JPEE 실천공학교육논문지 JOURNAL OF PRACTICAL ENGINEERING EDUCATION

학제간융합교육

J. Pract. Eng. Educ. 16(4), 577-585, 2024

The Relationship Between GPS-Based Physical Activity Patterns and Depression

Kwang Ho Seok[1], Sung Man Bae[2]*

[1]School of AI Drone, Global Cyber University, Cheonan 31228, Korea
[2]Department of Psychology and Psychotherapy, Dankook University, Cheonan 31116, Korea

[Abstract]

This study analyzed the relationship between GPS-based physical activity patterns and mental health using Kaggle Student Life data. Data were collected over a 10-week period from 48 students at Dartmouth College through Android smartphones and included GPS, dark, and phone lock data, and measures such as the Patient Health Questionnaire-9 (PHQ-9), Loneliness Scale, the Positive and Negative Affect Schedule (PANAS), and Perceived Stress Scale. Using latitude and longitude data obtained from GPS measurements, various physical activity indicators were calculated, including the total distance traveled, average distance traveled, average distance traveled in the morning, average distance traveled in the afternoon, average distance traveled in the evening, and average distance traveled in the middle of the night. Pearson's correlation analysis was performed to explore the relationship between GPS-based physical activity patterns and mental health. The study results indicated a significant negative correlation between the average distance traveled in the afternoon and PHQ-9 scores. Results indicated that the higher the afternoon activity, the lower the depressive symptoms. There was a positive correlation be-tween the PANAS-Pos score and the average distance traveled in the evening, indicating that positive emotions tended to increase as evening activities increased. This finding suggests a relationship between physical activity at specific times and mental health.

Key Words: Physical activity patterns, Depressive symptoms, Mental health, StudentLife, GPS

I. Introduction

Depression is a representative mental health problem that occurs in all age groups and has a high prevalence even in early adulthood, including college students [1]. Specifically, the college years represent a period during which students encounter crucial life tasks such as gaining independence from parents, forming interpersonal relationships, and exploring career opportunities. It has been reported that their perceived stress and depression levels are higher compared to other age groups [2]. Existing studies on depression have focused on psychological and social variables such as adverse childhood experiences [3], perceived stress [4], loneliness [3], and interpersonal problems [5]. However, studies relying on self-reported measures may reduce the reliability of the measurement because participants' social desirability is involved. Therefore, to predict depression more accurately, research that considers both self-reported measures and objective indicators is required. Recently, with the development of digital technology and smartphone

http://dx.doi.org/10.14702/JPEE.2024.577

Received 2 August 2024; **Revised** 12 August 2024
Accepted 16 August 2024

***Corresponding Author**
E-mail: spirit73@dankook.ac.kr

devices, the objective measurement of behavioral and functional indicators of depression has be-come possible, and related studies are increasing [6].

Several recent studies have confirmed a significant association between physical activity indicators based on smartphones and wearable data and mental health, such as depression, loneliness, positive and negative mood, and social anxiety [7-10]. Asare et al. [11] identified differences in sleep, physical activity, and GPS mobility between the de-pressed and non-depressed groups. Specifically, the depressed group showed lower mobility and location entropy than the non-depressed group, and visited fewer different locations. In a study on 45 young adults (19-30 years) by Ben-Zeev et al. [12], increased geo-spatial activity was associated with lower Patient Health Questionnaire-9 (PHQ-9) scores. A study by Laiou et al., involving 164 participants with Major Depressive Disorder (MDD) analyzed the relationship between geolocation data and depression levels measured using the PHQ [13]. After controlling for gender, age, and socioeconomic status, a median daily home stay over 2 weeks was positively related to more depressive symptoms. The association between home stay and severity of depressive symptoms was stronger on weekdays.

Shin and Bae systematically reviewed the association between location and depression [6]. They reviewed 31 articles in Scopus, PubMed, and Web of Science based on terms related to location data and depression. The results showed that location data (entropy, homestay, distance, and irregularity) were consistently and significantly related to depression in most studies. Wang et al. analyzed the correlation between automatic objective sensor data collected from smartphones and the mental well-being of college students [14]. The results showed that conversation levels, daily activity patterns, and sleep data collected from smartphones were significantly associated with college students' mental health.

