Assessing Student Quality of Life: Analysis of Key Influential Factors

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Abstract. The article focuses on the employment of a logistic regression model for feature selection, aiming to assess factors impacting student health and well-being. Recognizing the complexity of students' well-being, our research employed a comprehensive questionnaire distributed among a cohort of 544 participants, featuring 201 carefully designed questions across seven thematic blocks. These blocks were tailored to explore various dimensions of students' health and lifestyle, including physical health, mental well-being, academic stress, eating habits, etc. By leveraging machine learning techniques, the study meticulously selects the most relevant features from a dataset, analyzing their correlation with the target variable through F-value ANOVA. This process involves a systematic selection of top features, data transformation, and the division into training and testing sets, ensuring balanced representation of the target variable through stratified sampling. The logistic regression model is then trained and its predictive accuracy evaluated across varying feature sets, demonstrating the significance of feature selection on model effectiveness. The proposed method for feature selection is described and analyzed. The research highlights the model's ability to identify key determinants of quality of life among students, emphasizing the role of healthy lifestyle choices on their overall well-being and academic performance. Apart from logistic regression, we conducted a comprehensive evaluation with 4 different classification models, and assessed their key metrics on predicting the well-being score.

Keywords: quality of life · data analysis · machine learning · predictive models

1 Introduction

In recent years, there has been a trend among young people towards deteriorating health, a steady increase in the incidence of chronic illnesses, leading to serious limitations in working capacity in adulthood and shortening the average life expectancy [1, 2]. The increase in psycho-emotional burdens, coupled with insufficient healthy lifestyle skills,

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complicates the adaptation of student youth and leads to overloading of various bodily systems and conditions that can transform into various illnesses [3]. In these circumstances, the creation of a monitoring system for the health status of student youth is relevant. This system would enable educational institutions' management and medical services to assess the current state of students at a preclinical level and develop general and personalized approaches to maintaining their health [4]. Measuring students' quality of life indicators, understanding their impact, and identifying the most significant indicators are essential for enhancing the quality of educational services provided by educational institutions. In our previous work [5], an architecture of an approach to automating the decision-making process using machine learning by constantly collecting data on student conditions was proposed. In [6] we note the factors influencing the psychological state of a student's health, such as: absence of parents, disability of parents, family members with disabilities, single-parent family status and even environmental problems of the region of residence. The need for developing a digital health profile for students in the Republic of Kazakhstan emerged from the critical challenge of aggregating data across various Medical Information Systems (MIS) in a coherent, structured manner without compromising patient confidentiality. Self-reported health data occupies a pivotal role in facilitating effective primary disease prevention and health promotion strategies. As delineated in [7], employing questionnaire-based data collection methodologies stands out as a particularly effective approach for capturing health-related information directly from individuals. This strategy not only enriches the quality and granularity of health data but also aligns with global best practices in preventive healthcare, underpinning the necessity for a comprehensive digital health profiling system tailored to the student population.

Transforming raw information obtained from various sources into knowledge and recommendations that support the decision-making process, pattern identification, search for regularities, and data visualization using artificial intelligence methods will enable a comprehensive assessment of students' physical condition and the development of managerial solutions for a preventive environment and health enhancement.

2 Related Work

The transition to university life represents a pivotal and challenging phase for many, marked by significant personal and social adjustments. Students often navigate through a period of profound change, grappling with the absence of familiar support networks, the need to forge new social connections, adapting to a novel academic and living environment, and exercising increased self-discipline [8, 9]. Research indicates that students committed to maintaining a healthy lifestyle report higher levels of subjective well-being during their academic journey [10].

