

RESEARCH ARTICLE

Behavioral profiles and temporal patterns of problematic smartphone use: Associations with sleep hygiene and physical activity in adolescents

Mohamed Yaakoubi^{1,2}, Mustapha Bouchiba³, Ahmed Ghorbel^{1,2}, Ghada Regaieg¹, Georgian Badicu⁴, Adnene Gharbi^{2,5}, Luca Paolo Ardigo^{6*#}, and Omar Trabelsi^{1,2#}

¹High Institute of Sports and Physical Education of Kef, University of Jendouba, Kef, Kef Governorate, Tunisia

²Research Unit: Physical Activity, Sport and Health (UR18JS01), National Observatory of Sport, Tunis, Tunis Governorate, Tunisia

³Laboratoire Hypoxie & Poumon, UMR INSERM U1272, Université Sorbonne Paris Nord, Bobigny, Île-de-France, France

⁴Department of Physical Education and Special Motricity, Faculty of Physical Education and Mountain Sports, Transilvania University of Brasov, Braşov County, Romania

⁵Higher Institute of Sports and Physical Education, University of Sfax, Sfax, Sfax Governorate, Tunisia

⁶Department of Teacher Education, NLA University College, Oslo, Norway

*Corresponding author:
Luca Paolo Ardigo
(luca.ardigo@nla.no)

#These authors share last
authorship.

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Abstract

Background: Problematic smartphone use (PSU) is a heterogeneous behavior, yet little is known about how dominant-use profiles relate to sleep hygiene, physical activity, and temporal usage patterns in adolescents.

Objective: To categorize adolescents with PSU into predefined dominant-use profiles and examine their associations with sleep hygiene, physical activity, and temporal smartphone-use patterns.

Methods: A total of 220 Tunisian middle school students (aged 14–16 years) screening positive for PSU according to validated Smartphone Addiction Scale–Short Version cutoffs underwent one month of objective monitoring via iOS/Android tracking tools. Following data validation, 180 participants were categorized into four profiles: social media ($n = 52$), gaming ($n = 50$), streaming ($n = 40$), and fitness ($n = 38$). Associations with sleep hygiene (Sleep Hygiene Index [SHI]) and physical activity (Physical Activity Questionnaire for Adolescents [PAQ-A]) were examined.

Results: Distinct behavioral profiles were associated with differences in health outcomes. Gaming and streaming profiles exhibited the highest total and late-night screen time, lowest physical activity, and poorest sleep hygiene (all $p < 0.001$), whereas the fitness profile demonstrated the most favorable pattern. Late-night screen time was associated with additional variance in SHI scores after adjustment for profile membership and demographics (standardized $\beta = 0.42$, $p < 0.001$).

Conclusion: Adolescent PSU manifests in distinct behavioral profiles with varying health-related associations. Nocturnal gaming and streaming are associated with poorer outcomes, potentially informing prevention efforts prioritizing usage patterns and timing over aggregate screen time. Consequently, digital well-being

interventions may need to be profile-specific and time-sensitive.

Keywords: Smartphone addiction; Behavioral profiles; Chronobiological patterns; Sedentary behavior; Middle school students; Tunisia

1. Introduction

The 21st century has witnessed a paradigm shift in adolescent development, inextricably linked to the proliferation of digital technology. The smartphone, in particular, has become a ubiquitous companion, reshaping the social, educational, and recreational landscapes of young people's lives. Global trends indicate a relentless increase in screen time, with adolescents now spending an average of several hours per day on their devices, a figure that saw a significant surge during and following the COVID-19 pandemic.¹ While these devices offer unprecedented access to information and social connection, their pervasive integration into daily life has sparked significant concern among researchers, clinicians, and parents regarding their potential impact on adolescent health and well-being. A substantial body of literature has explored correlations between screen time and various health outcomes, including sleep disruption, reduced physical activity, and psychological distress.^{2,3}

