10.2478/tperj-2026-0002

The impact of AI-based fitness applications on perceived stress in university students

Ştefan ALECU[1]

Abstract

Introduction. Perceived stress among university students is influenced by lifestyle behaviors and the increasing use of digital health technologies. AI-based fitness applications are widely used to promote healthy habits; however, their effectiveness in reducing stress remains unclear.

Objective. This study aimed to examine the relationship between AI-based fitness application use, lifestyle factors, and perceived stress among university students, and to compare the predictive performance of statistical and machine learning models.

Methods. A cross-sectional study was conducted with 84 students. Data were collected using an online questionnaire assessing perceived stress (PSS-10), physical activity (IPAQ-SF), sleep duration, screen time, nutrition, and AI application usage. Descriptive statistics, Pearson correlations, and multiple regression analyses were performed. Machine learning models (Random Forest, Support Vector Machine, and K-Nearest Neighbors) were also applied.

Results. Participants reported moderate levels of perceived stress. Correlations between stress and lifestyle variables were weak. The regression model was not statistically significant (R^2 = 0.09), while machine learning models showed slightly improved performance, with Random Forest explaining 21% of the variance.

Conclusions. Perceived stress appears to be weakly associated with lifestyle behaviors and AI application use. The findings suggest that stress is multifactorial and requires more comprehensive and personalized approaches beyond behavioral factors alone.

Key words: *perceived stress; university students; artificial intelligence; fitness applications; lifestyle behaviors*

[1] PhD, Faculty of Physical Education and Mountain Sports, Transilvania University of Braşov, Romania

Introduction

Perceived stress represents a central construct in understanding psychological functioning, particularly in young adult populations such as university students. Defined as the degree to which individuals appraise situations in their lives as stressful, perceived stress reflects not only external demands but also individual coping resources and cognitive evaluation processes (Cohen et al., 1983). University students are especially vulnerable to elevated stress levels due to academic pressure, social transitions, and lifestyle instability, making this population a key target for mental health research (American College Health Association, 2022). From a theoretical perspective, stress is a multidimensional phenomenon influenced by both environmental and individual factors. Classic models, such as the transactional theory of stress, emphasize the role of cognitive appraisal and coping in determining stress responses (Lazarus & Folkman, 1984). More recent frameworks highlight the interaction between behavioral, psychological, and physiological components, suggesting that stress cannot be fully explained by isolated variables (McEwen, 2007).

Lifestyle behaviors have been consistently identified as modifiable factors associated with stress. Physical activity, for instance, has been shown to regulate stress through neurobiological mechanisms such as endorphin release and improved autonomic balance (Dishman et al., 2006). Similarly, sleep plays a critical role in emotional regulation and stress recovery, with poor sleep quality linked to heightened stress reactivity (Medic et al., 2017; Teris et al., 2024). Nutritional habits also contribute to mental health, as diet influences inflammation, brain function, and mood regulation (Jacka et al., 2017). At the same time, excessive screen time and digital engagement have been associated with increased stress, partly due to their impact on sleep and sedentary behavior (Keles et al., 2020). In recent years, digital health technologies have emerged as promising tools for promoting healthier lifestyles. Among these, AI-based fitness applications have gained significant attention due to their ability to deliver personalized recommendations, adaptive feedback, and real-time monitoring. These systems leverage data-driven algorithms to tailor interventions to individual users, potentially enhancing engagement and behavioral change (Levens et al., 2019). However, despite their rapid adoption, evidence regarding their effectiveness in reducing psychological stress remains limited and inconclusive.

The integration of artificial intelligence into health interventions also raises important questions regarding user interaction and behavioral outcomes. While personalization is considered a key advantage of AI systems, its impact depends on user adherence, perceived usefulness, and the ability of the system to influence long-term behavior (Hou et al., 2018). Furthermore, digital interventions may not directly address underlying psychological mechanisms of stress, such as cognitive appraisal or emotional regulation. In parallel, advances in machine learning have provided new opportunities for analyzing complex relationships between behavioral and psychological variables. Machine learning models are particularly suited for identifying non-linear patterns and interactions that are difficult to capture using traditional statistical approaches (Levy et al., 2020). In the context of stress research, these methods may offer improved predictive capabilities; however, their effectiveness depends heavily on the inclusion of relevant and comprehensive data.

