

Prediction of quality of life parameters among university students for the optimization of health-enhancing recreational programs

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Abstract

Purpose. The present study sought to construct and empirically test predictive models of health-related quality of life (HRQoL) in a cohort of Ukrainian university students. The models incorporated behavioural patterns, psychosocial factors, and safety-related perceptions as key determinants. By doing so, the research aimed to generate evidence-based insights that could inform the development of more effective, context-sensitive recreational and health-promotion programs tailored to the challenges of studying and living under wartime conditions.

Material & Methods. The study involved 172 students (48.8% male, 51.2% female; aged 18–25 years) enrolled in Ukrainian higher education institutions. Data collection included standardized questionnaires: the SF-36 Health Survey (Physical Component Summary (PCS) and Mental Component Summary (MCS)), the International Physical Activity Questionnaire – Short Form (IPAQ-SF), the Satisfaction With Life Scale (SWLS), and the Service Quality Assessment Scale (SQAS) adapted to wartime conditions. Factor analysis identified two main domains («Motivation» and «Constraints»), and additional variables such as time and financial limitations were analysed separately. Predictive modelling was conducted using Gradient Boosting Trees (GBT) and Random Forest (RF) methods. Model performance was evaluated with MAE, RMSE, and MAPE metrics.

Results. The models demonstrated distinct predictive capacities for physical and mental components of HRQoL. PCS was effectively predicted using a simple GBT structure with high accuracy (MAE=5.53, RMSE=45.70, MAPE=0.102), while MCS required more complex modelling (130 trees). RF outperformed GBT for MCS prediction (RMSE=83.96 vs. 98.02; MAPE=0.180 vs. 0.198). Variable importance analysis revealed that safety was the strongest predictor of PCS, while life satisfaction (SWLS) and physical activity (IPAQ) were the most influential for MCS. In both models, sex and training frequency were the least significant predictors.

Conclusions. Machine learning approaches provide valuable tools for predicting HRQoL among students in challenging contexts. The findings confirm that physical well-being is strongly influenced by environmental safety, whereas mental well-being depends more on subjective life satisfaction and physical activity. These results highlight the need for integrated health-enhancing recreational programs combining physical activity with psychosocial support and safety measures in Ukrainian universities during wartime.

Keywords: physical activity, machine learning, quality of life, students, model, safety, Ukraine.

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Introduction

Quality of Life (QoL) is defined by the WHO as an individual's perception of their position in life in the context of the culture, and value systems in which they live and in relation to their goals, expectations, standards and concerns (WHO, 2020). For students who are in a critical period of socialisation and professional competence development, QoL is particularly important. Numerous studies confirm that low levels of physical activity and high levels of academic stress are associated with a deterioration in students' physical and mental well-being, while regular physical activity and adequate physical fitness contribute to an increase in QoL indicators (Kljajević et al., 2022). In particular, health-enhancing recreational physical activity (team sports, outdoor activities, structured physical activities) has been shown to have a positive impact on the mental health, socialisation, and overall well-being of young people (Obay et al., 2024; Rhodes et al., 2025; Rodríguez-Bravo et al., 2020).

Furthermore, recent studies emphasise that students' QoL is determined not only by their level of physical activity, but also by a complex of socio-psychological and educational factors (Schramlová et al., 2024). A heavy academic workload, limited access to recreational resources, and insufficient attention to psycho-emotional support have a negative impact on QoL, which justifies the need for targeted health-enhancing recreational programmes in higher education institutions.

The last decade has been characterised by growing interest in the use of machine learning (ML) methods in predicting health and well-being indicators (Abegaz et al., 2025). Tree-based ensemble algorithms, particularly Gradient Boosting Trees and Random Forest, demonstrate greater predictive accuracy than classical statistical models, particularly when dealing with nonlinear and multifactorial relationships (Oparina et al., 2025). ML models that integrate social determinants of health, behavioural indicators, and mental metrics are successfully used to predict HRQoL at the individual level, although they are accompanied by the methodological challenge of finding a balance between accuracy and interpretability of results (Raouf, 2025).

In the Ukrainian context, the relevance of the problem takes on an additional dimension. War significantly affects students' mental health and QoL, causing anxiety, depression and loneliness (Andrieieva et al., 2023; Byshevets et al., 2023). The safety of the educational environment becomes not only a prerequisite for the learning process, but also a basic predictor of students' emotional stability and viability (Stelter et al., 2025).

That is why the integration of safety indicators (infrastructure, warning systems, and organisational regulations) into QoL predictive models is conceptually and empirically justified.