Historically, research on digital media effects has heavily relied on self-reported measures of total screen time. Large-scale cross-sectional studies have consistently found that higher self-reported screen time is associated with poorer sleep quality, delayed sleep onset, and increased daytime fatigue.⁴ Similarly, a meta-analysis by Stiglic and Viner² concluded that higher levels of screen time are associated with adverse physical and mental health outcomes in children and adolescents. However, this reliance on total screen time as a monolithic metric is increasingly recognized as inadequate. As Browne *et al.*⁵ argued, it is not merely the quantity but the quality and pattern of use that determines its impact. The concept of "problematic smartphone use (PSU)" has thus emerged, shifting the focus from volume to the dysfunctional, dependency-like relationship some users develop with their devices, characterized by a loss of control, preoccupation, and use despite negative consequences.⁶ Validated tools such as the Smartphone Addiction Scale (SAS) and the SAS short version (SAS-SV) have been developed to identify adolescents at risk, capturing symptoms such as tolerance, withdrawal, and daily life impairment.⁷

The link between PSU and poor sleep hygiene is particularly robust and mechanistically explained. PSU is not just about duration; it is about the compulsive need to

be connected, which frequently intrudes upon the pre-sleep period.⁸ The relationship is bidirectional and multifaceted: the blue light emitted from screens suppresses melatonin production, delaying sleep onset,⁹ while the psychologically engaging and often stressful nature of the content induces cognitive arousal and emotional distress, hindering the ability to fall asleep.¹⁰ Furthermore, the displacement of leisure time is critical. Evening hours, once a period for relaxation and winding down, are now often dominated by smartphones, encroaching directly on time reserved for sleep and disrupting established bedtime routines.¹¹

This displacement of leisure time is equally pivotal when considering physical activity. The relationship between PSU and sedentarism is often framed through the lens of the displacement hypothesis, which posits that time spent on screens directly replaces time that could be spent in physical pursuits.¹² However, PSU introduces a more insidious dynamic. The compelling, algorithm-driven nature of smartphone applications is designed to maximize engagement, creating a powerful pull toward sedentary leisure activities. When an adolescent's leisure time is dominated by passive scrolling, immersive gaming, or compulsive social media checking, the opportunity cost is often moderate-to-vigorous physical activity.^{13,14} This creates a paradox in which a device full of potential tools for health promotion can simultaneously foster a lifestyle that undermines its own effectiveness.

This paradox is epitomized by the rise of fitness applications and trackers. The smartphone has become a central platform for health promotion, with a plethora of apps designed to monitor activity, set goals, and provide guided workouts. These technologies leverage gamification, social support, and self-monitoring, and have shown promise in increasing motivation for some users.¹⁵ However, their overall effectiveness in sustaining long-term behavioral change in adolescent populations is mixed, and their penetration does not negate the broader trend of declining physical activity.^{16,17} For many, these apps remain unused or quickly abandoned, while the more pervasive, habit-forming social and entertainment applications continue to dominate daily use. The crucial, unanswered question is how these competing behavioral forces, sedentary, problematic use versus active, health-promoting use, coexist and interact within individual

adolescents to shape their overall physical activity profile.

Even advanced subjective measures of PSU are susceptible to recall bias and may not accurately reflect actual, in-the-moment behaviors. This limitation points to a critical methodological gap: the scarcity of objective behavioral data. Most studies provide a transient snapshot, a single data point that fails to capture the dynamic and stable patterns of use over time. Recent research utilizing built-in smartphone applications for objective monitoring has revealed a startling discrepancy: the correlation between self-estimated and objectively measured screen time is often weak, suggesting that individuals are poor judges of their own usage.¹⁸ Therefore, the present study directly addresses these methodological gaps by integrating objective one-month monitoring, temporal (late-night) analysis, and a dominant-use classification to test associations with sleep hygiene and physical activity.

To address these gaps, the present study adopted a dominant-use classification framework to move beyond total screen time and examined distinct behavioral profiles of smartphone use. Prior research has shown that different types of use (e.g., social media, gaming, streaming, fitness) are associated with differential health outcomes.^{19–21} For example, gaming is more strongly linked to heavy involvement and sleep disruption, whereas social media use is closely tied to fear of missing out and emotional reactivity.^{19,21} Streaming services, with features such as auto-play and infinite scroll, contribute to mindless usage and cognitive overload, particularly during late-night hours.^{22,23}

In contrast, fitness-oriented smartphone use has shown mixed effects in the literature, with some umbrella reviews finding that digital interventions can be effective for increasing physical activity,²⁴ while others report no significant improvements,²⁵ and may support physical activity and healthier routines for some adolescents.^{26,27} This profile-based approach allows for a more nuanced understanding of adolescent digital behavior than aggregated screen time alone.

