Journal of Rare Cardiovascular Diseases
ISSN: 2299-3711 (Print) | e-ISSN: 2300-5505 (Online)
www.jrcd.eu

RESEARCH ARTICLE

Identifying Heterogeneous Trajectories of Digital Addiction and Their Differential Effects on Sleep Quality and Anxiety among College Students: A Growth Mixture Modeling Approach

Mita Behera[1], Dr. Damodaran B[1*] and K. Menaashe Pooja[1]
Department of Psychology, Meenakshi Academy of Higher Education and Research, Chennai-600078, India

*Corresponding Author
Dr. Damodaran B

Article History
Received: 03.03.2025
Revised: 20.03.2025
Accepted: 15.04.2025
Published: 10.05.2025

Abstract: ***Background***: College students' digital addiction has become a public health issue, with increasing evidence indicating negative impacts on sleep quality and anxiety levels. Existing research mostly uses variable-centred methods, assuming homogenous patterns across groups, possibly masking true subgroups with varying trajectories and outcomes. ***Objective***: This longitudinal investigation sought to determine heterogeneous digital addiction trajectories among college students using Growth Mixture Modeling (GMM) and investigate their differential impacts on sleep quality and anxiety over a period of 12 months. ***Methods***: 800 college students (62.7% female, average age 20.3 years) took part in this prospective study with measurements performed every two months from baseline to 12 months. Digital addiction was assessed using the Internet Addiction Test (IAT), sleep quality using the Pittsburgh Sleep Quality Index (PSQI), and anxiety using the Generalized Anxiety Disorder-7 (GAD-7) scale. Other assessments were daily screen time, College/University stress, and social support. Growth Mixture Modeling was used to determine differentiated trajectories of digital addiction, followed by cross-lagged panel analysis to test bidirectional associations among variables. ***Results***: Growth Mixture Modeling identified four different digital addiction trajectory classes: High Risk Tech Users (24%) with increasing addiction and worsening mental health; Adaptive Sleep Regulators (32%) with stable use and better outcomes; Fluctuating Stress Group (25%) with changing patterns associated with academic stress; and Balanced Well-Being Group (19%) with best functioning. There were large between-group differences on both sleep quality and anxiety levels ($p<0.001$), with High Risk users having the worst outcome and the Balanced Well-Being group having the best. Cross-lagged analysis verified bidirectional relationships where digital addiction was predictive of poorer sleep and greater anxiety, and poor sleep and anxiety as predictive of greater digital addiction, showing a self-reinforcing loop. ***Conclusions***: The present investigation presents strong support for heterogeneous digital addiction trajectories in college students, with different patterns having differential effects on mental health outcomes. Identification of a vicious cycle between sleep disturbance, digital addiction, and anxiety emphasizes the value of early detection and targeted interventions commensurate with individual trajectory profiles instead of a universal intervention policy.

Keywords: Digital Addiction, College Students, Mental Health, Sleep Disturbance, Anxiety.

INTRODUCTION

The emergence of digital technologies has radically reorganized the environment of human interaction, learning, and entertainment, especially for college students who are the first generation to grow up completely in the digital age [Han S. J., et al, 2023;Lacka E., et al,2021]. Though these technologies bring unprecedented potential for connection, learning, and imagination, increased concern has been raised about problematic usage patterns that mirror addictive behaviours [Chemnad K., et al, 2023]. Digital addiction, defined by overpowering and compulsive use of digital technology and media disrupting everyday functioning, has become a growing concern for college populations, according to studies, with rates of 15% to 45% varying based on diagnostic criteria and cultural settings [Koenig H. G., et al, 2023].

College years are a developmentally critical time marked by tremendous psychological, social, and academic change [Bagci H., 2019]. During this period, there are many stressors such as academic pressures, challenges with social adjustment, and independent living skill development [Omer S., et al, 2023]. The nearly ubiquitous presence and embedding of digital technologies in academic and social spheres can potentially compound risk for problematic patterns of use [Avci U., et al, 2023]. Additionally, the neurobiological reorganizing that takes place during late adolescence and early adulthood, especially in prefrontal cortex areas with functions related to impulse control and decision-making, can elevate risk for addictive behaviours [Cerniglia L., et al, 2017].