Despite this, Ukraine lacks comprehensive models for predicting students' QoL that combine behavioural metrics (e.g., IPAQ physical activity level), mental health indicators (SWLS life satisfaction) and specific wartime factors (educational environment safety index). This approach opens up prospects for the personalised design of health-enhancing recreational programmes aimed at identifying risk groups and targeting key components of QoL such as physical activity, mental resilience, and social support. Therefore, the creation and validation of predictive ML models of the physical and mental components of students' QoL, taking into account complex determinants (behavioural, mental, social, and security) is an urgent scientific problem. The results of such models can form the basis for improving the structure and content of health-enhancing recreational programmes in higher education institutions in Ukraine during wartime.

Material and methods

Participants

The study involved 172 university students aged 18 to 25 ($M=20$; $SD=20-21$) representing various courses and educational programmes at higher education institutions in Ukraine. The sample was balanced in terms of sex and included 84 young men (48.8%) and 88 young women (51.2%), which made it possible to identify sex-related differences in the level of physical activity and QoL indicators. The criteria for inclusion in the study were: active student status (bachelor's degree); no medical contraindications to physical activity; regular attendance at the university's sports and recreation centre (SRC); and voluntary consent. All participants confirmed their informed consent to participate in the study. For safety and ethical reasons, the conditions of studying under martial law were taken into account: students were involved only in cases where the educational process took place in a safe environment. Thus, the sample was a representative group of Ukrainian students who were in a period of high academic workload and adaptation to changes in the social and educational environment, which allowed us to investigate the relationship between physical activity, quality of life, and safety factors.

Research organization

In this study, several internationally validated instruments were employed to ensure the methodological robustness of data collection and interpretation. To evaluate perceptions of service

quality in the sphere of sports and health-related activities, the Sports and Health Service Quality Assessment Scale (SQAS) was applied. The instrument, originally developed for assessing the quality of sports services (Lam et al., 2005), was contextually adapted to the realities of wartime Ukraine. The modified version included 42 items, structured into seven analytical dimensions. Reliability diagnostics confirmed an exceptionally high level of internal consistency (Cronbach's $\alpha=0.991$) and stability of responses (split-half reliability = 0.994).

Assessment of health-related quality of life (HRQoL) was carried out using the Short Form-36 Health Survey (SF-36), one of the most widely implemented generic tools in clinical and health research. The instrument consists of 36 items, grouped into eight domains that collectively generate two composite indices: the Physical Component Summary (PCS) and the Mental Component Summary (MCS). Scores for each domain were calculated on a 0–100 scale, where higher values reflect better perceived health status. The psychometric evaluation in our sample confirmed satisfactory internal reliability (Cronbach's $\alpha=0.753$) and good test stability (split-half reliability = 0.810).

The International Physical Activity Questionnaire – Short Form (IPAQ-SF), adjusted to the Ukrainian sociocultural and environmental context, was used to obtain a quantitative estimate of physical activity. The short version of the IPAQ comprises seven questions covering vigorous and moderate physical activity, walking, and sedentary behavior during the previous week. Energy expenditure was calculated in metabolic equivalent minutes per week (MET-min/week) and categorized into three levels: low (<600), moderate (600–3000), and high (>3000). The reliability assessment demonstrated acceptable consistency for this cohort (test–retest correlation $r=0.79$).

Statistical analysis

Machine learning methods were used to predict the physical (PCS) and mental (MCS) components of QoL. The main model used was Gradient Boosting Trees (GBT) with the following parameters: 200 trees, maximum depth – 10, learning rate – 0.1. To verify the results, Random Forest (RF) models (40 trees, depth – 10) were additionally constructed.

In each case, the data was randomly divided into training (70%) and test (30%) samples. Cross-validation was used to avoid overfitting. The performance of the models was evaluated using the following standard metrics: MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), and MAPE (Mean Absolute Percentage Error). The calculations were performed in STATISTICA 14.0

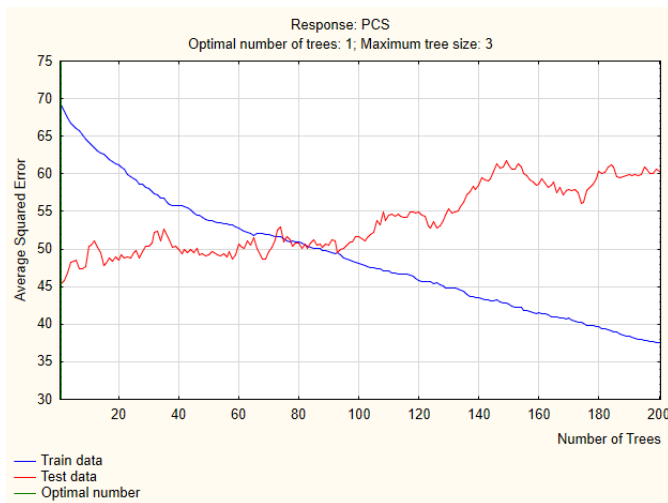
(StatSoft, USA).