Further investigations reveal a concerning prevalence of psychosocial emotional burnout among students in Kazakhstan, exacerbated by drastic lifestyle changes, anxiety over health risks, diminished motivation for learning, and altered perceptions of well-being [11]. A specialized study employing questionnaires and Learning Management System (LMS) performance data leverages machine learning to predict academic outcomes and identify key factors influencing student learning, offering data-driven feedback and intelligent recommendations to improve self-regulatory practices [12]. Moreover, research employing machine learning algorithms to analyze mental well-being indicators has proven effective in predicting mental health issues among students in Southeast Asia, utilizing data from various universities [13]. Another study conducted a multiple regression analysis on six demographic variables against the Health Promoting Lifestyle Profile II (HPLP-II) and its six subscales, aiming to assess their predictive power on healthy lifestyle choices among participants. The findings suggest potential pathways for universities to foster healthier lifestyle habits through targeted educational programs [14]. Overall, multiparametric linear regression and machine learning methodologies emerge as potent tools for dissecting and modeling the intricate factors affecting student life. Given the challenge of altering entrenched lifestyle habits in adulthood, especially within the constraints of a developing nation like Kazakhstan, universities offer a unique platform for instilling foundational health-promoting behaviors poised to benefit individuals beyond their middle years [15]. Students' dietary habits significantly influence cognitive function and academic performance [16]. Algorithms capable of predictive analytics provide significant insights into student health trends and risk factors. In [17], authors highlight the application of machine learning models to predict mental health issues among college students based on their lifestyle choices and academic pressures. This predictive approach allows for early intervention and customised support services, illustrating the crucial role of advanced analytics in student health management. Feature selection in logistic regression models enhances models' accuracy and interpretability, especially within health datasets. [18] provides a comprehensive overview of feature selection techniques in the context of high-dimensional biological data. Their analysis underscores the importance of robust feature selection in improving outcomes and reducing computational costs. On the other hand, [19] discusses the role of feature selection in machine learning and its implications for health data analysis, stressing the balance between model simplicity and predictive capabilities.

In this article we will try to identify the factors influencing student quality of life by using machine learning methods. It is the one important feature for the designed student health monitoring system.

3 Data Sources

Data collection for this study was primarily conducted through comprehensive questionnaires [20–25], meticulously designed to gather information across a broad spectrum of health-related and socio-demographic dimensions.

This extensive dataset was derived from the responses to 201 detailed questions by 544 participants, ensuring a rich and diverse pool of data for analysis. Designed to encapsulate a comprehensive overview of the respondents' health and lifestyle, each of the questionnaire's seven thematic blocks targets a specific area of interest, facilitating a comprehensive exploration of factors contributing to the overall well-being of the study population (Table 1).

The surveys were available in Kazakh, English, and Russian, catering to the university's multinational environment and its 30.3% foreign student population. The survey began with students from the Department of Clinical Disciplines for medical question

Table 1. A brief description of each questionnaire

	Name or direction of the questionnaire	Description
1	The" Nutrition " part	This questionnaire contains questions regarding the eating habits of students. It allows you to assess how healthy and balanced nutrition students prefer, including the level of consumption of fast food, fresh fruits and vegetables, as well as the importance of drinking water and PN
2	The "Nighttime Screen Use and Social Media" part	This questionnaire focuses on students' use of screens (e.g. smartphones, tablets, computers) at night and their social media activity. Such a survey will help determine how common this behavior is, whether addiction is present, and how it can affect sleep and mental health
3	The "Family History" part	Contains questions about hereditary factors and diseases in the student's family
4	The "Allergy and Respiratory Health" part	This questionnaire contains questions related to their state of the respiratory system, the presence of allergies and breathing problems. This will allow us to assess the prevalence of respiratory diseases and allergies among the respondents
5	The Part of the "Urinary System" part	It will allow you to identify possible problems related to the bladder, kidneys and other organs
6	The "Post-COVID Syndrome" part	This questionnaire contains questions about the possible consequences and symptoms after suffering COVID-19. It will help you understand how people cope with post-Covid syndrome and whether it affects their overall health
7	The "Mental Health" part	This block includes questions related to the general state of mental health of students, as well as symptoms of anxiety and depression. GAD-7 schools and the Beck scale are also included here, which allow you to assess the level of anxiety and severity of depressive symptoms

validation, then expanded to the Faculty of Information Technology and others. Participants were informed about potential studies using their data and consented to participate, although the objectivity of their responses cannot be guaranteed. Notably, 68.75% of respondents were female.