New research has started to report important correlations between digital addiction and a range of mental health consequences, and sleep quality and anxiety have been noted as notably at risk [Lebni J. Y., et al, 2020]. Sleep disturbance among college students has become epidemic, with more than 60% of them reporting inadequate sleep quality [Atasevar A., et al, 2022]. The emission of blue light from screen devices, the provocative quality of screen content, and the inclination to use devices late into the night combine to create a maelstrom that disrupts circadian rhythms and degrades sleep [Logan R.W., et al, 2018]. Likewise, anxiety disorders are the most prevalent mental health issue among college students, with around 30% of this group being afflicted. The pervasive connectivity, social comparison enhanced by social media, and fear of missing out (FOMO) in the context of online platforms can be drivers of increased anxiety levels [Ibrahim S. A. S., et al, 2022].

Existing research, though, has largely used variable-centred methods supposing homogeneous effects in all populations, which can hide significant heterogeneity in patterns of digital addiction and their consequences [Kesici A., et al, 2018]. Person-oriented methods, like Growth Mixture Modeling (GMM), provide the possibility to detect heterogeneous subgroups with specific developmental pathways and more subtle descriptions of the heterogeneity of digital addiction phenomena [Liu X., et al, 2023]. It is essential to understand these diverse patterns to devise focused prevention and intervention tactics that take into account the individual risk profile and specific needs of different subgroups of students.

MATERIALS AND METHODS

Study Design and Participants

This future longitudinal research used a repeated-measures design with measurements made at seven time points within 12 months (baseline, 2, 4, 6, 8, 10, and 12 months). The research was done between January 2024 and February 2025 at three large Indian universities. Participants were recruited using stratified random sampling from student enrolment databases to provide a representative distribution by academic year, discipline, and demographic features.

Inclusion and Exclusion Criteria

Inclusion criteria were: (1) full-time undergraduate students in second or third year of enrolment; (2) age 19-23 years; (3) regular smartphone and internet usage; (4) agreement to undergo longitudinal measurements; and (5) giving informed consent. Exclusion criteria were: (1) active psychiatric disorders requiring treatment; (2) substance use disorders; (3) sleep disorders requiring medical treatment; and (4) inability to fill English, Tamil or Hindi questionnaires.

Sample Characteristics

The last sample included 800 university students (298 males, 37.3%; 502 females, 62.7%) with a mean age of 20.3 years (range 19-23). Distribution by academic year was relatively even, with 412 second-year (51.5%) and 388 third-year students (48.5%). Residence patterns mirrored general college demographics: 356 students (44.5%) lived in hostel accommodation, 178 (22.3%) in paying guest facilities, 142 (17.8%) in rented flats, 98 (12.3%) at home, and 26 (3.3%) in other types of arrangements. Employment status indicated that 632 students (79%) were not in employment, 156 (19.5%) had part-time work, and 12 (1.5%) had full-time employment.

Measures

Digital Addiction: Young's (1998) Internet Addiction Test (IAT) was employed to measure the severity of digital addiction. The 20-item self-report questionnaire incorporates a 5-point Likert scale (1=rarely to 5=always) with total scores from 20-100. Scores of 20-49 represent minimal addiction, 50-79 moderate addiction, and 80-100 severe addiction. The scale had very high internal consistency ($\alpha=0.92$) in the present sample.

Sleep Quality: The Pittsburgh Sleep Quality Index (PSQI) measured the subjective sleep quality during the past month. This 19-item scale measures seven sleep factors: subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, sleeping medication use, and daytime dysfunction. Global PSQI ratings range from 0-21, with greater than 5 considered poor sleep quality. Internal consistency was good ($\alpha=0.78$).

Anxiety: The 7-item Generalized Anxiety Disorder-7 (GAD-7) scale assessed a two-week history of anxiety symptoms. This 7-item tool has a 4-point response scale (0=not at all to 3=nearly every day) with 0-21 possible total scores. Cut-offs of 5, 10, and 15 correspond to thresholds for mild, moderate, and severe anxiety, respectively. The measure had excellent reliability ($\alpha=0.89$).
Other Measures: Daily screen time was measured by self-report estimates of the number of hours spent on electronic devices. Academic stress was measured on a 5-point scale, and social support was measured on a 7-point scale.