Since the results of the factor analysis revealed two significant factors explaining 76.6% of the total variance (Factor 1 includes all motives for visiting SRC, and Factor 2 includes all limiting factors, except for lack of time and finances, four variables were created from the 19 available for further analysis: «Motivation» (average value of all motives), «Limitations» (average value of Factor 2 components), «Lack of time», and «Lack of finances». The decision to treat the factors «Lack of time» and «Lack of finances» as separate variables was justified by their unique influence and lack of correlation with other limiting factors.

Thus, the data set used for analysis included the following dependent variables: physical component (PCS) and mental component (MCS) of QoL, as well as independent variables: satisfaction with life (SWLS) assessed on a scale from 5 to 35 points; satisfaction with sports and health services (SQAS) consisted of seven factors (SQAS1 – staff, SQAS2 – locker room, SQAS3 – program, etc.) assessed on a Likert scale from 1 to 7 points; level of physical activity (IPAQ) assessed on a scale from 0 to 35 points; motivation to visit the SRC, average value for all motives was assessed on a Likert scale from 1 to 7 points; limiting factors, average value for all limiting factors, except for «lack of time» and «lack of finances», was assessed on a Likert scale from 1 to 7 points; lack of time assessed on a Likert scale from 1 to 7 points; and lack of finances scored on a Likert scale from 1 to 7 points. Categorical variables included sex: 1 – male, 0 – female; and group of respondents by frequency of visits to the SRC: 1 – 3 or more times a week, 2 – 1-2 times a week.

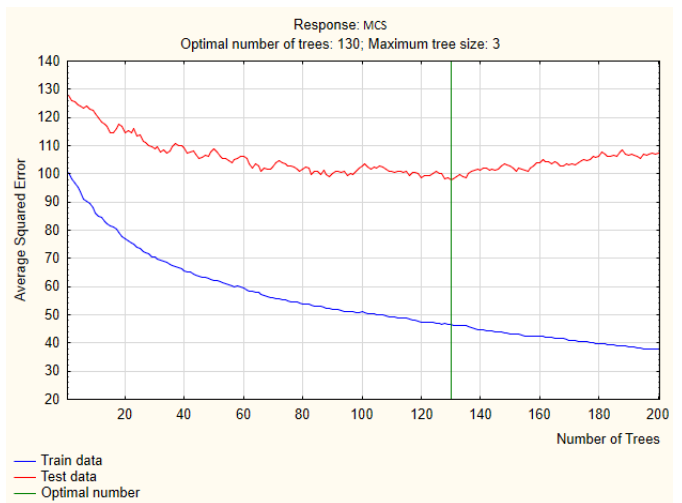
Results

To assess the relationship between independent variables and the physical component of QoL, the programme constructed a single tree. To predict PCS, there was a simple linear relationship that can be adequately described by a single tree, i.e. a simple set of rules (Fig. 1a). To predict the mental component of QoL based on the data studied, 130 trees were needed. As can be seen (Fig. 1b), the prediction error of the training data steadily decreases as more and more additive terms (trees) are added to the model. However, after 130 trees, the performance for the test data of independently taken samples actually begins to deteriorate, clearly indicating the point at which the model begins to overfit the data. The Boosted Trees algorithm automatically determines this point and calculates the predicted values (and generates deployment code to calculate the predicted values using rapid model deployment) for the corresponding number of trees.