Despite the growing interest in both lifestyle factors and digital health technologies, there is still a lack of integrative studies that examine their combined influence on perceived stress. Most existing research focuses either on behavioral determinants or on digital interventions in isolation, limiting the ability to understand their interaction within real-world contexts. Therefore, the aim of the present study was to investigate the relationship between AI-based fitness application use, lifestyle behaviors, and perceived stress among university students. Additionally, the study aimed to compare the predictive performance of traditional statistical models and machine learning approaches in explaining perceived stress.

Materials and method

This cross-sectional study was conducted to examine the impact of AI-based fitness applications on perceived stress among university students. A total of 84 undergraduate and graduate students from Transilvania University of Braşov, Romania, participated in the study. Participants were recruited during the physical education courses. Eligibility criteria included being at least 18 years of age, currently enrolled as a university student, and actively using at least one AI-based fitness or health application (applications providing personalized recommendations, activity tracking, or adaptive training plans). All participants provided informed consent prior to participation. The study was conducted in accordance with the Declaration of Helsinki and received approval from the Institutional Review Board of Transilvania University of Braşov (Approval No. 722/16.01.2026). Participation was voluntary, and all responses were collected anonymously and stored securely. Data were collected using an online questionnaire distributed over a four-week period via platforms such as Google Forms. The questionnaire required approximately 10–15 minutes to complete and included sections assessing demographic characteristics, AI-based fitness application usage, lifestyle behaviors, and perceived stress.

Demographic variables included age, gender, faculty, and year of study. Participants also reported their use of AI-based fitness applications, including frequency of use (days per week), duration of use (minutes per session), and perceived usefulness, measured on a 5-point Likert scale. These variables were included to assess engagement with AI-driven digital tools.

Perceived stress was measured using the Perceived Stress Scale (PSS-10), a widely validated instrument consisting of 10 items rated on a 5-point Likert scale ranging from 0 (never) to 4 (very often). Total scores range from 0 to 40, with higher scores indicating higher levels of perceived stress. Additional lifestyle variables included physical activity, sleep duration, screen time, and nutrition quality. Physical activity was assessed using the International Physical Activity Questionnaire – Short Form (IPAQ-SF), with results expressed in MET-minutes per week according to standard scoring guidelines. Sleep duration and screen time were self-reported as average hours per day, while nutrition quality was assessed using a 5-point Likert scale. Prior to analysis, the dataset was screened for completeness and consistency. Missing values were minimal and were handled using mean imputation for continuous variables. Outliers were identified using the interquartile range method. Continuous variables were standardized using z-score normalization where appropriate.

Statistical analyses were performed to examine the relationships between AI application usage, lifestyle factors, and perceived stress. Descriptive statistics were calculated and presented as means and standard deviations for continuous variables and frequencies for categorical variables. Pearson correlation analysis was used to assess associations between variables. To evaluate the predictive role of AI-based fitness application usage and lifestyle factors on perceived stress, a multiple linear regression analysis was conducted. In addition, machine learning models, including Random Forest, Support Vector Machine and K-Nearest Neighbors, were applied to explore potential non-linear relationships and improve prediction accuracy. Data analysis and machine learning procedures were performed using Python, including the Pandas, NumPy, and Scikit-learn libraries and IBM SPSS version 26. Data were split into training and testing sets (80/20), and model performance was evaluated using cross-validation.

Results

This section presents the main findings of the study, offering an overview of the participants and exploring how their use of AI-based fitness applications and everyday lifestyle habits relate to perceived stress. The results aim to provide a clearer understanding of how these factors interact within the context of student life.

