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Original Article

Predicting quality of life components in university students based on physical fitness and gender using neural networks

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Abstract.
This study aimed to develop a predictive framework for assessing quality of life (QoL) components in university students by integrating physical fitness parameters and gender into an artificial neural network (ANN) model. Physical fitness was evaluated using a standardized battery of motor ability tests, and QoL was measured with the SF-36 Health Survey. A multilayer perceptron artificial neural network (ANN) was trained to predict both the physical and mental component summaries of quality of life (QoL). The model identified endurance as the most influential predictor, showing the strongest activation of hidden neurons and a consistent positive association with physical QoL. Speed and flexibility had moderate effects; however, flexibility was primarily associated with negative weights, suggesting a potential to reduce both physical and mental QoL scores. Strength, agility, and speed-strength abilities showed weaker predictive contributions. Gender emerged as a secondary but notable factor, with slightly greater model sensitivity observed in female participants. Model visualization revealed a clear endurance–physical QoL gradient in male students, where higher endurance corresponded to improved physical well-being, whereas no comparable linear trend was evident for mental QoL, suggesting complex nonlinear dynamics. Performance metrics indicated higher predictive accuracy for physical components (mean absolute error (MAE) = 2.78; root mean square error (RMSE) = 3.56) than for mental components (MAE = 8.43; RMSE = 10.19). Scenario simulations demonstrated that enhancing endurance, with other variables held constant, produced a 6.5–8.8% increase in predicted physical QoL scores, highlighting its practical value in health-promotion strategies. These findings confirm the efficacy of ANN modeling in capturing multidimensional and nonlinear relationships between gender, motor abilities, and QoL indicators. The results provide a foundation for developing evidence-based, personalized physical education programs aimed at improving health and well-being among university students.
Keywords: endurance capacity, flexibility assessment, machine learning algorithms, wellness analytics, health-related outcomes, psychophysical well-being.

Introduction

In contemporary society, the quality of life (QoL) among university students is viewed as a multifaceted measure encompassing physical, psychological, and social well-being (Andrieieva et al., 2025; Orikhovska et al., 2020). Yet, a growing body of research highlights a decline in students' physical activity levels, which in turn has an adverse impact on their overall life quality. There is a need to develop tools that would allow for timely assessment and prediction of the state of QoL, taking into account individual physical abilities and sexual characteristics (Petrachkov et al., 2023). In this context, the use of artificial intelligence methods, in particular neural networks, opens up new opportunities for creating accurate prediction models, which can become the basis for personalized programs of physical education and health improvement for students (Drozdovska et al., 2020). The problem of the relationship between physical abilities and QoL of student youth is actively discussed in the scientific literature (Steinacker et al., 2023$ Thian et al., 2025). In particular, studies (Karataş, 2024; Lemes et al., 2024) indicate a significant impact of physical fitness on the physical component summary (PCS) of QoL. Previous studies highlight how gender differences shape the perception of quality of life, particularly regarding psycho-emotional well-being and social adaptation (Galan et al., 2021; Rollero et al., 2014).

In recent years, the application of machine learning (ML) techniques in health sciences and QoL prediction has gained significant momentum. Empirical evidence demonstrates that neural networks are particularly effective in modeling and forecasting complex medical and psychophysical parameters (Jannani et al., 2023). A growing body of research highlights the increasing integration of ML into healthcare to estimate QoL outcomes for individuals with severe health conditions. For instance, Alexander et al. (2023) proposed an ensemble learning framework to assess the impact of Parkinson's disease on patient well-being, providing valuable support for clinical decision-making and individualized care planning. Likewise, Su (2025) employed a random forest algorithm to examine the prevalence of geriatric syndromes among older adults and their

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relationship with QoL, emphasizing the importance of a holistic evaluation that accounts for the interaction of multiple age-related health conditions.

Earlier work by Yamamura (2003) demonstrated the advantages of artificial neural networks (ANNs) in predicting pharmacokinetic parameters in critically ill patients, outperforming multiple regression analysis when using condition severity indicators as input variables. Similarly, Takehira (2011) utilized a three-layer ANN to model discrepancies between QoL assessments provided by cancer patients, pharmacists, and nurses. While pharmacists and nurses yielded comparable mean scores, the ANN analysis revealed that their evaluations were based on distinct criteria shaped by professional responsibilities and the nature of patient interactions – showcasing the capability of neural networks to uncover nuanced differences in human judgment.

