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Quality of life, resilience, marital adjustment, and satisfaction with life in assessing pregnancy risk among rural and agricultural communities

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Abstract

Pregnancy is a critical period marked by significant physiological and psychological changes that influence both maternal and fetal outcomes. Traditional risk assessments prioritize physical and obstetric factors such as maternal age and gestational complications. However, recent research highlights the growing importance of psychological well-being in pregnancy outcomes. This study focuses on analyzing the significance of variables, *viz.* Quality of life (QOL), satisfaction with life (SWL), marital adjustment (MAT), and Resilience, among high-risk and low-risk pregnant women. Logistic and probit regression models were used to explain the variability in binary outcomes (high-risk vs. low-risk pregnancies). McFadden's pseudo R^2 and the marginal effects of each psychological variable were calculated to assess their influence on the likelihood of being in the high-risk group. Both models identified quality of life as the most significant factor in reducing the likelihood of high-risk pregnancy, followed by marital adjustment, resilience, and satisfaction with life. McFadden's pseudo R^2 values of 0.7828 (logistic) and 0.7704 (probit) indicate a strong model fit and significant improvement over the null model.

The findings underscore the importance of incorporating psychological well-being, particularly quality of life, resilience, and marital adjustment, into standard prenatal care. By integrating these factors into pregnancy risk assessments, healthcare providers can better identify high-risk pregnancies and implement targeted interventions to improve outcomes for both mothers and babies.

Keywords: High-risk pregnancy, Low-risk pregnancy, marital adjustment, quality of life, satisfaction with life, resilience, logistic and probit regression

1. Introduction

Pregnancy is defined by the International Classification of Diseases as a delivery occurring between 37 weeks and 0 days and between 41 weeks and 6 days [1]. A high-risk pregnancy refers to any unexpected or potentially hazardous medical condition that poses risks to the health of both the mother and fetus during pregnancy, childbirth, and delivery. The National Institute of Health and Clinical Excellence (NICE) classifies low-risk pregnancies on the basis of the absence of certain risk factors associated with obstetric history, maternal health, and potential complications that may arise during pregnancy [2]. The majority of pregnancies are deemed low risk, indicating an absence of active complications and no maternal or fetal factors that increase the risk of complications.

Marital adjustment (MAT) refers to the level of satisfaction and happiness experienced by couples within their marriage. Various factors influence the marital adjustment of couples, including their age, length of marriage, communication patterns, ability to meet each other's needs and expectations, shared decision-making, interactions with family members, agreement on leisure activities, and management of the family budget [3].

According to the American Psychological Association (APA), Quality of life (QOL) is the extent to which an individual is satisfied with their life. A high quality of life is dependent on a number of factors, including physical, mental, and emotional health; engagement in social interactions; opportunities for personal (such as skill) development; exercising rights and making independent lifestyle decisions; and involvement in society.

A person's overall appraisal of their quality of life on the basis of a cognitive evaluation is known as Satisfaction with Life (SWL). The life satisfaction component of subjective well-being is measured by SWL. According to the APA, Resilience (RES) is defined as the process and result of effectively coping with challenging or difficult situations in life, especially through behavioral, emotional, and mental flexibility and adaptability to demands from the inside as well as the outside of the body.

Pregnancy is a pivotal period marked by significant physiological and psychological changes that can affect both maternal and fetal health. Traditional pregnancy risk assessments tend to focus on physical and obstetric factors, such as maternal age, preexisting medical conditions, and pregnancy complications. However, increasing evidence underscores the crucial role of psychological well-being in shaping pregnancy outcomes. Studies have shown that factors such as stress, depression, anxiety, and diminished quality of life are linked to adverse maternal outcomes, including preterm labour, low birth weight, and postpartum depression. The increasing importance of psychological variables in determining the health conditions of pregnant women and fetuses has been studied by many researchers. Women who experienced lower levels of satisfaction with life had a greater risk of experiencing preterm birth [4]. The QOL of pregnant women is possibly linked to the incidence of low birthweight and preterm deliveries [5]. Enhancing MAT could serve as a means to encourage women to become familiar with the role of parenthood [6]. Women with low resilience are more likely to deliver low-birth-weight infants [7]. Resilience in women during pregnancy prevents complications and fosters a positive pregnancy experience [8]. As such in this study four variables, namely, quality of life (QOL), Resilience (RES), Satisfaction with Life (SWL) and Marital adjustment (MAT) are considered to study the effects of these variables on women with high- and low-risk pregnancies. Therefore, in this study, the independent variables are QOL, RES, SWL and MAT, and the dependent variables are binary in nature (high-risk and low-risk pregnancies). Regression models: Logistic and probit models were fitted to the data obtained from pregnant women admitted to the Department of Obstetrics and Gynecology, JSS Hospital Mysore, to understand how the considered variable influences pregnancy risk, and feature extraction was performed to understand the variation in the dependent variable.

