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Feasibility of Using Passive Digital Phenotyping Data from Smartphones as Emerging Health Sensors in Medical Students: A Pilot Exploratory Study

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ABSTRACT

Background: Noncommunicable diseases and mental-health-related risks are rising among young adults in low- and middle-income countries. With near-universal smartphone use among Indonesian students, passively captured digital traces may offer low-cost signals of lifestyle balance relevant to student wellbeing.
Objective: To characterize smartphone-derived behavioral signatures of daily balance (screen exposure, sleep regularity, mobility, and notification-pickup dynamics) among Indonesian medical students and test their group-level associations as an exploratory foundation for future early-warning models.
Methods: Cross-sectional study of undergraduate medical students (UNISSULA, Indonesia) using iPhones ≥6 months. Anonymized screenshots from Apple Health and Screen Time (July-August 2024) provided daily steps, sleep duration, screen time, notifications, pickups, and dominant app category (social vs entertainment; two independent raters). Normality was assessed; non-parametric tests (Spearman's rho, Kruskal-Wallis) were applied where appropriate.
Results: Forty-three students participated (n=43). Means (±SD): steps 3,546 ± 1,987/day, screen time 7.0 ± 2.3 h/day, sleep 4.2 ± 1.6 h/night, notifications 304 ± 151/day, pickups 143 ± 57/day. App-use distribution showed a polarity: 53.5% social-dominant vs 46.5% entertainment-dominant users. Screen time correlated negatively with sleep ($\rho = -0.531$, $p < 0.001$). Notifications correlated positively with pickups ($\rho = 0.781$, $p < 0.001$). Entertainment dominance application usage was associated with fewer steps than social dominance one ($\rho = -0.455$, $p = 0.002$; Kruskal-Wallis $p = 0.03$). Longer screen time predicted lower step count ($p = 0.031$).
Conclusions: Smartphone-derived metrics reveal a behavioral signature of imbalance: longer screen exposure, entertainment-heavy use, and high notification; pickup intensity linked to lower mobility and shorter sleep. These exploratory findings support the feasibility of smartphone data as candidate early-warning inputs for student wellbeing dashboards in resource-limited settings. Future longitudinal studies with psychometric/clinical labels, multi-device inclusion, and privacy-preserving pipelines are warranted.