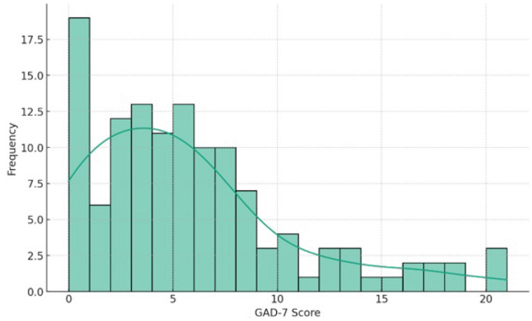

Fig. 1. Overall distribution of GAD-7 scores within respondent's population

Based on the results of the GAD-7 questionnaire 48.41% of students do not experience anxiety, 34.13% of students have mild anxiety, 9.52% of students have moderate anxiety requiring further consultation, 7.94% of students have severe anxiety requiring further consultation.

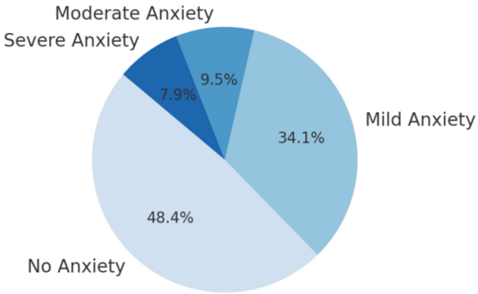

Fig. 2. Anxiety levels distribution according to the GAD-7 scores over respondents

The graph in Fig. 1 shows the distribution of GAD-7 scores among students, and the graph in Fig. 2 shows the distribution of each anxiety level category as a proportion. Figure 3 shows Beck scale scores, while Fig. 4 displays depression levels among students.

The interpretation showed 70.63% of students do not have depressive symptoms, 11.11% of students have mild depression, 5.56% of students have moderate depression, 7.94% of students have moderate depression, 4.76% of students have severe depression (Fig. 5).

There is a positive correlation between GAD-7 anxiety scores and the Beck Depression Inventory, with a correlation coefficient of approximately 0.62. This means that there is a relationship between anxiety levels and depression levels: students with higher scores on the GAD-7 anxiety scale also tend to have higher scores on the Beck Depression Inventory.

As can be seen from graph Fig. 6, most students prefer breakfasts that include mainly proteins or carbohydrates.