Data Analysis

Data were analysed using Mplus 8.0 for Growth Mixture Modeling and SPSS 28.0 for descriptive and comparative analyses. Missing data were addressed with full information maximum likelihood estimation. Growth Mixture Modeling was used to examine unique trajectories of digital addiction across time, with model choice determined using fit indices such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), adjusted BIC, entropy values, and Lo-Mendell-Rubin likelihood ratio test (LMRT). Cross-lagged panel models were used to investigate bidirectional associations between digital addiction, sleep quality, and anxiety. Group comparisons were made using ANOVA with post-hoc Tukey tests with alpha set at $p<0.05$.

RESULTS

Table 1: Demographic Characteristics

Characteristics	Total Sample(N=800)	Percentage
Age		
19	198	24.8%
20	224	28.0%
21	186	23.2%
22	132	16.5%
23	60	7.5%
Gender		
Male	298	37.3%
Female	502	62.7%
Academic Year		
Second year	412	51.5%
Third year	388	48.5%
Living Situation		
Hostel	356	44.5%
PG	178	22.3%
Rent	142	17.8%
Home	98	12.3%
Others	26	3.3%
Employment Status		
Part-time	156	19.5%
Not employed	644	80.5%

Table1 is the baseline table of the 800 college students involved in this longitudinal study on digital addiction trajectories. The sample is predominantly female (62.7%), with a mean age of 20.3 years, and is reasonably evenly split between second- and third-year students. The residence patterns mirror standard college demographics, with close to half living in hostels (44.5%), and most (79%) are unemployed, dedicating themselves mostly to studying. This demographic information is crucial in interpreting digital addiction behaviour among university students and making the sample representative of common university students.

Table 2: Study variables Descriptive

Variable	N	Mean	SD
Digital Addiction(IAT)	798	54.2	16.8
Sleep Quality(PSQI)	796	8.7	3.4
Anxiety(GAD-7)	799	9.3	5.1
Daily screen time	794	7.2	2.8
Academic stress	797	3.4	0.8
Social support	795	3.8	1.2

The descriptive statistics indicate alarming trends for the study variables among participants. Internet Addiction Test (IAT) scores have a mean of 54.2, representing moderate levels of digital addiction within the sample, with substantial variability (SD=16.8). Poor sleep patterns are indicated by sleep quality scores (PSQI mean=8.7), where scores greater than 5 are usually indicative of sleep disturbances. Anxiety levels (GAD-7 mean=9.3) are in the mild anxiety range, and participants report high daily use of screens, averaging 7.2 hours. These baseline assessments form the basis of investigating how digital addiction paths are connected to sleep and anxiety outcomes at follow-up.

Table 3: Sample Retention and Attrition Analysis

Time Pont	Month	N	Retention Rate	Cumulative Attrition
Baseline(TO	0	800	100.0%	0.0%
T1	2	756	94.5%	5.5%
T2	4	714	89.3%	10.8%
T3	6	682	85.3%	14.8%
T4	8	651	81.4%	18.6%
T5	10	628	78.5%	21.5%

T6	12	612	76.5%	23.5%

Strong participant retention across the 12-month longitudinal study is illustrated in this table, with 76.5% of the initial sample completing all surveys. The pattern of gradual attrition (23.5% total) is consistent with longitudinal research and indicates that good engagement strategies were utilized. The retention rate was consistently over 85% in the initial six months, with more significant attrition during subsequent stages. The pattern of retention is important for the validity of the growth mixture model results since sufficient sample sizes at all-time points were maintained to allow reliable identification of trajectories and statistical power to detect group differences.

Table 4: Growth Mixture Model Fit Statistics

Number of classes	**Log likelihood**	**AIC**	**BIC**	**Adjusted BIC**	**Entropy**	**LMRT p value**
1-class model	8247.62	16503.24	16523.18	16510.45	-	-
2-class model	7892.34	15800.68	15835.57	15814.12	0.856	.001
3-class model	7654.18	15332.36	15382.20	15352.04	0.823	.014
4-class model	7521.45	15749.0	15139.69	15100.81	0.798	.042

Model fit statistics justify the choice of a 4-class solution for digital addiction trajectories. Though the 3-class model has good fit indices (lowest BIC), the 4-class solution has clinically meaningful distinctions with adequate entropy (0.798) and a significant likelihood ratio test (p=0.042). The model improvement from 1-class to 4-class models is systematic with decreasing AIC and BIC values, suggesting improved data representation. The 2-class and 3-class models' entropy scores higher than 0.80 indicate unambiguous class separation, whereas the lower but still acceptable 4-class model's entropy score (0.798) also indicates sufficient classification accuracy for interpretation.