Previous studies have confirmed the relationship between objective indicators of physical activity, mobility, and depressive symptoms. However, a more specific approach is required to improve our understanding of the association between physical activity and depression. For example, the relationship between physical activity at specific times of the day and depression has not been sufficiently studied [15]. Additionally, many studies analyzed participants' data over a short period of time, such as 1-2 weeks, which is a limitation in clarifying the relationship between physical activity and depression [16].

This study explored the relationship between GPS-based physical activity patterns (particularly GPS-based travel distance, Dark, and Phonelock data) and mental health (depression and loneliness). Specifically, this study measured activity patterns according to various time periods (average travel distance in the morning, average travel distance in the afternoon, average travel distance in the evening, and average travel distance in the middle of the night) and investigated the relationship between these patterns and mental health outcomes. This study is expected to provide a direction for future depression re-search and the development of depression prevention and intervention programs by investigating the association between data collected through smartphone devices and depression.

II. Materials and Methods

In this study, Kaggle's StudentLife dataset was used [17]. Data were collected from 48 students at Dartmouth University over 10 weeks using Android smartphones. All participants were undergraduate and graduate students who voluntarily participated in a CS65 smartphone programming class provided by Dartmouth College during the spring semester of 2013. Of the 48 students who completed this study, 30 were undergraduates and 18 were graduates. Eight students were in the 4th grade, 14 in the 3rd grade, six in the 2nd grade, two new students, three in the doctoral course, one in the 2nd year of their master's degree, and 13 in the 1st year of their master's degree. The sex distribution was 10 female and 38 male students. In terms of race, there were 23 Caucasians, 23 Asians, and two African Americans. Forty-eight participants completed a preliminary psychological survey approved by the Institutional Review Committee of Dankook University. To explore the correlation between GPS-based physical activity patterns and mental health outcomes, this study used GPS, PhoneDark, and PhoneLock data sensed on smartphones, mental health survey data, Patient Health Questionnaire-9 (PHQ-9), Loneliness Scale, Positive and Negative Affect Schedule (PANAS), and Perceived Stress Scale (PSS) data.

Kaggle's StudentLife dataset includes GPS, PhoneDark, and PhoneLock data collected over 10 weeks from 48 students. The GPS-based physical activity patterns were calculated based on the User ID (UID), timestamp, latency, and longitude values in the GPS da-ta. In this study, the Total Moving Distance, Average Moving Distance, Morning Average Moving Distance, Afternoon Average Moving Distance, Evening Average Moving Distance, Late-night Average Moving Distance, time stamp, latitude, and longitude data were used. The Total Moving Distance represents the cumulative distance traveled over 10 weeks. The Average Moving Distance represents the average daily travel distance based on timestamps. The Morning Average Moving Distance represents the average daily travel distance from 6 a.m. to 12 p.m., and the Afternoon Average Moving Distance represents the average daily travel distance from 12 p.m. to 6 p.m. Evening Average Moving Distance represents the average daily travel distance from 6 p.m. to midnight, and late night aver-age moving distance represents the average daily travel distance from midnight to 6 a.m. By analyzing these indicators, insights into students' movement patterns and the amount of activity can be obtained. The partitioning composition of these parameters can provide important information for a broader exploration of behavioral patterns. Additionally, PhoneDark and PhoneLock collected from smartphones were used in this study. The PhoneDark and PhoneLock data contain timestamp values corresponding to the start and end, respectively. PhoneDark represents the time when the smartphone screen is dark and PhoneLock represents the time when the smartphone is locked. In this study, the average daily Phone DarkHour and PhoneLockHour values were calculated using start and end timestamps. In this study, the Total Moving Distance, Average Moving Distance, Morning Average Moving Distance, Afternoon Average Moving Distance, Evening Average Moving Distance, Late-night Average Moving Distance, PhoneDarkHour, and PhoneLockHour were expressed as TMD, AMD, MAMD, AAMD, EAMD, LAMD, PDH, and PLH, respectively. This was confirmed by the results shown in Table 1. This notation facilitates the understanding of the results by presenting the key indicators analyzed in the study clearly and concisely. Table 2 presents the results of the technical statistical analyses for TMD, AMD, MAMD, AAMD, EAMD, LAMD, PDH, and PLH. Of the 48 students, 46 were included, excluding two whose GPS values were not measured. The averages of TMD, AMD, MAMD, AAMD, EAMD, and LAMD were 1517.09 km, 24.10 km, 5.74 km, 6.96 km, 6.47 km, and 4.93 km, respectively. This shows an average daily activity of 24 km, with activity being highest in the afternoon, evening, morning, and late at night.