The novelty of the present study does not lie in the use of objective smartphone monitoring itself, as this approach has been adopted in previous research. Rather, its contribution resides in the integration of several key features: (i) adolescents identified with PSU, (ii) a one-month objective monitoring period exceeding the duration of most ecological momentary assessment (EMA) studies, (iii) a dominant-use classification framework based on predefined application categories, (iv) the simultaneous assessment of sleep hygiene and physical activity, and (v) a North African context (Tunisia), which remains underrepresented in the digital health literature. This

approach moves beyond total screen time to better characterize how distinct smartphone-use profiles are associated with health outcomes in an at-risk adolescent population.

This study addresses gaps in the literature on adolescent smartphone use and health behaviors by combining validated PSU screening with one month of objective behavioral monitoring. It provides a more accurate characterization of usage patterns by integrating objective screen-time metrics with self-reported measures, capturing sustained behavioral patterns over a one-month period rather than single-time snapshots. The study also focuses on a relatively under-explored cultural context—Tunisian adolescents—contributing to cross-cultural understanding of digital media effects. Importantly, it moves beyond total screen time to examine distinct behavioral profiles and their relationships with health-related outcomes, potentially informing future targeted interventions.

The primary objective of the study is to investigate the relationships between adolescents' behavioral patterns of smartphone use, the timing of use, and key health outcomes, specifically sleep hygiene and physical activity. We hypothesized that distinct behavioral profiles of smartphone use would be significantly associated with differences in both sleep hygiene and physical activity. Specifically, we predicted that greater late-night smartphone use would be associated with poorer sleep hygiene, and that physical activity levels would vary meaningfully across profiles, with the most sedentary digital behaviors linked to the lowest activity.

2. Materials and methods

2.1. Study design

A cross-sectional comparative study was conducted over a two-month period to examine associations between PSU behavioral profiles and health-related behaviors, specifically physical activity and sleep hygiene, among adolescents. Recruitment followed a two-stage process: school-based enrollment and subsequent PSU screening. Eligible participants then underwent behavioral monitoring, and objective screen-time data were used to derive smartphone-use profiles. The overall study design, participant flow, and profile classification process are presented in [Figure 1](#). This study was reported following the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines for cross-sectional studies.²⁸

2.2. Participants and sampling procedures

A multi-stage sampling strategy was implemented within a public secondary school setting. Schools were