INTRODUCTION

Noncommunicable diseases (NCDs) such as cardiovascular diseases, obesity, type 2 diabetes, and mental disorders are rising globally, with an increasingly heavy epidemiological burden in developing countries like Indonesia. Modern lifestyle changes-declining physical activity, prolonged screen time, and dietary shifts-are major contributors to this trend.[1] Particularly concerning is the growing burden of mental health-related NCDs among young people aged 15-25 years, especially in low- and middle-income countries.[2] This phenomenon has far-reaching implications for Indonesia's 2045 demographic dividend: today's university students will form the country's productive workforce and leadership core in two decades. Their mental and physical health, therefore, represent not only personal well-being but also the foundation of national competitiveness. In parallel, Indonesia's digital environment is overwhelmingly mobile-smartphone use dominates national internet access patterns, making screen-based behaviors a salient and measurable part of student lifestyles. According to the Indonesian Internet Service Providers Association, individuals aged 19-34 years-representing the typical university demographic-constitute 98.64% of the country's total internet users, highlighting the near-universal digital engagement within this age group.[3,4] Positioning student health within the Indonesia 2045 agenda further underscores the strategic value of preventive, data-informed approaches that can scale within local health and education ecosystems.[5,6] Medical students are among the most vulnerable populations facing psychological distress. A global meta-analysis estimated the prevalence of depression at 27% and suicidal ideation at 11% in this group.[7] Furthermore, 45-60% of medical students experience academic burnout, with chronic stress peaking during the first and third years of training.[8] The combination of intensive academic schedules, heavy workloads, early exposure to patient suffering, and poor work-life balance contributes to reduced physical activity, sleep disturbance, and excessive screen exposure-all of which exacerbate mental health deterioration. Early screening and preventive interventions for this population thus represent not only individual care but also a strategic investment to nurture future physicians capable of sustaining preventive-health practices. These global estimates align with long-standing evidence on medical student distress and its downstream risks for learning, professionalism, and patient care.[7] In Indonesia, this risk is amplified by high smartphone engagement among youth, suggesting that everyday digital traces could serve as feasible early warning signals when ethically leveraged.[4,9] Traditional screening methods, however, remain limited by access, stigma, and resource demands. Against this backdrop, a novel behavior-based technological approach has emerged-digital phenotyping-defined as the moment-by-moment quantification of individual behavior, mobility, social interaction, and digital usage patterns through passive smartphone sensors to dynamically reflect one's health state.[9] Indonesian university students, being digital natives with near-universal smartphone penetration, generate rich passive data-daily steps, sleep duration, screen time-that can serve as low-cost, non-invasive behavioral biomarkers.[10-12] While the potential of digital phenotyping has been well-demonstrated in high-income settings[13], evidence from Indonesia remains scarce-particularly within medical student populations. Addressing this gap is crucial to build locally relevant evidence on how accessible, data-driven tools can enable early detection of burnout and mental distress, strengthen digital health literacy, and ultimately prepare a healthy, resilient generation for Indonesia's 2045 demographic dividend. Digital phenotyping, first conceptualized by Onnela and colleagues, has evolved into a scalable framework for behavioral and clinical monitoring, supported by open platforms such as Beiwe that enable passive and active data collection at population scale.[10,12] While its feasibility and utility have been demonstrated in high-income settings, evidence from low- and middle-income countries remains limited-particularly regarding its adaptation to local infrastructure, ethics, and population health needs. Global guidance highlights that the cost-effectiveness and sustainability of digital health tools depend on context-specific validation and robust safeguards for privacy, consent, and data protection.[14] Aligning with Indonesia's national health transformation and RPJPN 2025-2045 vision[5], this study seeks to address that gap by exploring the applicability of digital phenotyping among Indonesian medical students through the characterization of smartphone-derived behavioral signatures of daily balance (screen exposure, sleep regularity, mobility, and notification-pickup dynamics). The study aims to generate an exploratory, locally relevant evidence base showing which passively captured metrics most strongly relate to behavioral imbalance, thereby establishing a foundation for future early-warning models of student wellbeing to be validated with clinical or psychometric outcomes in subsequent studies.

METHOD

Participants and Study Design

This study employed a cross-sectional design to evaluate the relationship between digital behavior patterns and health indicators among students of the Faculty of Medicine, Universitas Islam Sultan Agung (UNISSULA), Indonesia. Participants were active undergraduate students aged 18-25 years who had been using an iPhone for at least six months and voluntarily agreed to share their digital data via Google Form. The use of iPhone devices was selected to ensure measurement validity and reliability, as the built-in Apple Health and Screen Time applications provide highly accurate tracking of physical activity and digital usage patterns.[15,16]

Measurements and Procedure

Data collected included average daily steps, mean nightly sleep duration, average daily screen time, and dominant app categories (social media, entertainment, productivity, education, or health). All information was obtained through anonymized screenshots uploaded by participants from Apple Health (Steps/Sleep Analysis) and Screen Time (Settings → Screen Time → Daily Average).

Participants' most-used applications were classified into five mutually exclusive categories based on primary function:

1. SOCIAL APPS: Applications primarily used for social interaction and communication. Examples: Instagram, WhatsApp, Twitter/X, Facebook, TikTok, Telegram, LINE, Discord, User-generated content, messaging, social networking

2. ENTERTAINMENT APPS: Applications primarily used for passive media consumption. Examples: Netflix, YouTube, Spotify, Disney+, Prime Video, Apple Music, gaming apps (Mobile Legends, PUBG, Genshin Impact)
3. PRODUCTIVITY APPS: Tools for work or task management. Examples: Microsoft Office, Google Workspace, Notion, Todoist, Calendar apps
4. EDUCATION APPS: Learning platforms and academic resources. Examples: Google Classroom, Zoom, Duolingo, Quizlet, Khan Academy, university learning management systems
5. HEALTH & FITNESS APPS: Wellness tracking and health monitoring. Apple Health, MyFitnessPal, Strava, Headspace The "dominant app category" was defined as the category with the highest total screen time across all apps within that category during the measurement period. Classification was performed by two independent raters based on app descriptions from the Apple App Store; discrepancies were resolved through discussion to reach consensus.