Table 1. Parameter notation for sensing data

Parameter	Unit	Notation
Total Moving Distance	km	TMD
Average Moving Distance	km	AMD
Morning Average Moving Distance	km	MAMD
Afternoon Average Moving Distance	km	AAMD
Evening Average Moving Distance	km	EAMD
Late−night Average Moving Distance	km	LAMD
PhoneDarkHour	h	PDH
PhoneLockHour	h	PLH

Table 2. Descriptive statistics for sensing data

	Num	mean	std	min	median	max
TMD	46	1517.09	2907.29	45.55	603.18	16028
AMD	46	24.10	43.25	1.14	11.03	239.23
MAMD	46	5.74	17.47	0.06	0.29	103.42
AAMD	46	6.96	17.47	0.38	3.13	37.48
EAMD	46	6.47	17.47	0.26	2.75	66.49
LAMD	46	4.93	17.47	0.06	0.96	89.85
PDH	46	3.49	0.48	2.60	3.45	4.80
PLH	46	3.36	0.59	2.30	3.30	4.80

Kaggle's StudentLife dataset contains PHQ-9, Loneliness Scale, Perceived Stress Scale, and PANAS data for 48 students. PHQ-9 is a self-reported questionnaire that assesses the severity of depressive symptoms experienced by individuals [18]. It consists of nine questions addressing various aspects of depression, such as changes in mood, energy levels, and sleep patterns. Each question is scored on a scale from 0 to 3, and the overall score indicates the severity of the depressive symptoms. An overall score between 1 and 4 indicates minimal depression. A score between 5 and 9 indicates mild depression and a score between 10 and 14 indicates moderate depression. A score between 15 and 19 indicates moderate or high depression, and a score between 20 and 27 indicates severe depression. In this study, the calculated level of depression was expressed on a scale of 0 to 4.

The Loneliness Scale (LSCale) is a tool used to measure the subjective experience of loneliness that an individual feels [19]. The scale consists mainly of statements or questions related to feelings of isolation and lack of social connections. Each of the 20 questions is scored on a scale from 0 to 3, with the total score representing an individual's level of loneliness. An overall score between 0 and 28 indicates a low level of loneliness. A score between 29 and 43 represents an average level of loneliness, and a score above 44 represents a high level of loneliness. In this study, the calculated level of loneliness was ex-pressed on a scale of 1 to 3.

Perceived Stress Scale (PSS) is a widely used psychological tool that measures how stressful an individual perceives a situation in everyday life [20]. It consists of several questions dealing with emotions related to unpredictability, being out of control, and widowhood. Each of the 10 questions is scored on a scale from 0 to 4, and the total score represents the perceived stress level. An overall score between 0 and 13 indicates a normal stress level. A score between 14 and 16 indicates a slight stress level, and a score between 17 and 18 indicates a moderate stress level. A score above 19 indicates severe stress. In this study, the calculated stress level was expressed on a scale of 0 to 3.

The Positive and Negative Affect Schedule is a psychological questionnaire used to measure and evaluate two main emotional states [21]: positive (PA) and negative emotions (NA). It is composed of several words or phrases related to positive or negative emotions that indicate the degree to which each emotion is experienced. Respondents represented the degree of experience of each emotion, and the PANAS evaluated an individual's emotional well-being by capturing both positive and negative emotional states. This scale consists of 20 items, with 10 adjectives each for positive emotions and 10 adjectives for negative emotions. Each of the 20 questions is scored on a scale from 0 to 4, and the higher the total score, the higher the frequency of emotional experience. In this study, the total score for positive emotions was indicated as the PANAS-Pos Score

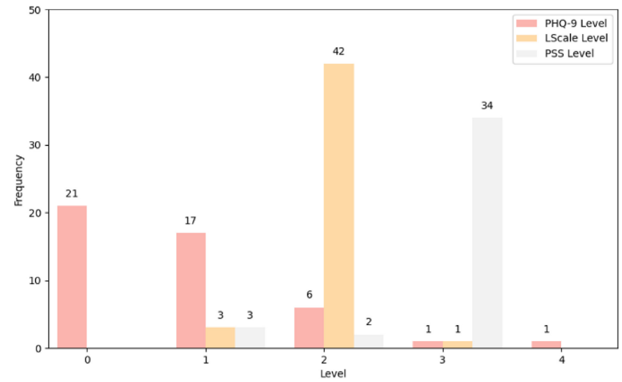


Fig. 1. Frequency analysis results of the PHQ-9, LScale, and PSS level.