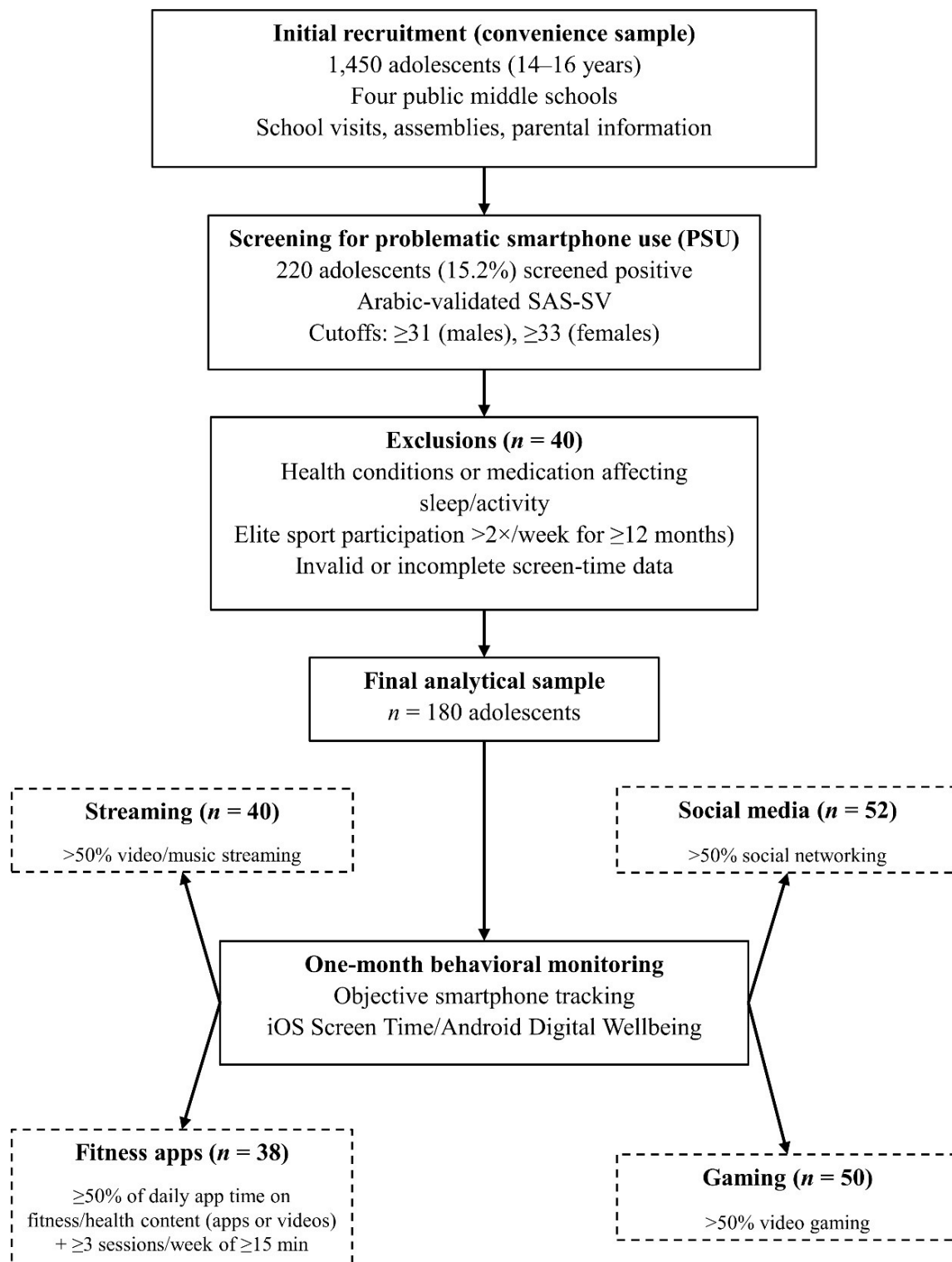


Figure 1. Participant flow and behavioral profile classification based on objective smartphone-use data
Abbreviation: SAS-SV: Smartphone Addiction Scale-Short Version.

selected using purposive convenience sampling to ensure socioeconomic heterogeneity. Of the six public middle schools initially contacted, four agreed to participate, yielding a school-level participation rate of 66.7%.

Eligible students were aged 14–16 years, owned a personal smartphone, and had no prior diagnosis of sleep disorders or psychiatric disorders. Although a precise student-level response rate could not be determined due to the two-week consent-collection period, 1,205 of the 1,450 students present during recruitment (83.1%) returned signed parental consent forms and underwent screening.

Problematic smartphone use was identified in 220 participants (15.2%) using the Arabic-validated SAS-SV,²⁹ applying established sex-specific cutoffs (≥ 31 for males; ≥ 33 for females).

To minimize confounding, participants were excluded if they: (i) reported medical or psychological conditions or medication use potentially influencing sleep, cognition, or physical activity; (ii) engaged in organized sports more than twice weekly for at least 12 months (this criterion was applied to reduce heterogeneity in baseline physical activity, but it may limit generalizability to more active adolescents); and (iii) provided unreliable or incomplete screen-time data (e.g., shared devices, use of digital restriction tools such as iOS Downtime or Android Focus Mode, or irregular usage patterns). Participants using restriction tools were excluded because these features modify natural smartphone behavior by limiting app access, thereby potentially biasing objective monitoring of spontaneous use. This exclusion may have omitted adolescents with stronger self-regulatory behaviors, a limitation acknowledged in Section 4 (Discussion).