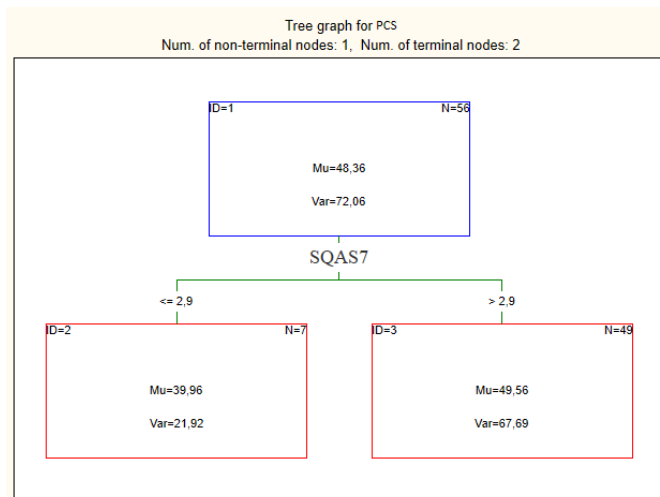


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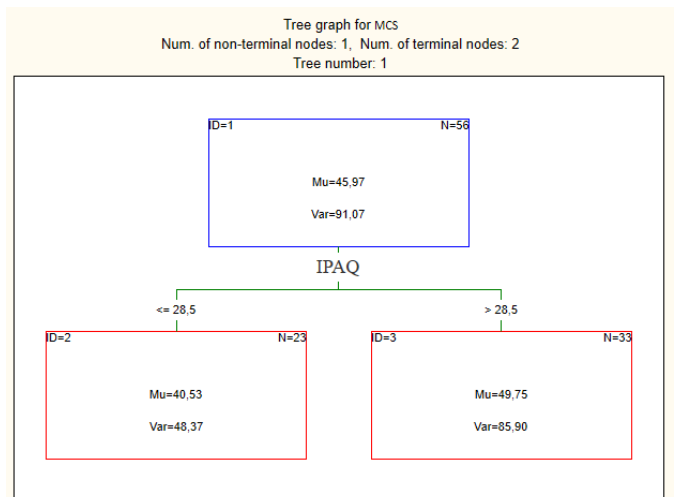
Figure 1. Summary of Boosted Trees.



b



a



b

Figure 2. Examples of trees for the physical and mental components of students' quality of life.

This indicates that the relationship between independent variables and MCS is much more complex than the relationship between them and PCS. For MCS models, more trees were needed to reveal these complex relationships and make accurate predictions.

Figure 2 illustrates the trees obtained for the physical (a) and mental (b) components (Fig. 2).

The average PCS value for the root node is 48.36 ± 8.49 (where 8.49 is the standard deviation calculated as the square root of the variance Var). This means that the PCS values in the root node deviate from 48.36 by an average of 8.49 units.

If the SQAS7 'Safety' score exceeds 2.9 points (average and above), the average PCS value increases to 49.56 ± 8.23 . In a node where the SQAS7 score is below 2.9, the average PCS value is 39.96 ± 4.68 . Thus, when the SQAS7 score exceeds 2.9 points, the average PCS value increases by approximately 9.6 units ($49.56 - 39.96$), which

is 24% of the average PCS value in a node with a lower SQAS7 score (39.96) (Fig. 3a). To predict MCS, 130 trees were constructed using the Gradient Boosting Trees algorithm. Each tree in this algorithm sequentially corrects the errors of the previous ones, and the final prediction is the sum of the predictions of all 130 trees. As an example, let us consider one of the trees in this model. If the physical activity score (IPAQ) exceeds 28.5 points, the average MCS value increases by approximately 9.22 units ($49.75 - 40.53$). This represents 22.7% of the average MCS value in the node where the IPAQ score is below 28.5 points (40.53) (Fig. 3b).

Model 1 determines the relative importance of factors influencing the physical and mental components of QoL. With regard to PCS, it should be noted that safety (availability of shelters, timely air raid warnings, safety during air raids and resumption of classes after them, general safety) has the greatest weight (1.0), especially during