The COVID-19 pandemic has further intensified academic interest in QoL determinants. Pinochet et al. (2023) developed a theoretical ANN-based model to investigate the influence of smart retail technologies (e.g., online ordering, contactless payments) on consumer QoL during the pandemic. Their findings identified perceived safety from infection as the dominant factor mediating the relationship between technology use and subjective well-being. Such results underscore the potential of ANNs for capturing the dynamic effects of crisis situations on population-level QoL. Recent research highlights the complex interrelations between physical fitness, physical activity, and QoL among university students, with a growing emphasis on the mediating and moderating roles of psychological and demographic factors. Neural network and association analyses reveal significant links between students' physical fitness indicators and gender differences (Pang et al., 2022). Physical exercise positively impacts life satisfaction through the mediation of self-efficacy and health literacy (Ye et al., 2025). Studies focusing on female students demonstrate that physical activity and socio-demographic variables influence their QoL (Kotarska et al, 2021). Structural equation modeling further clarifies that body mass index mediates, while gender moderates, the relationship between physical activity and both physical and mental components of QoL (Hoseini et al, 2022). Additionally, self-efficacy regarding physical fitness shapes subjective well-being via physical activity, with gender serving as a significant moderator (Gao et al., 2025). Despite these advances, there remains a need to comprehensively integrate these factors to better understand how physical fitness and activity contribute to students' holistic well-being, considering gender-specific pathways and psychological mediators.

Overall, the reviewed literature confirms the growing importance of machine learning – particularly neural network architectures – in predicting multifactorial, subjective indicators such as QoL across diverse population groups. Evidence from medicine, pharmacy, and social sciences indicates that ANNs are capable of detecting both linear and nonlinear dependencies, integrating physiological, psychological, and social determinants, and offering enhanced predictive performance compared to traditional statistical models. However, an analysis of Ukrainian and foreign sources indicates a lack of work devoted to the comprehensive prediction of components of students' QoL, taking into account physical abilities and gender, using neural networks (Byshevets et al., 2024 a,b). On our part, we are considering the possibility of identifying indicators that can improve the students' quality of life through systematic influence. The complexity of the scientific problem of assessing quality of life and creating resources to improve it necessitates a focus on modern technological solutions for modelling neural networks. Integrating artificial intelligence systems as a tool to analyse the interrelationships between components of students' quality of life and other indicators is likely to create a multi-level analysis structure. This determines the relevance of this study.

Materials and methods

Participants

The study involved 172 students of higher education institutions of Ukraine aged 18 to 25. Among the participants, there were 84 boys (48.8%) and 88 girls (51.2%), which ensured a relative gender balance in the sample. The median age was 20 years (interquartile range: 20–21 years), which corresponds to the typical profile of student youth. The sample was formed on the basis of clear inclusion criteria: age up to 25 years inclusive, Ukrainian citizenship, absence of medical contraindications to physical activity, regular physical activity, and complete and correct completion of the questionnaire. Of the initial 182 questionnaires, 172 participants whose data met the specified requirements were included in the final analysis. An important contextual factor of the study is that it was conducted in conditions of martial law, which is characterized by an increased level of stress among young people and can potentially affect the physical and psycho-emotional state of the participants. All study procedures were conducted in accordance with ethical standards, including the provisions of the World Medical Association Declaration of Helsinki (2013) and applicable national and international bioethical regulations. Participants were informed about the aims, procedures and potential risks of the study and provided written informed consent to participate. All data were collected in compliance with the principles of anonymity, voluntary participation and protection of personal information.

Research organization

To assess physical fitness, a system of standard tests for the development of basic motor skills was used, and the level of QoL was determined using the SF-36 questionnaire. An automated neural network was used to predict the PCS and mental components summary (MCS) of the QoL of higher education students depending on their gender and the development of their motor skills. The process of building and training the model included the following stages: creation of several data subsamples (the method of randomly creating 2 independent subsamples from the original data set was applied); division of each subsample into subsets (each of the two created subsamples was randomly divided into three subsets in the following ratio: training sample: 70% of the total data volume in each subsample, which was used to train the neural network parameters; control sample: 15% of the total data volume in each subsample, which was used to monitor the learning process and prevent overtraining; test sample: 15% of the total data volume in each subsample, which was used for the final independent evaluation of the trained model; automated process of building and training (the use of an automated neural network assumed that certain aspects of the network architecture (e.g., number of layers, number of neurons in layers, activation functions) and training parameters (e.g., learning rate, number of epoch) be determined and optimized by the Statistica 10.0 program (StatSoft) automatically based on data characteristics and results on the control sample; reproducibility (the initial value of the random number generator was set to 1000 to ensure reproducibility of the process of dividing the data into subsets within each created subsample).