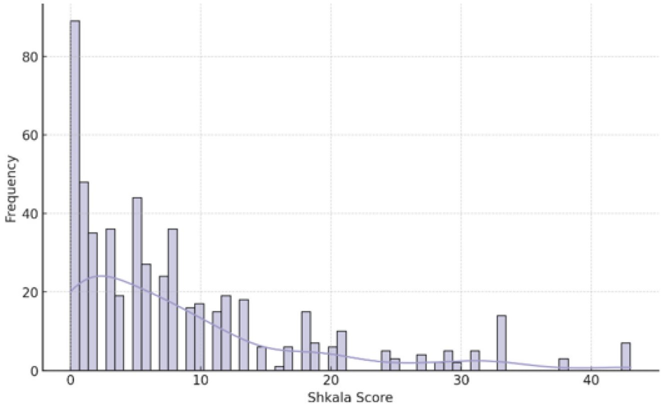

Fig. 3. Distribution of Beck scale scores

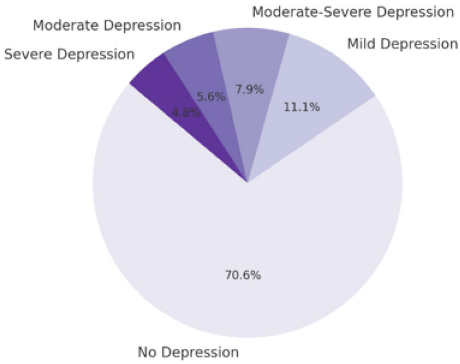

Fig. 4. Depression level distribution over respondents

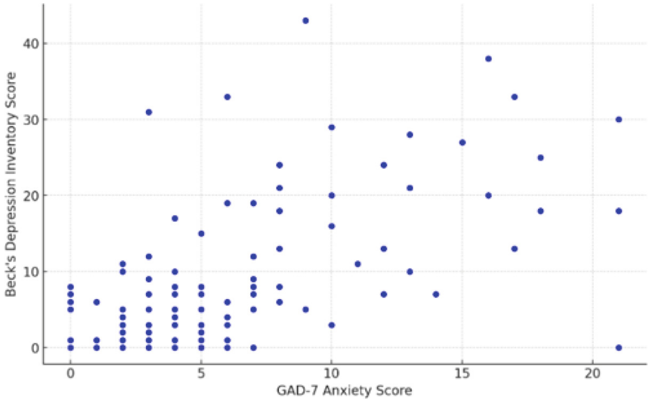

Fig. 5. GAD-7 anxiety scores and the Beck Depression Inventory

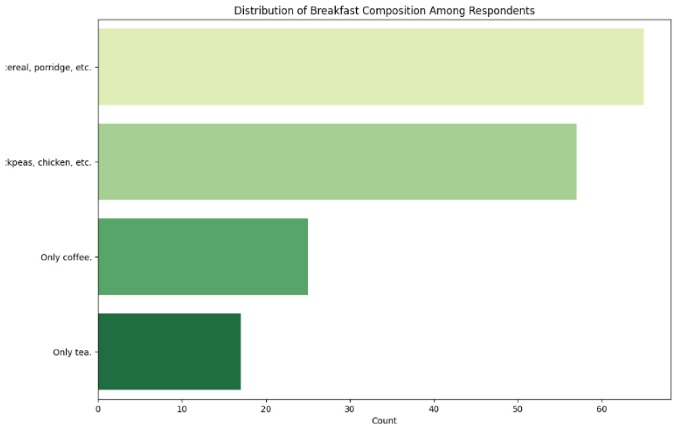

Fig. 6. Breakfast preferences data

4 Data Preprocessing and Construction of Student Well-Being Score

To quantify the overall well-being of students, we developed an aggregated "Student Well-being Score". This score was calculated using the responses to a set of questions encompassing both physical and mental health indicators. The questions ranged from psychological feelings such as anxiety, worry, irritability, fear, and feelings of failure or guilt to perceptions of self-image, ease of work, and interpersonal interest. Physical symptoms and conditions such as sleep quality, tiredness, appetite and weight changes, as well as health concerns, were also considered.

Each question was scored on a Likert scale from 1 (never) to 3 (always), allowing students to indicate the frequency of their feelings or conditions. Negative indicators such as anxiety, worry, and negative feelings towards oneself, were reverse coded so that a higher score always indicated better well-being. The Student Well-being Score was then calculated by taking the mean of these 27 variables for each student. This method ensured that each question had an equal contribution to the total well-being score, and created a final score that was easy to interpret and compare. For instance, a Student Well-being Score of 1 would indicate a student who always experiences negative emotions or physical symptoms, and never experiences positive feelings or states, while a score of 5 would represent a student who never experiences negative conditions and always experiences positive states. We utilized this aggregated score as our primary outcome measure in the subsequent analyses, examining its associations with various demographic, lifestyle, and health-related factors. This comprehensive approach allowed us to capture a holistic view of student well-being.

The study has been ethically approved by the Local Ethics Committee of Al-Farabi Kazakh National University (No. IRB-A148). Participation is voluntary, based on informed consent and in compliance with the Helsinki Declaration. Anonymity is maintained using identification numbers in all records.

5 Logistic Regression Model for Predicting Student's Well-Being Score

We have implemented a procedure to evaluate the impact of feature selection on the predictive performance of a logistic regression model. In particular, we have employed a machine learning approach to choose the top k features from the dataset based on their relationship with the target variable, using the ANOVA F-value (f_classif). The process is iteratively executed with different values of k, ranging from 20 to 140, in steps of 10.

For each iteration:

1. The top k features are selected using SelectKBest and the dataset is transformed accordingly.
2. The transformed dataset is then split into training and test sets, ensuring that the target variable's distribution remains consistent across both sets by using stratified sampling.
3. A logistic regression model is trained using the selected features on the training set.
4. The trained model is then used to make predictions on the test set.
5. The accuracy of the predictions is calculated and stored.

Additionally, for the iteration where $k = 28$, the importance of each feature, as determined by the coefficients of the logistic regression model, is extracted and stored. The features are sorted based on their importance, and the column names of the most influential features are printed.