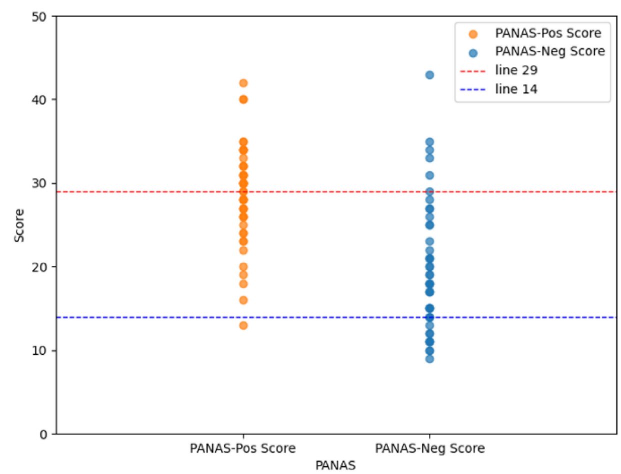


Fig. 2. Analysis results of the PANAS-Pos Score and PANAS-Neg Score.

and the total score for negative emotions was indicated as the PANAS-Neg Score. In general, positive emotions appeared strongly when the PANAS-Pos Score was above 29, and negative emotions appeared strongly when the PANAS-Neg Score was above 14.

Fig. 1 & Fig. 2 shows the mental health data used in this study. The PHQ-9, LScale, and PSS level frequency analysis results for 46 students who responded to the PHQ-9, Loneliness Scale, and Perceived Stress Scale, and PANAS-Neg Score distribution results for 39 students who responded to the PANAS. This indicates higher severity of the PHQ-9, LScale, and PSS scores. Regarding the PHQ-9 level, most students had low levels of depression. A survey of the LScale Level showed that the majority of students experienced average levels of loneliness. In addition, looking at PSS levels, the majority of students showed high stress levels. According to the analysis results of the PANAS-Pos Score, 23 students showed strong positive emotions, and 35 students showed strong negative emotions according to the survey results of the PANAS-Neg Score.

In this study, a correlation analysis was performed to investigate the effects of GPS-based physical activity patterns and smartphone activity parameters for 10 weeks, that is, dark screen activity time and locked activity time, on mental health such as depression, loneliness, stress, and positive/negative emotions. Analyses and evaluations were conducted using Python and SPSS programs to verify the hypothesis that GPS-based physical activity patterns affect mental health. TMD, AMD, MAMD, AAMD, EAMD, LAMD, PDH, and PLH were set as independent variables, and the indirect effects of these parameters on the dependent variables PHQ-9, LScale, PSS, and PANAS were evaluated. The Pearson Correlation Coefficient used in the analysis is a statistical metric employed to measure the linear correlation between two variables, indicating the strength of their linear relationship. Ranging from -1 to 1, this coefficient quantifies how strongly the variables are linearly related. A value close to 1 signifies a strong positive linear correlation, 0 denotes no linear correlation, and a value near -1 indicates a strong negative linear correlation. This metric allows for a quantitative assessment of both the strength and direction of the relationship between the two variables, facilitating a nuanced understanding of their correlation.

III. Results

This chapter describes the correlation analysis between GPS-based physical activity patterns and mental health outcomes, such as depression, loneliness, stress, and positive/negative emotions. First, the correlation between GPS-based physical activity patterns and depression was analyzed. The effect of these parameters on the dependent variable, PHQ-9, was investigated as an independent variable. The dependent variable, PHQ-9, was categorized into two components: PHQ-9 Score, representing the total score derived from survey responses, and PHQ-9 Level, indicating the level of depression based on this score.