Statistical methods

To identify and model the relationships between the indicators of motor skills development, the gender of students and their PCS and MCS of QoL, a multilayer neural network (MLP) was used. The architecture of the selected MLP 8-4-2 model included an input layer with eight neurons corresponding to the independent variables, one hidden layer with four neurons and an output layer with two neurons for predicting the PCS and MCS of the QoL. The network was trained on the corresponding data sample using the backpropagation error algorithm. The quality of the trained model was assessed on the test sample of each of the two created subsamples. For a generalized assessment of the predictive ability of the automated neural network, traditional metrics were used that provided a comprehensive assessment of the model: mean absolute error (MAE); root mean square error (RMSE); coefficient of determination (R2), which shows the explanatory power of the model. To interpret the impact of individual predictors on the predicted values, sensitivity analysis and model weighting analysis were conducted.

Result

The study showed that of the proposed MLP models, 8-4-2 (model No. 1) is the most suitable for solving the tasks, since it has the highest test performance (0.661), the lowest test error (58.295), and the control error is also small (51.089). At the same time, model No. 1 uses activation: hyperbolic tangent on hidden neurons, which determines the type of nonlinearity introduced into the model at each level of hidden layers, and the same function at the output (a linear function where the output is equal to the input), which is often good for regression or scaled outputs such as QoL indicators. At the same time, a more compact architecture (8-4-2), i.e. a model with fewer parameters compared to other models, reduces the risk of overfitting (Table 1).

Table 1 – Comparative analysis of model performance

Architecture	Test productivity	Test error	Control error	Hidden neuron activation function	Activation function of output neurons
MLP 8-4-2	0.661	58.295	51.089	Hyperbolic	Identical
MLP 8-10-2	0.641	58.763	51.346	Hyperbolic	Identical
MLP 8-9-2	0.626	60.999	50.748	Logistic	Identical
MLP 8-12-2	0.625	61.138	51.767	Logistic	Identical
MLP 8-4-2	0.612	62.145	53.887	Hyperbolic	Exponential

The study allowed us to examine how sensitive the model's predictions are to changes in each individual input variable. According to the trained model, gender is the most important factor influencing the predicted values of the QoL of students in the test sample, followed by endurance and other motor ability indicators in descending order of their sensitivity coefficients (Fig. 1).

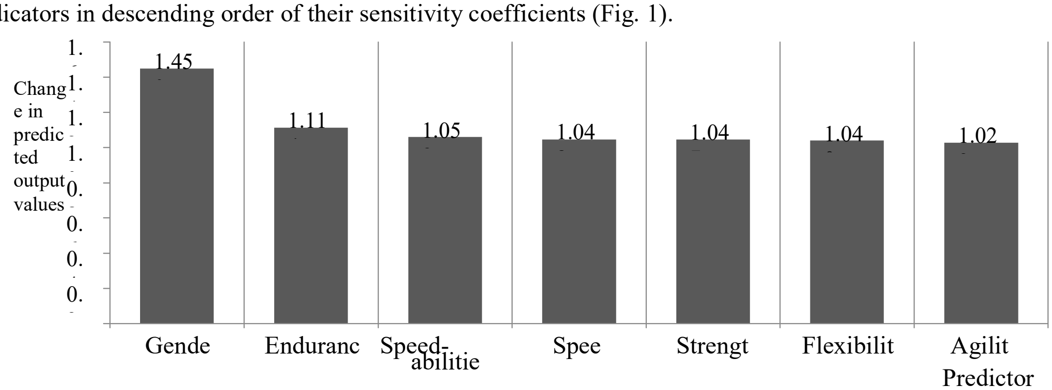

Figure 1 – Ranking of variables' importance

For example, for gender (coded as 1 – male, 0 – female), a coefficient of 1.450 means that when changing "Gender" from female to male (or vice versa), the predicted values of PCS and MCS change by 1.450 points on average. Regarding indicators of motor qualities ("Endurance", "Speed", etc.), a single change means an increase or decrease in the value by 1 point. For example, a coefficient of 1.114 for the predictor "Endurance" means that an increase in the "Endurance" indicator by 1 point leads to a change in the predicted PCS and MCS by 1.114 points on average. Analysis of correlation coefficients on the test sample revealed a significant difference in the ability of the model to predict the PCS and MCS of QoL. The high correlation coefficient for the PCS (r = 0.898) indicates a strong agreement between the predicted and actual values, explaining about 80.6% of the variance of this variable. In contrast, for the MCS, a much weaker linear relationship is observed (r = 0.424), which corresponds to approximately 18% of the explained variance. Thus, the constructed model demonstrates significantly better predictive ability for the PCS of QoL compared to the MCS (Fig. 2).

