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Saba Zaidi

Aligarh Muslim University

Rashid Imran Ahmad Khan

Aligarh Muslim University

Mohammad Naved Qureshi

Aligarh Muslim University

Aman Javed

Aligarh Muslim University

Gopinath Halder

`gopinath_haldar@yahoo.co.in`

Aligarh Muslim University

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**Modeling Psychosocial Stress--Cortisol Interactions in Menstrual Cycle Dynamics
through Machine Learning: A Systems Engineering Approach**

Saba Zaidi^a, Rashid Imran Ahmad Khan^b, Mohammad Naved Qureshi^c, Aman Javed^d,
Gopinath Halder^{*e}

^aDepartment of Manafeul Aza, Faculty of Unani Medicine, Aligarh Muslim University, Uttar
Pradesh-202002, India

^bCentre for Food Science & Technology, Aligarh Muslim University, Uttar Pradesh-202002,
India

^cElectrical Engineering Section, Aligarh Muslim University, Uttar Pradesh-202002, India

^dDepartment of Computer Science, Aligarh Muslim University, Uttar Pradesh-202002, India

^eDepartment of Chemical Engineering, National Institute of Technology Durgapur, Durgapur-
713209, India

***Corresponding author:**

Prof. Gopinath Halder

Telephone: +91-94347-88189

E-mail: ghalder.che@nitdgp.ac.in

Abstract

This study interrogates the interdependence between psychosocial stress, serum cortisol and temperament (Mizaj) in determining the dynamics of menstrual cycles, a blend of classical inferential statistics with machine-learning analytics. The cohort of 119 women 19-28 years old was assessed in the serum cortisol, psychosocial stress, and temperament (Safrawi vs Balghami), and menstrual parameters duration, flow, blood loss, intensity of pain, and regularity. Statistical results demonstrated significant differences between the two groups of women, which were connected to their temperaments: Safrawi females had shorter (5 days) yet heavier and more regular cycles, and Balghami females had longer (6 days) yet lighter and less regular cycles ($t = 5.11$, $p < 0.001$). The temperamental differences of menstrual flow ($U = 943.5$, $p < 0.001$) and blood loss ($U = 563.5$, $p < 0.001$) were significant, whereas the level of pain was strongly related to the psychosocial stress ($r = 0.64$, $p < 0.001$). The use of logistic regression established temperament as the first predictor of regularity in cycles ($B = +2.89$, $p < 0.001$). Random-Forest and Logistic-Regression models were able to accurately predict regularity (78 %) and pain (81%) and found serum cortisol and BMI to be the most predictive. Combining constitutional typology with psychoneuroendocrine and computational analytics, the paper defines cortisol as the primary factor relating to menstrual and reproductive physiology to psychosocial stress and highlights temperament as a key factor of reproductive resilience that can be used as a hybrid assessment of menstrual-health relationships.

Keywords: *Psychosocial Stress; Serum Cortisol; Temperament (Mizaj); Menstrual Cycle Dynamic; Machine Learning in Reproductive Health.*

1. Introduction:

Menstrual health is the interaction of the endocrine regulation, psychological condition, and environmental factors that is mainly mediated by the hypothalamic-pituitary- ovary axis (HPO). Such system ensures cyclical reproductive homeostasis with neuroendocrine feedback systems that are tightly controlled yet very vulnerable to both internal and external interference, especially to stressors in the psychosocial environment [1], [2]. Disturbances of menstrual timing, flow and pain in relation to stress are becoming acknowledged as evidence of disrupted neuroendocrine signalling, and not unique gynaecological abnormalities [3].

Hypothalamic-pituitary-adrenal (HPA) axis is activated by psychosocial stress, which leads to release of high levels of cortisol. Although acutely adaptive, chronic exposure to cortisol alters the pulsatility of gonadotropin-releasing hormone (GnRH) and luteinizing hormone (LH) and

follicle-stimulating hormone (FSH) secretions and disturb estrogen-progesterone balance, resulting in disruption of menstrual pattern and presentation [4], [5], [6]. High levels of cortisol have also been associated with an increase in uterine contractility, inflammatory signalling, and pain sensitive perception, which increase dysmenorrhea and the severity of premenstrual symptoms[7], [8].

Although there is extensive evidence that stress and cortisol are both associated with menstrual dysfunction there is still a significant inter-individual variability. This heterogeneity implies the constitutional moderators that determine the stress responsivity and reproductive outcomes. In the Unani system of medicine, temperament (Mizaj) is a stable biopsychological state a combination of metabolic rate, emotional responsiveness, and physiological stability. The traits of Safrawawi (hotdry) and Balghamami (coldmoist) temperaments include the increased neuroendocrine responsiveness and metabolic activity and reduced metabolic momentum and stress reactivity respectively [9], [10]. These constitutional variations can be systematically resolved into the translation of psychosocial stress into endocrine and menstrual products, but this research hypothesis has rarely been addressed empirically and computationally [11].

The current research fills this gap because it focuses on temperament as a moderating variable, and serum cortisol as a physiological mediator variable between psychosocial stress and menstrual variability (Figure 1). The combination of a psychological (perceived stress), biological (serum cortisol), constitutional (Mizaj), and physiological indicator is a step forward in developing a biopsychosocial framework that is not reductionist by focusing on hormones only [12][13].



Figure 1: Methodological Framework

Measures of menstrual outcomes include duration of the cycle, regularity, intensity of menstrual flow, blood loss and severity of menstrual pains which are used in order to measure

reproductive functioning in a holistic manner[14], [15]. The classical statistical testing (t-tests, Mann -Whitney U tests, 02 tests, logistic regression) is used to establish group- vs. group- contrasts and inferential relationships. Machine-learning models of Logistic Regression and Random Forest classifiers are used to complement these approaches and are trained and validated on 80:20 data split to reveal non-linear interactions and predictive hierarchies between stress, cortisol and BMI and temperament (Figures 2) [7].