Finally, the accuracy of the logistic regression model for each value of k is printed (Fig. 7). From the analysis, it was determined the set of most important features for classification tasks.

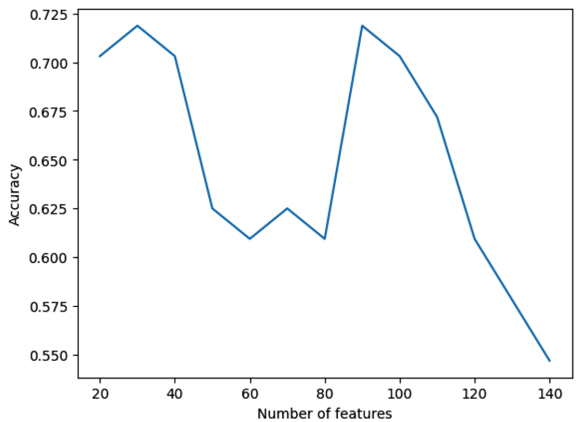

Fig. 7. Accuracy of the logistic regression model for various numbers of features.

In Table 2 we present the top 28 features with their respective scores.

Each row in the table corresponds to a specific question in the questionnaire. The question's identifier or label will help you understand which question is being referred to.

Table 2. Regression model weights

Coefficient(b_n)	Question (X_n)
3.08E−01	How many ml of sugary carbonated drinks do you consume per day?
1.28E−01	How often do you eat food prepared outside the home?
6.40E−02	Do you eat red meat (beef, horse, lamb)?
−9.06E−04	What do you do if someone smokes in the premises of a hospital, clinic, dormitory, university?
8.99E−01	How often do you go to the dentist for a preventive checkup?
3.84E−01	How often do you change your toothbrush?
3.32E−01	Do you eat fish (tuna, cod, herring, perch, carp, zander, trout, salmon, sturgeon)
2.86E−01	How many times a day do you brush your teeth?
8.47E−02	How do you feel about alcohol?
5.42E−01	How many days of the week do you usually eat fresh vegetables and herbs?
6.73E−01	Do you have any special food preferences?
−3.51E−01	Disability group (if applicable) \n',
−1.42E−01	How often do you eat during the day?
4.39E−01	Do you have a chronic illness? \n
−1.78E−02	How often do you use energy drinks (Red Bull, Dizzy, Adrenalin, Gorilla, etc.) during the day?
9.88E−01	How salty is your regular food
−1.05E+00	What's in your lunch?
2.47E−01	Do you have extra work? Write if there is additional work
5.18E−01	How often do you eat lunch?', 'What is included in your breakfast?
1.73E−01	How many days of the week do you usually eat fresh fruit?
−5.44E−01	Do you use iodized salt when cooking at home?
−5.85E−02	How do you feel about smoking?', 'What goes into your meals?',
−1.47E−01	Have you ever had food poisoning? \n! If there is poisoning, describe in what conditions (for example, a student dormitory)!',
−2.49E−01	What time do you have dinner?',
7.47E−01	Do you feel pain in your upper abdomen?',
1.09E+00	How often do you eat breakfast?',
5.71E−01	How many liters of clean water do you drink per day? (excluding soups, tea, coffee, sugary drinks)',
−5.69E−02	Is there a temper?'

This is the estimated coefficient for each question in the logistic regression model. It reflects the relationship between the predictor variable (question response) and the log-odds of the outcome. Positive coefficients indicate that a higher response to the question is associated with a higher likelihood of the positive outcome, while negative coefficients suggest the opposite.

From the analysis it was found that the majority of the features that contribute to the student quality of life related to eating habits and lifestyle choice. Students eating healthy foods are much more likely to feel comfort and experience less anxiety, health complications.

Data preprocessing and cleaning were crucial to ensure the accuracy and reliability of our analyses. We systematically integrated separate questionnaires into a single dataset, addressed missing values using imputation or removal, encoded categorical data, identified and treated outliers, normalized numerical data, handled duplicates, anonymized sensitive information, converted data types appropriately, and created new features such as a "health index" from related questions. These steps ensured a clean and consistent dataset for subsequent exploratory data analysis and modeling.