Thus, the largest positive signal to neuron 1 comes from variable I4 "Endurance" (+0.564), that is, it has the strongest positive effect on the activation of the first hidden neuron. To neuron 2, the largest positive signal comes from variable I1 "Speed" (+0.227), indicating its key positive role in the activation of the second hidden neuron. Neuron 3 is also most positively activated by input variable I4 (+1.034), and the strength of this influence is the highest among all input signals to hidden neurons. To neuron 4, the largest signal is negative and comes from input variable "Flexibility" I6 (-0.547), which indicates a decrease in the activation of the fourth hidden neuron along with an increase in students' "Flexibility". Regarding the influence of hidden neurons on output variables, the largest positive signal to output 1 (PCS) comes from neuron 4 (+0.537).

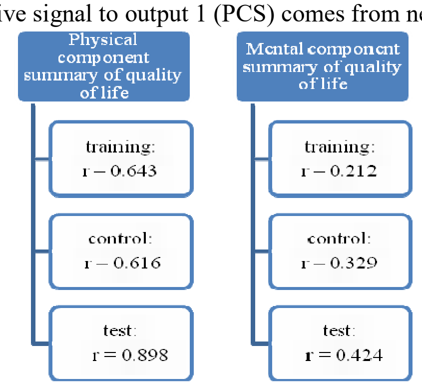

Figure 2 – Correlation analysis of model predictions with actual values (by samples)

However, given that neuron 4 itself receives the largest negative signal from I6, this may indicate a complex, possibly mediated negative effect of I6 on the PCS through the activation of neuron 4. Output 2 (MCS) also receives the largest absolute signal from neuron 4, but it is negative (-0.573). This indicates a strong negative relationship between the activity of the fourth hidden neuron and the value of MCS. Again, given the negative input signal to neuron 4 from I6, this increases the likelihood of a negative effect of I6 on MCS (Fig. 3).

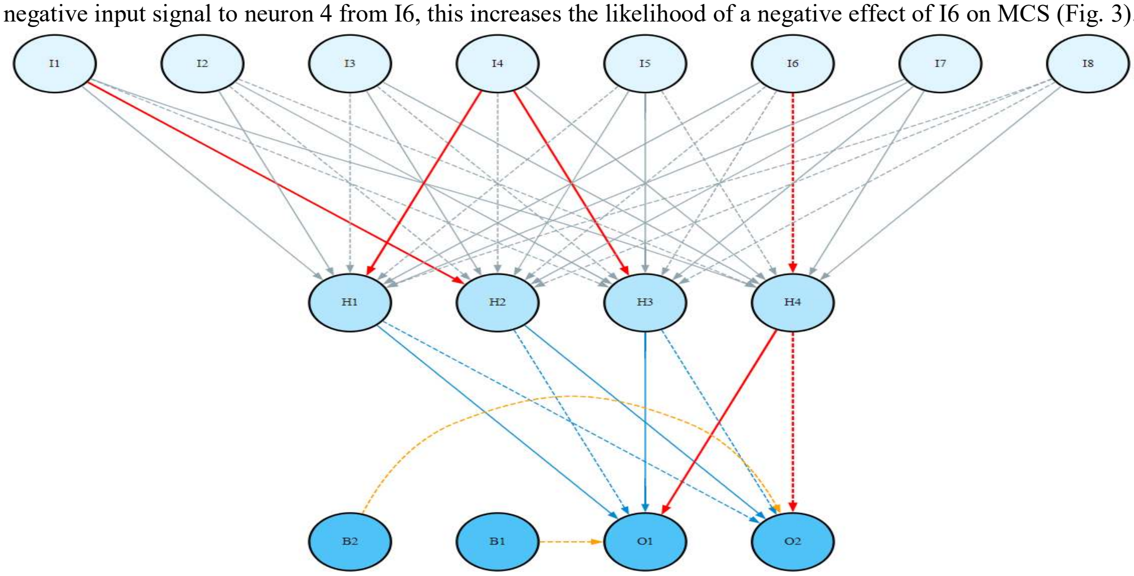

Figure 3 – Multilayer perceptron model for analyzing the influence of gender and motor abilities on PCS and MCS.

