance, memory errors, or culturally shaped response tendencies. Participants were married, employed adults residing in Tehran, and the findings may not generalize to unemployed individuals, rural populations, unmarried adults, separated couples, or families from other cultural and economic contexts. Although the sample was sufficient for the selected models, the independent test set was relatively limited, which may have widened the uncertainty around performance estimates. The study also did not include potentially important variables such as marital satisfaction, organizational support, occupational control, personality traits, physical health, caregiving burden, or the spouse's assessment of family functioning.

Future research should employ longitudinal and prospective designs to determine whether changes in family cohesion, work–family conflict, and emotion regulation predict subsequent changes in quality of life. Larger multisite samples should be recruited from different cities, occupational groups, socioeconomic levels, and cultural contexts to test the transportability of the model. Dyadic studies incorporating data from both spouses would make it possible to examine actor and partner effects and determine whether one partner's occupational stress or emotion regulation influences the other partner's quality of life. Future studies should compare additional algorithms, conduct external validation in independent populations, and evaluate model calibration and fairness across demographic subgroups. Incorporating objective indicators such as working schedules, sleep duration, physiological stress, and digital measures of daily routines may reduce reliance on self-report data. Experimental studies could also examine whether interventions that strengthen family cohesion, reduce work–family conflict, or improve cognitive reappraisal lead to measurable improvements in quality of life and corresponding changes in model-generated risk estimates.

In practice, family counselors, psychologists, workplace health professionals, and organizational managers should assess quality of life through an integrated framework that considers family relationships, occupational-family interference, and emotional regulation. Screening programs should give particular attention to adults who simultaneously report low family cohesion, high strain-based work interference, and frequent expressive suppression, as this configuration may indicate increased vulnerability. Couple- and family-based interventions should strengthen emotional support, shared decision making, communication, and equitable distribution of responsibilities. Emotion-regulation training should emphasize cognitive reappraisal, emotional awareness, constructive expression, and reduction of rigid suppression. Employers can contribute by promoting flexible scheduling, manageable workloads, predictable working hours, access to family-supportive supervision, and policies that reduce the transfer of occupational strain into home life. Machine learning models may be used as supplementary decision-support tools for identifying risk profiles, but their outputs should be interpreted by qualified professionals and should not replace individualized clinical or organizational assessment.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contributed to this article.

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