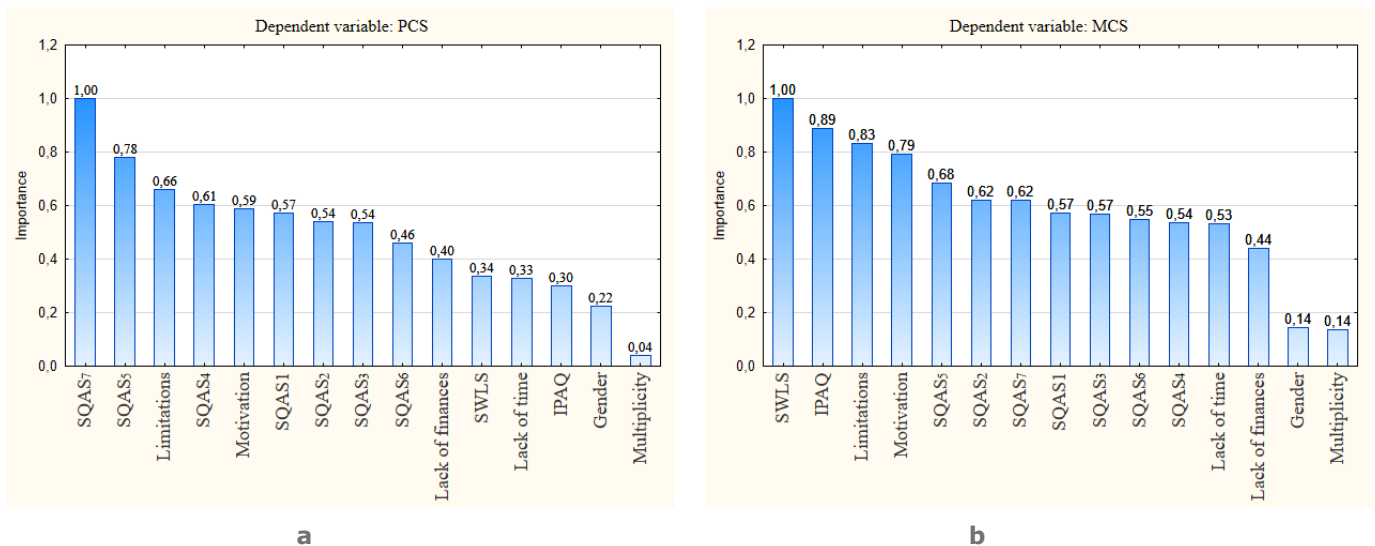


Figure 3. Relative importance of variables for predicting physical and mental components of QoL (Model 1)

wartime. This indicates that safety is a primary factor affecting students' physical well-being and emphasises the importance of creating a safe environment for physical education and sports in wartime. The high weight of the predictor «Events» (0.782), which includes the frequency of events, their informational support and quality, suggests that the quality and organisation of events play an important role in the physical component of QoL. In addition, the factors «Limitations» (lack of motivation, poor health, fear or shyness, lack of support, inaccessibility of sports infrastructure, lack of interesting programmes) and «Training facilities» (comfort of the hall/pool, modern equipment, adequacy of signage, variety and accessibility of equipment, overall service) also have a significant impact (0.652 and 0.606, respectively). This indicates that the limitations faced by students and the quality of training facilities play an important role in their physical well-being (Fig. 3a). The mental component of QoL (MCS) includes the following most significant factors. Among them is SWLS (Satisfaction with Life), which, as expected, has the greatest weight (1.0). This confirms that mental well-being is closely related to overall life satisfaction. The next most important factor is IPAQ (Physical Activity), whose high weight (0.886) emphasises its importance for mental well-being. This confirms that physical activity not only improves physical health but also has a positive effect on mental health. Factors such as «Constraints», «Motivation» (improving physical health and mental well-being, socialisation and communication, achieving sporting goals, obtaining pleasure, relieving stress and tension, increasing productivity, development of useful habits, the opportunity for self-expression) and «Activities» also have a significant impact (0.833, 0.792 and 0.685, respectively), indicat-

ing that students' mental well-being depends on various factors, including limitations, motivation, and activities. In addition, «Programmes» and «Safety» have a weight of more than 0.6, indicating that training programmes and safety are of significant importance (Fig. 3b).

When building Random Forest models, we found that about 10 trees are needed in an ensemble to predict PCS, and about 15 trees are needed for MCS (see Fig. 4a and 4b).

An analysis of significant factors influencing the physical component of QoL (PCS), obtained using the Random Forest model, revealed that satisfaction with life (SWLS) is the most significant predictor (weight 1.00). The following factors also have a significant impact (weight 0.98–0.99): Staff (possession of the necessary knowledge/skills, neatness and clothing, willingness to help, sociability, response to complaints, etc.); Adaptability (convenient schedule and format of classes, student support, inclusiveness); Locker room (general service, cleanliness of showers, accessibility, safety). As for the significant factors influencing the mental component of QoL (MCS), the priority factor was «Safety» (SQAS7) (weight 1.00). The next most significant factors, satisfaction with life (SWLS) and locker room, have significantly lower weights: 0.782 and 0.715, respectively (Fig. 5). Irrespective of the predictive approach applied (Gradient Boosting Trees or Random Forest), the variables «Sex» and «Frequency of classes» demonstrated minimal explanatory power in relation to both the physical and mental domains of students' quality of life. By contrast, under wartime conditions, the «Safety» factor emerged as a critical determinant, consistently showing strong predictive weight across both modeling strategies for the physical and mental components of QoL. To evaluate the relative per-