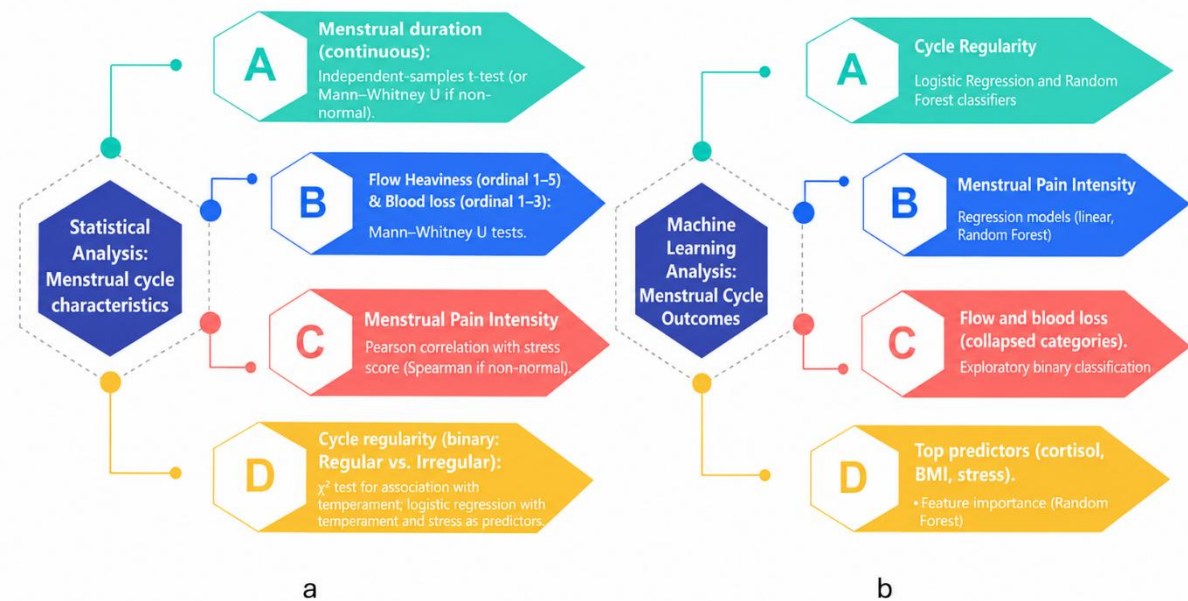


Figure 2: Statistical (a) and machine learning framework (b) for menstrual cycle outcome analysis

The originality of this composition consists in the interdisciplinary synthesis. Although other studies have examined psychosocial stress, cortisol dysregulation, or menstrual disorders separately [2], [7], [12], none has investigated the sensitivity of constitutional temperament to the cortisol-menstrual axis, and, as far as we can ascertain it, none have confirmed the interaction of these two variables in machine-learning analytical algorithms. This paper advances the psychoneuroendocrinology and systems biology to fit traditional constitutional theory by operationalizing Mizaj as a statistically tractable construct [16].

In theory, the results can be interpreted as supporting a triadic theory where the perturbing force is psychosocial stress, the biochemical mediator is cortisol and the regulatory matrix is temperament, which determines the vulnerability or resilience of individuals[8]. Menstrual variability does not therefore arise as a consistent pathological reaction but it is an

individualization of physiological expression of stress-constitution interaction. This school of thought is consistent with the modern paradigms of precision medicine, allostasis, and customized women health, which implies biological individuality, rather than universal norms [17], [18].

The current study combines both explanatory and predictive understanding regarding the stress-related dysregulation of menstruation through the combination of statistical inference and machine-learning analytics [19]. The framework provides a platform on which constitution-sensitive risk stratification and custom-made intervention programs are grounded and introduces temperament-informed computational modelling as a potential direction of integrative reproductive health studies [20].

2. Methodology

2.1. Study Design and Participants

It was a cross-sectional observational study involving 119 women aged 19-28 years. The formation of two dominant temperament (Mizaj) groups (Safrawwii $n = 59$, Balghamii $n = 60$) was based on a standardized questionnaire on Unani medicine. There was a selection of only those people who had clearly dominant temperament profile in order to guarantee constitutional homogeneity[21], [22].

All the participants had apparently good health with no historical background of endocrine disorders, chronic systemic illnesses, or hormonal medication consumption, which reduced confounding factors on menstrual characteristics (Figure 3). The protocol of the study was endorsed by the Institutional Ethics Review Board and the informed consent of all the participants was taken in writing before enrolling into the study [23].



Figure 3: Recruitment and consent session with baseline physiological assessment for the stress-menstrual study

2.2. Study Procedure

The participants were first screened on an interview basis as a way of establishing the eligibility requirements as well as the temperament. Informed consent was obtained, and they were made aware of the study goals and study processes and the ethical issues surrounding the study. The standardized data collection conditions were used to guarantee the reproducibility of data such as the similar timing of the testing (08:00-10:00 h), ambient temperature, and the testing environment.

The questionnaires filled in by each participant were the temperament (Mizaj) questionnaire, Anxiety, Depression, and Stress Scale - Behavioural Science, Psychology Stress Assessment (ADSSBSPSA), and a structured Menstrual Cycle Questionnaire. Blood samples were withdrawn to estimate serum cortisol in venous blood and physiological measures viz. body mass index (BMI), pulse rate, and blood pressure taken. Strict conditions were upheld in participant confidentiality and voluntary participation during the course of the study [23].

2.3. Data Collection Instruments

Data were assorted using standardized and validated instruments designed to comprehensively capture constitutional, psychological, biochemical, and menstrual characteristics relevant to the study objectives. The selected tools ensured methodological consistency and facilitated integrated analysis across biopsychological domains[24].

2.3.1. Semi-Structured Interview

The semi-structured interview was used to gather socio-demographic and lifestyle data, such as age, level of education, food habits, sleep, exercise, physical activity and medical history. This action guaranteed homogeneity of participants and it was easy to rule out the possibility of confounding variables that were affecting stress levels or menstrual functionality.

2.3.2. Temperament (Mizāj) Assessment

The evaluation of temperament was done through a validated Unani medicine questionnaire which has ten classical diagnostic parameters namely: tactile perception, sleep patterns, pulse, complexion, excretory functions and behavioural traits. According to the composite scores, the participants were divided into Safrawy (hot-dry) and Balgham (cold-moist) based on the known Unani diagnostic criteria.

2.3.3. Psychosocial Stress Evaluation

Psychological stress was assessed with the help of the ADSSBSPSA, which is a standardized measure of perceived stress in cognitive, emotional, and physical dimensions. The rating was done using a 4-point Likert scale, and cumulative scores were applied in categorizing stress severity as mild, moderate, and severe.

2.3.4. Serum Cortisol Estimation

The morning venous blood samples were taken between 08:00 to 10:00h as that is the maximum secretion of cortisol. Samples were centrifuged with serum cortisol level being determined by means of a chemiluminescent immunoassay (CLIA) on an automated analyzer (Roche Elecsys E170 module). The level of cortisol was in µg/dl.

2.3.5. Regulation of Circadian and Menstrual Phase Variability

All of the blood samples were taken at the follicular phase of the menstrual cycle (days 39) to reduce circadian and hormonal variability. The subjects were advised not to consume any food, caffeine, or smoke at least 30 minutes before sampling. The values of cortisol were then compared with regards to perceived stress scores and the classification of temperament [25][26].

2.4. Statistical and Machine-Learning Analysis

A dual-analytic processing was used that combined classical statistical inference with machine-learning-based predictive modelling. Demographic, physiological, stress-related and menstrual variables were initially summarized using descriptive statistics. Independent-samples t-tests were used to parallel normally distributed variables (e.g., menstrual cycle duration) and Mann Whitney U tests to match non-normally distributed ones (e.g., flow heaviness and blood loss) between the Safrawi and Balghamis temperaments in groups. The Pearson correlation coefficient was used to test the associations amidst continuous variables (stress scores and pain intensity). Regularity of menstrual cycle (regular vs. irregular) was analyzed through binary logistic regression in order to estimate the value of temperament and psychosocial stress.