2. Methodology

2.1. Data collection: Data were collected from women with high-risk and low-risk pregnancies at the Department of Obstetrics and Gynecology at JSS Hospital, Mysore, between March and June 2024. After the pregnant woman provided consent, questionnaires were given, and some qualitative interviews were performed to extract more relevant information.

Sample size: Since the prevalence rate of high-risk pregnancies is not known, the P value is assumed to be 0.5, and at the 5% level of significance, the z table value is 1.96, and the error is 0.05. Therefore, the sample size, $n = \frac{Z_{\alpha} * P(1-P)}{\epsilon^2}$, is 196. However, between the given time periods, the total sample collected from the hospital was 154; hence, 154 sample units were used for the analysis.

Operational definition of high-risk pregnancy

In this study, a high-risk pregnancy is operationally defined as one that poses potential dangers to the mother or fetus and generally requires specialized care from trained professionals. Risk factors include high blood pressure; gestational diabetes; antepartum hemorrhage; teenage or advanced maternal age (35+); multiple pregnancies; chronic diseases (e.g., asthma, epilepsy, tuberculosis, hypertension, and cardiac disorders); thyroid disorders; and recurrent pregnancy loss.

The inclusion criteria for women were high-risk pregnancies and low-risk pregnancies at JSS Hospital, Mysore.

The exclusion criteria were pregnant women who were experiencing chronic medical conditions and pregnant women who were diagnosed with severe psychological conditions (mania/psychosis).

Measurement scales used in the study

- **Marital Adjustment Scale (MAT):** Developed by Wallace, K. M. and Locke, H. J. (1959) [9], this scale measures the level of marital satisfaction and adjustment.
- **Quality of Life Scale (QOLS):** Designed by Carol S. Burakhardt [10], this scale evaluates the overall quality of life across multiple dimensions.
- **Satisfaction with Life Scale (SWLS):** Created by Diener, E., Emmons, R. A., Larsen, R. J., and Griffin (1985) [11], this scale measures general life satisfaction.
- **Bharathiar University Resilience Scale:** Developed by Annalakshmi N (2009) [12], this scale assesses an individual's resilience, or the ability to cope with stress and adversity.

Statistical models used

Logistic regression model: A logistic regression model was selected because logistic regression models are designed to capture nonlinear relationships between independent variables and the probability of a binary outcome, making them a suitable choice for many datasets with binary outcomes.

The fitted logistic model is given as

Pregnancy risk ~ MAT+SWL+QOL+RES+Ɛ

Probit regression model: Probit models are specifically designed to handle binary dependent variables. Probit models assume a nonlinear relationship between the independent variables and the probability of the outcome. This is often more realistic than assuming a linear relationship, as it allows for situations where small changes in independent variables can lead to large changes in the probability of the outcome. Therefore, a probit regression model is fitted to the collected data.

The fitted probit model is given as

Pregnancy risk ~MAT+SWL+QOL+RES

Other tests used are, Network structure analysis, correlation analysis and Shapiro wilk test for checking normality of the data. All the analysis was done using R software.

3. Results

3.1 Dataset Overview

The dataset used in this study consists of psychological metrics collected from pregnant women. The dataset contains both predictor variables and a binary target variable representing pregnancy risk**.** The total number of data points is 154, of which 77 are high-risk pregnant women and 77 are low-risk pregnant women. The following network structure provides information about the participants who are in the high-risk and low-risk categories. In Fig.1, the numbers originating from the central node refer to the serial number given to the participants while the data are collected.

Fig. 1 shows that participants with serial numbers (for example, 3, 13, 25, etc.) belong to the high-risk category represented in the main node (red), and participants with serial numbers (for example, 19, 39, 67, etc.) belong to the low-risk category represented in the main node (blue).