Note. I1 – Speed; I2 – Agility; I3 – Speed-strength abilities; I4 – Endurance; I5 – Strength; I6 – Flexibility; I7 – Gender (Female); I8 – Gender (male); H1, …, H4 – hidden neurons; O1 – PCS; O2 – MCS; B1, B2 – hidden bias; the most important predictors are highlighted; the dotted highlighting illustrates the negative influences

Thus, “Endurance” is an important positive predictor for certain aspects that affect the PCS and MCS through neurons 1 and 3. At the same time, “Flexibility” can be associated with factors that negatively affect the activation of neuron 4, which in turn is positively correlated with PCS, but negatively with MCS. Fig. 4 presents a simplified model of an artificial neural network (perceptron), which demonstrates the influence of the input parameter (“Speed”) on two output indicators - PCS and MCS. The data is transmitted through a hidden layer with four neurons (H1–H4), where each connection has a certain weight: blue values indicate a positive influence, red - a negative one. Additionally, biases (Bias, B1 and B2) are taken into account, which correct the output signals.

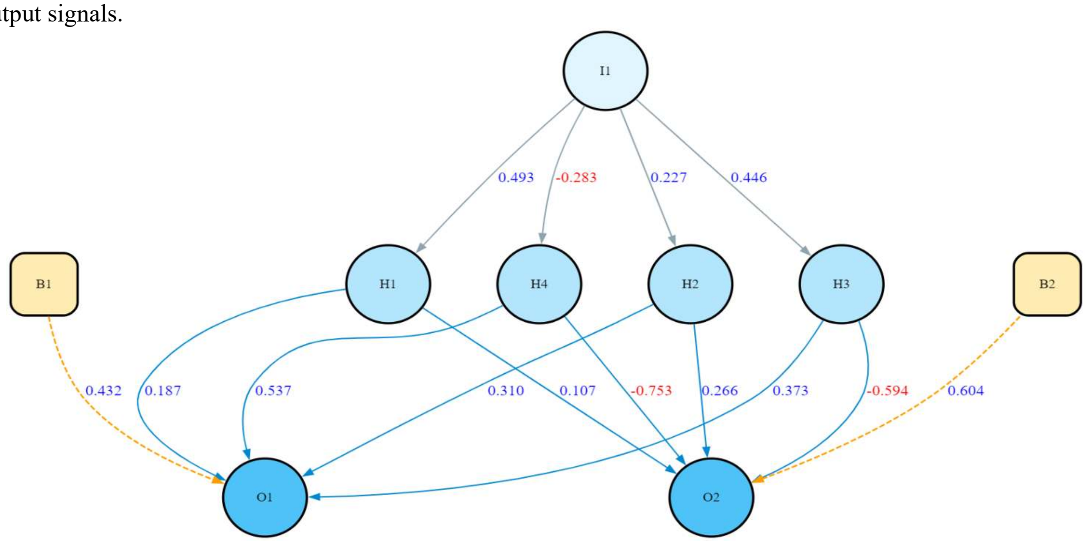

Figure 4 - Architecture of a neural network for predicting PCS and MCS based on speed

The full matrix of weights of the neural network (Table 2) includes all the studied predictors, except for speed - its topology is already illustrated in Fig. 4.

Table 2 - Weights of neural network connections (excluding speed)