Machine-learning analyses of the results in the form of Logistic Regression and Random Forest classifiers, and Random Forest regression models were performed to complement and validate the results of the inferential analyses. Anticipated predictors were temperament, serum cortisol, BMI, stress score, age, and the level of pain. Training and testing models were done on an 80:20 train test split. The measures of the performance were accuracy, precision, recall, F1-score, Receiver Operating Characteristic Area Under the Curve (ROC–AUC), as well as Precision Recall. The methods used in establishing dominant predictors in outcome variables were feature-importance analyses [27][28].

This combined analysis system allowed the joint assessment of the statistical effects related to groups and the predictive behaviour of individuals, which had a stronger methodologic standing and increased translational significance in detecting determinants of menstrual health [29], [30].

3. Results

The final dataset included 119 women, aged 19–28 years (mean 22.3 ± 2.2). The mean BMI was 24.2 ± 8.6 kg/m², with values spanning 14.6 to 60.8, indicating a heterogeneous group from underweight to obese. Average systolic and diastolic blood pressure were within the normal range ($112.8/70.2$ mmHg), and mean pulse was 75.7 ± 8.8 beats per minute. Serum cortisol levels varied widely (mean 12.0 ± 4.4 µg/dL, range 5.3–19.9), while psychosocial stress scores averaged 8.5 ± 2.2 on the 14-point scale. Baseline summary statistics are displayed in Table 1.

Table 1: Descriptive statistics for demographics, vitals, and menstrual metrics

Variable	Mean $\pm$ SD (Range)
Age (years)	22.3 ± 2.2 (19–28)
BMI (kg/m ²)	24.2 ± 8.6 (14.6–60.8)
Systolic BP (mmHg)	112.8 ± 9.1 (90–132)
Diastolic BP (mmHg)	70.2 ± 8.9 (50–98)
Pulse (bpm)	75.7 ± 8.8 (46–103)
Cycle duration (days)	5.4 ± 1.4 (2–9)
Cycle period length (days)	28.8 ± 3.9 (21–40)
Serum cortisol (µg/dL)	12.0 ± 4.4 (5.3–19.9)
Stress score (0–14)	8.5 ± 2.2 (5–13)

Having established baseline differences, we next examined the effects of psychosocial stress and temperament on menstrual cycle characteristics. Specifically, we tested whether temperament (Balghamī vs. Safrāwī) and stress levels influenced menstrual bleeding duration, flow heaviness, blood loss, pain intensity, and cycle regularity. The results for each outcome are detailed below.

3.1 Statistical Analysis of Psychosocial Stress Effects on Menstrual Cycle Characteristics Across Temperaments

3.1.1 Menstrual Bleeding duration

Distinct variations in menstrual bleeding duration were evident between the two temperament groups (Figure 4b). Balghamī women exhibited comparatively longer menstrual periods, averaging around six days, whereas Safrāwī women demonstrated shorter durations, averaging

about five days. This variation reached statistical significance ($t_{117} = 5.11, p < .001$), underscoring that temperament exerts a substantial influence on the temporal length of the menstrual phase. In essence, menstrual-cycle duration serves as a distinguishing physiological marker between the Safrāwī and Balghamī constitutions.

3.1.2 Mensuration Flow Heaviness

Self-reported menstrual flow intensity exhibited clear temperament-based variation (Figure 4a). Safrāwī women more often characterized their flow as heavy or excessive, whereas Balghamī women predominantly reported light to moderate flow levels. The Mann–Whitney U test substantiated this disparity ($U = 943.5, p < .001$), indicating that the Safrāwī temperament traditionally defined as hot and reactive is linked to greater flow intensity, in contrast to the Balghamī temperament, which reflects a cooler and less physiologically reactive disposition. The distribution plot illustrates this divergence, where violin width signifies data density and the inner box represents the interquartile range, visually reinforcing the statistical difference in flow patterns across temperament groups.

3.1.3 Mensuration Blood Loss:

A comparable trend was observed in the overall menstrual blood loss (Figure 4c). Safrāwī women were considerably more inclined to report higher blood-loss volumes, whereas Balghamī participants predominantly clustered around low to moderate levels. This contrast was statistically robust (Mann–Whitney $U = 563.5, p < .001$) as shown in figure 8, reinforcing the notion that temperament significantly governs both the subjective perception of menstrual heaviness and the objective volume of blood expelled. The accompanying histogram with superimposed kernel-density curves illustrates this divergence, depicting distinct distribution profiles for each *Mizaj* group, as validated by the non-parametric Mann–Whitney U test, which confirms the substantial group-level variation.

3.1.4 Mensuration Pain Intensity

In contrast to the preceding parameters, menstrual pain intensity exhibited a more direct association with psychosocial stress (Figure 4d). Participants with higher stress scores experienced markedly greater levels of dysmenorrhea ($r = 0.64, p < .001$), indicating a strong positive correlation. This substantial effect underscores that psychological stress intensifies menstrual pain irrespective of temperament, functioning as a universal aggravating factor. Although Safrāwī and Balghamī women differed in their overall cycle characteristics, both

demonstrated an equivalent stress–pain correlation, reaffirming that elevated psychosocial stress heightens pain sensitivity across constitutional types. The corresponding scatter plot visualizes this linear relationship, where each point denotes an individual observation, and the solid regression line represents the fitted trend, annotated with Pearson’s r and p values to convey the magnitude and statistical significance of the association is depicted in figure 7.