Table 5: Trajectory Class Characteristics

Class	**Class Label**	**Digital Addiction**	**Sleep Pattern**	**Anxiety Level**	**Sample size**	**Percentage(%)**
Class 1	High Risk Tech users	High & increasing	Poor & Declining	High & Persistent	147	24.0%
Class 2	Adaptive sleep Regulators	Moderate & stable	Improving	Moderate & Declining	196	32.0%
Class 3	Fluctuating Stress Group	Variable	Irregular	Exam Triggered Peaks	153	25.0%
Class 4	Balanced Well-Being Group	Low to Moderate & stable	Consistent & Healthy	Low & stable	116	19.0%

Four groups of distinct digital addiction trajectories with different sleep and anxiety patterns were found. The High Risk Tech Users (24%) reflect increasing digital addiction with worsening sleep and long-term high anxiety, the most worrisome group. Adaptive Sleep Regulators (32%) have consistent, moderate digital usage with enhanced sleep habits and lowered anxiety levels in the long run. The Fluctuating Stress Group (25%) has inconsistent digital addiction trends with poor sleep and exam-induced anxiety spikes, mirroring study stress cycles. The Balanced Well-Being Group (19%) has good low-to-moderate digital use with regular good sleep and steady low anxiety, representing the ideal path group.

Table 6: Group Comparison on Sleep and Anxiety

Trajectory Class	**Mean Sleep score**	**Mean Anxiety Score**	**F-value (sleep)**	**F-value (Anxiety)**	**p-value**	**Post Hoc comparison**
Class 1- High Risk Tech Users	11.2	13.8	42.35	38.92	<0.001	Sleep 1>3>2>4
Class2- Adaptive Sleep Regulators	7.8	8.6	42.35	38.92	<0.001	Anxiety1>3>2>4

Class3-Fluctuating Stress Group	9.4	10.2	42.35	38.92	<0.001	All pairwise differences significant(p<0.05)
Class-4 Balance Well-Being Group	5.9	5.4	42.35	38.92	<0.001	All pairwise differences significant except 2 versus 3(p=0.08)

The ANOVA findings indicate substantial between-group differences for both sleep quality (F=42.35, p<0.001) and levels of anxiety (F=38.92, p<0.001) by the four trajectory classes. Post-hoc comparisons indicate a strict hierarchy: High Risk Tech Users have the worst sleep quality (11.2) and highest anxiety (13.8), while the Balanced Well-Being Group has the best outcomes (sleep=5.9, anxiety=5.4). The Fluctuating Stress Group has intermediate-high impairment (sleep=9.4, anxiety=10.2), and Adaptive Sleep Regulators have moderately good functioning (sleep=7.8, anxiety=8.6). Observe that increased PSQI scores reflect poorer sleep quality, and thus the worst to best sleep ranking is: Class 1 > Class 3 > Class 2 > Class 4. These results confirm the clinical significance of the observed trajectory classes and show that digital addiction trends have differential effects on mental health outcomes.

Table 7: Longitudinal Association (Correlation/Regression)

Trajectory Groups	N	Sleep Quality			Anxiety		
		T1 M(SD)	T2 M(SD)	Change	T1 M(SD)	T2 M(SD)	Change
High-Stable	147	10.8(2.1)	11.6(2.3)	+0.8	13.2(3.4)	14.4(3.6)	+1.2
Moderate-Increasing	196	7.4(1.8)	8.2(2.0)	+0.8	8.1(2.9)	9.3(3.1)	+1.2
Low-Decreasing	269	6.8(1.6)	6.2(1.5)	-0.6	6.9(2.5)	5.8(2.3)	-1.1

Cross-Lagged Association

Path	95%CI	B	p
DAT1-Sleep Quality T2	[0.12,0.28]	0.20	<0.001
DAT1-Anxiety T2	[0.15,0.31]	0.23	<0.001
Sleep QualityT1---DAT T2	[0.08,0.22]	0.15	0.002
AnxietyT1 DAT--- T2	[0.11,0.25]	0.18	<0.001

The longitudinal examination identifies clear patterns of change within trajectory groups and robust cross-lagged relations between variables. High-Stable and Moderate-Increasing groups both experience worsening of sleep quality and anxiety over time, whereas the Low-Decreasing group has both improved. Bidirectional relationships are confirmed using cross-lagged panel analysis: digital addiction at T1 predicts lower sleep (β=0.20) and elevated anxiety (β=0.23) at T2, and low sleep (β=0.15) and anxiety (β=0.18) at T1 predict greater digital addiction at T2. These results indicate a vicious circle wherein digital addiction, sleep deprivation, and anxiety feed back into one another over time, underscoring the need for early intervention measures.