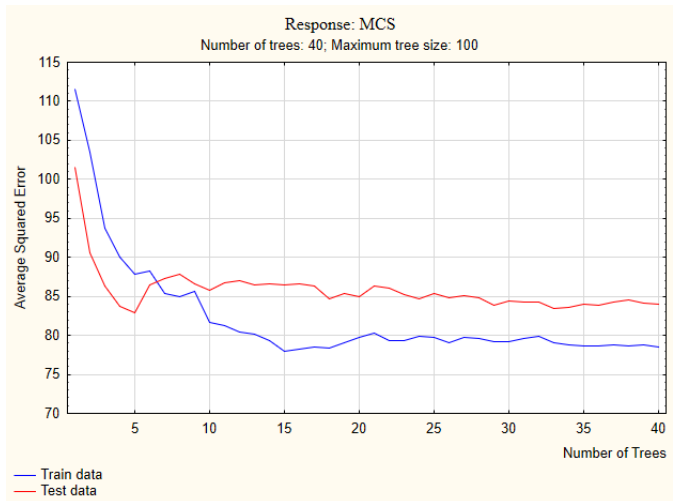
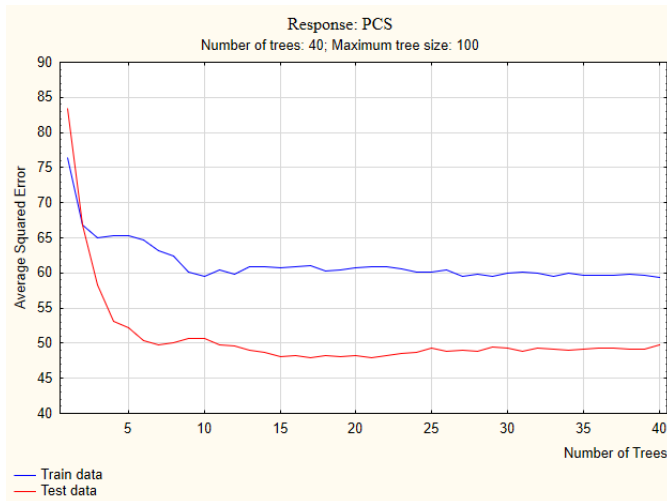


Figure 4. Summary of Random Forest

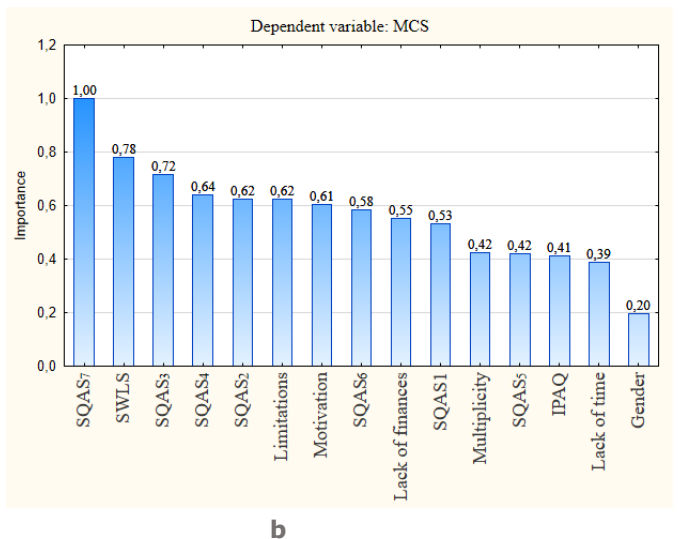
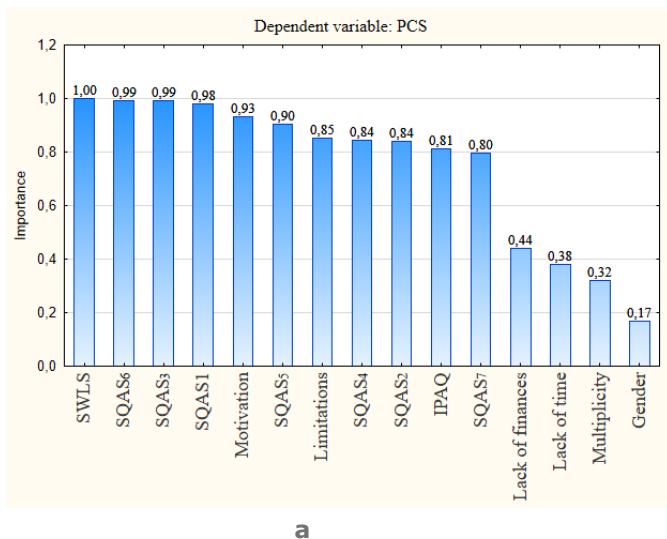


Figure 5. Relative importance of variables for predicting physical and mental components of QoL (Model 2)

formance of the two algorithms in forecasting the Physical Component Summary (PCS) and Mental Component Summary (MCS), a residual analysis was conducted.

