

Proceedings of the

# **Baltic–Nordic–Ukrainian Network Workshop on Survey Statistics 2026**

## **EMPOWERING SURVEY SAMPLING WITH MODERN TECH**

**August 24–28, 2026**

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# MONITORING PTSD FACTORS IN WOMEN OF REPRODUCTIVE AGE USING SUPERVISED AND UNSUPERVISED MACHINE LEARNING METHODS

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## Abstract

Post-traumatic stress disorder (PTSD) has emerged as a critical public health consequence of the ongoing armed conflict between Ukraine and the Russian Federation, disproportionately affecting the mental health of civilian populations — particularly every woman of reproductive age.

This study presents a rigorous statistical analysis of an anonymous population-based survey, employing a comprehensive suite of machine learning (ML) methodologies to develop a rapid screening framework for individuals at elevated PTSD risk. The analytical pipeline integrated both supervised and unsupervised learning approaches, encompassing classical logistic regression, Bayesian logistic regression, Random Forest, Stochastic Gradient Boosting, and Neural Network Classification. This multi-method framework enabled systematic deconstruction of the underlying data architecture and identification of key biopsychosocial predictors of PTSD onset.

Unsupervised Random Forest clustering was subsequently applied to achieve objective sample segmentation based on identified predictive factors. The analysis yielded two statistically robust clusters demonstrating significant divergence in diagnosed PTSD prevalence ( $p < 0.001$ ). The resulting predictive model confirms that PTSD risk stratification is feasible using demographic and behavioral markers augmented by a minimal set of targeted psychological indicators — without recourse to clinical laboratory assessment. This operational simplicity renders the proposed framework directly deployable by social workers, primary care providers, and civil protection personnel operating under wartime resource constraints.

**Keywords:** PTSD, machine learning, supervised learning, clustering, women's health

## 1 Context and Motivation

The armed aggression against Ukraine (2014–2026) constitutes a catastrophic stressor with profound systemic implications for the mental health of the civilian population. This impact is particularly critical among women of reproductive age, as their health trajectory fundamentally determines the nation's demographic resilience and future public health outcomes (Horbatiuk 2025, p. 20).

Exposure to active warfare is characterized by chronic life-threatening conditions, bereavement, forced displacement, and the abrupt disintegration of social networks and established socio-economic structures. These factors converge to induce a state of prolonged psychological strain, facilitating the onset of diverse psychiatric and clinical pathologies. Among these sequelae, Post-Traumatic Stress Disorder (PTSD) emerges as one of the most prevalent and debilitating manifestations of sustained high-intensity stress (Kharun 2025, pp. 3–4).



## 2 Software and Visualization

Statistical computations and modeling were performed using JASP (version 0.19.36; JASP Team, 2024), an open-source graphical software for scientific analysis. Out of the initial 100 survey items, 77 variables with complete data profiles were selected for final analysis. For variables representing age and Body Mass Index (BMI), missing values were addressed using the mean imputation method (JASP Impute Missing Values module). To ensure the integrity of the age variable, responses regarding marital status and children’s ages were cross-referenced for consistency. Initial data distribution analysis and outlier detection were conducted using descriptive statistics and Raincloud Plots, which provided a robust visual synthesis of the raw data, probability density, and key central tendencies.

## 3 Methodology and Model Performance

The study analyzed a cohort of 608 women of reproductive age, among whom 222 individuals were diagnosed with PTSD. A comprehensive supervised machine learning framework was implemented, utilizing Logistic Regression (LR), Bayesian Logistic Regression, Random Forest (RF), Stochastic Gradient Boosting (SGB), and Neural Network (NN). The identification of specific dietary, behavioral, and health-related markers within this group enabled the subsequent application of unsupervised Random Forest-based clustering to delineate high-risk PTSD phenotypes.

Initial baseline analysis using classical Logistic Regression identified five predictors statistically significant at the  $p < 0.05$  level. These findings were further validated and expanded upon by RF and SGB algorithms. By modeling non-linear interactions, these ensemble methods successfully captured latent structural dependencies within the survey data, yielding superior classification accuracy (see Table 1) (Lu, J. 2025, p. 5).