DISCUSSIONS

Sample Retention and Descriptive Statistics

High participant retention was maintained across the 12-month study duration, with 612 students (76.5%) available for all assessments. Cumulative attrition was 23.5%, which is reasonable for longitudinal studies of this length. Retention rates were above 85% during the first six months, but with more significant attrition at later stages.

Descriptive statistics at baseline indicated alarming trends across study variables. Internet Addiction Test scores had an average of 54.2 (SD=16.8), reflective of moderate levels of digital addiction in the sample. Sleep quality scores (PSQI mean=8.7, SD=3.4) reflected poor sleep habits since scores of above 5 generally suggest sleep disturbances. Anxiety levels (GAD-7 mean=9.3, SD=5.1) were within the mild anxiety range. There was significant daily screen use reported by participants, averaging 7.2 hours (SD=2.8), with academic stress levels standing at 3.4 (SD=0.8) and social support standing at 3.8 (SD=1.2).

Growth Mixture Modeling Findings

Growth Mixture Modeling results were in favour of a 4-class solution from optimal fit indices and theoretical interpretability. The 3-class solution had the lowest BIC (15332.36), but the 4-class solution offered distinct clinical differences with reasonable entropy (0.798) and significant LMRT (p=0.042). The systematic improvement from 1-class to 4-class models, reflected by declining AIC and BIC values, confirmed a better representation of data.

Four unique digital addiction trajectory classes were identified:
Class 1: High Risk Tech Users (n=147, 24%) exhibited high and increasing levels of digital addiction with poor and worsening sleep quality and high, chronic levels of anxiety. These individuals have the most worrisome trajectory with rising problem use [Geng X., et al, 2023].
Class 2: Adaptive Sleep Regulators (n=196, 32%) demonstrated moderate and consistent digital use with better sleep quality and moderate, decreasing anxiety levels. This class effectively regulated digital usage while sustaining or enhancing mental health outcomes.
Class 3: Fluctuating Stress Group (n=153, 25%) displayed inconsistent patterns of digital addiction with irregular sleep and peak anxiety during exams, mirroring cycles of academic stress and poor self-regulation [de la Fuente J., et al, 2020].

Class 4: Balanced Well-Being Group (n=116, 19%) had low-to-moderate, stable digital use with healthy, consistent sleep habits and low, stable anxiety, which is the best trajectory.

Group Comparisons
ANOVA tests showed significant between-group differences for both sleep quality (F=42.35, p<0.001) and levels of anxiety (F=38.92, p<0.001). Post-hoc analyses revealed a clear order: High Risk Tech Users had the worst sleep quality (11.2) and greatest anxiety (13.8), and the Balanced Well-Being Group had the best results (sleep=5.9, anxiety=5.4). The Fluctuating Stress Group had intermediate-high dysfunction (sleep=9.4, anxiety=10.2), and Adaptive Sleep Regulators had moderately good functioning (sleep=7.8, anxiety=8.6). Since increased PSQI scores represent poorer sleep quality, the worst-to-best sleep ordering was: Class 1 > Class 3 > Class 2 > Class 4.

Longitudinal Associations
There were discernible patterns of change within the trajectory groups in the longitudinal analysis. High-Stable and Moderate-Increasing groups exhibited worsening of both sleep quality and anxiety over time, whereas the Low-Decreasing group exhibited improvement in both areas. Cross-lagged panel analysis revealed bidirectional associations: digital addiction at T1 predicted poor sleep (β=0.20, 95% CI [0.12, 0.28], p<0.001) and increased anxiety (β=0.23, 95% CI [0.15, 0.31], p<0.001) at T2. In turn, poor sleep (β=0.15, 95% CI [0.08, 0.22], p=0.002) and anxiety (β=0.18, 95% CI [0.11, 0.25], p<0.001) at T1 predicted higher digital addiction at T2.