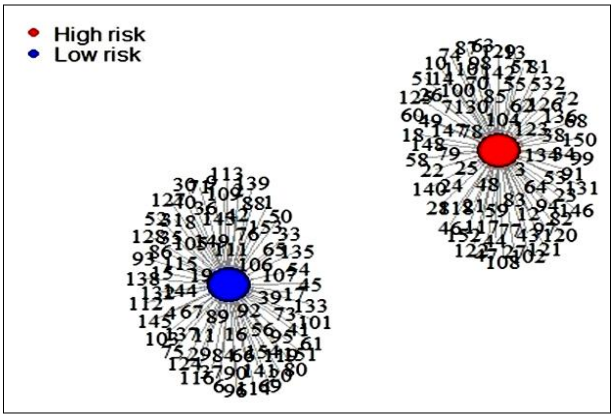

Fig 1: Network plot: Participants and Risk Categories

3.2 Correlation analysis

A feature correlation analysis was conducted to identify relationships between the psychological parameters and the risk category. As shown in Figure 2, QOL and Resilience have strong negative correlations with pregnancy risk (-0.66 for both). These findings suggest that lower scores for these parameters increase the likelihood of a high-risk pregnancy.

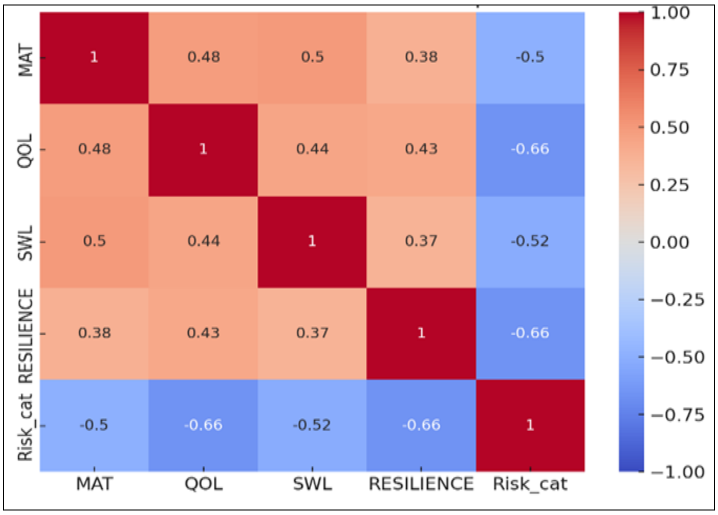

Fig 2: Correlation map showing the relationships between the psychological features and pregnancy risk categories.

The table below provides a summary of the primary data collected.

Table 1: Summary of the data collected

Var.	N	Mean	Median	Min	Max	Range	Skew	Kurt	SE	S–W (p value)
MAT	154	128.11	128.0	85	159	74	-0.24	0.93	0.97	0.0334*
QOL	154	93.59	96.0	58	135	77	-0.40	2.45	0.81	1.387e-05**
SWL	154	27.43	28.0	18	35	17	-0.40	-0.41	0.29	0.001146**
RES	154	114.82	114.5	98	135	37	0.39	-0.21	0.60	0.03271*