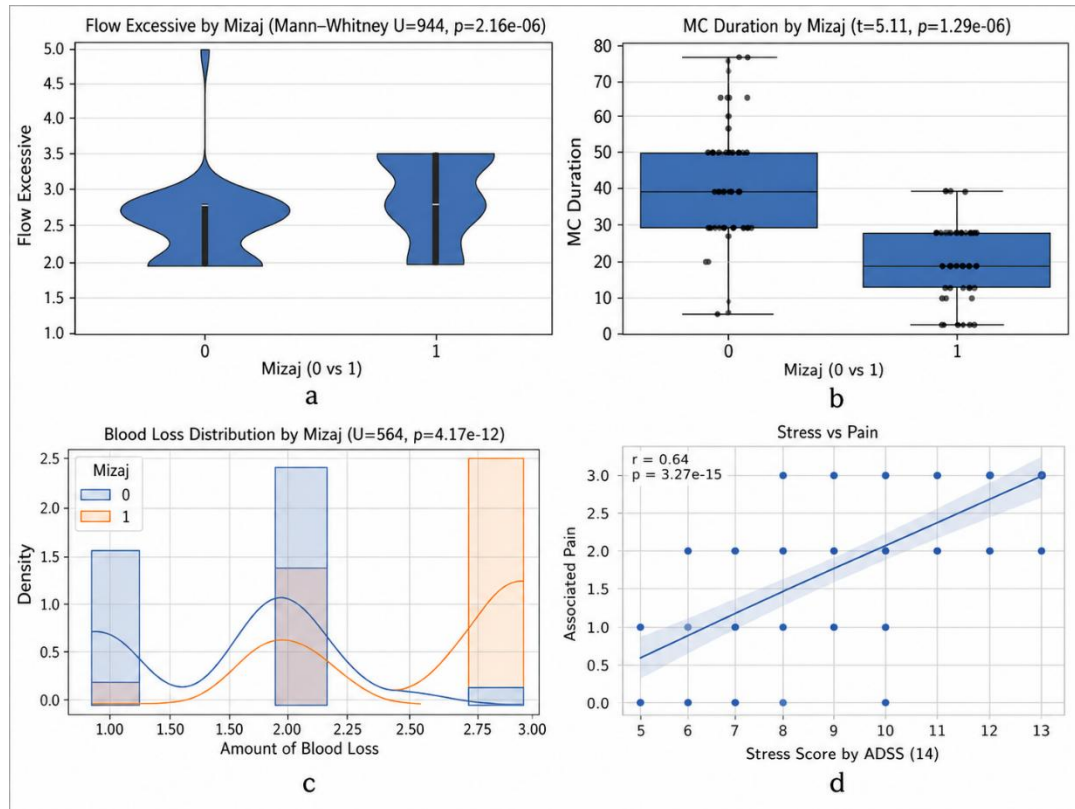


Figure 4: Menstrual cycle outcomes by Mizaj and stress: (a) flow excessive, (b) MC duration, (c) blood loss, and (d) stress–pain correlation.

3.1.5 Mensuration Cycle Regularity

It was determined that temperament was mainly responsible for the regularity of the menstrual cycle, rather than stress factors. The women of Safrāwī had significantly higher odds of having regular menstrual cycles ($B = +2.89$, $p < .001$) while psychosocial stress scores did not have a statistically significant effect on regularity ($B = -0.25$, $p = .116$) in logistic regression analysis. The overall regression model was highly significant (likelihood ratio $p = 8.62 \times 10^{-5}$) and temperament was confirmed as a major factor affecting cyclical stability. Stress intensity increases the pain of menstruation, but it's the constitutional type that mainly influences the periodicity and regularity of the cycle. This relationship is further illustrated in the model-based prediction curves in figure 5, which show the change in the probability of maintaining a regular

cycle as stress increases – and are clearly separated for the two groups of Mizaj (Mizaj = 0 and Mizaj = 1).

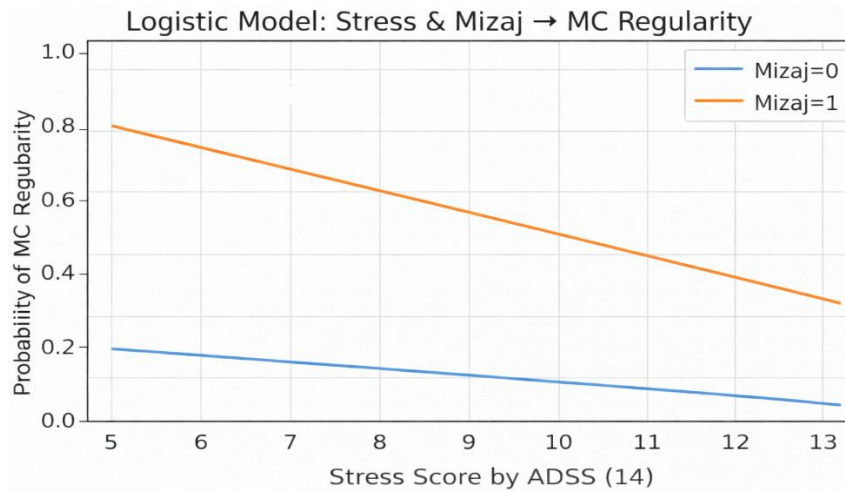


Figure 5: Predicted Probability of Menstrual Cycle Regularity vs Stress Score (Logistic Model).

The consolidated heatmap of p-values (shown in figure 6a) offers a nuts-and-bolts visualization of the significance levels of all statistical tests performed, giving a quick overview of the significance levels of other menstrual parameters. The figure also shows that the p-values of all the variables analysed, which were menstrual-cycle duration (t-test), flow heaviness (Mann–Whitney U), blood loss (Mann–Whitney U), and association of menstrual cycle with stress–pain (Pearson correlation) were very significant, well below the significance level of 0.001. The colors (from light to dark) reflect the relative size of the statistical significance, with darker colors reflecting larger effects. Interestingly, three of the strongest relationships were between blood loss and temperament ($p = 4.17 \times 10^{-12}$) and between the correlation of stress and pain, and temperament ($p = 3.27 \times 10^{-15}$). This visualization vividly demonstrates the uniformity and the robustness of the statistical evidence for the study's main hypotheses regarding variability in menstrual characteristics related to temperament and stress-induced modulation of such characteristics. Correlation matrix of continuous variables showing the inter-relations among the variables of menstrual-cycle duration, flow intensity, blood loss, stress score (ADSS-14) and pain score as shown in figure 6b. Negative and positive correlations are indicated by the cool and warm colors, respectively, of the heatmap. The findings show that stress score and pain intensity are most strongly correlated ($r = 0.64$), providing further confirmation that a higher stress level is associated with more intense dysmenorrhea. Also, there is a moderate positive correlation between blood loss and blood flow heaviness ($r = 0.45$), signifying that the

subjective and objective measurement of blood flow were consistent with each other. On the other hand, most parameters are poorly correlated with menstrual cycle duration, indicating that the duration of the cycle may be somewhat independent of either stress or flow related measures. Together, these matrices highlight the integration of a structure of inter-variables, where stress and physiological load are the most salient variables influencing the menstrual experience.