No.	Connection MLP 8-4-2	Weight
1	Speed --> hidden neuron 2	0.227
2	Agility --> hidden neuron 2	-0.072
3	Speed-strength abilities --> hidden neuron 2	0.172
4	Endurance --> hidden neuron 2	0.218
5	Strength --> hidden neuron 2	0.086
6	Flexibility --> hidden neuron 2	-0.042
7	Gender (female) --> hidden neuron 2	-0.069
8	Gender (male) --> hidden neuron 2	-0.051
9	Speed --> hidden neuron 3	0.446
10	Agility --> hidden neuron 3	-0.037
11	Speed-strength abilities --> hidden neuron 3	0.604
12	Endurance --> hidden neuron 3	1.034
13	Strength --> hidden neuron 3	0.156
14	Flexibility --> hidden neuron 3	0.681
15	Gender (female) --> hidden neuron 3	-0.160
16	Gender (male) --> hidden neuron 3	-0.170
17	Speed --> hidden neuron 4	-0.283
18	Agility --> hidden neuron 4	0.176
19	Speed-strength abilities --> hidden neuron 4	-0.249
20	Endurance --> hidden neuron 4	-0.194
21	Strength --> hidden neuron 4	-0.238
22	Flexibility --> hidden neuron 4	-0.547
23	Gender (female) --> hidden neuron 4	0.178
24	Gender (male) --> hidden neuron 4	0.072
25	input bias --> hidden neuron 1	0.011
26	input bias --> hidden neuron 2	-0.087
27	input bias --> hidden neuron 3	-0.272
28	input bias --> hidden neuron 4	0.201
29	hidden neuron 1 --> PCS	0.187
30	hidden neuron 2 --> PCS	0.310
31	hidden neuron 3 --> PCS	0.373
32	hidden neuron 4 --> PCS	0.537

33	hidden neuron 1 --> MCS	0.107
34	hidden neuron 2 --> MCS	0.266
35	hidden neuron 3 --> MCS	-0.594
36	hidden neuron 4 --> MCS	-0.753
37	hidden bias --> PCS	0.432
38	hidden bias --> MCS	0.604

Analysis of the influence of predictors in the model, based on the sum of the absolute values of the weights from the input layer to all neurons of the hidden layer, revealed that endurance has the most significant impact on predicting the components of the QoL of higher education applicants. "Speed" and "Flexibility" demonstrate approximately the same noticeable impact, slightly inferior to "Endurance". "Speed-strength abilities" also have a noticeable impact, but smaller than the previous two features. "Strength" and especially "Agility" play a much smaller role in prediction. The feature "Gender" has a moderate impact, and the impact of female gender (0.634) is slightly higher than the impact of male gender (about 0.476) (Fig. 5).

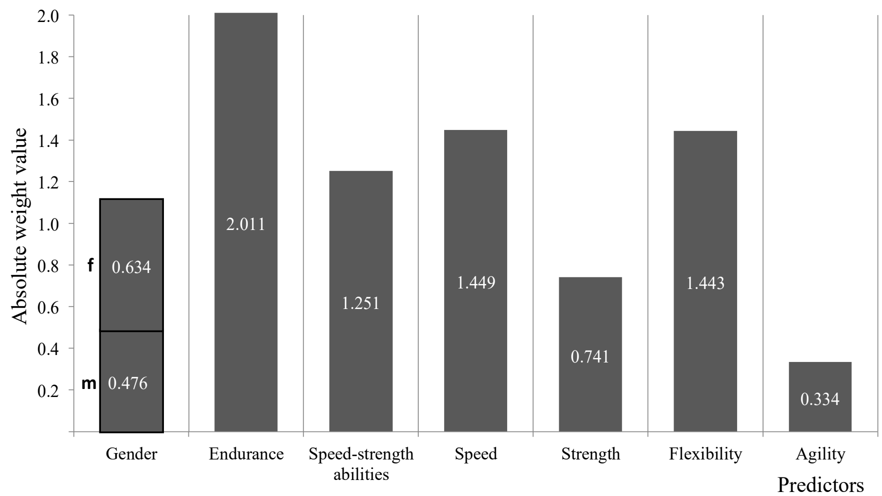

Figure 5 – Influence of features on the model (MLP 8-4-2)

Visualization of the relationship between gender, endurance (as the most influential trait) and the PCS component of QoL revealed a clear trend: low endurance scores, especially among men, corresponded with reduced PCS scores, while high endurance was usually accompanied by higher values of this component (Fig. 6a). In contrast, a similar visualization for the MCS component of QoL did not demonstrate a similar linear relationship, demonstrating a more complex and possibly nonlinear nature of the relationship between "Endurance" and PCS (Fig. 6b).