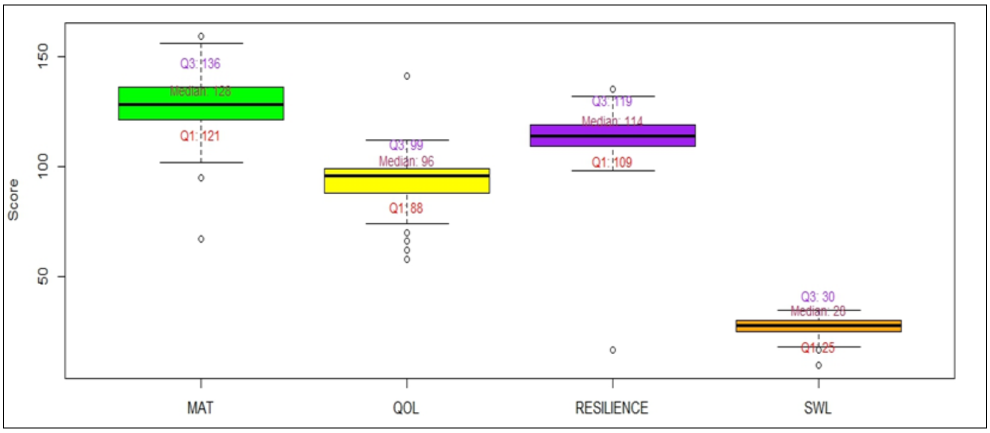

Fig 3: Box plot: Variables and Score

Table 1 and Fig.3 summarize the data collected and depict the box plot for the scores of each variable. The above table and figure indicate that there are 154 observations in total, of which 77 are in the high-risk category and 77 are in the low-risk category. The pooled data of both categories were examined for descriptive statistics: the means of the MAT, QOL, SWL and RES variables were 128.11, 93.59, 27.43 and 114.82, respectively, and the standard errors for the respective variables were 0.97, 0.81, 0.29, and 0.60. Skewness and kurtosis were also calculated to inspect the normality of the data and from the values, for example, QOL, with a skewness of 0.81 and kurtosis of 2.45, which significantly differ from 0 and 3, respectively. This provides an idea about the non-normality of the variable.

Therefore, the Shapiro–Wilk test was conducted for each of the variables, and the p value shows that the variables are not normal, i.e., the p values are less than 0.05 and 0.01.

Upon being non-normal, the values are transformed via the “bestnormalize” package in R-Studio, which analyses and applies appropriate transformations to the data.

For the normalized data, statistical techniques such as logistic regression analysis and probit regression analysis were used to understand and estimate the relationships between the dependent binary variables and the predictor variables. The fitted logistic model adjusted odds ratio was computed to infer the change in odds of the outcome (High risk) for a unit change in the value of the predictor variables. The fitted probit regression model was used to estimate the marginal effects of all the predictors on the outcome of the model (High risk), which explains the change in the probability of being in the high-risk category for a unit change in the value of the predictors. Finally, using the probit regression model, variable importance and its direction of influence were obtained and plotted, which depicts the percentage and direction of contribution of each variable to high-risk pregnancy.

3.3 Results of Logistic and probit models

In this section, the results obtained from the logistic and probit regression models are discussed.

From the fitted Logistic model, various results are obtained, and the following table provides a summary of the results.

Table 2: Summary of the logistic regression

Variable	Estimate	SE	Z Value	P Value
Intercept	0.3385	0.3987	0.849	0.395909
Resilience	-2.1218	0.6776	-3.132	0.005292*
QOL	-3.1542	0.8279	-3.610	0.000139**
SWL	-0.8554	0.4871	-1.756	0.079052
MAT	-1.8504	0.6635	-2.789	0.001739**
M.F Pseudo R^2	0.7828088			

Table 2 provides the results of the fitted logistic model. The table shows that McFadden’s pseudo R^2 value is 0.7828, which indicates that the model fits the data well and provides a significant improvement over the null model, which has only an intercept. In general, pseudo R^2 values between 0.2 and 0.4 are considered decent, so a value of 0.78 indicates a very good fit to the data, implying that the model has strong predictive power.

When estimates of each of the variables in the table are considered *viz*. MAT = -2.1218 indicates that for each one-unit increase in MAT, the log-odds of being in the high-risk category decreases by 2.1218 units. This suggests that MAT is negatively associated with the likelihood of being in the high-risk category. In other words, higher values of MAT reduce the likelihood of being classified as high risk. Similarly, QOL = -3.1542 indicates that for each one-unit increase in QOL, the log-odds of being in the high-risk category decreases by 3.1542 units. This suggests a strong negative association between QOL and being high risk. Higher QOL scores are strongly associated with a lower probability of being high risk. In the same way, inference about the other variables SWL and RES can also be drawn.

Additionally, the probability values of all the variables, QOL, MAT and RES, suggest that these variables significantly contribute to low-risk pregnancy. The negative sign indicates that the outcome of the model in which high-risk pregnancy is negatively related to all of these variables. QOL has the strongest negative effect, followed by MAT**,** RES, and then SWL. This suggests that improving QOL might have the greatest impact on reducing the likelihood of being classified as high risk, whereas increasing SWL has the least effect among these predictors.

Thus, individuals with higher MAT, QOL, SWL, and RES scores are more likely to be in the low-risk category. If the goal is to reduce high-risk outcomes, interventions that improve QOL and MAT would likely have the greatest impact according to your model.

To understand and present the relationship between each predictor and the odds of being in the high-risk category while controlling for the other variables in the model, adjusted odds ratios were calculated for the fitted logistic model. These adjusted odds ratios are better for inference than odds ratios, which do not account for confounding factors. The adjusted odds ratios provide more insight by controlling for other factors, ensuring that the effect of each predictor on the high risk category is assessed independently of the others. Table 4 provides adjusted odds ratio estimates with confidence intervals.