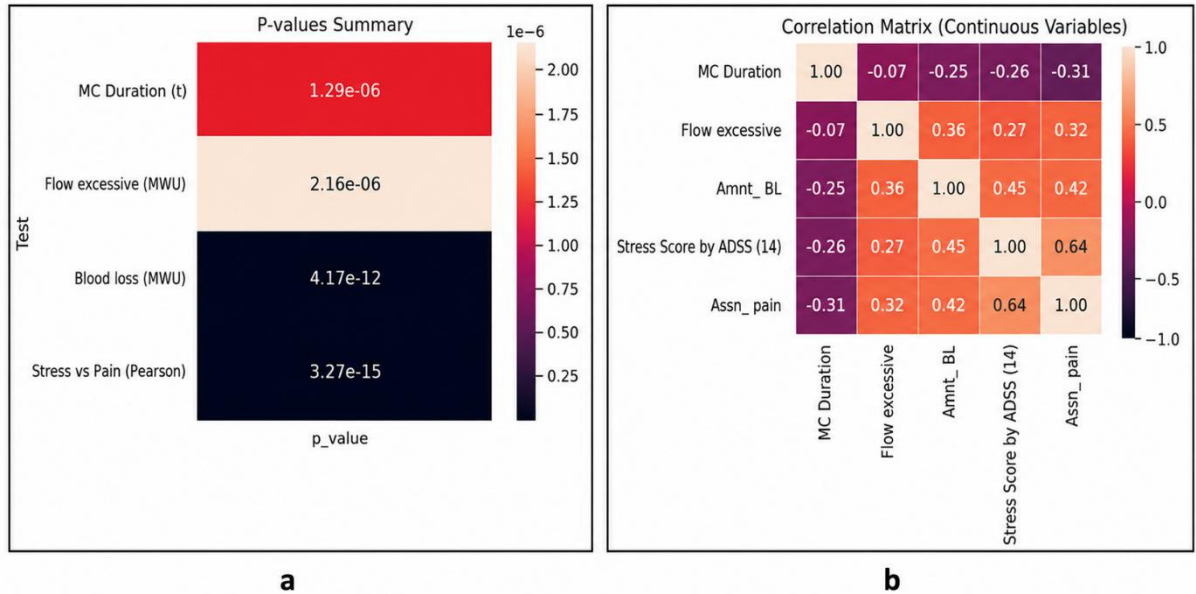


Figure 6: (a) Heatmap summarizing the *p*-values obtained from all statistical comparisons, (b) Correlation Matrix of Continuous Variables (Heatmap).

3.2. Machine-Learning Results: Regression and Classification.

3.2.1. Validation of Menstrual Cycle regularity using machine-learned methods

In order to confirm the inferential results, the Logistic Regression (LR) and Random Forest (RF) classifiers were trained to predict menstrual cycle regularity (regular vs. irregular) based on the predictors of temperament, psychosocial stress score, serum cortisol, BMI, age and pain intensity. The models both had an overall accuracy in the classification of 78 percent on the held-out test set. Table 2 is the summary of statistical tests of the menstrual results, and Table 3 is the performance measures of the machine-learning models of cycle regularity.

Although similar in accuracy, the performance of the model was influenced by class imbalance, with uneven cycles being more popular in the data. Therefore, the two models had a high sensitivity to irregular cycles (recall = 0.93) and low sensitivity to regular cycles (recall = 0.25).

This imbalance means that the models are biased to be able to detect irregularity, which is a data distribution as well as threshold selection.

Table 2: Statistical tests for menstrual cycle characteristics

Outcome	Test Used	Statistic / Coef.	p-value	Significance
MC Duration	t-test	t = 5.11	<0.001	Significant
Flow (1–5)	Mann–Whitney U	U = 943.5	<0.001	Significant
Blood Loss (1–3)	Mann–Whitney U	U = 563.5	<0.001	Significant
Pain vs Stress	Pearson r	r = 0.64	<0.001	Significant
Cycle Regularity	Logistic Reg.	Mizaj B = +2.89 (p < .001); Stress B = -0.25 (p = .116)	<0.001 (model)	Partially

Table 3: Machine-learning model performance for cycle regularity prediction

Model	Accuracy	AUC	Precision (Reg/Irreg)	Recall (Reg/Irreg)	Notes
Logistic Regression	78%	0.72	0.50 / 0.81	0.25 / 0.93	High recall for irregular; poor for regular
Random Forest	78%	0.71	0.50 / 0.81	0.25 / 0.93	Cortisol & BMI strongest predictors

The random Forest model, feature-importance analysis showed that serum cortisol and BMI were the most significant predictors of cycle regularity, followed by age and stress score, and temperament and pain intensity also played a relatively minor role on cycle regularity when physiological variables were involved (Figure 8a). This level of hierarchy indicates that the level of activity in HPA-axis and metabolic context would be more effective determinants of the cycle regularity in comparison to the perceived stress.

ROC and Precision-Recall (PR) curves were also used to assess the model discrimination. The ROC analysis showed moderate level of discriminative power of both the models (AUC = 0.72 of LR, 0.71 of RF) (Figure 7a). The mean precision values of PR curves were 0.46 to 0.52, which indicated in the effect of imbalance between classes and validated that PR measurements are more informative than accuracy (Figure 7b).

All these results support the statistical results: although temperament is linked to menstrual regularity, physiological indicators (namely serum cortisol and BMI) appear to be the most influential in the case of multivariate and non-linear analysis.

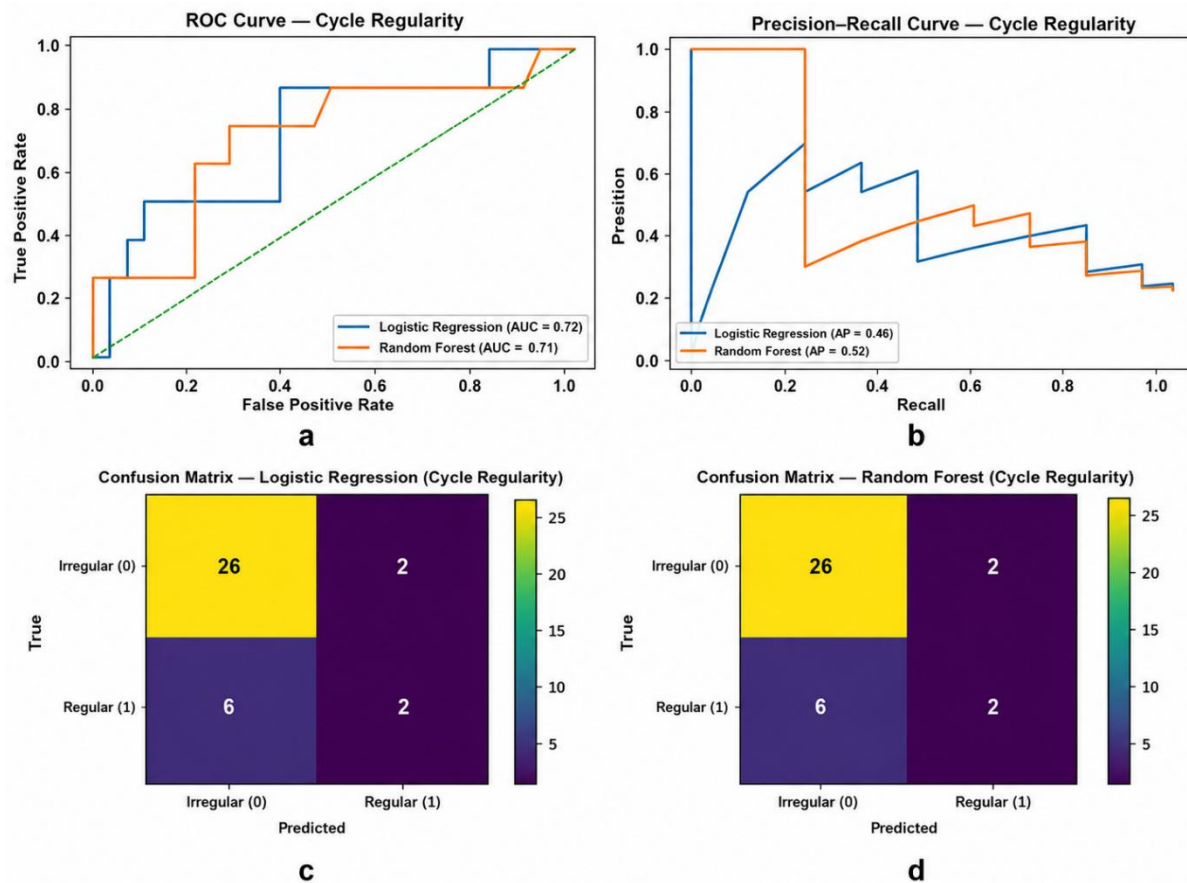


Figure 7: Performance evaluation of Logistic Regression and Random Forest models for menstrual cycle regularity: (a) ROC curves, (b) precision–recall curves, (c) Logistic Regression confusion matrix, and (d) Random Forest confusion matrix.