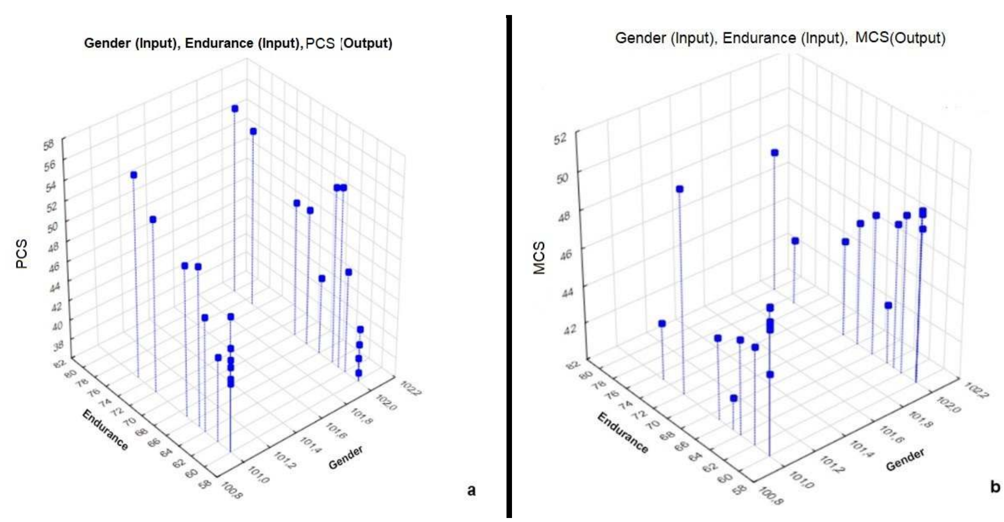

Figure 6 – Dependence of PCS and MCS components of students' QoL on gender and endurance (n = 172)

Given the higher predictive ability of the model for the PCS, the patterns identified for the PCS are more reliable for interpretation. During the assessment of the quality of the model, it was found that on average the predicted PCS values deviate from the actual values by 2.777 points (MAE). The RMSE for the PCS is 3.561 points. For comparison, the mean absolute deviation of the predicted MCS values from the actual ones is 8.425 points (MAE), and the RMSE for the PCS is significantly higher – 10.193 points. The larger difference between RMSE (10.193) and MAE (8.425) indicates a larger variance of errors in predicting the MCS, which may indicate a larger number or larger magnitude of significant errors in predicting the MCS compared to the PCS one. Using the constructed model, it was determined that, provided that the indicators of the development of motor abilities of a male student are estimated at 75 points (at the "good" level for each of the seven corresponding predictors), it can be predicted that his PCS will be 53.45 points, and MCS - 44.29 points. For a female student with similar indicators of motor abilities, the predicted values are 58.56 points and 41.62 points, respectively. In the case of an increase in endurance to 90 points in a male student (with other indicators unchanged), the expected level of PCS will increase by 8.8% (to 58.13 points), and in a female student - by 6.5% (to 62.35 points).

Discussion

Contemporary research increasingly employs machine learning – particularly artificial neural networks – to predict subjective indicators such as QoL across diverse population groups (Ramón-Arbués et al., 2022). This methodological shift reflects the growing demand for predictive frameworks capable of capturing non-linear, multifactorial relationships between physiological, psychological, and environmental determinants of well-being (Lebedeva & Yakovlev, 2024; Jannani et al., 2023). The ability of ANNs to identify latent interactions among variables makes them particularly well-suited for analyzing the multidimensional nature of QoL (Maltsev et al, 2022).

Our findings confirm the predictive value of physical capacities – endurance, strength, coordination, and speed-strength abilities – for the physical, psychological, and social components of QoL among university students (Petrachkov et al., 2022). This aligns with Ukrainian research indicating that higher physical fitness correlates with greater emotional resilience, stress tolerance, and vitality, thereby promoting life satisfaction and self-efficacy in both academic and social contexts (Andrieieva et al., 2022). Similarly, Hakman et al. (2020) observed that improved motor skills enhance life engagement, physical comfort, and social adaptability, noting that coordination and speed are particularly influential in fostering positive self-perception and active leisure participation.

These national findings resonate with international evidence. W. Jiang et al. (2021) demonstrated that regular physical activity improves subjective well-being, life satisfaction, self-esteem, and stress management skills among students. Their study also revealed gender disparities, with female students reporting lower physical activity levels, often due to motivational constraints, societal expectations, and body image concerns-suggesting that gender-responsive interventions may be essential to fully leverage the health benefits of physical fitness. Kotarska et al. (2021) further highlighted that women's QoL gains from physical activity may be mediated by social support and perceived competence, emphasizing the need for culturally and socially tailored approaches.

From a methodological perspective, our neural network model effectively detected both linear and nonlinear associations between physical fitness metrics, gender, and QoL dimensions. This is consistent with earlier findings by Takehira et al. (2011) and Yamamura (2003), who showed that ANNs can reveal subtle, profession-specific or condition-specific differences in QoL perception that traditional regression techniques fail to capture. Such advanced modeling capabilities are particularly valuable when investigating complex constructs like QoL, where interactions between predictors are often synergistic rather than additive.