All information was obtained through anonymized screenshots uploaded by participants from Apple Health (Steps/Sleep Analysis) and Screen Time (Settings → Screen Time → Daily Average). Data were taken from July-August 2024

Statitical Analysis

Numeric data were extracted from the screenshots and analyzed using SPSS version 26. Data distribution was assessed with the Kolmogorov-Smirnov test; bivariate relationships were examined using Pearson or Spearman correlation tests as appropriate; and multiple linear regression was applied to evaluate the contribution of step count, screen time, sleep duration, and app-use proportions to digital activity balance indicators. A p-value < 0.05 was considered statistically significant. All analyses were interpreted within the conceptual framework of balance and moderation in daily digital behavior. Ethical approval was obtained from the Research Ethics Committee of the Faculty of Medicine, UNISSULA.

RESULTS AND DISCUSSIONS

A total of 43 medical students from the Faculty of Medicine, Universitas Islam Sultan Agung (UNISSULA) participated and met all inclusion criteria. Digital behavior data were obtained through anonymized screenshots from Apple Health and Screen Time applications on participants' iPhones, encompassing daily step count, sleep duration, screen time, number of notifications, device pickups, and dominant app categories. On average, participants recorded 3,546 ± 1,987 daily steps, a screen time of 7.0 ± 2.3 hours per day, and sleep duration of 4.2 ± 1.6 hours per night. They received approximately 304 ± 151 notifications daily and checked their phones 143 ± 57 times per day. App-use distribution revealed a behavioral polarity: 53.5% of students primarily engaged with social media, while 46.5% were dominated by entertainment apps-reflecting a clear divide between socially interactive and passively consumptive digital habits. Normality assessment using Kolmogorov-Smirnov tests revealed that several variables deviated from normal distribution ($p < 0.05$), prompting the use of non-parametric tests (Spearman's rho and Kruskal-Wallis).

Table 1. Descriptive statistics of physical and digital behavior indicators among medical students (n = 43)

Domain	Variable	Range (Min-Max)	Mean ± SD	Interpretation
Physical activity	Body weight (kg)	42 - 100	63.6 ± 15.3	Moderate variation; typical for young adults
	Body height (cm)	148 - 183	163.4 ± 8.7	Normal height distribution
	Daily steps (count)	690 - 9 324	3 545.7 ± 1 986.7	High variability in movement levels
	Walking distance (km)	0.25 - 6.70	2.19 ± 1.38	Mirrors step-count dispersion
	Active energy (kcal)	0.24 - 338	74.4 ± 63.0	Indicates generally low energy expenditure
Rest & recovery	Sleep duration (h/night)	2 - 8	4.19 ± 1.65	Below optimal sleep range for students
Digital engagement	Screen time (h/day)	3 - 12	6.98 ± 2.27	Prolonged daily screen exposure
	Notifications (count/day)	73 - 733	304 ± 150.9	High message frequency and alert load
	Pickups (count/day)	52 - 285	143.4 ± 56.9	Frequent device checking behavior

Overall, table 1 showed participants displayed wide variation in physical activity and digital engagement. Average sleep duration (≈ 4 h/night) was notably below the recommended 7-8 hours, while mean screen time approached 7 h/day. Frequent notifications and phone pickups suggest a pattern of continuous digital connectivity, aligning with the correlation findings indicating reduced sleep and physical activity among heavy smartphone users.

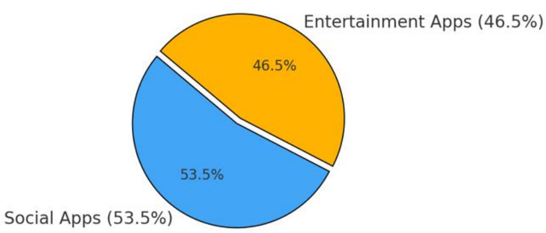

Figure 1. Distribution of favorite app categories among participants

The pie chart shows the distribution of participants' favorite mobile application categories. A total of 53.5% primarily used social apps (e.g., social media, messaging, or community platforms), while 46.5% preferred entertainment apps (e.g., streaming, gaming, or music). This near-equal split illustrates two distinct patterns of digital engagement - *socially interactive* versus *passively consumptive* - both of which may shape daily screen-time duration and physical-activity levels.