Table 3. The correlation analysis results between physical activity patterns and depression

Sensing	Mental Health				
	N	PHQ−9 Score		PHQ−9 Level	
		r	*p*	*r*	*p*
TMD	46	−0.188	0.212	−0.151	0.317
AMD		−0.191	0.204	−0.156	0.299
MAMD		−0.154	0.305	−0.143	0.342
AAMD		−0.324*	0.028	−0.307*	0.038
EAMD		−0.084	0.578	−0.036	0.811
LAMD		−0.114	0.449	−0.070	0.643
PDH		−0.031	0.837	−0.123	0.414
PLH		−0.071	0.640	−0.127	0.400

Note. $^{*}p < .05$; $^{**}p < .01$

Specifically, PHQ-9 Score represents the cumulative sum of scores obtained from survey responses, while PHQ-9 Level signifies the depression level corresponding to this score. Table 3 shows the results of the correlation analysis between the GPS-based physical activity patterns and depression. From these results, it can be concluded that the correlation between the two variables is not statistically significant. However, in the case of AAMD, the p-value of the PHQ-9 Score was 0.028, which is significant at a significance level of 0.05; therefore, it can be concluded that there is a negative correlation between the PHQ-9 Score and AAMD. In addition, the negative correlation between AAMD and PHQ-9 levels was interpreted as statistically significant, as the p-value was 0.038, which was smaller than the significance level of 0.05. These results indicate that depressive symptoms tended to decrease as activity levels increased in the afternoon.

Second, the correlation between GPS-based physical activity patterns and loneliness was analyzed. TMD, AMD, MAMD, AAMD, EAMD, LAMD, PDH, and PLH were set as independent variables, and the effects of these parameters on the dependent variable, LScale, were investigated. The dependent variable, L Scale, was classified into L Scale Score, total L Scale score, and L Scale level of L Scale. Table 4 shows the results of the correlation analysis between GPS-based physical activity patterns and loneliness. From these results, it can be concluded that the correlation between the two variables is not statistically significant. This result indicates that there was no significant relationship between

Table 4. The correlation analysis results between physical activity patterns and loneliness

Sensing	N	Mental Health			
		LScale Score		LScale Level	
		r	p	r	p
TMD	46	−0.128	0.396	0.011	0.944
AMD		−0.129	0.393	0.012	0.936
MAMD		−0.099	0.511	0.048	0.751
AAMD		−0.224	0.134	−0.004	0.978
EAMD		−0.077	0.611	−0.034	0.825
LAMD		−0.063	0.677	0.007	0.961
PDH		−0.046	0.762	0.122	0.419
PLH		−0.113	0.453	−0.151	0.317

Note. $^{*}p < .05$; $^{**}p < .01$

Table 5. The correlation analysis results between physical activity patterns and stress

Sensing	N	Mental Health			
		PSS Score		PSS Level	
		r	p	r	p
TMD	39	−0.007	0.966	−0.017	0.917
AMD		−0.007	0.964	−0.009	0.956
MAMD		−0.062	0.707	−0.141	0.391
AAMD		−0.143	0.386	−0.023	0.889
EAMD		0.106	0.521	0.134	0.414
LAMD		0.069	0.677	0.059	0.719
PDH		−0.043	0.795	0.014	0.934
PLH		−0.205	0.210	−0.058	0.725

Note. $^{*}p < .05$; $^{**}p < .01$

physical activity patterns and loneliness.

Third, the correlation between GPS-based physical activity patterns and stress was analyzed. TMD, AMD, MAMD, AAMD, EAMD, LAMD, PDH, and PLH were set as independent variables, and their effects on PSS were investigated. The dependent variable, PSS, was classified into PSS Score, total PSS score, PSS Level, the PSS level. Table 5 shows the results of the correlation analysis between GPS-based physical activity patterns and stress. From these results, it can be concluded that the correlation between the two variables is not statistically significant. This result indicates that there is no significant relationship between physical activity patterns and stress.

Finally, the correlation between the GPS-based physical activity patterns and positive and negative emotions was analyzed. TMD, AMD, MAMD, AAMD, EAMD, LAMD, PDH, and PLH were set as independent variables, and the effects of these parameters on PANAS were investigated. The dependent variable, PANAS, was classified into the PANAS-Pos Score, positive total score for PANAS, and PANAS-Neg Score, and negative total PANAS score. Table 6 shows the results of the correlation analysis between GPS-based physical activity patterns and positive/negative emotions. From these results, it can be concluded that the correlation between the two variables is not statistically significant. However, the correlation coefficient between PANAS-Pos and EAMD scores was 0.301. The P-value for this correlation was 0.045, which was less than the significance level of 0.05. Therefore, the correlation between the PANAS-Pos Score and EAMD was statistically significant, and EAMD tended to increase as the PANAS-Pos Score increased. This suggests that positive emotions tend to increase as activity levels increase in the evening.