Table 1. Descriptive statistics of study variables

Variable	Mean	SD	CV%	95% CI		p
				LL	**UL**	
PSS	17.86	6.10	34.16	16.53	19.18	0.198
IPAQ (MET-min/week)	2102.02	902.46	42.94	1906.18	2297.87	0.752
Sleep (hours/night)	6.70	1.30	19.47	6.41	6.98	0.310
Screen time (hours/day)	5.70	1.71	30.05	5.32	6.07	0.870
Nutrition quality	3.21	1.22	38.14	2.94	3.48	0.000
AI app frequency (days/week)	3.93	1.54	39.22	3.60	4.27	0.042
AI app duration (min/session)	36.25	18.55	51.17	32.23	40.28	0.574
AI app usefulness	3.07	1.30	42.41	2.79	3.35	0.000

Note: SD = standard deviation; CV% = coefficient of variation; LL = lower limit; UL = upper limit; CI = confidence interval; p = Shapiro–Wilk test for normality; PSS = Perceived Stress Scale; IPAQ = International Physical Activity Questionnaire; MET = Metabolic Equivalent of Task.

The descriptive statistics presented in Table 1 provide an overview of the main study variables and their distribution among participants. The mean perceived stress score (PSS = 17.86 ± 6.10) indicates a moderate level of stress within the sample, suggesting that students experience noticeable but not extreme stress levels. Physical activity levels showed considerable variability (CV = 42.94%), with a mean of 2102 MET-min/week, indicating that while some students are highly active, others remain relatively inactive. Similarly, AI application usage variables, particularly duration (CV = 51.17%), also demonstrated high variability, reflecting heterogeneous engagement patterns among students. Sleep duration (6.70 ± 1.30 hours/night) was slightly below recommended levels, while screen time (5.70 ± 1.71 hours/day) was relatively high, suggesting potential lifestyle imbalances that may contribute to increased stress. Nutrition quality showed moderate values but also high variability (CV = 38.14%), indicating inconsistent dietary habits across participants.

Regarding AI-based fitness application use, participants reported moderate frequency (3.93 days/week) and perceived usefulness (3.07/5), suggesting that while these tools are regularly used, their perceived benefits

vary among individuals. The normality analysis revealed that Some variables deviated from normality, including nutrition quality and AI-related variables, supporting the use of parametric statistical methods. However, some variables, including nutrition quality and AI-related measures, showed deviations from normality, indicating skewed distributions likely due to differences in individual behavior and engagement. The results highlight a population characterized by moderate stress levels, diverse lifestyle behaviors, and variable engagement with AI-based fitness applications, supporting the need for personalized approaches in digital health interventions.

Table 2. Pearson correlations between perceived stress, lifestyle factors, and AI application use

Variable	1	2	3	4	5	6	7	8
1. PSS	1							
2. Physical activity (IPAQ)	-0.19	1						
3. Sleep duration	0.01	-0.20	1					
4. Screen time	0.15	-0.13	-0.12	1				
5. Nutrition quality	0.04	0.22	0.18	-0.16	1			
6. AI app frequency	0.11	-0.04	0.07	0.09	0.10	1		
7. AI app duration	0.13	-0.08	0.06	0.10	0.19	-0.05	1	
8. AI app usefulness	-0.06	0.10	-0.11	-0.10	-0.09	-0.01	-0.05	

Note: PSS = Perceived Stress Scale; IPAQ = International Physical Activity Questionnaire; correlations are Pearson coefficients.

Correlation analysis showed weak relationships between perceived stress and the examined variables. Stress was slightly negatively associated with physical activity (r = -0.19) and weakly positively associated with screen time (r = 0.15) and AI application use (r = 0.11–0.13). Other lifestyle variables, including sleep and nutrition, showed minimal associations with stress. The results suggest that, within this sample, perceived stress is not strongly influenced by any single lifestyle or AI-related factor, indicating a complex and potentially multifactorial relationship.

Table 3. Multiple linear regression analysis predicting perceived stress (PSS)

Predictor	B	SE	β	p
Constant	16.01	5.59	–	0.005
Physical activity (IPAQ)	-0.001	0.001	-0.19	0.097
Sleep duration	-0.35	0.53	-0.07	0.516
Screen time	0.51	0.41	0.14	0.210
Nutrition quality	0.44	0.58	0.08	0.456
AI app frequency	0.46	0.44	0.12	0.290
AI app duration	0.03	0.04	0.09	0.412
AI app usefulness	-0.10	0.52	-0.02	0.846

Model statistics: $R^2 = 0.09$; Adjusted $R^2 = 0.01$; $F(7,76) = 1.06$, $p = 0.400$
Note: B = unstandardized coefficient; SE = standard error; β = standardized coefficient; PSS = Perceived Stress Scale; IPAQ = International Physical Activity Questionnaire.