The box-and-whisker plot compares daily step counts between users of social and entertainment applications. Median step counts were higher among social-app users, indicating greater physical activity, whereas entertainment-app users showed lower mobility levels.

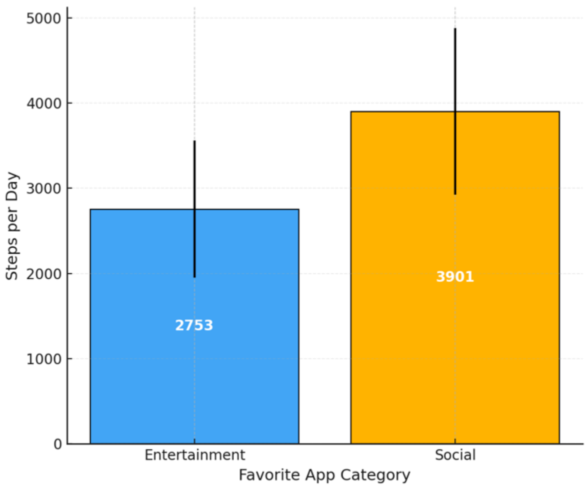

Figure 2. Step count differences by favorite app category

This pattern suggests that social digital interaction may correlate with more active behaviors, while entertainment consumption is associated with more sedentary habits.

The correlation analyses uncovered distinct and meaningful behavioral patterns. There was a strong negative correlation between screen time and sleep duration (ρ = −0.531; p < 0.001), indicating that prolonged screen exposure consistently shortened sleep. Conversely, a very strong positive correlation emerged between the number of notifications and device pickups (ρ = 0.781; p < 0.001), illustrating a self-reinforcing digital feedback loop-where every alert draws users back into interaction. Furthermore, app type was significantly associated with physical activity: students who predominantly used entertainment apps took markedly fewer daily steps than those using social applications (ρ = −0.455; p = 0.002). The Kruskal-Wallis test reinforced this association (p = 0.03), showing clear behavioral divergence in mobility across app categories. In addition, screen time exerted a significant negative effect on step count (p = 0.031), suggesting that extended digital engagement displaces opportunities for physical movement. Although the relationship between sleep duration and pickup frequency was not statistically significant (ρ = −0.108; p = 0.490), the negative trend still pointed toward sleep-restricted users being more phone-reactive.

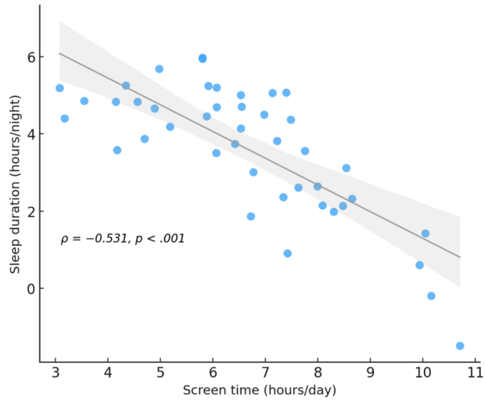

Figure 3. Relationship between screen time and sleep duration

Scatter plot showing the negative correlation between daily screen time and sleep duration among participants (*ρ* = −0.531, *p* < .001). Each dot represents one respondent; the gray line indicates the regression trend with 95% confidence interval. Longer screen exposure was associated with shorter nightly sleep duration, suggesting the potential behavioral impact of prolonged digital use on sleep hygiene.

Taken together, these findings reveal a behavioral signature of imbalance: longer screen exposure, entertainment-heavy app usage, and high notification-pickup intensity are consistently linked to lower physical activity and poorer sleep regulation. Beyond simple digital metrics, this pattern reflects the emerging human cost of hyperconnectivity. The results strengthen the proposition that smartphone-derived behavioral data can function as a low-cost, real-time biosensor for detecting early signs of lifestyle dysregulation and mental-physical disequilibrium-a foundational insight for advancing Public Health 5.0 in university populations.