3.2.2. Diagnostic Model Behaviour

Similar misclassification patterns were observed in the confusion matrices of both Logistic Regression and Random Forest models (Figure 7 c and d). In both cases, irregular cycles were identified with high sensitivity, whereas regular cycles were more frequently misclassified. This asymmetry reflects overlapping feature distributions and class imbalance rather than model underfitting. These findings indicate that threshold optimization, class weighting, or cost-sensitive learning could improve balance between classes, albeit potentially at the expense of sensitivity for clinically relevant irregular cycles.

3.2.3. Menstrual Pain Intensity

The psychosocial stress and level of menstrual pain had a strong positive relationship ($r = 0.64$, $p < 0.001$), meaning that the higher the perceived stress, the greater the severity of dysmenorrhea, regardless of temperament. This association was also supported by machine-

learning analyses that established that psychophysiological factors are the major causes of menstrual pain and not constitutional type.

Random Forest (RF) regression model accounted a moderate percentage of variance in pain intensity ($R^2 = 0.38$; $MSE = 0.77$), serum cortisol, and perceived stress score were found to be the strongest predictors, then BMI and age. At the dichotomous level of pain intensity (low vs. high pain), the RF classifier showed an 81 percent accuracy with strong discriminative performance ($ROC\ AUC = 0.87$) and a high level of robustness in case of unequal distribution of classes (average $pr = 0.94$). These findings suggest valid identification of women that have high menstrual pain.

Table 4 provides an overview of the performance of both RF methods: regression and classification, which illustrate a stable predictive value in continuous and categorical pain outcomes.

Table 4: Performance metrics for pain-intensity models

Approach	Metric	Result
Regression (RF)	R^2	0.38
	MSE	0.77
Classification (RF)	Accuracy	81%
	Precision (Low/High)	0.72 / 0.89
	Recall (Low/High)	0.87 / 0.76
	F1-score (Low/High)	0.79 / 0.82
	ROC AUC	0.87
	Average Precision	0.94

3.2.3.1 Impact of Features to Regression of Pain Intensity.

Analysis of feature-importance of the RF regression model (Figure 8b) indicated that serum cortisol and stress score were the most important predictors of the intensity of menstrual pain, followed by the BMI and age and temperament scored insignificantly. This ranking would be in line with the high stress-pain correlation, and would indicate non-linear relationships between activity of the HPA-axis and perceived stress.

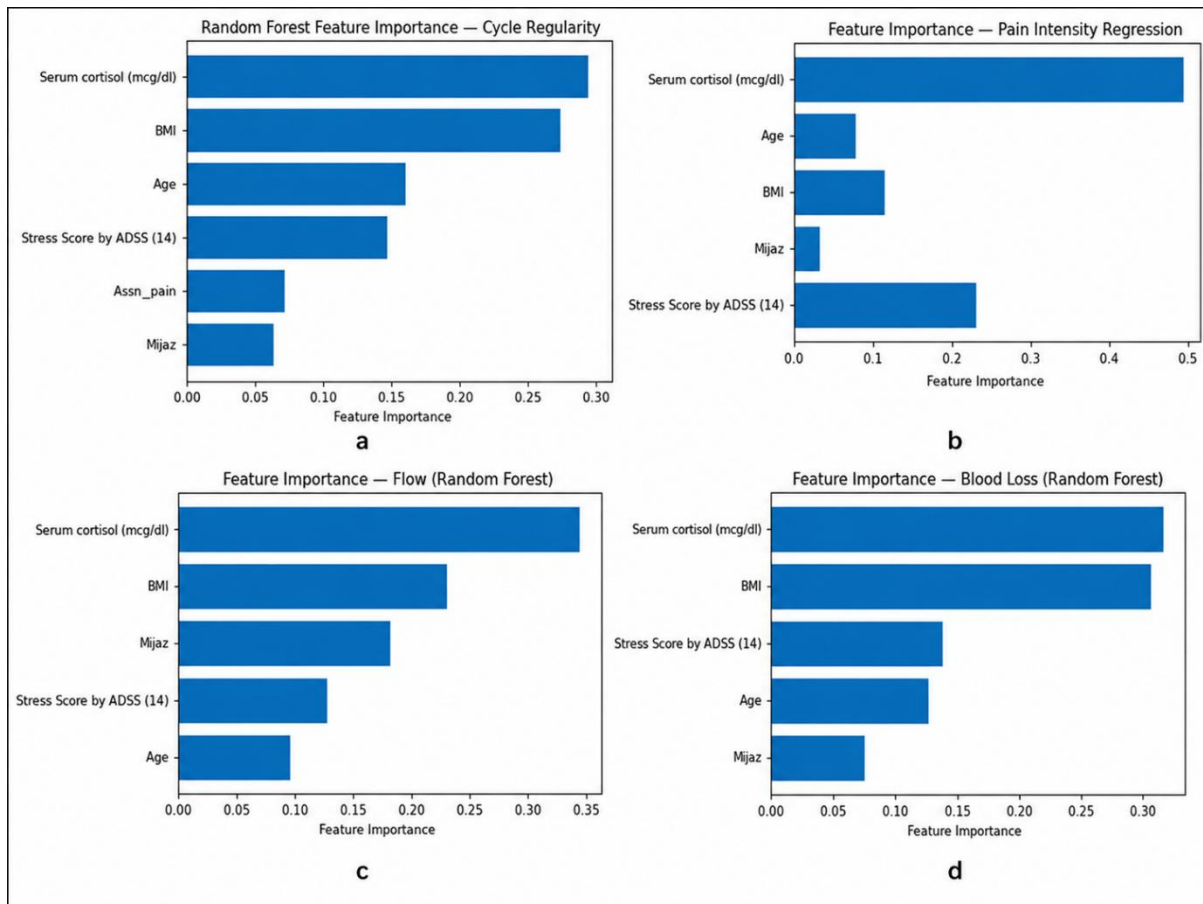


Figure 8: Random Forest feature importance for menstrual outcomes: (a) cycle regularity prediction, (b) pain intensity regression, (c) menstrual flow classification, and (d) menstrual blood loss prediction.

