

UDC 004.8; 004.93

## MODELING THE RELATIONSHIP BETWEEN TECHNOLOGY USE AND STRESS: A DATA-DRIVEN BEHAVIORAL ANALYSIS

<sup>+</sup> *Turimov D.<sup>1</sup>, Saydirasulov N.<sup>1</sup>, Kilichev D.<sup>2</sup>*

<sup>1</sup> Department of Computer Engineering, Gachon University,  
Sujeong-gu, Seongnam-si, Republic of Korea

<sup>2</sup> Samarkand branch of Tashkent University of Economics, Samarkand, Uzbekistan

<sup>+</sup> *dilmurod@gachon.ac.kr*

**Abstract.** Understanding how daily behavioral patterns contribute to stress is increasingly important in a digitally saturated world. This study investigates the relationship between technology use, lifestyle behaviors, and stress levels using a data-driven machine learning framework. A gradient boosting regressor was trained on a behavioral dataset containing screen time, physical activity, sleep, and dietary patterns, excluding sensitive mental health indicators. The model achieved high predictive accuracy ( $R^2 = 0.979$ ), significantly outperforming a baseline. Feature importance and SHAP analyses revealed that social media usage, work-related screen time, and low physical activity were the most impactful predictors of stress, while sleep quality and exercise were associated with lower stress levels. These results suggest that behavioral data alone can provide interpretable and reliable stress assessments, offering practical applications for digital wellness platforms and personalized feedback systems. The findings highlight the importance of monitoring digital habits as a non-clinical approach to mental well-being.

**Keywords:** stress prediction, technology use, machine learning, screen time, behavioral data, SHAP, lifestyle analysis, wellness modeling, social media, physical activity.

### 1 INTRODUCTION

In an era defined by digital immersion, technology has become an inseparable part of daily life, shaping how individuals work, socialize, entertain themselves, and manage personal well-being. While digital tools and devices have enhanced connectivity and convenience, growing evidence suggests that their pervasive use may also contribute to rising stress levels. Excessive screen time, disrupted sleep, and constant digital engagement have been linked to negative physical and psychological outcomes, including anxiety, cognitive overload, and poor emotional regulation [1]. Research also highlights a “dual role” of technology – where it simultaneously acts as a source of stress and a tool for managing it – reflecting the complex ways it influences everyday emotional states [2]. As stress continues to emerge as a major global health concern, especially among digitally active populations, understanding how patterns of technology use and lifestyle behaviors intersect with stress becomes an urgent research priority [3].

Although considerable attention has been given to the impact of technology on stress, much of the existing research focuses on isolated behaviors – such as screen time or work overload – without integrating broader lifestyle factors like sleep quality, physical activity, or nutrition. Recent studies have shown that chronic stress is influenced by a combination of physiological and behavioral patterns, including daily technology use and health-related behaviors tracked through wearable sensors [4]. Yet, these studies often focus on specific populations (e.g., females or patients with chronic illness), limiting generalizability. Similarly, while digital footprints and lifestyle behaviors are known to offer predictive insight into well-being, their integration into a unified, data-driven framework for stress prediction remains underdeveloped [5]. Furthermore, systematic reviews highlight a significant gap in modeling how lifestyle variables mediate or moderate the relationship between technology use and stress across diverse demographic groups [6]. Thus, there is a clear need for holistic, data-driven approaches that combine behavioral, technological, and demographic data to predict and better understand stress levels in the general population.

Despite the growing awareness that both digital technology usage and lifestyle behaviors play critical roles in shaping mental well-being, there is a lack of comprehensive models that examine how these factors jointly influence individual stress levels. Existing studies tend to analyze either technology use or lifestyle choices in isolation, missing the complex interplay between screen time, device use, physical activity, sleep, nutrition, and stress. Moreover, the literature lacks scalable, data-driven approaches capable of modeling

this relationship across diverse populations using real-world behavioral data. This study addresses that gap by asking: How do patterns of technology use and lifestyle behaviors influence individuals' stress levels? Using a machine learning-based analysis of a large behavioral dataset, this research aims to uncover predictive patterns and quantify the relative contribution of various behavioral factors to self-reported stress, offering insights that can inform both digital wellness strategies and mental health interventions.