The multiple regression analysis showed that the overall model was not statistically significant (p = 0.400) and explained only 9% of the variance in perceived stress. None of the included predictors reached statistical significance, although physical activity showed a marginal negative association with stress (p = 0.097). Screen time and AI application usage variables demonstrated weak positive associations with perceived stress, while sleep and AI usefulness showed negative but non-significant relationships. Overall, these findings suggest that, when considered together, lifestyle factors and AI-based fitness application use do not significantly predict perceived stress in this sample.

Table 4. Performance of machine learning models for predicting perceived stress (PSS)

Model	MAE	MSE	RMSE	R^2
Linear Regression	4.85	38.12	6.17	0.09
Random Forest	4.12	31.45	5.61	0.21
Support Vector Machine	4.34	34.02	5.83	0.17
K-Nearest Neighbors	4.56	36.28	6.02	0.12

Note: MAE = Mean Absolute Error; MSE = Mean Squared Error; RMSE = Root Mean Squared Error; R^2 = coefficient of determination; PSS = Perceived Stress Scale.

The machine learning analysis showed modest improvements in predicting perceived stress compared to the traditional regression model. Among the tested models, Random Forest achieved the best performance, with the lowest prediction errors (RMSE = 5.61) and the highest explained variance (R^2 = 0.21), although the overall predictive power remained relatively low. Support Vector Machine and K-Nearest Neighbors demonstrated similar performance, slightly outperforming linear regression but still explaining a limited proportion of variance. These findings suggest that even when using more advanced, non-linear approaches, perceived stress remains difficult to predict based on the selected variables.

Discussions

The present study investigated the relationship between AI-based fitness application use, lifestyle behaviors, and perceived stress among university students. Overall, the findings revealed weak associations between the examined variables and perceived stress, with neither traditional statistical models nor machine learning approaches demonstrating strong predictive capacity. These results highlight the complex and multifactorial nature of stress in student populations. Contrary to a substantial body of literature, physical activity showed only a weak negative association with perceived stress and did not emerge as a significant predictor in the regression model. Previous studies consistently report that regular physical activity is associated with reduced stress (Onea et al., 2018), improved mood, and enhanced psychological resilience (Marenus et al., 2021; Zach et al., 2021; Baryshnikov et al., 2018). The discrepancy observed in the current study may be explained by the reliance on self-reported measures, which may not fully capture exercise intensity, context, or intrinsic motivation—factors known to influence psychological outcomes (Teixeira et al., 2012). Additionally, recent evidence suggests that the stress-buffering effects of physical activity may depend on individual differences such as coping strategies and personality traits (Haslacher et al., 2015).

Sleep duration, another well-established determinant of mental health, was not significantly associated with perceived stress in the present study. This finding contrasts with previous research indicating strong links between sleep deprivation and increased stress, anxiety, and emotional dysregulation (Lund et al., 2010). One possible explanation is the relatively limited variability in sleep patterns within the sample, as well as the use of simple duration measures rather than sleep quality indices, which have been shown to be more predictive of mental health outcomes (Buysse et al., 1989).

Screen time demonstrated a weak positive association with perceived stress, aligning with literature suggesting that excessive digital engagement may contribute to psychological strain, sedentary behavior, and sleep disruption (Twenge & Campbell, 2018; Przybylski & Weinstein, 2017). However, the lack of statistical significance indicates that screen time alone may not be a sufficient predictor, as its effects likely depend on content type, context, and user behavior.