Discussion

Relationship Between Screen Time and Sleep Duration This study identified a significant negative correlation between screen time and sleep duration among medical students. The longer the time spent in front of a smartphone screen, the shorter the average sleep duration. This finding aligns with a study among students in Lebanon, which reported that spending more than four hours per day on screens significantly reduced sleep duration and quality while increasing daytime fatigue.[17] Consistent results have also been observed in Asian adolescents, where those who used digital devices for more than four hours per day were more likely to experience sleep disturbances compared to those who used them for less than one hour. One hypothesized mechanism involves exposure to blue light from digital screens at night, which suppresses melatonin production-the hormone responsible for regulating sleep cycles-thus disrupting circadian rhythm and delaying sleep onset.[18] Consequently, excessive smartphone use has been consistently linked to poor sleep quality among university students.[19] Empirical evidence repeatedly demonstrates that prolonged screen time is associated with sleep problems; recent studies even conclude that excessive smartphone use correlates with lower sleep quality as well as higher levels of depression, anxiety, and stress in students.[20] These findings reinforce the importance of limiting screen time before bedtime to improve sleep hygiene and prevent circadian rhythm disturbances.

Correlation Between Notification Frequency and Pickups

The study also found a strong positive correlation between the number of notifications received and the frequency of phone pickups. This indicates that the more notifications a user receives, the more frequently they check their phone-confirming that continuous notifications can trigger habitual checking behavior. Supporting evidence shows that smartphone users receive nearly 300 notifications per day and perform about 93 pickups daily on average.[21] High notification frequency can create a sense of urgency to respond immediately, leading to more frequent device interactions. Moreover, device-initiated pickups triggered by notifications have been linked to higher daily stress levels.[12] The mechanism may be explained by repeated interruptions-such as sounds or vibrations-that heighten alertness and disrupt concentration, ultimately increasing stress burden. Although the direct link between pickup frequency and anxiety remains unclear, researchers have proposed technostress and fear of missing out (FOMO) as contributing factors; individuals with higher anxiety tend to check their phones more often to ensure they are not missing important updates.[11]

Therefore, managing notifications-such as by activating silent or *do not disturb* modes-can serve as a practical intervention to reduce unnecessary pickups and mitigate notification-related stress.

Comparison of Social vs. Entertainment App Users in Relation to Physical Activity

A comparative analysis of favorite app categories revealed distinct physical activity patterns between users of social apps and entertainment apps. Students who primarily used entertainment apps (e.g., video streaming, gaming) tended to have lower daily step counts and walking distances than those who used social apps more frequently. Entertainment-oriented users appeared more physically sedentary, likely due to the prolonged sitting involved in passive media consumption.

In contrast, social app usage may be associated with more active social engagement, such as meeting friends or participating in group activities, which indirectly increases physical movement. Although few studies have directly examined app-category differences in physical activity, this finding aligns with the sedentary-active behavior framework. Barkley et al. (2013) reported that heavy smartphone users often sacrificed physical activity opportunities for sedentary phone use (e.g., entertainment browsing), while lighter users were more socially engaged and used phones as motivation for physical activity.[12]

In other words, excessive entertainment use may contribute to sedentary lifestyles, whereas socially oriented smartphone use may foster higher physical engagement. Additional studies also indicate that prolonged screen time, regardless of app type, is associated with lower physical activity and fitness levels-for example, frequent cell phone use has been linked to reduced daily activity and cardiorespiratory fitness.[12]

Hence, our findings enrich current literature by demonstrating that not only the total screen time but also the type of dominant app influences activity levels: students who spend more time on entertainment apps tend to move less than those engaging in social interactions through their phones. Practically, interventions to promote physical activity among students could consider usage patterns-such as encouraging entertainment-heavy users to balance screen time with movement, or leveraging social/community apps to facilitate group-based physical activities.

Relationship Between Screen Time and Physical Activity

Results further demonstrated a significant effect of screen time on students' physical activity levels, with a meaningful difference in average daily steps across groups with varying screen durations (Kruskal-Wallis test, p = 0.031). Correlationally, longer screen time was associated with lower physical activity levels.