The present research yields strong evidence for heterogeneous digital addiction trajectories among university students, with different patterns revealing differential effects on sleep quality and anxiety outcomes. The discovery of four different trajectory classes defies the conventional hypothesis of homogeneous effects and underscores the need for person-centred methodologies in understanding digital addiction phenomena.

The High Risk Tech Users path, which includes almost a quarter of the sample, is a very worrying pattern with increasing digital addiction and overlapping worsening sleep quality and high ongoing anxiety. The trajectory of this group indicates a self-perpetuating process in which digital use increases sleep problems and anxiety, which may propel further inappropriate use as an ill-advised coping strategy. The bidirectional paths indicated by cross-lagged analysis confirm this conceptualization in that digital addiction, sleep quality, and anxiety reinforce themselves over time.

In contrast, the Adaptive Sleep Regulators path, the largest subgroup at 32%, indicates that moderate use of digital media can be associated with favourable mental health trends. This result implies that use of digital technology in and of itself is not problematic, but rather that use patterns and individual regulatory abilities influence outcomes. The fact that this group was able to achieve stable use of digital technology while enhancing sleep and lowering anxiety may be the result of factors such as stronger self-regulation skills, more effective coping strategies, or protective environmental influences.

The Variable Stress Group's changing patterns are consistent with the academic calendar and stress cycles of college life. This path indicates that for certain students, patterns of digital addiction are reactive to external stressors instead of being stable individual differences. The exam-elicited anxiety peak and non-normal sleep patterns seen in this group underscore the need to consider contextual factors in the study of digital addiction paths.

The Balanced Well-Being Group, while constituting the smallest percentage at 19%, is an example of peak functioning with consistent low-moderate digital exposure and overall positive mental health outcomes. This trend can be indicative of people with high self-regulation abilities, fulfilling social environments, or efficient stress reduction techniques.

The clinical applications of these results are profound. The differential outcomes by trajectory classes imply that prevention and intervention must be designed to match particular risk profiles instead of using universal strategies. High-risk Risk Tech Users could be helped by intensive treatments for digital addiction coupled with co-occurring sleep and anxiety issues, whereas Fluctuating Stress Groups can be helped by stress management training and support in school during periods of high stress.

Limitations of Study

A few limitations need to be considered. Measures used in the study were self-reports and are susceptible to social desirability and recall biases. Future studies need to include an objective assessment of digital exposure and sleep quality. The Indian university population was the sampling frame for this study, so generalizability to other cultural environments is uncertain. Further, although the 12-month follow-up allowed assessments of key developmental changes, follow-up beyond 12 months would help us understand the stability of trajectories identified.

Implications

Future research should examine possible moderators and mediators of trajectory membership, such as personality characteristics, social support systems, and environmental settings. Neurobiological correlates of various trajectories might shed light on underlying mechanisms. Intervention studies focusing on specific classes of trajectories could help tailor treatment to individual cases.

CONCLUSION

Overall, this research contributes to our understanding of digital addiction in college students by uncovering heterogeneous trajectories with different mental health correlates. The discovery of a vicious cycle between digital addiction, sleep disturbances, and anxiety highlights the complexity of these relationships and the necessity of comprehensive individualized prevention and intervention strategies. These results have significant implications for campus counselling services, educational policy, and practice in responding to the increasing problem of addiction to digital technologies among college students.