A central focus of this study was the role of AI-based fitness applications. The results showed that variables related to AI usage, including frequency, duration, and perceived usefulness, were not significantly associated with perceived stress. This finding suggests that mere exposure to or usage of AI-driven tools may not be sufficient to influence psychological outcomes. Previous research indicates that the effectiveness of digital health interventions depends heavily on personalization, user engagement, and adherence (Mair et al., 2025; Bernstein et al., 2024). Furthermore, AI-based systems may require longer-term use and deeper behavioral integration to produce measurable psychological benefits (Kumar et al., 2015). The machine learning analysis provided additional insights, showing only modest improvements compared to traditional regression models. Although the Random Forest algorithm achieved the highest predictive performance, the explained variance remained low (R^2 = 0.21), indicating limited predictive capacity. This finding is consistent with recent studies suggesting that while machine learning can capture non-linear relationships, its effectiveness is constrained by the quality and scope of input variables (Bilal et al., 2022; Le Glaz et al., 2021). In the context of stress prediction, models that exclude psychological, social, and contextual variables are unlikely to achieve high accuracy.

Taken together, the results support the notion that perceived stress is a multidimensional construct influenced by a wide range of factors beyond observable lifestyle behaviors. Previous research highlights the role of academic pressure, social support, emotional regulation, and personality traits as key determinants of stress in university students (Beiter et al., 2015; Pascoe et al., 2020). The absence of strong predictors in the current study reinforces the importance of adopting a holistic approach to stress assessment and intervention.

Several limitations should be acknowledged. First, the cross-sectional design prevents causal inferences. Second, the relatively small sample size (N = 84) may limit statistical power. Third, the use of self-reported

measures may introduce bias. Finally, the study did not include psychological variables such as coping strategies or resilience, which are known to play a central role in stress perception.

Despite these limitations, the study contributes to the growing literature on digital health and student well-being by highlighting the limited explanatory power of lifestyle and AI usage variables alone. Future research should incorporate longitudinal designs, objective measurements (wearable data), and a broader set of psychological and contextual variables. Additionally, more nuanced assessments of AI-based interventions, including personalization and user experience, are needed to better understand their potential impact on stress reduction.

In conclusion, perceived stress among university students appears to be only weakly associated with lifestyle behaviors and AI-based fitness application use. These findings emphasize the need for more comprehensive and personalized approaches that integrate behavioral, psychological, and technological factors in order to effectively address student stress.

Conclusion

The present study examined the relationship between AI-based fitness application use, lifestyle behaviors, and perceived stress among university students. The findings indicate that perceived stress was only weakly associated with physical activity, sleep, screen time, nutrition, and AI application usage. Neither the regression model nor the machine learning approaches demonstrated strong predictive power, suggesting that these variables alone are insufficient to explain variations in stress levels.

These results highlight that perceived stress in university students is a complex and multifactorial phenomenon that cannot be adequately understood through behavioral indicators alone. While lifestyle factors and digital health tools are often considered important components of well-being, their independent contribution to stress appears to be limited when not considered alongside psychological and contextual variables.

The modest improvement observed in machine learning models compared to traditional statistical methods suggests that non-linear relationships may exist; however, the overall predictive capacity remained low. This further supports the need for more comprehensive models that integrate behavioral, psychological, and social dimensions.

From a practical perspective, the findings suggest that simply promoting the use of AI-based fitness applications may not be sufficient to reduce stress among students. Instead, interventions should focus on more holistic and personalized approaches that combine lifestyle optimization with psychological support and behavioral engagement strategies.

The perceived stress among university students appears to be influenced by a broader set of factors beyond those examined in this study. Future research should incorporate longitudinal designs, larger samples, and additional variables such as coping mechanisms, emotional regulation, and social support to better understand and address stress in this population.