Table 3: Adjusted odds ratios

Variable	Adjusted Odds Ratio (AOR)	CI Lower (2.5%)	CI Upper (97.5%)
Intercept	1.40286138	0.15717911	3.2469597
Resilience	0.11981294	0.025023533	0.3743824
QOL	0.04267085	0.006109438	0.1678073
SWL	0.42512669	0.148948085	1.0407583
MAT	0.15717911	0.034144619	0.4815719

Table 3 shows that QOL, MAT and RES, have significant adjusted odds ratios below 1, meaning that they are strongly negatively associated with the odds of being in the high-risk category, even after controlling for the other predictors. SWL shows a reduction in odds, but the confidence interval suggests that this reduction is not statistically significant when adjusted for the other variables. The intercept represents the baseline odds and is not significant. In practical terms, this suggests that interventions targeting QOL, MAT and RES could significantly reduce risk, whereas the role of SWL is less clear after accounting for the other variables.

RES (AOR = 0.12, CI: 0.03 - 0.37): An AOR of 0.12 suggests that a one-unit increase in resilience is associated with an 88% decrease in the odds of the outcome (from 1 - 0.12 = 0.88). The 95% CI (0.03 - 0.37) does not include 1, indicating that this result is statistically significant.

QOL (AOR = 0.04, CI: 0.01 - 0.17), with an AOR of 0.04, indicates that a one-unit increase in QOL is associated with a 96% decrease in the odds of the outcome (1 - 0.04 = 0.96). The narrow CI (0.01 - 0.17) indicates a significant effect and that this is a strong predictor with a large negative influence on the outcome. A SWL (AOR = 0.43, CI: 0.15 - 1.04) with an AOR of 0.43 indicates a 57% decrease in the odds of the outcome for each one-unit increase in SWL. However, the CI (0.15 - 1.04) barely includes 1, suggesting that this result is not statistically significant at the 5% level.

Similarly, MAT (AOR = 0.16, CI: 0.03-0.48), with an AOR of 0.16, suggests that a one-unit increase in MAT is associated with an 84% decrease in the odds of the outcome. The CI (0.03 - 0.48) does not include 1, so this result is statistically significant, indicating a meaningful negative effect of MAT on the outcome.

The following table provides a summary of the probit regression model.

Table 4: Summary of the probit model

Variable	Estimate	SE	Z Value	P Value
Intercept	0.2196	0.2034	1.079	0.28039
Resilience	-0.9894	0.3045	-3.249	0.00116 **
QOL	-1.6449	0.3876	-4.243	2.2e-05 ***
SWL	-0.4098	0.2440	-1.679	0.09307
MAT	-1.0318	0.3180	-3.244	0.00118 **
MF-Pseudo R^2	0.7704428			

Table 4 provides the results of the fitted probit model. The table shows that McFadden's Psuedo R^2 value is 0.77048, which indicates that the model fits the data well and provides a significant improvement over the null model, which has only an intercept. In general, pseudo R^2 values between 0.2 and 0.4 are considered decent, so a value of 0.77 indicates a very good fit to the data, implying that the model explains a substantial portion of the variability in the dependent variable (high-risk and low-risk).

Upon seeing the estimates of each of the variables in the table, RES (-0.9894) implies that a one-unit increase in RES is associated with a decrease in the probit by 0.9894. Since probits map onto probabilities, a negative coefficient means that higher RES values lower the probability of the event, i.e., high risk. Similarly, QOL (-1.6449) indicates that a one-unit increase in QOL decreases the probit coefficient by 1.6449, which means that it has a strong negative effect on the probability of an event occurring. Similarly, the estimates of the other 2 variables can also be inferred.

Overall, all the predictors have negative coefficients, indicating that higher values reduce the likelihood of the outcome (high risk), which aligns with the patterns that have been observed in the logistic model.

Furthermore, the fitted probit regression model was used to calculate the marginal effects of each predictor variable on the binary predicted variable. The following table provides the marginal effects of each of the variables.

Table 5: Marginal effects of the predictors

Variables	RES	QOL	SWL	MAT
Marginal effects	-0.0933713	-0.1552291	-0.0386722	-0.0973696

The marginal effects computed via the fitted probit regression model represent the change in the probability of being in the high-risk category for a one-unit change in each predictor variable, with all other variables held constant. Therefore, the marginal effect estimates infer that RES, with an estimate of -0.0933713, indicates that a one-unit increase in RES is associated with a decrease of approximately 0.093 (or 9.3%) in the probability of being in the high-risk category. A value of -0.15522916 indicates that a one-unit increase in QOL is associated with a decrease of approximately 0.155 (or 15.5%) in the probability of being in the high-risk category. Similarly, SWL and MAT cause 0.039 (3.9%) and 0.097 (9.7%) changes in the probability of being classified into the high-risk category for a unit change in the respective values.