3.2.3.2 Classification Performance Low vs. High Pain

The confusion matrix (Figure 9c) shows equal classification performance and high-pain cases are classified with high-precision and recall. The error distribution was rather balanced, which indicates a stable boundary of the decisions and a low level of bias of the classes as an argument in favor of the usefulness of the model in the field of pain-risk stratification.

3.2.3.3 Discriminative Performance of the Pain Classifier

The ROC curve (Figure 9a) shows an excellent discriminative ability ($AUC = 0.87$), and the curve is well above the chance line throughout the thresholds, making it possible to trade-off sensitivity and specificity with the clinical priorities.

3.2.3.4 Precision–Recall Performance Under Class Imbalance

The Precision Recall curve (Figure 9b) produced an average precision of 0.94, which implies the existence of positive predictive value throughout a large recall range. The strength is especially applicable in the screening applications where the prevalence of classes can be different.

3.2.4 Menstrual Period and Blood loss

The strength of menstrual flow and menstrual blood loss was investigated to determine the impact of temperament and physiological stress indicators. In line with the statistical results, the influence of temperament was also large on both outcomes, as Safrawi participants mentioned having heavier menstrual flow and more blood loss than Balghami participants (flow: $U = 943.5$, $p < 0.001$; blood loss: $U = 563.5$, $p < 0.001$).

3.2.4.1 Machine-Learning Analysis of Menstrual Flow Heaviness

A random Forest (RF) classifier was trained to classify according to the category of menstrual flow (Low: 1-2 vs. Higher: 3-5). The model was moderate (ROC-AUC= 0.75) discriminative with an accuracy of 72%. In figure 9d, the confusion matrix, indicates that it strongly identified low-flow cases and had low sensitivity with higher-flow cases due to the imbalance in classes.

The ROC curve (Figure 9e) also shows that there are moderately separable categories of flows. The Precision-Recall analysis (Figure 9f) produced a relatively low average precision of 0.39, which shows the inability to detect relatively rare cases of heavy-flow. The analysis of feature-importance (Figure 8c) was based on the ranking of serum cortisol as the most powerful predictor, followed by BMI and temperament, and the stress score and age had fewer contributions. While the Table 5 and 6 sums up overall and class-wise performance metrics of flow classification.

Table 5: Random Forest performance for Flow heaviness (binary: Low (1–2) vs Higher (3–5))

Metric	Value
Accuracy	0.72
ROC AUC	0.75
Average Precision (PR)	0.39
Top predictors (RF importance)	Cortisol > BMI > Temperament > Stress > Age

Table 6: Class-wise metrics

Class	Precision	Recall	F1	Support
Low (1–2)	0.85	0.79	0.81	28

Higher (3–5)	0.40	0.50	0.44	8
Macro avg	0.62	0.64	0.63	36
Weighted avg	0.75	0.72	0.73	36

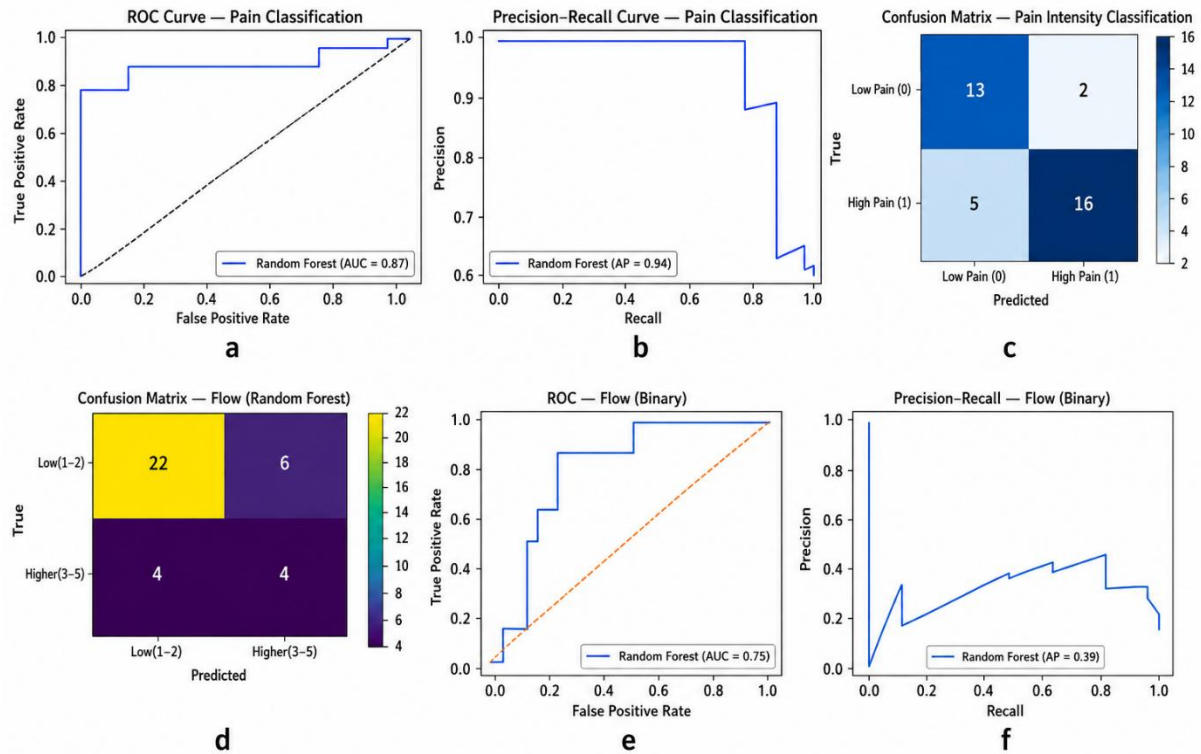


Figure 9: Random Forest performance for menstrual pain and flow classification: (a) pain ROC curve, (b) pain precision–recall curve, (c) pain confusion matrix, (d) flow confusion matrix, (e) flow ROC curve, and (f) flow precision–recall curve.

3.2.4.2 Machine-Learning Analysis of Menstrual Blood Loss

Menstrual loss of blood was theorized as a three-category outcome (1 = light, 2 = moderate, 3 = heavy). RF classifier had an overall accuracy of 58% and macro averaged ROC AUC of 0.77 which means moderate discrimination between classes. Figure 10a shows the confusion matrix and indicates that heavy blood loss was detected very well, and the light blood loss was not very well because of insufficient sample representation.

Figure 10b demonstrates the highest average precision of heavy loss of blood (AP = 0.71), then moderate and light classes (AP=0.57 and 0.47). Serum cortisol and BMI were again identified as the most significant predictors by the feature-importance analysis (Figure 8d) and the significance of stress score and age had a minor effect whereas the influence of temperament

had a small effect after adjustment. Figure 10c ROC curve: Macro-averaged gives an overall summary of the performance of the three blood-loss categories in classification. Table 7 summarizes the overall Random Forest performance for menstrual blood-loss classification, while Table 8 presents the class-wise precision, recall, F1-score, and support for the light, moderate, and heavy blood-loss categories. The class-wise results in Table 8 further show that the model performed best for heavy blood loss, with perfect recall and the highest F1-score, whereas light blood loss showed weak precision and recall, likely due to limited sample representation.