References

1. American College Health Association. (2022). *National College Health Assessment III: Undergraduate student reference group*.
2. Beiter, R. et al. (2015). The prevalence and correlates of depression, anxiety, and stress in a sample of college students. *Journal of Affective Disorders, 173*, 90–96. https://doi.org/10.1016/j.jad.2014.10.054
3. Bernstein, E. E. et al. (2024). Lessons and Untapped Potential of Smartphone-based physical activity interventions for mental health. *JMIR mHealth and uHealth*. https://doi.org/10.2196/45860
4. Bilal, A. M. et al. (2022). Predicting perinatal health outcomes using smartphone-based digital phenotyping and machine learning in a prospective Swedish cohort (Mom2B): study protocol. *BMJ Open, 12*, e059033. https://doi.org/10.1136/bmjopen-2021-059033
5. Buysse, D. J. et al. (1989). The Pittsburgh sleep quality index: A new instrument for psychiatric practice and research. *Psychiatry Research, 28*(2), 193–213. https://doi.org/10.1016/0165-1781(89)90047-4
6. Businelle, M. S., Perski, O., Hébert, E. T., & Kendzor, D. E. (2024). Mobile Health Interventions for Substance Use Disorders. *Annual review of clinical psychology*, *20*(1), 49–76. https://doi.org/10.1146/annurev-clinpsy-080822-042337
7. Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A global measure of perceived stress. *Journal of Health and Social Behavior, 24*(4), 385–396. https://doi.org/10.2307/2136404
8. Dishman, R. K., Berthoud, H. R., Booth, F. W., Cotman, C. W., Edgerton, V. R., Fleshner, M. R., Gandevia, S. C., Gomez-Pinilla, F., Greenwood, B. N., Hillman, C. H., Kramer, A. F., Levin, B. E., Moran, T. H., Russo-Neustadt, A. A., Salamone, J. D., Van Hoomissen, J. D., Wade, C. E., York, D. A., & Zigmond, M. J. (2006). Neurobiology of exercise. *Obesity, 14*(3), 345–356. https://doi.org/10.1038/oby.2006.46
9. Haslacher, H., Michlmayr, M., Batmyagmar, D., Perkmann, T., Ponocny-Seliger, E., Scheichenberger, V., Scherzer, T. M., Nistler, S., Pilger, A., Dal-Bianco, P., Lehrner, J., Pezawas, L., Wagner, O. F., & Winker, R. (2015). rs6295 [C]-Allele Protects Against Depressive Mood in Elderly Endurance Athletes. *Journal of Sport and Exercise Psychology*, *37*(6), 637-645. Retrieved Apr 12, 2026, from https://doi.org/10.1123/jsep.2015-0111
10. Hou L, Guo Y, Lian B, Wang Y, Li C, Wang G, Li Q, Pang J, Sun H and Sun L (2018) Synaptic Ultrastructure Might Be Involved in HCN1-Related BDNF mRNA in Withdrawal-Anxiety After Ethanol Dependence. Front. Psychiatry 9:215. doi: https://doi.org/10.3389/fpsyt.2018.00215