Overall, the marginal effects of all the predictors are negative, indicating that increases in each predictor variable are associated with a decrease in the probability of being classified as high risk. QOL has the largest marginal effect, meaning that it has the strongest influence on reducing the likelihood of the event. SWL has the smallest marginal effect, but it still contributes to reducing the probability. It can be observed that both models fit the data well and results of one is complimented by the other.

Variable importance plot

Variable importance indicates the relative contribution of each independent variable to the model's ability to predict the binary outcome. This information can be crucial for understanding the factors that drive the outcome and for making informed decisions. The absolute value of the coefficient is used as a simple measure of importance. By using the fitted probit model for the data, the predictor variable importance and direction of its effect were obtained. The plot shows how much each of the variables contributes and in which direction to the outcome (high risk). The plot (Fig. 4) reveals that QOL is the most significant factor influencing the occurrence of high-risk pregnancies. All predictor variables have a negative association with the outcome, suggesting that higher values of these variables are linked to a lower likelihood of high-risk pregnancies. QOL accounts for 40.4% of the variation in the outcome, followed by MAT at 25.3%, RES at 24.3%, and SWL at 19.5%. Therefore, it can be inferred that improving the quality of life of pregnant women significantly reduces their chances of being in the high-risk pregnancy category.

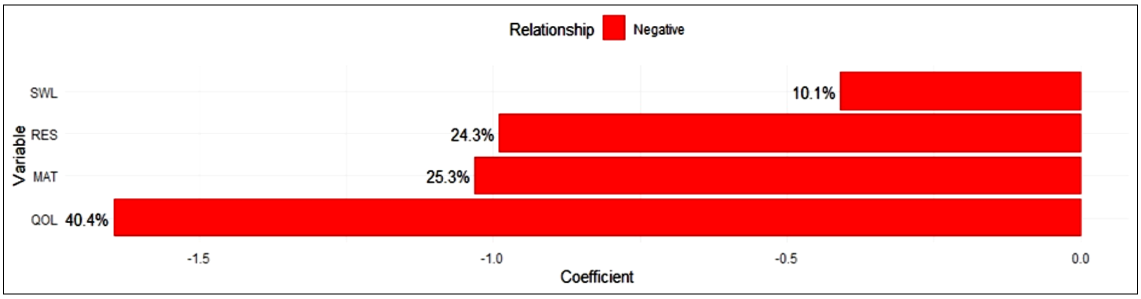

Fig 4: Variable Importance and Direction

4. Discussion

The findings of this study provide strong evidence that psychological variables, especially Quality of life, Resilience, Satisfaction with life and Marital adjustment, play critical roles in determining high-risk pregnancies. The results of the logistic and probit regression models revealed that all the predictor variables considered in this study were negatively related to high-risk pregnancy. To understand how changes in predictor variables affect the probability of being classified as 'High risk', marginal effects were calculated. Additionally, a variable importance plot was generated to rank the predictor variables on the basis of their relative contribution to the model's predictive power. The marginal effects and variable importance plot indicate that Quality of life is the most important factor in determining high-risk pregnancy, followed by Marital adjustment, Resilience and Satisfaction with Life. This study emphasizes the need for healthcare providers to focus on evaluating and improving the quality of life, resilience, and marital adjustment of pregnant women. Integrating these psychological evaluations into standard prenatal care and pregnancy risk prediction models could enable earlier identification of high-risk pregnancies and the implementation of targeted interventions to improve maternal and fetal outcomes. Future studies should investigate the inclusion of additional psychological and behavioral factors to more accurately determine high-risk pregnancies. Furthermore, machine learning and artificial intelligence techniques can be employed to predict pregnancy risk via both psychological and physiological factors.

Limitations of the study: In addition to the key findings of this study, some of the limitations of the study include a small sample size and few psychological variables. Therefore, it is recommended that researchers may consider more variables to understand the effects of psychological variables on pregnancy outcomes comprehensively.

The author(s) confirm the use of generative artificial intelligence (AI) technology to refine the language.

Conflicts of Interest

There are no conflicts of Interest.

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