Following a one-month monitoring period and application of exclusion criteria, 40 participants were excluded, resulting in a final analytical sample of 180 adolescents. Twenty-two adolescents were excluded because their smartphone use did not meet criteria for any dominant-use category (i.e., mixed-use profiles), while 18 were excluded because of health-related conditions or incomplete data.

To differentiate fitness-related use from general streaming and social media activities on platforms such as YouTube, TikTok, and Instagram, two trained research assistants independently reviewed a random sample comprising 20% of participants' weekly usage logs. Activities were classified as fitness when their primary purpose involved exercise instruction, physical activity participation, or health-related self-monitoring (e.g., following workout sessions, tracking steps, or recording running activities). Streaming use was defined

as predominantly passive consumption of audiovisual content (e.g., entertainment videos, music clips) without an explicit health or exercise objective. Social media use was assigned when the principal activity involved social engagement (e.g., posting, commenting, liking, or sharing content), irrespective of whether fitness-related material was incidentally viewed.

Inter-rater reliability was excellent (Cohen's $\kappa = 0.92$), indicating a high level of agreement between coders. The remaining logs were coded according to the same classification framework, with any ambiguities resolved through review by the principal investigator.

To assess potential selection bias, baseline characteristics of the mixed-use group ($n = 22$) were compared with those of the included participants ($n = 180$). No significant differences were observed for age (15.2 vs. 15.2 years, $p = 0.91$), sex distribution (45.5% vs. 48.3% female, $p = 0.78$), PSU severity as measured by the SAS-SV (34.1 vs. 33.8, $p = 0.62$), or Sleep Hygiene Index (SHI) scores (31.2 vs. 32.0, $p = 0.44$). In contrast, adolescents with mixed-use profiles reported lower total daily screen time (7.1 vs. 8.2 h/day, $p = 0.02$) and less late-night smartphone use (1.1 vs. 1.6 h/day, $p = 0.04$). Given the relatively small size of the mixed-use subgroup, these findings should be interpreted with caution.

Participants were recruited from four public secondary schools: School A ($n = 48$), School B ($n = 42$), School C ($n = 45$), and School D ($n = 45$). Owing to anonymization procedures, profile-specific distributions within individual schools were not retained. Nevertheless, recruitment was conducted across all schools using identical procedures and eligibility criteria, thereby reducing the likelihood that the findings were driven by school-specific characteristics.

Participants were classified into four behavioral profiles based on aggregated objective screen-time data:

- (i) Fitness ($n = 38$): Participants for whom fitness- or health-related smartphone use (including fitness-tracking apps and actively viewed fitness content on platforms such as YouTube, TikTok, or Instagram) accounted for $\geq 50\%$ of total daily app usage time, with at least three sessions per week of ≥ 15 minutes each. This threshold ensured a dominant and recurrent pattern. Participants who did not meet both criteria were not included. The high threshold may overestimate meaningful engagement.
- (ii) Social media ($n = 52$): Social networking applications (e.g., Instagram, TikTok, Snapchat, Facebook) accounted for $> 50\%$ of total daily app usage time.
- (iii) Gaming ($n = 50$): Video gaming applications accounted for $> 50\%$ of total daily app usage time.

- (iv) Streaming ($n = 40$): Video or music streaming applications (e.g., YouTube, Netflix, Spotify) accounted for >50% of total daily app usage time.

Participants with mixed usage patterns that did not meet any single threshold (e.g., 40% gaming + 40% streaming) were excluded from profile analysis.

2.3. Measures and instruments

2.3.1. Smartphone addiction assessment

Problematic smartphone use was identified using the Arabic-validated SAS-SV,²⁹ originally developed by Kwon *et al.*⁷ This comprehensive 10-item instrument employs a 6-point Likert scale (1 = “strongly disagree” to 6 = “strongly agree”) to assess core components of behavioral addiction, including daily life disturbance, withdrawal symptoms, tolerance, and loss of control. Total scores range from 10 to 60, with higher scores indicating greater addiction severity. The Arabic version has demonstrated strong psychometric properties, including excellent internal consistency (Cronbach’s $\alpha = 0.91$) and convergent validity with other behavioral addiction measures in Arab adolescent populations. In the present sample, the SAS-SV also showed good internal consistency (Cronbach’s $\alpha = 0.89$).