6 Classification Methods for Predicting the Well-Being Level of Students

The inter-variable linear relationships within the dataset were rigorously evaluated using a correlation matrix, the results of which were illustrated in a heatmap (Fig. 8). This matrix encapsulates the Pearson correlation coefficients (r) between each pair of variables, with the r-values spanning from −1 to 1. These values represent perfect negative to perfect positive linear correlations, respectively, while coefficients near 0 indicate a minimal linear relationship between variables.

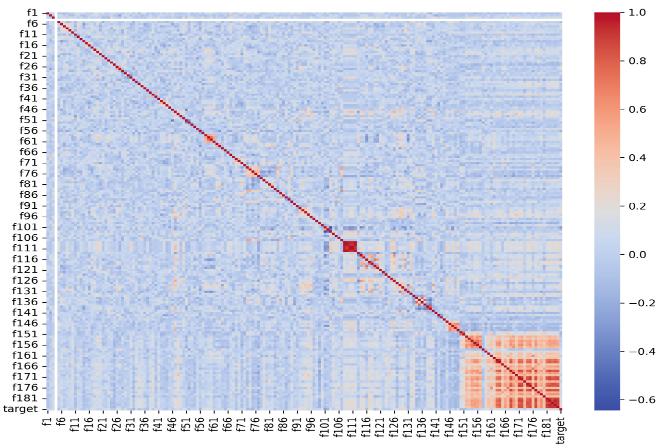

Fig. 8. Correlation matrix among features of the dataset.

A critical observation from the correlation analysis revealed that only a select few variables exhibit moderate to high degrees of correlation. Consequently, in the classification phase, we chose not to eliminate any features, opting to retain the entire relevant feature set. This decision is based on the premise that preserving a comprehensive array of variables could potentially enrich the model's predictive capacity, despite the minimal correlation observed among most features (Table 3).

Table 3. Comparative method comparison table

Model	F1-Score	Accuracy	AUC
Logistic Regression	0.4375	0.5609	0.5525
Random Forest	0.2000	0.6097	0.7000
Support Vector Machine	0.2200	0.6097	0.4850
XGBoost	0.2962	0.5365	0.5575

To predict students' well-being scores, we categorized them into five distinct classes based on a predefined scale. The dataset was split into training and testing sets with a 70–30% ratio, respectively. We evaluated model performance using three principal metrics: Area Under the Curve (AUC), F1-Score, and Accuracy. Our analysis encompassed several classification techniques, including Logistic Regression, Random Forest, Support Vector Machines (SVM), and XGBoost.

Logistic Regression emerged as a statistical model predicting binary outcomes, achieving an F1-Score of 0.4375. This score reflects moderate precision and recall for the positive class. Its accuracy stood at 0.5610, indicating the overall rate of correct predictions, while the AUC was 0.5525, slightly above random chance, suggesting minimal predictive capability.

Random Forest, an ensemble method utilizing decision tree classifiers, despite a lower F1-Score of 0.2000, recorded the highest model accuracy at 0.6098. It achieved the highest AUC score of 0.7000, demonstrating superior class differentiation capability among the models tested.

Support Vector Machine (SVM), recognized for its robustness in finding the optimal class-separating hyperplane, was also employed. In comparison, XGBoost, an implementation of gradient-boosted decision trees known for its efficiency and performance, yielded an F1-Score of 0.2963. Its accuracy was 0.5366, with an AUC of 0.5575, indicating a performance comparable to Logistic Regression in terms of discrimination power.

7 Conclusion

The article details the study's contribution to understanding how the choice of factors affects the predictive accuracy of logistic regression in assessing the quality of life of students. The application of machine learning methods to select the most significant factors from a dataset is described, analyzing their relationship with the target variable.

The procedure involves selecting key features, transforming the data, and dividing into training and test sets using stratified sampling to preserve the distribution of the target variable. The trained logistic regression model is then used to make predictions, and its accuracy is assessed by the accuracy of the predictions. The results of the study demonstrate that the correct selection of characteristics significantly increases the effectiveness of the predictive model, highlighting the most important factors contributing to the quality of life of students. Such factors include healthy diet and lifestyle, which are directly associated with reduced anxiety levels and improved academic performance, providing a basis for future preventative and supportive interventions.

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