The primary objective of this study is to develop a predictive model that quantifies the relationship between individuals' stress levels and a range of behavioral factors, including daily technology use, screen time habits, sleep quality, physical activity, and nutritional choices. Using a dataset containing diverse self-reported and behavioral variables, this research applies a machine learning approach – specifically, a HistGradientBoostingRegressor pipeline – to identify which features most strongly predict stress outcomes. The scope of the analysis intentionally excludes direct mental health diagnoses, focusing instead on safe, non-sensitive lifestyle indicators such as device usage duration, sleep patterns, and caffeine intake. By leveraging explainable, data-driven techniques, this study seeks to not only improve predictive accuracy but also generate actionable insights into which combinations of behaviors are most closely associated with elevated stress. The findings are intended to inform future research, personal wellness tools, and public health strategies targeting stress management through behavior modification.

Understanding the behavioral roots of stress through a data-driven lens has practical implications for both individual well-being and public health policy. By identifying which everyday actions – such as extended screen time, insufficient sleep, or low physical activity – contribute most to stress, this study offers guidance for designing targeted interventions, digital wellness applications, and personalized behavioral recommendations. Moreover, the use of interpretable machine learning models ensures that insights are not only predictive but also transparent and applicable in real-world contexts. The remainder of this paper is organized as follows: Section 2 reviews related literature on technology use, lifestyle behaviors, and stress. Section 3 details the dataset, feature selection, and modeling methodology. Section 4 presents the results of the predictive analysis. Section 5 discusses the findings in the context of existing research, and Section 6 concludes with practical implications, limitations, and suggestions for future work.

## 2 LITERATURE REVIEW

### 2.1 Overview of the Relationship Between Technology Use and Stress

The rise of digital technologies has prompted extensive inquiry into how technology-related behaviors affect stress. Early findings linked excessive screen time, device multitasking, and digital overload to increased psychological strain, particularly in work and academic contexts [7]. However, recent studies have emphasized the nuanced and often bidirectional nature of this relationship. For instance, wearable-sensor-based studies have shown that technology use can both predict and modulate chronic stress, depending on context and user habits [4].

### 2.2 Lifestyle Factors in Stress Modeling

Beyond technology use, lifestyle behaviors such as diet, sleep, physical activity, and caffeine intake significantly contribute to stress levels. Multiple studies confirm that inadequate sleep, unhealthy diets, and lack of physical exercise are positively associated with higher perceived stress [8]. Adolescents and students, in particular, show lower stress levels when engaging in regular physical activity or mindfulness practices such as yoga [9].

### 2.3 Sex and Demographic Differences

Sex-specific differences in stress-lifestyle relationships have also been reported [10]. For instance, female workers experience greater stress from inadequate sleep and nutrition, while male workers' stress correlates more with overtime work [11]. These findings highlight the importance of demographic variables in building predictive models of stress.

### 2.4 Gaps in the Literature

Despite strong evidence linking technology use and lifestyle behaviors with stress, few studies have integrated both domains into a single predictive model [12]. Most analyses are limited to small sample sizes, focus on single populations (e.g., adolescents or medical students), or rely on self-reported survey data without behavioral measurements [13]. Moreover, while some recent work leverages wearable sensor data for chronic stress prediction, such studies often exclude behavioral features like media consumption or wellness app usage [4].

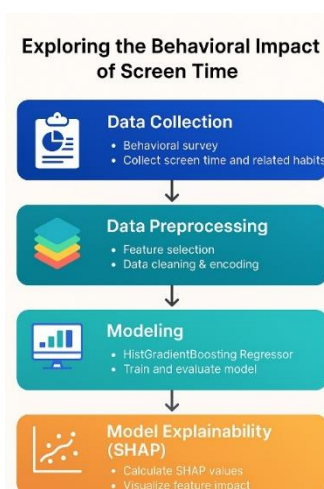
Table 1 presents a structured taxonomy of key studies that examine the relationship between technology use, lifestyle behaviors, and stress across various populations. The studies vary in focus, including areas such as sleep, diet, screen time, physical activity, wearable sensor data, and occupational stress. Methodologically, they range from cross-sectional surveys and machine learning approaches to systematic reviews and longitudinal studies. This taxonomy highlights the diverse methodological approaches and populations studied while revealing a common finding: unhealthy lifestyle patterns and unbalanced technology use are consistently associated with elevated stress levels. However, the fragmented and siloed nature of existing research underscores the need for an integrative, data-driven approach that combines these variables within a unified modeling framework.