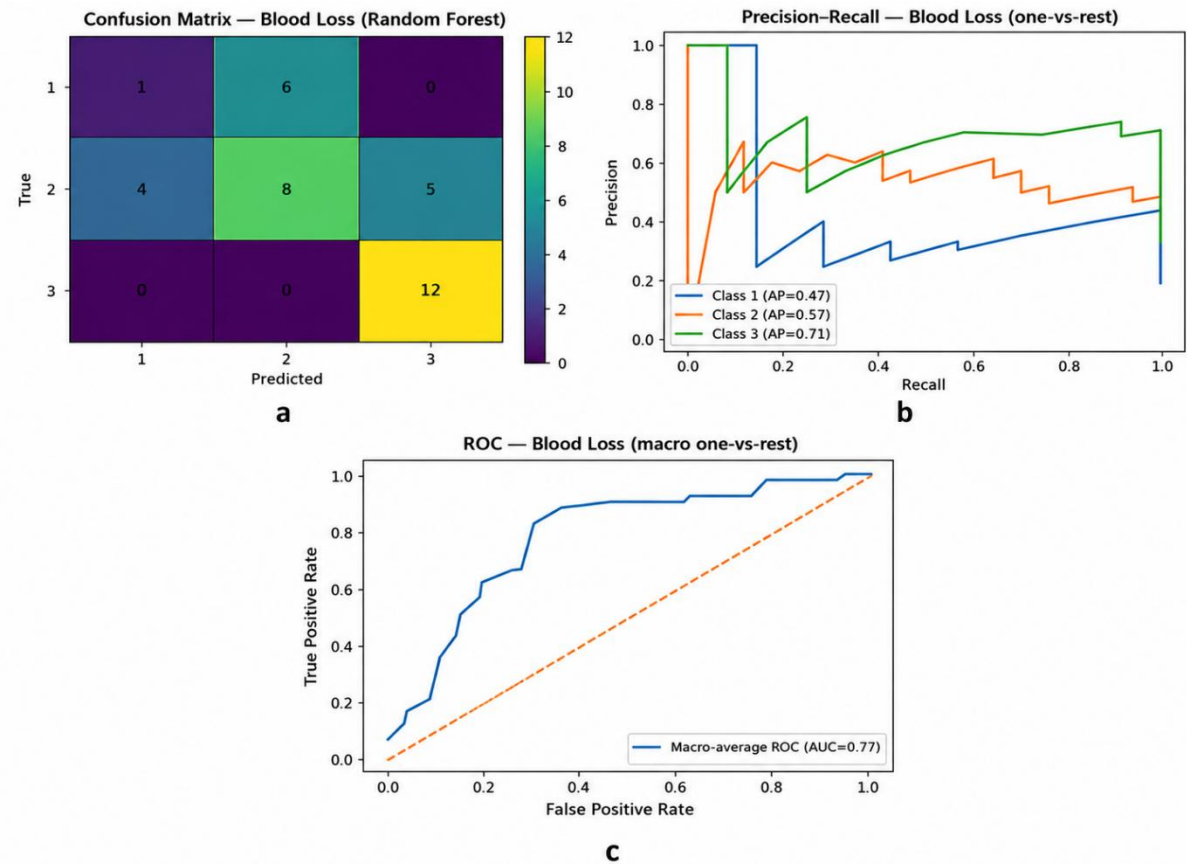


Figure 10: Random Forest performance for menstrual blood loss classification: (a) confusion matrix for three classes (light, moderate, heavy), (b) one-vs-rest precision–recall curves, and (c) macro-averaged ROC curve (AUC = 0.77).

Table 7: Random Forest performance — Blood loss (three classes: 1–3)

Metric	Value
Accuracy	0.58
Macro ROC AUC (OvR)	0.77

Per-class Average Precision (PR)	Class 1: 0.47 · Class 2: 0.57 · Class 3: 0.71
Top predictors (RF importance)	Cortisol $\approx$ BMI > Stress $\geq$ Age > Temperament

Table 8: Class-wise metrics

Class	Precision	Recall	F1	Support
1 (light)	0.20	0.14	0.17	7
2 (moderate)	0.57	0.47	0.52	17
3 (heavy)	0.71	1.00	0.83	12
Macro avg	0.49	0.54	0.50	36
Weighted avg	0.54	0.58	0.55	36

3.2.4.3 Integrated Interpretation

In both menstrual flow and blood loss outcomes, machine-learning models indicated that physiological markers, especially serum cortisol and BMI were the best predictors, but in multivariate models, temperament was not as influential as physiological markers. Extreme phenotypes had highest predictive performance particularly those of heavy blood loss and those that were lighter and those that were intermediate were more difficult to differentiate because of the overlapping features distributions, and class imbalance.

4. Conclusion

This study shows that the combined influence of psychosocial stress, neuroendocrine control, and constitutional temperament determined the influence of menstrual physiology. Temperament appeared as constancy determinant of menstrual patterning: Safrawi women tended to have shorter, heavier and more regular cycles and Balghami women tended to have longer, lighter and less regular cycles. Conversely, psychosocial stress did not significantly affect cycle regularity, however, exhibited the strong and consistent relationship with the intensity of menstrual pain, which points to its operation as a cross-constitutional escalator of dysmenorrhea. Serum cortisol, which is the main biochemical correlate of stress, was in line with unfavourable menstrual outcomes, which indicates that the psychosocial stress is mediated through the HPA–HPO axis interaction.

These inferential results were supported and furthered by machine-learning analyses quantifying multivariate and non-linear relationships. Menstrual pain classification had the best predictive performance with high discrimination (AUC = 0.87; AP = 0.94), and medium

menstrual flow and blood loss, most notably in the recognition of heavy phenotypes of clinical significance. Serum cortisol and BMI were always found to be the most effective predictors and the perceived stress and temperament were found to be complementary in all models. These findings support the fact that physiological indicators of stress and metabolic burden contribute more to variability of menstruation than the psychosocial indicators alone, but constitutive temperament moderates the expression of these factors.

Together, the results catapult menstrual health studies beyond single-factor and purely symptom-based approaches and refute a precision-oriented approach where temperament-based reactivity and endocrine changes caused by stress all concur in menstrual expression. This research will provide a scalable solution to detecting individuals susceptible to stress-affected menstrual disruptions through the combination of constitutional profiling and psychophysiological biomarkers and computational modelling. Further studies must use wider physiological signals, tracking of the longitudinal cycles, and a more comprehensive class-balancing procedures to enhance prediction in the entire range of menstrual phenotypes. This work can establish a groundwork by showing that biological individuality relevantly conditions reproductive outcomes, which should allow personalized assessment and specific intervention in the menstrual health of women.

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