**Table 1:** Comparative Analysis of Model Performance Metrics

| Quality Metric | Logistic<br>Regression | Random<br>Forest | Boosting | Neural<br>Network |
|----------------|------------------------|------------------|----------|-------------------|
| Accuracy       | 0.711                  | 0.793            | 0.793    | 0.744             |
| AUC            | 0.741                  | 0.838            | 0.851    | 0.740             |
| Sensitivity    | 0.486                  | 0.611            | 0.583    | 0.694             |
| Specificity    | 0.839                  | 0.871            | 0.882    | 0.765             |
| Precision      | 0.635                  | 0.667            | 0.677    | 0.556             |
| F-measure      | 0.551                  | 0.638            | 0.627    | 0.617             |
| Brier score    | 0.184                  | 0.146            | 0.141    | 0.181             |
| H-measure      | 0.248                  | 0.452            | 0.469    | 0.252             |

Feature importance in the RF model was evaluated using Permutation Importance (mean decrease in accuracy) and Gini Importance (mean decrease in impurity). For the SGB model, parameter contribution was quantified through Relative Influence metrics. The resulting Relative Influence Plot identifies sleep characteristics as the dominant predictor within the hierarchy. This methodological consistency — where SGB results align precisely with RF outputs — underscores the robustness of the model and confirms the high predictive power of somatic sleep markers in the PTSD construct (see Fig. 1) (Vali, M. 2025, pp. 13–14).

In addition to sleep patterns, both RF and SGB identified alcohol consumption, financial constraints affecting nutrition, and post-invasion (Feb 24, 2022) appetite changes as critical predictors. Furthermore, forced displacement, persistent fatigue, and the exacerbation of chronic conditions following COVID-19 infection emerged as significant risk factors. Finally, the optimization of the Neural Network Classification architecture on the expanded dataset

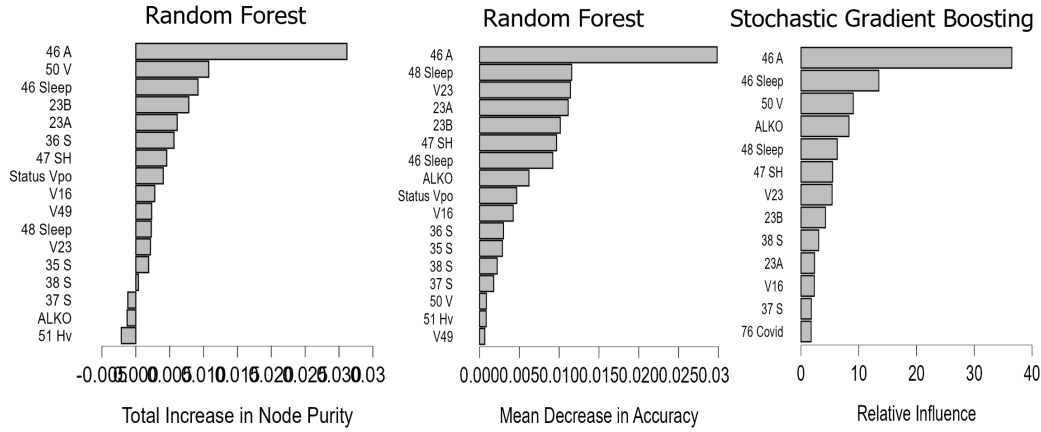


**Figure 1:** Estimating the relative importance of factors in the Random Forest and Stochastic Gradient Boosting models.

corroborated the predictive significance of these variables, demonstrating high generalization capacity with an accuracy of 75.2% on test data and 71% on validation sets.

To capture complex non-linear dependencies within the predictor space, a Multilayer Perceptron (MLP) Neural Network architecture was implemented. The network topology comprised four structural levels: (1) an input layer consisting of 17 clinical and behavioral variables; (2) two hidden layers containing a total of 3 nodes (2 nodes in Hidden Layer 1 and 1 node in Hidden Layer 2) optimized via a sigmoidal activation function; (3) an explicit bias term (intercept) providing additive offsets; and (4) a binary output layer mapping onto 2 nodes via the Softmax activation function to determine PTSD diagnostic probability.

Model training, hyperparameter optimization, and generalization performance were evaluated on the total sample of  $N = 608$  observations, stratified into training ( $n_{\text{train}} = 389$ ), validation ( $n_{\text{val}} = 98$ ), and testing ( $n_{\text{test}} = 121$ ) subsets. The optimal configuration achieved a validation accuracy of 0.673 and demonstrated robust generalization performance on unseen test data with an accuracy of 0.744.

To quantify the individual contribution of predictors within the optimized Multilayer Perceptron (MLP) architecture, a Permutation Feature Importance analysis was executed based on 50 data permutations. The relative significance of each variable was mapped utilizing the Mean Dropout Loss metric, mathematically formulated as  $1 - \text{AUC}$ .