**Table 1.** Structured taxonomy of key studies that examine the relationship between technology use, lifestyle behaviors, and stress across various populations

Study	Focus Area	Population	Method	Key Finding
[8]	Diet, smoking, physical activity	Adults	Cross-sectional	Unhealthy lifestyle factors linked to high stress
[4]	Wearables, physiology, lifestyle	Healthy females	Machine learning with sensors	Behavioral and physiological data predicted chronic stress
[9]	Beverage intake, physical activity	Adolescents	Cross-sectional	Exercise and yoga associated with lower stress
[11]	Sleep, diet, work	Japanese workers	Logistic regression	Gender-specific links between lifestyle and stress
[14]	Entrepreneurial lifestyle, stress	Entrepreneurs	Systematic review	Technology and stress management affect business success
[15]	Children's stress and lifestyle	Children (5–12 years)	Longitudinal	Stress influenced eating and activity behaviors
[13]	Perceived stress, lifestyle habits	Students	Descriptive study	Health behaviors mediate stress effects
[16]	Work stress during COVID-19	Nurses	Correlational	Inverse link between healthy lifestyle and work stress
[17]	Fertility, quality of life, stress	Women	Review	Stress and QoL impact reproductive function
[18]	Stress and coping adequacy	Health professionals	Cross-sectional	Coping skills improve lifestyle behaviors
[19]	Stress and cell aging	General	Review	Healthy lifestyle buffers stress at cellular level
[20]	Tech and work stress	Call center employees	Review	Technology overload increases work stress
[21]	Type A behavior and lifestyle	Urban residents	Path analysis	Healthy lifestyle lowers perceived stress

### 3 METHODS

This study adopts a data-driven machine learning approach to investigate how screen time and lifestyle behaviors predict perceived stress levels. The research pipeline consists of four main stages: data collection, preprocessing, modeling, and model explainability, as illustrated in Figure 1.



**Fig. 1.** Overall study architecture illustrating each step from behavioral data collection to interpretable machine learning analysis

The core objective of this study is to model stress level  $\hat{y}$  as a function of observed behavioral and demographic factors. This relationship is captured by the general expression  $\hat{y} = f(\mathbf{x})$ , where  $\mathbf{x}$  includes features related to technology use  $\mathbf{x}^{(tc)}$ , lifestyle behaviors  $\mathbf{x}^{(lf)}$ , and demographics  $\mathbf{x}^{(dm)}$ . The function  $f(\cdot)$  represents a machine learning model trained to learn patterns in these inputs that most accurately predict perceived stress. This formulation allows for a flexible, data-driven analysis of how daily behaviors contribute to mental well-being.

$$\hat{y} = f(\mathbf{x}) = f\left(\left[\mathbf{x}^{(tc)}, \mathbf{x}^{(lf)}, \mathbf{x}^{(dm)}\right]\right).$$

### 3.1 Data Collection and Data Preprocessing

The dataset consists of individual-level behavioral, lifestyle, and demographic data obtained via structured surveys. Each record represents a unique individual, with the following feature groups:

- a) Demographic Features
  - user\_id: unique identifier (used for grouped data splitting);
  - age: respondent's age;
  - gender: categorical (e.g., male, female, other);
  - location\_type: urban, suburban, or rural.
- b) Technology Use Patterns
  - daily\_screen\_time\_hours: total daily screen time
  - phone\_usage\_hours, laptop\_usage\_hours, tablet\_usage\_hours, tv\_usage\_hours: device-specific usage
  - social\_media\_hours, work\_related\_hours, entertainment\_hours, gaming\_hours: purpose-specific usage categories
- c) Lifestyle and Wellness Indicators
  - sleep\_duration\_hours: average hours of sleep per night
  - sleep\_quality: self-rated quality of sleep (categorical)
  - physical\_activity\_hours\_per\_week: weekly hours of physical activity
  - uses\_wellness\_apps: binary indicator of wellness app usage
  - eats\_healthy: binary indicator of healthy eating behavior
  - caffeine\_intake\_mg\_per\_day: daily caffeine intake in mg
  - mindfulness\_minutes\_per\_day: average minutes spent on mindfulness or meditation
- d) Outcome Variables
  - stress\_level: self-reported stress (continuous target variable)
  - mood\_rating: general mood score (used optionally for reference)
  - mental\_health\_score, weekly\_anxiety\_score, weekly\_depression\_score: sensitive mental health metrics (excluded from modeling)

The preprocessing stage involved:

Feature Selection: Excluded all sensitive mental health outcomes to maintain data safety and privacy.