Table 6. The correlation analysis results between physical activity patterns and positive/negative affect

Sensing	N	Mental Health			
		PANAS−Pos Score		PANAS−Neg Score	
		r	p	r	p
TMD	39	0.266	0.077	−0.095	0.535
AMD		0.261	0.083	−0.099	0.517
MAMD		0.170	0.264	−0.117	0.445
AAMD		0.290	0.053	−0.188	0.215
EAMD		0.301*	0.045	−0.014	0.926
LAMD		0.165	0.279	−0.028	0.856
PDH		−0.276	0.066	0.214	0.158
PLH		−0.127	0.407	−0.056	0.713

Note. $^{*}p < .05$; $^{**}p < .01$

A strong positive correlation has been observed among TMD, AMD, MAMD, AAMD, EAMD, and LAMD. There appears to be a tendency for increased movement distances across various time periods as the overall activity level rises. Moreover, when activity intensifies during specific time frames, there is a likelihood of a concurrent increase in movement distances across other time periods. This suggests that an individual's regular activity patterns or routine movements may be evenly distributed throughout different times of the day. In essence, the overall trend indicates that as overall activity increases, movement distances during various time periods tend to increase as well.

IV. Discussion

This study investigated the relationship between GPS-based physical activity pat-terns and various mental health indicators such as depression, loneliness, stress, and positive/negative emotions. This study utilized Kaggle's StudentLife dataset, which includes 10 weeks of GPS, PhoneDark, and PhoneLock data for 48 students. Several metrics, such as Total Moving Distance (TMD), Average Moving Distance (AMD), and morning, afternoon, evening, and late-night average moving distance (MAMD, AAMD, EAMD, LAMD) were calculated to provide insight into students' movement patterns and activity levels. In addition, metrics such as PhoneDarkHour (PDH) and PhoneLockHour (PLH) were derived from smartphone data.

The main focus of this study was to investigate the correlation between GPS-based physical activity patterns and mental health indicators. Therefore, a correlation analysis between TMD, AMD, MAMD, AAMD, EAMD, LAMD, PDH, PLH, PHQ-9, LScale, PSS, and PANAS scores was performed. A negative correlation was found between the AAMD and PHQ-9 scores, indicating a tendency for depressive symptoms to decrease with increasing afternoon activity. No significant correlations were found between loneliness (LSCale) and perceived stress (PSS) or GPS-based activity patterns. There was a positive correlation be-tween the PANAS-Pos score and the EAMD, indicating that positive emotions tended to increase as evening activities increased. Furthermore, there was no evident correlation between the smartphone being powered off or locked and mental health indicators. This implies that the frequency of smartphone access, whether frequent or infrequent, did not show significant associations with the observed mental health metrics. These findings suggest that factors other than the operational status or security measures of the smartphone may exert a more substantial influence on health outcomes.

Overall, these findings suggest that certain GPS-based activity patterns are primarily associated with depression and positive emotions. In previous studies, the relationship between physical activity, mobility, and symptoms of depression has already been established. However, a more specific approach is deemed necessary. For instance, the relationship between physical activity during specific time periods and depression has not been adequately explored. This study aimed to ascertain the temporal differences in the impact on mental health. A tendency for a decrease in depression was observed as after-noon activity increased, prompting a discussion on the possible reasons behind this phenomenon. Afternoons are times when most individuals engage in activities and experience active social interactions. Social activities positively influence mental health, potentially leading to a reduction in depression. Furthermore, the afternoon may be a period of decreased routine tasks and stress compared to the morning, resulting in reduced mental fatigue and stress, which could contribute to a decrease in depression. In some cases, the lack of a significant correlation emphasizes that the relationship between physical activity and mental health is complex and requires further exploration. This study acknowledges the limitation that the sample size was small and could be affected by confounding variables. Individuals can exhibit diverse preferences regarding their activities or lifestyle patterns, and they may engage in activities differently based on natural circadian rhythms or personal systems. Additionally, variables such as an individual's schedule, work commitments, and family situations can serve as influencing factors for depression. Therefore, considering these aspects, it is imperative to further validate whether these patterns are generally observable through additional experiments and investigations, taking into ac-count the necessity for multiple comparisons. In future studies, various datasets may be utilized to explore additional factors that contribute to mental health outcomes and improve generalization. In conclusion, this study provides a comprehensive overview of findings, emphasizing the subtle relationship between GPS-based physical activity pat-terns and various mental health indicators among students.