As delineated in Fig. 2, the structural variables V24 and V23 demonstrated the highest predictive leverage with a mean dropout loss of 0.334 and 0.324, followed closely by somatic and baseline health markers such as 57A Holesterinbig (0.309) and sleep character alterations 46A (0.302). Characteristically, somatic sleep parameters (46 Sleep) and displacement/lifestyle metrics (V49, ALKO, VPO) maintained consistently high-ranking positions. This distribution indicates that the neural network relies on a complex, multi-layered intersection of behavioral shifts, sleep fragmentation, and sociodemographic stressors to successfully isolate high-risk PTSD phenotypes.

## 4 Analysis of Internally Displaced Persons

From the overall sample of 608 women, a subpopulation was isolated consisting of women who changed their place of residence and hold IDP status due to the russian invasion of Ukraine. This subpopulation consists of 95 women, 46 of whom were diagnosed with PTSD. The corresponding four-predictor classical logistic regression model demonstrated exceptional predictive power and

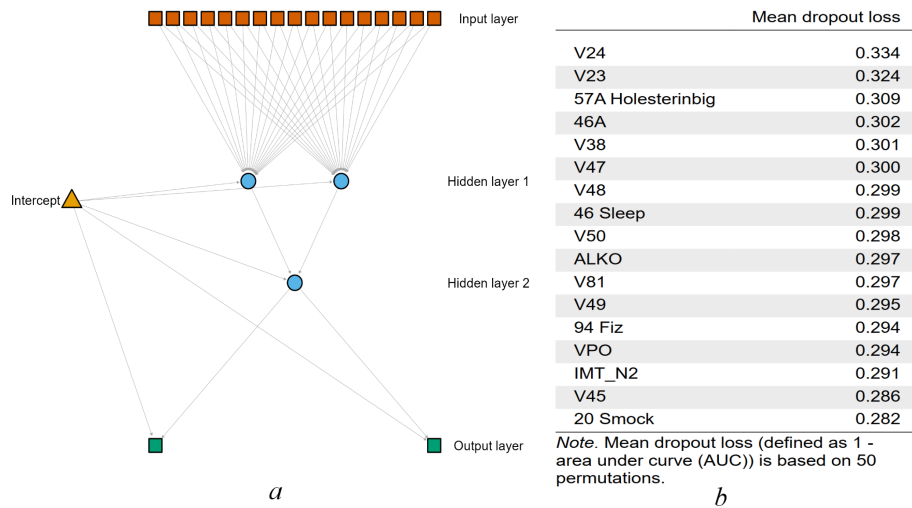


**Figure 2:** Topology of the implemented Multilayer Perceptron (MLP) neural network showcasing input, hidden, and output layers (a), alongside feature importance metrics (b).

structural validity. Receiver operating characteristic (ROC) analysis yielded an area under the curve (AUC) of 89.4% (95% CI: 82.7–96.1%), confirming high statistical reliability in class discrimination. Overall classification accuracy reached 83.2% (95% CI: 74.4–89.4%). The model exhibited pronounced symmetry in diagnostic performance, achieving a sensitivity of 84.8% (95% CI: 71.8–92.4%) and a specificity of 81.6% (95% CI: 68.6–90.0%). The correlation between the predictor variable **Vpo** and the dependent variable PTSD was found to be at the level of 0.1.

Subsequent analysis of this subpopulation via Bayesian logistic regression provides valuable insight into how candidate predictor combinations account for the variance in PTSD onset. Among all candidate model topologies, the full configuration incorporating all 4 empirical predictors yielded the highest posterior probability; notably, however, a parsimonious model restricted to sleep pattern alterations and persistent fatigue attained a comparably robust coefficient of determination. This finding suggests that preliminary risk stratification within displaced populations can be effectively operationalized using targeted survey instruments, without necessitating exhaustive clinical diagnostics (see Fig. 3).

## 5 Sleep Pattern Alterations

Based on the empirical findings yielded by the aforementioned analytical methods, it was concluded that predictors associated with sleep alterations (specifically, 46Sleep and 46A) exerted the most robust positive effect on the dependent variable. Consequently, a more granular investigation was conducted to evaluate the clinical implications of the respondents' answers regarding shifts in their sleep patterns. To achieve this, the complete cohort was stratified into distinct subsamples based on the nature of sleep disturbances.