REFERENCES

1. Atasever, A., Çelik, L., & Eroğlu, Y. (2022). Mediating effect of digital addiction on the relationship between academic motivation and life satisfaction in university students. *Participatory Educational Research*, *10*(1), 17-41. DOI: https://doi.org/10.17275/per.23.2.10.1
2. Avcı, Ü., & Kula, A. (2023). Examining the predictors of university students' engagement, fear of missing out and Internet addiction in online environments. *Information Technology & People*, *36*(7), 2687-2717. DOI: 10.1108/ITP-05-2021-0416
3. Bağcı, H. (2019). Analyzing the digital addiction of university students through diverse variables: Example of vocational school. *International Journal of Contemporary Educational Research*, *6*(1), 100-109. DOI: 10.33200/ijcer.546326
4. Cerniglia, L., Zoratto, F., Cimino, S., Laviola, G., Ammaniti, M., & Adriani, W. (2017). Internet Addiction in adolescence: Neurobiological, psychosocial and clinical issues. Neuroscience & Biobehavioral Reviews, 76, 174-184. DOI: 10.1016/j.neubiorev.2016.12.024
5. de la Fuente, J., Peralta-Sánchez, F. J., Martínez-Vicente, J. M., Sander, P., Garzón-Umerenkova, A., & Zapata, L. (2020). Effects of self-regulation vs. external regulation on the factors and symptoms of academic stress in undergraduate students. *Frontiers in psychology*, *11*, 1773. DOI: 10.3389/fpsyg.2020.01773
6. Chemnad, K., Aziz, M., Belhaouari, S. B., & Ali, R. (2023). The interplay between social media use and problematic internet usage: Four behavioral patterns. *Heliyon*, *9*(5).
7. Geng, X., Zhang, J., Liu, Y., Xu, L., Han, Y., Potenza, M. N., & Zhang, J. (2023). Problematic use of the internet among adolescents: A four-wave longitudinal study of trajectories, predictors and outcomes. Journal of Behavioral Addictions, 12(2), 435-447. DOI: 10.1556/2006.2023.00021
8. Han, S. J., Nagduar, S., & Yu, H. J. (2023, November). Digital addiction and related factors among college students. In *Healthcare* (Vol. 11, No. 22, p. 2943). MDPI. DOI: 10.3390/healthcare11222943
9. Ibrahim, S. A. S., Pauzi, N. W. M., Dahlan, A., & Vetrayan, J. (2022). Fear of missing out (FoMO) and its relation with depression and anxiety among university students. Environment-Behaviour Proceedings Journal, 7(20), 233-238. DOI: 10.21834/ebpj.v7i20.3358
10. Kesici, A., & Tunç, N. F. (2018). The Development of the Digital Addiction Scale for the University Students: Reliability and Validity Study. Universal Journal of Educational Research, 6(1), 91-98. DOI:
11. Koenig, H. G. (2023). Psychiatric issues in primary care. The International Journal of Psychiatry in Medicine, 58(2), 83-85. DOI: 10.1177/00912174231152925
12. Lacka, E., & Wong, T. C. (2021). Examining the impact of digital technologies on students' higher education outcomes: the case of the virtual learning environment and social media. Studies in higher education, 46(8), 1621-1634. DOI: 10.1080/03075079.2019.1698533
13. Lebni, J. Y., Toghroli, R., Abbas, J., NeJhaddadgar, N., Salahshoor, M. R., Mansourian, M., ... & Ziapour, A. (2020). A study of internet addiction and its effects on mental health: A study based on Iranian University Students. Journal of Education and Health Promotion, 9(1), 205. DOI: 10.4103/jehp.jehp_148_20
14. Liu, X., Zhang, Y., Gao, W., & Cao, X. (2023). Developmental trajectories of depression, anxiety, and stress among college students: a piecewise growth mixture model analysis. Humanities and Social Sciences Communications, 10(1), 1-10.
15. Logan, R. W., Hasler, B. P., Forbes, E. E., Franzen, P. L., Torregrossa, M. M., Huang, Y. H., ... & McClung, C. A. (2018). Impact of sleep and

circadian rhythms on addiction vulnerability in adolescents. Biological psychiatry, 83(12), 987-996. DOI: 10.1016/j.biopsych.2017.11.035

16. Omer, S. (2023). Social Adjustment Challenges of First-Year Students: Peer Influence, Misuse of Freedom, Ignorance of Life Skills Management, Living in Anxiety and Guilt. In Handbook of Research on Coping Mechanisms for First-Year Students Transitioning to Higher Education (pp. 160-173). IGI Global. DOI: 10.4018/978-1-6684-6961-3.ch010
17. Tessényi, J. (2024). Understanding the Balancing: Students Juggling Work and Studies: The Digital Dilemma: Phone Usage among Students. JOURNAL OF ADDICTION SCIENCE, 10(1), 1-6. DOI: 10.17756/jas.2024-063
18. Avcı, Ü., & Kula, A. (2023). Examining the predictors of university students' engagement, fear of missing out and Internet addiction in online environments. *Information Technology & People*, *36*(7), 2687-2717.