V. Conclusions

This study explored the relationship between GPS-based physical activity patterns and mental health indicators. Kaggle's StudentLife dataset analyzed data from 48 students over 10 weeks to gain insights into their movement patterns and activity levels. One of the main findings was the negative correlation between AAMD and PHQ-9 scores, which showed a tendency for depressive symptoms to decrease as afternoon activity in-creased. However, there was no statistically significant correlation between mental health indicators such as loneliness, stress, and GPS-based activity patterns. These results high-light the complex relationship between physical activity and mental health. Future studies need to consider sample size and confusion variables and utilize various datasets to improve generalization. Taken together, this study provides new insights into the interaction between students' GPS-based physical activity patterns and mental health indicators, and presents comprehensive results.

Acknowledgments

Funding: This research was funded by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea grant number [NRF-2022S1A5A2A03050428].

Institutional Review Board Statement: The study was approved by the Institutional Review Board of Dankook University (IRB no. 2023-08-015).

References

[1] G. S. Yang and H. Y. Hong, "The effects of insecure attachment on depression in early adulthood: The mediating effects of mentalization and distress tolerance," *Korea Journal of Counseling*, vol. 23, no. 2, pp. 147-166, 2022.

[2] S. H. Kim and E. H. Lee, "The effect of internalized shame on depression in early adulthood: The mediation effect of emotional regulation," *The Journal of Learner Centered Curriculum and Instruction (JLCCI)*, vol. 23, no. 14, pp. 15-26, 2023.

[3] S. M. Bae, "The association between adverse childhood and adulthood experiences, social isolation, loneliness, and depression among young adults in South Korea," *International Journal of Environmental Research and Public Health*, vol. 20, no. 19, 6900, 2023.

[4] X. Li, W. Guo, W. Tang, Q. Lv, Y. Zhang, H. Yu, Q. Wang, W. Deng, L. Zhao, X. Ma, Y. Meng, M. Li, H. Wang, T. Chen, Y. Liu, Z. Tang, X. Du, A. J. Greenshaw, and T. Li, "The interactions between childhood adversities and recent stress were associated with early-adulthood depression among Chinese undergraduate students," *Depression and Anxiety*, vol. 38, issue. 9, pp. 961-971, 2021.

[5] S. M. Vargas, C. Wang, M. Rubenson, N. Jafarzadeh, and S. J. Huey, "Depression, perceived burdensomeness, thwarted belongingness, and suicide risk trajectories among emerging adults during the early Covid-19 pandemic," *Journal of Social and Clinical Psychology*, vol. 42, no. 5, pp. 487-510, 2023.

[6] J. Shin and S. M. Bae, "A systematic review of location data for depression prediction," *International Journal of Environmental Research and Public Health*, vol. 20, issue 11, 5984, 2023.

[7] P. Ayranci, C. Bandera, N. Phan, R. Jin, D. Li, and D. Kenne, "Distinguishing the effect of time spent at home during cOVID-19 pandemic on the mental health of urban and suburban college students using cell phone geolocation," *International Journal of Environmental Research and Public Health*, vol. 19, issue 12, 7513, 2022.

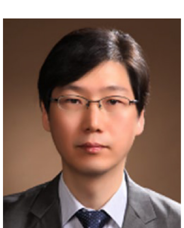
[8] M. Boukhechba, A. R. Daros, K. Fua, P. I. Chow, B. A. Teachman, and L. E. Barnes, "DemonicSalmon: Monitoring mental health and social interactions of college students using smartphones," *Smart Health*, vol. 9, pp. 192-203, 2018.

[9] J. J. Chow, J. M. Thom, M. A. Wewege, R. E. Ward, and B. J. Parmenter, "Accuracy of step count measured by physical activity monitors: The effect of gait speed and anatomical placement site," *Gait & Posture*, vol. 57, pp. 199-203, 2017.