The frequency of positive outcomes varies significantly across the four cohorts (Fisher's exact test with pairwise comparisons yields  $p < 0.001$  for the majority of pairs). The "Normal" sleep profile demonstrates the lowest prevalence (16.8%, 95% CI: 12.6–23.3%), whereas the "Insomnia" cohort exhibits the highest (62.9%, 95% CI: 46.3–76.8%). The "Intermittent" sleep (45.9%, 95% CI: 39.4–53.4%) and "Sensitive" sleep (40.0%, 95% CI: 34.3–48.8%) groups show no statistically significant difference from each other, yet both substantially exceed the baseline established by the "Normal" sleep profile, as delineated in Table 2.

The analysis for all four subcohorts was conducted utilizing stepwise logistic regression,

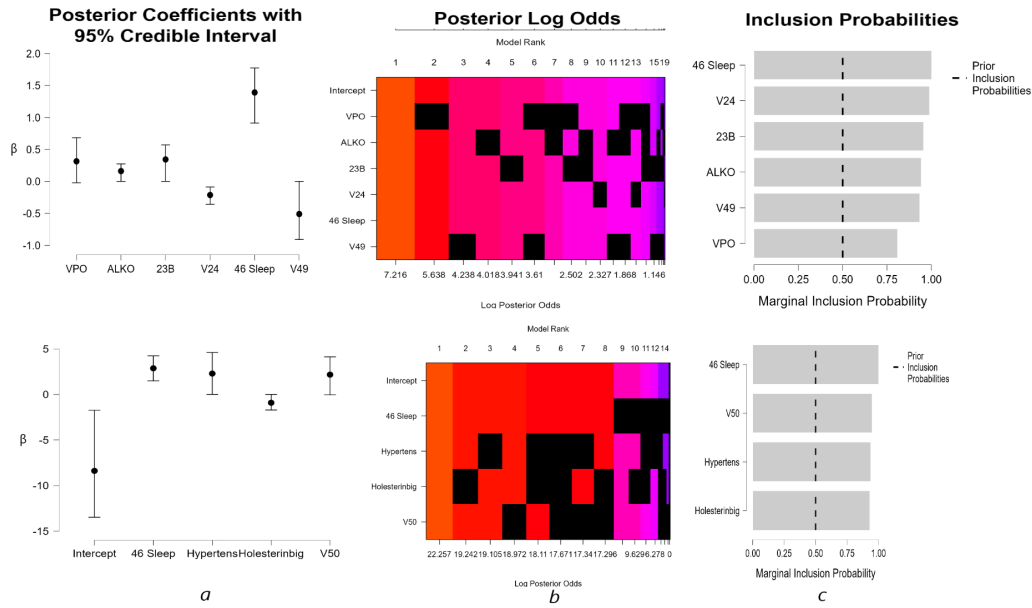


**Figure 3:** Visualized parameters of the Bayesian Logistic Regression model Beta Prime: (a) posterior distributions of the  $\beta$  coefficients for PTSD risk factors (top: model 608; bottom: model for IDP status); (b) heatmap of log-posterior odds for model ranks (top: baseline model 608; bottom: model for IDP status); (c) marginal inclusion probabilities of the predictors.

evaluating the reduction in model performance resulting from the exclusion of statistically non-significant predictors at the 5% significance level. Complete performance metrics were derived across all configurations. Notably, certain predictors, despite lacking formal statistical significance, exerted a substantial impact on model sensitivity; such variables warrant inclusion in future studies in a refined or expanded capacity. For instance, the inclusion of the BMI factor for the “Intermittent” sleep cohort increased the sensitivity value by up to 5%. Subsequently, Bayesian logistic regression was applied to all four subcohorts, parameterized based on the baseline findings from the classical logistic regression. For each predictor, key parameters including the posterior mean and Bayes factor inclusion ( $BF_{incl}$ ) were calculated. Finally, model parameters optimized with the most robust subset of predictors were evaluated, as detailed in Table 2.