This is consistent with multiple studies reporting negative correlations between smartphone use and physical activity indicators. For instance, Smith-Ricketts et al. (2022) found a moderate negative correlation ($r \approx -0.25$) between daily smartphone screen time and step count among university students, showing that those with the longest usage had the fewest daily steps.[13] Similar findings were reported by Lepp et al. (2013), who classified smartphone use as a sedentary behavior that displaces time for physical exercise, thereby reducing fitness levels.[9] Partial causal evidence has also emerged from intervention studies. In an experimental study in

France, participants who reduced smartphone use by at least 60 minutes per day for one week increased their daily physical activity by 89%, whereas 74% of those who failed to reduce usage became more sedentary.[14] This suggests that limiting screen time may free up time for exercise and improve daily movement balance.

Long-term effects of excessive screen time on physical health are also noteworthy: a cardiology conference report revealed that students using smartphones ≥5 hours per day had a 43% higher risk of obesity compared to those using them less than 5 hours.[15] This increased risk was attributed to reduced activity and unhealthy habits accompanying prolonged screen use, such as high-calorie snacking. Overall, screen time serves as an early warning indicator of sedentary behavior and related health risks. These findings underscore the need to balance digital use with physical activity-for example, through digital health education that promotes mindful screen habits and daily movement among students.

Potential of Smartphone Digital Data as an Early Screening Tool for Student Health Balance

The findings collectively highlight the potential of smartphone digital data as a preventive health monitoring tool in student populations. Parameters such as screen time, sleep patterns, pickup frequency, step count, and app usage preference are closely linked to physical and mental health indicators. Regular monitoring of these parameters could serve as an early screening method for detecting lifestyle imbalances, aligning with the concept of digital phenotyping, where passive smartphone sensor data is used to infer health conditions in real-time.

Recent reviews show that among university students, smartphone sensor data (e.g., physical activity, sleep, and app use) have been successfully used to track behaviors related to mental and physical health.[16] From a public health perspective, integrating digital data into screening systems can enhance early detection of disease risk. The World Health Organization (WHO) also advocates for digital technology utilization in noncommunicable disease (NCD) prevention, emphasizing that mobile applications can help individuals track modifiable risk factors-smoking, poor diet, alcohol use, and physical inactivity-and adopt healthier lifestyles.[17]

In the student context, daily smartphone data can be transformed into personalized feedback dashboards. For example, weekly notifications comparing screen time with physical activity and sleep could act as behavioral “mirrors.” If imbalances are detected-such as high screen time coupled with low steps and insufficient sleep-early interventions could be initiated (e.g., digital counseling, wellness programs). Evidence from Serbia further supports this approach: excessive smartphone use among medical students was significantly associated with poor sleep quality, higher stress, anxiety, and depression.[10] Such findings indicate that smartphone data can function as a proxy indicator of mental health status. With appropriate algorithms, patterns such as high pickup frequency or chronic late-night use could flag potential stress or insomnia, allowing early support before issues escalate.

Ultimately, using smartphone-based digital data as a health balance screening tool aligns with the Health 5.0 paradigm, in which information technology and personal sensors drive preventive care. This approach provides a cost-effective, continuous, and real-time method for monitoring individual lifestyle balance. While challenges such as data privacy, measurement accuracy, and clinical validation remain, the current evidence demonstrates strong potential. Integrating digital monitoring into campus health services could help identify at-risk students (e.g., highly sedentary or sleep-disrupted individuals) and guide targeted interventions-such as nutrition counseling, structured exercise programs, or screen-time management coaching. Thus, this study not only contributes scientific insight but also opens practical avenues for leveraging smartphone data in health screening and promotion, supporting balanced physical-mental wellbeing among students in today's digital era.

Contextualizing the Alarming Patterns

An average sleep duration of 4.2 h/night in this sample of medical students indicates severe sleep deprivation-roughly 40-50% below the ≥7 h/night recommended for adults-and chronic short sleep is linked to cognitive and health risks.[22] Coupled with ~7 h/day of screen time-exceeding the ≤3 h/day recreational benchmark in the Canadian 24-Hour Movement Guidelines-this profile adds sedentary load and is likely to worsen fitness and sleep quality.[23,24] Moreover, exposure to ≈304 notifications/day is consistent with a state of continuous partial attention: experiments show that smartphone alerts increase inattention/hyperactivity and impair cognitive control, and that even the mere presence of a smartphone can reduce available cognitive capacity.[25-28] If such patterns persist during medical training, downstream consequences are plausible: contemporary evidence links sleep-related impairment in physicians with higher odds of clinically significant medical errors, and resident duty-schedule trials highlight safety impacts associated with sleep loss.[29] Given the severe sleep restriction, excessive screen exposure, and near-continuous notification load observed, institutions should prioritize smartphone-derived early-warning dashboards and targeted digital health literacy to protect learning capacity and wellbeing.