For the PCS, the residuals exhibited a normal distribution, as confirmed by the Shapiro-Wilk W test, thereby allowing the application of Student's t -test for independent samples. The comparison revealed no statistically significant differences between Gradient Boosting Trees and Random Forest models ($t=1.793$; $df=99$; $p=0.0868$). In contrast, the residuals for the MCS demonstrated deviations from normality in the Gradient Boosting Trees model ($W=0.911$; $p=0.0009$). Consequently, a non-parametric Mann-Whitney U test was employed to compare model performance for this component. This approach allowed for a more robust comparison of the predictive accuracy between the two methods when distributional assumptions were not met. The analysis did not

reveal any statistically significant differences between the MCS models either ($U=1220.0$; $Z=-0.855$; $p=0.3926$). This indicates that both models perform equally well on the data. On the other hand, the findings of a comparative analysis of model quality metrics demonstrated that Gradient Boosting Trees exhibited the following outcomes in predicting physical (PCS) and mental (MCS) components of QoL (Table 1).

The results showed that the Gradient Boosting Trees model demonstrates higher prediction quality, as evidenced by lower metric values: MAE (5.53 vs. 5.70), RMSE (45.70 vs. 49.76) and MAPE (0.102 vs. 0.119). In addition, the simplicity of the Gradient Boosting Trees model, which performs effectively with a single tree, is an additional advantage over Random Forest, which requires an ensemble of about 10 trees for stabilisation. Unlike PCS prediction, the Random Forest model showed better results for MCS. The RMSE

Table 1. Model quality assessment based on test samples

Model	PCS			MCS		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE
1	Gradient Boosting Trees					
	5.53	45.70	0.102	7.46	98.02	0.198
2	Random Forest					
	5.70	49.76	0.119	7.69	83.96	0.180

(83.96) and MAPE (0.180) metrics for Random Forest are lower than those for Gradient Boosting Trees (98.02 and 0.198, respectively). This indicates that Random Forest provides more accurate MCS predictions. In both cases, the models showed better results for predicting the physical component (PCS) than for the mental component (MCS). The result obtained is important for understanding the peculiarities of modelling subjective assessments of the physical and mental components of QoL. It shows that the physical component of QoL is more predictable than the mental component, which is more complex and variable.

Discussion

The results confirm that the level of safety is a determining predictor of both the physical and mental components of the QoL among higher education students. This conclusion is consistent with the findings of previous studies of Ukrainian researchers, which have emphasised the critical role of socio-psychological factors in maintaining the well-being of students under conditions of increased stress, particularly during wartime (Andrieieva et al., 2022, 2025; Maltsev et al., 2022; Petrachkov et al., 2023). A sense of security can be seen as a basic condition for the implementation of adaptive mechanisms that ensure the preservation of physical and mental health.

The identified impact of physical activity and life satisfaction on the indicators of QoL is consistent with reported data. Ramón-Arbués et al. (2022) demonstrated that regular physical activity among students is closely correlated with higher QoL indicators. Similar results were obtained by researchers, emphasising the integral importance of physical culture for maintaining vitality and psycho-emotional stability (Hakman et al., 2020; Steinacker et al., 2023).

Intelligent data analysis revealed that machine learning models are capable of accurately predicting the physical and mental components of QoL taking into account the multifactorial nature of the phenomenon. This is in line with current scientific trends, where machine learning algorithms are used to model individual trajectories of mental and physical health (Zhang et al., 2023). Similar approaches have already demonstrated their effectiveness in identifying hidden patterns

of correlation between physical fitness levels and psychological indicators in students (Pang & Wang, 2022).

The results of the study reinforce the current understanding of quality of life as a multidimensional construct, where physical, psychological, and social factors are intertwined (WHOQOL Group, 2020). Under conditions of war and social instability, when traditional sources of well-being are limited, the importance of safety, physical activity, and life satisfaction increases significantly. This highlights the need to integrate QoL prediction methods into the practice of educational institutions, which will allow for the timely identification of at-risk groups of students and the development of targeted health-enhancing recreational programmes.