Missing Value Imputation:

- Numeric columns: filled with median values;
- Categorical columns: filled with the most frequent category.

Feature Encoding and Scaling:

- Categorical variables (e.g., gender, sleep quality) were one-hot encoded;
- Numeric variables were standardized using StandardScaler.

### 3.2 Modeling

The core predictive model used was the HistGradientBoostingRegressor, chosen for its:

- Strong performance with mixed data types;
- Resistance to overfitting;
- Native handling of missing values.

A grouped train-test split (80% training, 20% testing) was performed using user\_id (if available) to ensure that individuals did not appear in both sets.

Evaluation Metrics:

- MAE (Mean Absolute Error);
- RMSE (Root Mean Squared Error);
- R<sup>2</sup> (Coefficient of Determination).

Model Explainability. To ensure that the predictive model is not only accurate but also interpretable, this study employed two complementary model explanation techniques:

a) Permutation Feature Importance:

To assess the relative contribution of each behavioral feature to stress prediction, we used permutation-based feature importance. This technique measures how the model's performance ( $R^2$ ) changes when each feature's values are randomly shuffled. The greater the performance drop, the more important that feature is for accurate prediction. Importance scores were averaged across 10 permutations for robustness. Results were visualized using a bar plot ranking the top 10 predictors of stress.

This method provides an intuitive, model-agnostic ranking of features that most influence the model, offering a scientific basis for behavioral interpretation.

b) SHAP (SHapley Additive Explanations):

In addition to global rankings, SHAP values were used to explore local feature contributions—how each individual's specific behaviors affect their predicted stress level. SHAP offers additive, game-theoretic attributions that explain predictions in terms of actual feature values, making the results interpretable at both the individual and population levels.

## 4 RESULTS

The initial model was trained using all non-sensitive behavioral, lifestyle, and demographic features. Table 2 shows the performance compared to a naive baseline model that predicts the mean stress level for all individuals.

**Table 2.** Model vs. Baseline Performance (All Features)

Metric	Model	Baseline
<b>MAE</b>	<b>0.284</b>	2.509
<b>RMSE</b>	<b>0.427</b>	2.912
<b>R<sup>2</sup></b>	<b>0.978</b>	-0.002

The model demonstrates excellent predictive accuracy, with an  $R^2$  of 0.978, indicating that approximately 97.8% of the variance in stress levels is explained by the behavioral features. In contrast, the baseline performs poorly, confirming the model's utility.

To understand which behaviors most strongly influence stress predictions, permutation-based feature importance was applied. The top 10 predictors are shown in Table 3.

**Table 3.** Top 10 Most Important Features for Stress Prediction

Rank	Feature	Importance Score
<b>1</b>	Social media usage (hours/day)	<b>1.1707</b>
<b>2</b>	Work-related screen time	0.0524
<b>3</b>	Entertainment screen time	0.0185
<b>4</b>	Physical activity (hours/week)	0.0106
<b>5</b>	Total screen time (hours/day)	0.0049
<b>6</b>	Age	0.0027
<b>7</b>	Gaming time	0.0005
<b>8</b>	Sleep quality	0.0002
<b>9</b>	Phone usage (hours/day)	0.0001
<b>10</b>	Caffeine intake (mg/day)	0.0001

The results highlight social media usage as the dominant predictor of stress, with a far greater impact than other features. This suggests that time spent on social platforms may be a key behavioral driver of psychological stress in this population.

Based on the feature importance scores, a new model was trained using only the top 10 most important features. Table 4 shows the updated performance metrics.

**Table 4.** Model Performance Using Top 10 Features

Metric	Model (Top 10 Features)	Baseline
<b>MAE</b>	<b>0.279</b>	2.509
<b>RMSE</b>	<b>0.423</b>	2.912
<b>R<sup>2</sup></b>	<b>0.979</b>	-0.002

This simplified model slightly outperforms the full-feature version, suggesting that much of the predictive power is concentrated in a small subset of behavioral variables. This enhances interpretability while preserving accuracy.