Policy and Educational Implications

The practical implications of this study are particularly relevant for Indonesian medical education institutions, aligning with the ongoing transformation toward data-informed and preventive health systems:

1. Early Detection (Deteksi Dini): Smartphone-derived metrics can be integrated into student wellness programs as an early-warning system to identify high-risk students before clinical symptoms manifest.
2. Cost-Effectiveness: Unlike traditional screenings that require professional manpower and time, passive smartphone monitoring is highly feasible for resource-limited educational settings in Indonesia.
3. Scalability: With smartphone penetration exceeding 90% among university students, this approach can be implemented at scale across

medical faculties nationwide to support systematic wellbeing monitoring.

4. Digital Health Literacy: The findings can serve as empirical evidence for developing digital health literacy curricula that prepare future physicians to interpret and utilize digital biomarkers responsibly.

Future research with larger samples and longitudinal designs is essential to confirm temporal patterns, establish causal relationships, and evaluate predictive accuracy. Such work will enable the transition from exploratory feasibility to validated, ethically governed digital phenotyping frameworks for student wellbeing in Indonesia's higher-education system.

Strengths and Limitations

This study represents one of the first exploratory applications of digital phenotyping in an Indonesian medical student population, leveraging passively captured smartphone metrics-screen time, step count, sleep duration, notifications, and pickups-as behavioral indicators of daily balance. The approach demonstrated high feasibility and acceptability, evidenced by 100% participant compliance using only anonymized screenshots without additional applications or sensors. The use of validated smartphone data sources (Apple Health and Screen Time) strengthened measurement reliability.[15,16] While the integrative analysis of physical and digital activity patterns provided a holistic view of student lifestyle balance within a single behavioral framework. The study also contributes locally relevant evidence to the growing global literature on digital health and preventive medicine, aligning with Indonesia's Health Transformation and RPJPN 2025-2045 agendas.

Several limitations should be acknowledged. First, the cross-sectional design precludes causal inference; observed associations represent correlations rather than directional effects. Second, the sample size (n = 43) limits generalizability and statistical power. Third, reliance on self-reported screenshot uploads introduces potential reporting bias and restricts temporal granularity, as daily fluctuations and diurnal variation in smartphone behavior could not be captured. Fourth, the study was restricted to iPhone users, introducing potential selection bias given socioeconomic differences in smartphone ownership. Fifth, no validated psychometric measures (e.g., PHQ-9, DASS-21) were collected, precluding direct linkage between digital behavior and mental health outcomes. Finally, the absence of real-time or sensor-based continuous monitoring limits the ability to assess moment-to-moment behavioral dynamics.

Despite these constraints, the study successfully establishes methodological feasibility and provides foundational insights to guide future longitudinal and sensor-based research integrating psychometric validation, multi-device inclusion, and privacy-preserving real-time data pipelines.

Conclusion

This pilot exploratory study demonstrates that smartphone-derived behavioral data (passively captured from everyday device use) can feasibly serve as low-cost, real-time biosensors of lifestyle imbalance among Indonesian medical students. Analysis of 43 participants revealed a striking behavioral signature: severe sleep deprivation (4.2 h/night), excessive screen exposure (7.0 h/day), and high notification-pickup intensity (304 alerts, 143 checks daily) were significantly linked to reduced physical activity and poorer sleep regulation. Screen time negatively correlated with sleep duration ($\rho = -0.531$, $p < 0.001$), entertainment-dominant app users showed markedly lower daily steps than social-app users ($p = 0.03$), and extended digital engagement directly predicted sedentary behavior ($p = 0.031$). These findings establish the foundational feasibility of digital phenotyping as a scalable, non-invasive early-warning system for student wellbeing in resource-limited settings-offering actionable potential for integration into campus health programs aligned with Indonesia's 2045 demographic dividend vision, while highlighting the urgent need for longitudinal validation with psychometric outcomes and privacy-preserving real-time monitoring frameworks.

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