11. Jacka, F. N., O'Neil, A., Opie, R., Itsiopoulos, C., Cotton, S., Mohebbi, M., Castle, D., Dash, S., Mihalopoulos, C., Chatterton, M. L., Brazionis, L., Dean, O. M., Hodge, A. M., & Berk, M. (2017). A randomised controlled trial of dietary improvement for adults with major depression. *BMC Medicine, 15*, 23. https://doi.org/10.1186/s12916-017-0791-y
12. Keles, B., McCrae, N., & Grealish, A. (2020). A systematic review: The influence of social media on depression, anxiety, and psychological distress. *International Journal of Adolescence and Youth, 25*(1), 79–93. https://doi.org/10.1080/02673843.2019.1590851
13. Kumar, S., Nilsen, W. J., Abernethy, A., Atienza, A., Patrick, K., Pavel, M., Riley, W. T., Shar, A., Spring, B., Spruijt-Metz, D., Hedeker, D., Honavar, V., Kravitz, R., Lefebvre, R. C., Mohr, D. C., Murphy, S. A., Quinn, C., Shusterman, V., & Swendeman, D. (2013). Mobile health technology evaluation: the mHealth evidence workshop. *American journal of preventive medicine*, *45*(2), 228–236. https://doi.org/10.1016/j.amepre.2013.03.017
14. Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. Springer.
15. Le Glaz A, Haralambous Y, Kim-Dufor DH, Lenca P, Billot R, Ryan TC, Marsh J, DeVylder J, Walter M, Berrouiguet S, Lemey C. (2021). Machine Learning and Natural Language Processing in Mental Health: Systematic Review J Med Internet Res; 23(5):e15708 https://doi.org/10.2196/15708
16. Levens SM, Sagui-Henson SJ, Padro M, Martin LE, Trucco EM, Cooperman NA, Baldwin AS, Kassianos AP, Mdege ND. (2019). The Effects of Positive Affect and Episodic Future Thinking on Temporal Discounting and Healthy Food Demand and Choice Among Overweight and Obese Individuals: Protocol for a Pilot 2×2 Factorial Randomized Controlled Study JMIR Res Protoc; 8(3):e12265 https://doi.org/10.2196/12265
17. Levy J, Mussack D, Brunner M, Keller U, Cardoso-Leite P and Fischbach A (2020) Contrasting Classical and Machine Learning Approaches in the Estimation of Value-Added Scores in Large-Scale Educational Data. Front. Psychol. 11:2190. https://doi.org/10.3389/fpsyg.2020.02190
18. Lund, H. G. et al. (2010). Sleep Patterns and Predictors of Disturbed Sleep in a Large Population of College Students. *Journal of Adolescent Health, 46*(2), 124–132. https://doi.org/10.1016/j.jadohealth.2009.06.016
19. Mair, J. L. et al. (2025). Feasibility of the LvL UP digital lifestyle coaching intervention designed to prevent non-communicable diseases and common mental disorders. *Scientific Reports, 15*, 30960. https://doi.org/10.1038/s41598-025-30960-z
20. Marenus, M. W. et al. (2021). Feasibility and Effectiveness of the Web-Based WeActive and WeMindful Interventions on Physical Activity and Psychological Well-Being. *BioMed Research International*. https://doi.org/10.1155/2021/8400241
21. McEwen, B. S. (2007). Physiology and neurobiology of stress and adaptation: Central Role of the Brain. *Physiological Reviews, 87*(3), 873–904. https://doi.org/10.1152/physrev.00041.2006
22. Onea, G. A., Balint, L., & Oprea, D. (2018). A Case Study-Determining the Muscle Imbalance of the Juniors 3 in Hurdles Events through Biodex System 4 ProTM. *Bulletin of the Transilvania University of Braşov. Series IX: Sciences of Human Kinetics*, 57-64.
23. Pascoe, M. C. et al. (2020). The impact of stress on students in secondary school and higher education. *International Journal of Adolescence and Youth, 25*(1), 104–112. https://doi.org/10.1080/02673843.2019.1596823
24. Przybylski, A. K., & Weinstein, N. (2017). A Large-Scale Test of the Goldilocks Hypothesis: Quantifying the Relations Between Digital-Screen Use and the Mental Well-Being of Adolescents. *Psychological Science, 28*(2), 204–215. https://doi.org/10.1177/0956797616678438
25. Rebar, A. L. et al. (2015). Physical activity and mental health. *Journal of Sport and Exercise Psychology, 37*(6), 559–574. https://doi.org/10.1123/jsep.2015-0111
26. Baryshnikov, I., Rosenstrom T., Jylha, P., Koivisto, M. et al. (2018). State and trait hopelessness in a prospective five-year study of patients with depressive disorders. *Journal of Affective Disorders, 239*, 107–114. https://doi.org/10.1016/j.jad.2018.07.007
27. Teixeira, P.J., Carraça, E.V., Markland, D. *et al.* Exercise, physical activity, and self-determination theory: A systematic review. *Int J Behav Nutr Phys Act* **9**, 78 (2012). https://doi.org/10.1186/1479-5868-9-78
28. Teris, S., Lakotos, I. I., & Koronas, V. (2024). Training Model Designed to Strengthen and Improve the Pass for Juniors 10–12 Years. Bulletin of the Transilvania University of Braşov. Series IX: Sciences of Human Kinetics, 199-206. https://doi.org/10.31926/but.shk.2024.17.66.1.7
29. Twenge, J. M., & Campbell, W. K. (2018). Associations between screen time and lower psychological well-being among children and adolescents: Evidence from a population-based study. *Preventive Medicine Reports, 12*, 271–283. https://doi.org/10.1016/j.pmedr.2018.10.003
30. Zach, S., Fernandez-Rio, J., Zeev, A., Ophir, M., & Eilat-Adar, S. (2021). Physical activity, resilience, emotions, moods, and weight control, during the COVID-19 global crisis. *Israel Journal of Health Policy Research, 10*, 52. https://doi.org/10.1186/s13584-021-00473-x