Figure 2 presents a SHAP summary plot that illustrates the impact of the top behavioral and demographic features on the model's stress level predictions. Each dot represents a single individual's SHAP value for a given feature, where:

- Position on the x-axis indicates the direction and magnitude of impact on the predicted stress level.
- Color reflects the feature value (blue = low, red = high).

Key Observations:

- Social media usage is the most influential predictor. Higher usage (red dots) is consistently associated with increased stress levels (positive SHAP values), while lower usage (blue dots) correlates with decreased stress.
- Work-related screen time also shows a positive relationship with stress — individuals with higher values tend to experience elevated stress predictions.
- Entertainment hours and physical activity hours per week have mixed effects. For some users, high entertainment correlates with higher stress (possibly due to excessive screen time), while physical activity generally contributes to stress reduction, as seen by negative SHAP values for higher values.
- Daily screen time and age have moderate effects. Younger individuals and those with more screen time tend to show slightly higher stress, though the variance is smaller than for top predictors.
- Gaming hours, sleep duration, and TV usage show relatively weak or inconsistent effects. These features exhibit lower SHAP values overall, suggesting they are less critical in determining stress predictions in this model.
- Caffeine intake has a minimal but slightly positive impact, with high intake (red dots) leaning toward increased stress, aligning with established physiological effects of caffeine on cortisol and anxiety.

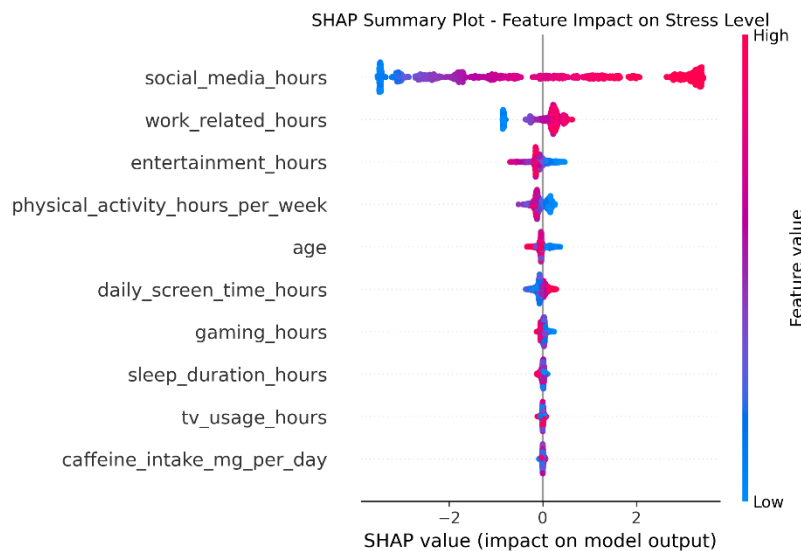


Fig. 2. SHAP summary plot that illustrates the impact of the top behavioral and demographic features

## 5 DISCUSSION

The results of this study reveal that specific behavioral patterns, particularly related to screen time and lifestyle choices, are highly predictive of individuals' stress levels. Among all features analyzed, social media usage emerged as the most influential predictor, with higher usage consistently associated with elevated stress. Work-related screen time and entertainment hours also contributed positively to stress, while physical activity appeared to have a protective effect, reducing predicted stress levels [Lachance]. These findings align with prior research suggesting that digital overload and sedentary behavior may exacerbate psychological strain, whereas active lifestyles promote resilience.

The model's strong performance, with an  $R^2$  of up to 0.979, highlights the effectiveness of behavioral data in estimating stress without relying on sensitive clinical information. Additionally, the use of SHAP values provided interpretable insights, making the model not only accurate but also explainable [Prendin].

These findings offer practical applications in digital wellness tools, allowing for personalized stress feedback and behavior recommendations. However, the study remains correlational and relies on self-reported data, indicating the need for future work using real-time behavioral inputs and causal analysis frameworks.

## 6 CONCLUSION

This study demonstrated that stress levels can be accurately predicted using a compact set of behavioral features related to technology use, lifestyle habits, and demographics. By applying a machine learning model with high predictive power and explainability, we found that social media usage, work-related screen time, and physical inactivity are among the most significant contributors to elevated stress. In contrast, behaviors like physical exercise and sufficient sleep quality serve as protective factors.