**Table 2:** Stratification of PTSD Prevalence by Sleep Pattern Alterations

| Sleep Profile | Total Respondents ( $N$ ) | PTSD Diagnosed ( $n$ ) | Proportion (%) |
|---------------|---------------------------|------------------------|----------------|
| Normal        | 190                       | 32                     | 16.84%         |
| Sensitive     | 174                       | 72                     | 41.38%         |
| Intermittent  | 194                       | 89                     | 45.87%         |
| Insomnia      | 35                        | 22                     | 62.86%         |
| Other         | 15                        | 6                      | 40.00%         |

## 6 Results and Validation

To validate the robustness of the empirical findings, an unsupervised machine learning approach utilizing Random Forest Clustering was implemented. This two-stage validation framework —

integrating supervised machine learning and unsupervised Random Forest clustering — confirms the structural stability of the identified predictors. The Random Forest cluster analysis partitioned the complete cohort ( $N = 608$ ) into two distinct subsamples: Cluster 1 ( $n = 428$ ), which likely encapsulates the bulk of the data with high internal variance, and Cluster 2 ( $n = 180$ ), which represents a more homogeneous subgroup clearly isolated by the model. t-SNE Cluster Plot was used to visualize clustering. As a non-linear dimensionality reduction technique, t-SNE effectively demonstrates the spatial separability of the data into distinct topological groups. The low-dimensional projection onto a two-dimensional plane showcases the relative compactness of Cluster 1 (indicated in pink,  $n = 428$ , encompassing 201 individuals diagnosed with PTSD) and the clear isolation of the smaller subgroup, Cluster 2 (indicated in turquoise,  $n = 180$ , with 21 PTSD-positive cases). A comparative analysis utilizing the Chi-squared ( $\chi^2$ ) test revealed a highly significant difference in PTSD prevalence between the two clusters ( $p < 0.001$ ), thereby statistically confirming the efficacy and clinical relevance of the clustering configuration. Fig. 4 illustrates the visualization of this high-dimensional dataset mapped via the t-SNE algorithm.

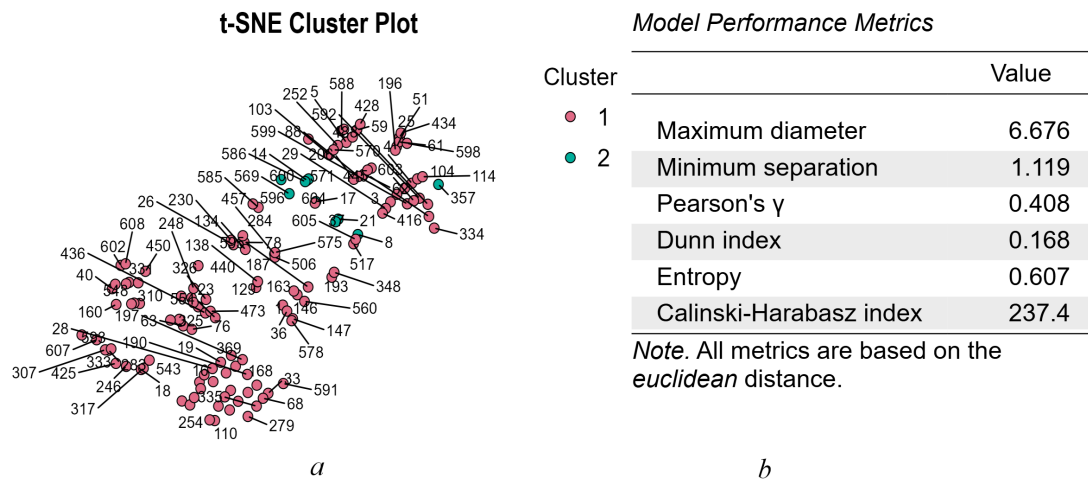


**Figure 4:** Evaluation of unsupervised Random Forest clustering using a 7-predictor model space. (a) t-SNE two-dimensional visualization of identified clusters; (b) Model performance metrics.

As you can see in Figure 4, the 7-predictor configuration demonstrated superior geometric compactness and cluster differentiation compared to higher-dimensional feature sets. The model achieved an exceptional Calinski-Harabasz index of 237.4, indicating a highly favorable ratio of between-cluster variance to within-cluster variance. The structural boundary between the two clusters is further reinforced by an increased minimum inter-cluster separation of 1.119 paired with a quite small maximum intra-cluster diameter of 6.676, yielding an improved Dunn index of 0.168. Moreover, Pearson's  $\gamma$  coefficient is to 0.408, confirming a strong statistical alignment between the underlying Euclidean proximity matrix and the resulting cluster topology, while the entropy measure (0.607) remains low, reflecting high distributional stability.

## 7 Conclusions

The findings can serve as a foundation for refining early screening questionnaires and developing tools for the preliminary risk assessment of psychoemotional disorders in women exposed to wartime events. Looking ahead, such methodologies could prove highly valuable for the civil defense system — specifically for physicians, psychologists, social workers, and specialists



involved in providing public assistance during emergencies, evacuations, humanitarian crises, and post-war recovery.

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