2.3.2. Physical activity measurement

Physical activity levels were assessed using the Arabic-validated Physical Activity Questionnaire for Adolescents (PAQ-A) by Bajamal & Robbins,³⁰ derived from the original instrument developed by Janz *et al.*³¹ This nine-item self-report measure comprehensively evaluates moderate to vigorous physical activity during the previous seven days across multiple contexts, including physical education classes, lunch breaks, recess periods, after-school hours, evenings, and weekends. Items are scored on a five-point scale, with higher scores indicating greater physical activity engagement. The Arabic version has demonstrated robust psychometric properties, including good reliability (Cronbach’s $\alpha = 0.82$) and convergent validity with accelerometer data in adolescent populations across the Middle East and North Africa. In the present sample, the PAQ-A also showed acceptable internal consistency (Cronbach’s $\alpha = 0.79$).

2.3.3. Sleep hygiene evaluation

Sleep hygiene practices were measured using the Arabic-validated SHI,³² based on the original instrument developed by Mastin *et al.*³³ This 13-item self-report questionnaire assesses a comprehensive range of sleep-related behaviors and environmental factors across cognitive, behavioral, and environmental domains. Items are scored on a 5-point Likert scale (0 = “Never” to 4 = “Always”), with

total scores ranging from 0 to 52. Higher scores indicate poorer sleep hygiene practices. The Arabic version has demonstrated adequate internal consistency (Cronbach’s $\alpha = 0.74$) and has maintained the original factor structure while demonstrating cultural appropriateness for Arab adolescent populations. In the present sample, the SHI showed acceptable internal consistency (Cronbach’s $\alpha = 0.76$).

2.3.4. Objective smartphone usage monitoring

Objective screen-time data were collected weekly through built-in smartphone analytics systems (iOS Screen Time or Android Digital Wellbeing), providing detailed documentation of application-specific usage duration and categorical engagement patterns. This methodology allowed for precise quantification of time allocation across application categories, including social media, gaming, fitness, and streaming platforms. Following established protocols from objective smartphone monitoring research,³⁴ participants with shared devices or those utilizing “Downtime” or “Focus” modes during recording weeks were excluded to ensure data accuracy and ecological validity.

2.3.5. Chronobiological analysis

Temporal usage patterns were analyzed according to established chronobiological principles,³⁵ with the 24-hour day partitioned into four biologically meaningful intervals: morning (06:00–12:00), afternoon (12:00–18:00), evening (18:00–23:00), and late-night (23:00–06:00). For each participant, the mean percentage of daily screen time occurring within each interval was calculated across the four-week monitoring period, enabling characterization of distinct temporal patterns associated with each behavioral profile.

2.3.6. Covariate assessment

Several covariates were systematically measured to account for potential confounding factors. Age and gender were recorded for each participant. Prior physical activity level was assessed through a detailed self-report of structured activity history, providing important contextual information about baseline activity patterns preceding the study period. Body Mass Index (BMI) was measured for descriptive purposes only and was not used as a covariate in the primary analyses.

Due to the cross-sectional design and the focus on exploratory profiling, no additional covariates (e.g., socioeconomic status, parental monitoring, chronotype, mental health symptoms) were collected. This limitation is acknowledged in Section 4 (Discussion).

2.4. Procedure

2.4.1. Phase I: Screening and recruitment (Week 0)

The initial screening phase involved the standardized administration of the SAS-SV and health screening questionnaire to all 1,450 potential participants through structured Google Forms during face-to-face sessions, ensuring consistent assessment conditions, maximizing response rates, and maintaining data anonymity.

2.4.2. Phase II: Behavioral monitoring and profile classification (Weeks 1–4)

The 220 adolescents identified with PSU underwent comprehensive behavioral monitoring for four consecutive weeks. During this period, objective screen-time data were systematically collected through built-in smartphone analytics, capturing both application category usage and precise temporal patterns. Participants received standardized instructions on data-sharing procedures and were regularly monitored for compliance with study protocols.