These findings emphasize the potential of data-driven behavioral analysis in mental wellness applications. The interpretable nature of the model enables practical deployment in digital health platforms, where users can receive personalized, behavior-based feedback on their stress risk. Future research should aim to validate these results using real-time, sensor-based data and explore causal mechanisms through longitudinal studies.

## REFERENCES

- [1] D. Villani, P. Cipresso, A. Gaggioli, and G. Riva, "Positive technology for helping people cope with stress," in *Research Anthology on Rehabilitation Practices and Therapy*, IGI Global, 2021, pp. 787–814. Accessed: Oct. 10, 2025. [Online]. Available: <https://www.igi-global.com/chapter/positive-technology-for-helping-people-cope-with-stress/261375>
- [2] S. Hodđo Bakås, M. P. Woźniak, J. Herstad, P. W. Woźniak, and J. Niess, "The Dual Model for Everyday Stress Technology: Understanding the Lived Experience of Data-Driven Stress," in *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*, Yokohama Japan: ACM, Apr. 2025, pp. 1–18. doi: 10.1145/3706598.3713174.
- [3] C. Kılıç, "Organizational stress and performance from the perspective of technological developments," *İnsan Ve Toplum Bilim. Araştırmaları Derg.*, vol. 12, no. 4, pp. 2323–2343, 2023.
- [4] N. Magal, S. L. Rab, P. Goldstein, L. Simon, T. Jiryis, and R. Admon, "Predicting Chronic Stress among Healthy Females Using Daily-Life Physiological and Lifestyle Features from Wearable Sensors," *Chronic Stress*, vol. 6, p. 24705470221100987, Jan. 2022, doi: 10.1177/24705470221100987.
- [5] J. A. Cice, "Digital Footprints and Lifestyle: What Do Our Technological Behaviors Say About Our Style of Life?," *J. Individ. Psychol.*, vol. 77, no. 1, pp. 96–101, 2021.
- [6] R. Kaur and P. Mohali, "A SYSTEMATIC REVIEW STUDY ON STRESS AMONG STUDENTS: GAPS IN THE EXISTING LITERATURE", Accessed: Oct. 10, 2025. [Online]. Available: [https://bssspublications.com/PublishedPaper/Publish\\_408.pdf](https://bssspublications.com/PublishedPaper/Publish_408.pdf)
- [7] S. I. Khalid et al., "Machine learning-based detection of sarcopenic obesity and association with adverse outcomes in patients undergoing surgical treatment for spinal metastases.," *J. Neurosurg. Spine*, pp. 1–10, 2023, doi: 10.3171/2023.9.SPINE23864.
- [8] A. Dakanalis et al., "Overweight and obesity is associated with higher risk of perceived stress and poor sleep quality in young adults," *Medicina (Mex.)*, vol. 60, no. 6, p. 983, 2024.
- [9] B. K. Watode, J. Kishore, and S. Gupta, "Lifestyle practices and stress among school adolescents in Delhi," *Ind J Youth Adol Health*, vol. 6, pp. 14–9, 2019.
- [10] J. Badger, P. A. Quatromoni, and J. S. Morrell, "Relationship between stress and healthy lifestyle factors of college students," *Health Behav. Policy Rev.*, vol. 6, no. 1, pp. 43–55, 2019.
- [11] A. Suzuki and R. Akamatsu, "Sex differences in relationship between stress responses and lifestyle in Japanese workers," *Saf. Health Work*, vol. 5, no. 1, pp. 32–38, 2014.
- [12] J. Brinsley et al., "Effectiveness of digital lifestyle interventions on depression, anxiety, stress, and well-being: systematic review and meta-analysis," *J. Med. Internet Res.*, vol. 27, p. e56975, 2025.
- [13] Z. Al Mohsen, "The effect of academic stress on lifestyle habits among medical students," *J Educ Technol Health Sci*, vol. 10, no. 2, pp. 29–34, 2023.
- [14] R. R. Cahyani, A. L. Riani, M. Harsono, and S. Sunaryo, "The Impact of Entrepreneurial Lifestyle on Business Success: A Systematic Literature Review," *J. Ecohumanism*, vol. 3, no. 4, pp. 3395–3405, 2024.
- [15] A. Cruz-Jentoft et al., "Prevalence of and interventions for sarcopenia in ageing adults: a systematic review. Report of the International Sarcopenia Initiative (EWGSOP and IWGS)," *Age Ageing*, vol. 43, pp. 748–759, 2014, doi: 10.1093/ageing/afu115.