The results of the study confirm the effectiveness of using intelligent data analysis methods, in particular stochastic gradient boosting trees (GBDT) and random forest, in predicting the physical and mental components of QoL. The results are consistent with previous studies, which indicate the high accuracy of machine learning algorithms in modelling multifactorial processes related to health and physical activity.

A comparison of the models used revealed that GBDT demonstrates higher predictive power than Random Forest, which may be due to its ability to take into account complex relationships between variables and optimise the learning process through adaptive tree weight updating. However, it should be noted that the use of GBDT requires careful tuning of hyperparameters to achieve maximum performance, which may be a limitation in its application for real-time analysis of large data sets.

An analysis of the factors that most influence the predicted components of QoL showed that physical activity level, subjective perception of one's own health, and stress level play a key role. These findings are consistent with studies that emphasise the importance of a healthy lifestyle and psycho-emotional state in shaping a person's overall well-being. At the same time, the interaction between individual factors indicates the need for a comprehensive approach to predicting QoL.

Despite the positive results, this study has certain limitations. First, the study sample was

relatively limited, which may affect the generalisability of the conclusions. Second, only quantitative indicators were taken into account without a detailed analysis of individual socio-economic factors, which may also have a significant impact on QoL. Further studies should include larger samples and consider additional social and psychological aspects to improve the accuracy of the models.

Practical Implications

The outcomes of this research extend beyond theoretical considerations and hold direct applicability for the organization of student support systems in higher education. The pronounced influence of safety-related perceptions on both physical and mental quality-of-life domains demonstrates that the creation of secure educational and living environments should be regarded as a strategic priority, particularly in conflict-affected regions. Such measures may include not only infrastructural improvements but also the expansion of psychological counseling services and stress-management initiatives.

Equally important is the role of physical activity, which emerged as a consistent determinant of quality of life across both physical and mental dimensions. This finding provides a strong rationale for the integration of structured physical education, recreational programs, and individualized exercise interventions into the daily routines of students. In doing so, universities may counterbalance the adverse health consequences of reduced mobility and sedentary behaviors that are often exacerbated in crisis conditions.

The study also highlights the contribution of life satisfaction, motivational factors, and activity-related limitations to students' well-being. These insights suggest that effective health-promotion strategies should adopt a multifaceted approach, combining physical training with psychological resilience-building, motivational support, and opportunities for social participation.

Finally, the demonstrated effectiveness of machine learning methods (GBT and RF) in predicting quality of life supports their application as innovative tools for data-driven monitoring and personalized intervention design. Embedding such models into institutional health frameworks could facilitate early identification of at-risk groups and inform tailored interventions aimed at sustaining both physical and mental health outcomes.

Conclusions

The application of the Gradient Boosted Trees (GBT) method revealed notable differences in the complexity of relationships between independent variables and the QoL components. For the physical component, the model generated a single

tree, while for the mental component, 130 trees were required, indicating a substantially more intricate interplay between predictors and students' psychological well-being in wartime conditions.

Both the GBT and RF models consistently identified "Safety" (SQAS7) as a critical determinant, highlighting its priority for students under conditions of armed conflict. Regular physical activity (IPAQ) was also a significant contributor to both physical (RF; 0.821) and mental (GBT; 0.886) domains of quality of life. Additional influential factors included overall life satisfaction (SWLS), functional limitations, motivation, and engagement in daily activities. Conversely, variables such as "Sex" and "Frequency of classes" showed no significant effect on students' quality of life. The findings emphasize the importance of incorporating the war-related context into quality-of-life research.

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Supplementary Information

Author's contribution

Olena Andrieieva: Conceptualization, Methodology, Check, Formal Analysis, Investigation, Resources, Writing – Rough Preparation, Writing – Review and Editing, Visualization, Supervision, Project Administration; **Nataliia Byshevets:** Conceptualization, Methodology, Software, Formal Analysis, Investigation, Resources, Data Curation, Writing – Rough Preparation, Visualization; **Andriy Vindyk:** Conceptualization, Methodology, Investigation, Resources, Writing – Review And Editing; **Vadym Stepanuk:** Methodology, Software, Investigation, Resources, Writing – Review And Editing; **Inna Khrypko:** Investigation, Resources. All authors have read and agreed with the published version of the manuscript.

Declarations

Conflict of Interest

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