Nevertheless, the Ukrainian context presents distinct challenges for QoL modeling. The ongoing military conflict has significantly altered lifestyle patterns, increased psycho-emotional stress, and disrupted access to structured physical activity. Byshevets et al. (2023, 2024a, 2024b) reported heightened prevalence of anxiety, depression, and stress-related disorders among Ukrainian students during wartime, alongside the moderating effect of physical activity in mitigating these conditions. Similarly, Andrieieva et al. (2022) documented a decline in physical activity during distance learning, further exacerbating risks to mental health. These findings suggest that models based solely on physical fitness parameters may have reduced predictive validity under conditions of chronic stress and environmental instability.

Therefore, the most effective predictive frameworks should adopt an integrative approach, combining physical fitness metrics with psycho-emotional indicators (e.g., stress resilience, mood stability), contextual variables (e.g., access to facilities, safety perceptions), and social support measures. The inclusion of such factors has been shown to improve both predictive accuracy and explanatory depth in QoL modeling (Hoseini et al., 2022; Pinochet et al., 2023). While physical fitness remains a critical determinant, its influence on QoL is embedded within a complex network of psychological and social mediators, particularly during periods of societal crisis. In conclusion, our study reinforces the central role of endurance and other physical attributes in shaping QoL among students, while also highlighting the methodological and contextual considerations necessary for developing robust, generalizable predictive models. Future research should prioritize hybrid frameworks that merge physiological, psychological, and socio-environmental inputs, enabling more precise and context-sensitive QoL forecasting. Such approaches hold promise for informing targeted interventions in higher education settings, especially in regions facing acute socio-political challenges.

Conclusions

The student years are one of the most important stages in a person's development, as they prepare to take on certain social roles in the future. Maintaining a high quality of life among students establishes a solid foundation for future professional success, as well as physical and mental well-being.

A systematic analysis of students' quality of life indicators and their interrelationships was carried out during the study, allowing us to discover new approaches to predicting quality of life among students.

The histogram, constructed on the basis of the sum of the absolute values of the weights of each feature, indicates a different degree of their influence on predicting the QoL of students. The most significant predictor was "Endurance", the influence of which significantly exceeds the influence of other factors. "Speed" and "Flexibility" have a relatively high and close influence. "Speed-strength abilities" are also an important predictor, but less significant. "Strength" and agility demonstrate the smallest influence on the predicted values. It is also worth noting the moderate influence of gender, with a slight predominance of the female gender. In the sensitivity analysis, the predictor "Gender" was the most influential, while in the analysis of weights such a trend was not established, so it is worth noting that the sensitivity analysis shows the direct influence of a single change, and the analysis of weights shows the general involvement of the feature in the internal representation of the model. Considering that this variable is binary, a large sensitivity coefficient for gender means that gender features lead to a relatively large change in the predicted components of QoL. On the other hand, a feature with a larger sum of weights is considered to be more influential in forming the internal representation of the data in the network. Large weights for endurance may mean that this feature strongly influences the activation of many hidden neurons, which, in turn, affects the final prediction. Thus, the developed MLP 8-4-2 model demonstrates significantly better prediction quality of the PCS of QoL compared to the MCS. The model demonstrates stable agreement between predicted and actual values for the PCS and slightly higher error variability when predicting the MCS.

Thus, during the course of the study, we determined a list of quality-of-life components and the individual indicators that influence them, and implemented a process of modelling these components. In our opinion, the proposed approaches are innovative in that they are structured from the perspective of a multifaceted assessment of students' quality of life. We envisage the practical application of these approaches in the form of guidance on daily physical activity and the physical education system in higher education institutions, with the aim of supporting a high quality of life among students according to identified indicators.

Future research could focus on developing technology to improve students' quality of life, taking into account the factors that influence important quality-of-life components and the indicators that affect them.

Declaration of generative AI and AI-assisted technologies in the writing process. During the preparation of this paper, we used the Gemini large language model (developed by Google) to generate visualizations of the architecture of the resulting network. The program code for generating graphs using the Graphviz library was developed and optimized with the help of generative AI tools, after which the authors manually verified and adapted it. Having used this tool/service, the authors reviewed and edited the content as necessary, taking full responsibility for the publication's content.

Conflict of interest Authors state no conflict of interest.

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