- [16] B. Garcia-Reyna et al., “Anxiety and COVID-19: Coronavirus Anxiety Scale scores in medical and non-medical personnel in urban hospitals in Guadalajara. A cross-sectional survey study,” *Death Stud.*, vol. 46, no. 3, pp. 581–589, Mar. 2022, doi: 10.1080/07481187.2021.1936297.
- [17] S. Palomba, J. Daolio, S. Romeo, F. A. Battaglia, R. Marci, and G. B. La Sala, “Lifestyle and fertility: the influence of stress and quality of life on female fertility,” *Reprod. Biol. Endocrinol.*, vol. 16, no. 1, p. 113, Dec. 2018, doi: 10.1186/s12958-018-0434-y.
- [18] N. Hirooka, T. Kusano, S. Kinoshita, and H. Nakamoto, “Influence of perceived stress and stress coping adequacy on multiple health-related lifestyle behaviors,” *Int. J. Environ. Res. Public Health*, vol. 19, no. 1, p. 284, 2021.
- [19] M. Nyandra and W. Suryasa, “Lifestyle for stress buffer and reverse cell aging,” *Int. J. Health Sci.*, vol. 3, no. 1, pp. 17–23, 2019.
- [20] A. Khalid, A. Sarfaraz, S. Ahmed, and F. Malik, “Prevalence of stress among call center employees,” *Pak. J. Soc. Clin. Psychol.*, vol. 11, no. 2, p. 58, 2013.
- [21] S. Maruyama and K. Morimoto, “The effects of lifestyle and type a behavior on the life-stress process,” *Environ. Health Prev. Med.*, vol. 2, no. 1, pp. 28–34, Apr. 1997, doi: 10.1007/BF02931226.

Received: June 25, 2025

**Citation:** Turimov D., Saydirasulov N., Kilichev D. 2025. Modeling the relationship between technology use and stress: a data-driven behavioral analysis. *International journal of theoretical and applied issues of digital technologies*. Volume 8, Issue 4, pp. 33-40. <https://doi.org/10.62132/ijdt.v8i4.300>.

## МОДЕЛИРОВАНИЕ ВЗАИМОСВЯЗИ МЕЖДУ ИСПОЛЬЗОВАНИЕМ ТЕХНОЛОГИЙ И СТРЕССОМ: ПОВЕДЕНЧЕСКИЙ АНАЛИЗ НА ОСНОВЕ ДАННЫХ

+ Туримов Д.<sup>1</sup>, Сайдирасулов Н.<sup>1</sup>, Киличев Д.<sup>2</sup>

<sup>1</sup> Университет Гачон, Соннам, Республика Корея

<sup>2</sup> Самаркандский филиал Ташкентского экономического университета, Самарканд, Узбекистан

+ dilmurod@gachon.ac.kr

**Аннотация.** Понимание того, как повседневные поведенческие привычки влияют на уровень стресса, приобретает всё большее значение в условиях цифровой насыщенности. В данном исследовании изучается взаимосвязь между использованием технологий, образом жизни и уровнем стресса с применением машинного обучения. Градиентный бустинг-регрессор был обучен на поведенческом наборе данных, включающем время экрана, физическую активность, сон и диету, при этом чувствительные психические показатели были исключены. Модель продемонстрировала высокую точность прогнозирования ( $R^2 = 0.979$ ), значительно превзойдя базовую модель. Анализ важности признаков и интерпретируемости (SHAP) показал, что использование социальных сетей, экранное время, связанное с работой, и низкая физическая активность наиболее сильно влияют на уровень стресса, тогда как качество сна и физические упражнения ассоциированы с его снижением. Эти результаты подтверждают, что только на основе поведенческих данных можно создавать надёжные и понятные модели оценки стресса, что открывает возможности для применения в цифровых системах благополучия и персонализированной обратной связи. Полученные выводы подчёркивают важность контроля цифровых привычек как неклинического подхода к поддержанию психического здоровья.

**Ключевые слова:** прогнозирование стресса, использование технологий, машинное обучение, экранное время, поведенческие данные, SHAP, анализ образа жизни, моделирование благополучия, социальные сети, физическая активность.