[10] J. C. Hong, H. C. Juan, and W. C. Hung, "The role of family intimacy in playing collaborative e-sports with a Switch de-vice to predict the experience of flow and anxiety during COVID-19 lockdown," *Computers in Human*

Behavior, vol. 132, 107244, 2022.
[11] K. O. Asare, I. Moshe, Y. Terhorst, J. Vega, S. Hosio, H. Baumeister, L. P. Raback, and D. Ferreira, "Mood ratings and digital biomarkers from smartphone and wearable data differentiates and predicts depression status: A longitudinal data analysis," *Pervasive and Mobile Computing*, vol. 83, 101621, 2022.
[12] D. Ben-Zeev, E. A. Scherer, R. Wang, H. Xie, and A. T. Campbell, "Next-generation psychiatric assessment: Using smartphone sensors to monitor behavior and mental health," *Psychiatric Rehabilitation Journal*, vol. 38, no. 3, pp. 218-226, 2015.
[13] P. Laiou, D. A. Kaliukhovich, A. A. Folarin, Y. Ranjan, Z. Rashid, P. Conde, C. Stewart, S. Sun, Y. Zhang, F. Matcham, A. Ivan, G. Lavelle, S. Siddi, F. Lamers, B. W. Penninx, J. M. Haro, P. Annas, N. Cummins, S. Vairavan, N. V. Manyakov, V. A. Narayan, R. J. Dobson, M. Hotopf, and R. C., "The association between home stay and symptom severity in major depressive disorder: preliminary findings from a multicenter observational study using geolocation data from smartphones," *JMIR mHealth and uHealth*, vol. 10, no. 1, e28095, 2022.
[14] R. Wang, F. Chen, Z. Chen, T. Li, G. Harari, S. Tignor, X. Zhou, D. B. Zeev, and A. T. Campbell, "StudentLife: assessing mental health, academic performance and behavioral trends of college students using smartphones," In Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing, pp. 3-14, 2014.
[15] K. L. Szuhany, M. Malgaroli, and G. A. Bonanno, "Physical activity may buffer against depression and promote resilience after major life stressors," *Mental Health and Physical Activity*, vol. 24, 100505, 2023.
[16] M. Hallgren, M. Kraepelien, N. Lindefors, Z. Zeebari, V. Kaldo, and Y. Forsell, "Physical exercise and internet-based cognitive-behavioural therapy in the treatment of depression: randomised controlled trial," *The British Journal of Psychiatry*, vol. 207, no. 3, pp. 227-234, 2015.
[17] Kaggle StudentLife. Available online: (https://www.kaggle.com/datasets/dartweichen/studentlife?datasetId=942862&sortBy=dateRun&tab=profile).
[18] K. Kroenke, R. L. Spitzer, and J. B. Williams, "The phq-9 validity of a brief depression severity measure," *Journal of General Internal Medicine*, vol. 16, no. 9, pp. 606-613, 2001.
[19] D. W. Russell, "UCLA loneliness scale (version 3): Reliability, validity, and factor structure," *Journal of Personality Assessment*, vol. 66, issue 1, pp. 20-40, 1996.
[20] S. Cohen, T. Kamarck, and R. Mermelstein, "A global measure of perceived stress," *Journal of Health and Social Behavior*, vol. 24, no. 4, pp. 385-396, 1983.
[21] D. Watson, L. A. Clark, and A. Tellegen, "Development and validation of brief measures of positive and negative affect: the panas scales," *Journal of Personality and Social Psychology*, vol. 54, no. 6, pp. 1063-1070, 1988.

Kwang Ho Seok_Lifetime Member
2007 : Korea University of Technology and Education, Korea, Multimedia Engineering, B.S. degree
2009 : Korea University of Technology and Education, Korea, Multimedia Engineering, M.S. degree
2015 : Korea University of Technology and Education, Korea, Computer Science and Engineering, Ph.D.
2021 ~ Present : Global Cyber University, School of AI Drone, Assistant Professor
〈Research interests〉 AI, Big Data Analysis, VR/AR/XR, Metaverse



Sung Man Bae_Regular Member
2003 : Chung-Ang University, Korea, Psychology, M.S. degree
2011 : Chung-Ang University, Korea, Psychology, Ph.D.
2015 ~ Present : Dankook University, Department of Psychology and Psychotherapy, Associate Professor
〈Research interests〉 Clinical and Health Psychology, Depression and Suicide, Trauma, Addiction