2.4.3. Phase III: Final assessment and data collection (Week 5)

The final sample of 180 participants completed the PAQ-A and SHI questionnaires during controlled administration sessions, conducted by trained research assistants using Google Forms. These sessions employed standardized protocols to ensure consistent administration conditions across all participants. Objective anthropometric measurements (height and weight) were obtained using calibrated instruments, following established protocols to ensure accurate BMI calculation in accordance with the World Health Organization (WHO) standards.

2.5. Statistical analysis

Statistical analyses were performed using SPSS Statistics (v.28.0, IBM, United States of America). An a priori power analysis using G*Power 3.1³⁶ indicated that a sample of 159 participants was required to detect a medium effect size ($f = 0.25$) with 80% power at an α of 0.05 for an analysis of covariance (ANCOVA) with four groups and two covariates (age and gender). Our final sample of 180 participants exceeded this requirement, ensuring sufficient statistical power.

Preliminary analyses confirmed assumptions for parametric testing. Normality of continuous outcomes (PAQ-A, SHI, and late-night screen time) was assessed via the Shapiro–Wilk test and Q–Q plots. Homogeneity of variances was evaluated with Levene's test, and homogeneity of regression slopes for ANCOVA was verified by testing interactions between behavioral profile and each covariate

(age and gender); no significant interactions were observed.

Descriptive statistics (means, standard deviations, frequencies) summarized demographic characteristics and smartphone usage. Baseline comparability across behavioral profiles was assessed using ANOVA for continuous variables and Chi-square tests for categorical variables; no significant differences were found.

Primary analyses employed one-way ANCOVA to compare PAQ-A and SHI scores across behavioral profiles, controlling for age and gender. Late-night screen time was analyzed with one-way ANOVA. Hierarchical linear regression assessed the incremental contribution of late-night screen time: SHI scores were first regressed on behavioral profile dummies and demographics (age and gender), and then late-night screen time was added.

Significant omnibus effects were followed by Tukey's honestly significant difference (HSD) post-hoc tests for pairwise comparisons. All tests were two-tailed with an α of 0.05. Because behavioral profiles were derived from aggregated objective smartphone-use metrics, partial overlap exists between classification variables and subsequent group comparisons. Accordingly, comparisons of screen-time characteristics across profiles are interpreted as descriptive rather than independent inferential tests. This approach is consistent with research that uses data-driven behavioral clusters primarily to contextualize health-related outcomes rather than as standalone predictors. Participants were recruited from multiple schools and classes; however, due to the exploratory nature of the study and the relatively small number of schools, we did not adjust for clustering in the primary analyses. This limitation is acknowledged in Section 4 (Discussion).

2.6. Ethical approval

This study received ethical approval from the local Committee for the Protection of Persons (CPP SUD; Approval No. 0554/2023). The research was conducted in full compliance with the ethical standards outlined in the Declaration of Helsinki (2013), ensuring the protection, dignity, and rights of all participants. Written informed consent was obtained from parents or guardians, and assent was obtained from all adolescent participants.

Participants submitted weekly screenshots of their iOS Screen Time or Android Digital Wellbeing dashboards through a secure, encrypted Google Forms platform. Two trained research assistants independently extracted app-level usage data and entered them into a coded database. During data entry, application names were immediately mapped to predefined usage categories (e.g., Instagram was classified as Social Media) to minimize the retention of personally identifiable information.

Raw screenshots were stored on a password-protected university server accessible only to the research team. Following data verification and aggregation, all screenshots and transcription records were permanently deleted.

No application names, timestamps, account identifiers, or other personally identifiable information were retained beyond the coding stage. Participants were informed of the voluntary nature of participation and their right to withdraw at any time without penalty. All study procedures complied with institutional ethical requirements and applicable data-protection regulations.

Data were anonymized using coded identifiers, with personal information stored separately from research responses. Raw screen-time data (screenshots or logs) were deleted after coding and aggregation to protect participant privacy.

3. Results

3.1. Sample characteristics and baseline comparisons

The demographic and baseline characteristics of the sample across the four behavioral profiles are presented in Table 1. The mean age ranged from 15.1 to 15.3 years, with no significant differences observed between groups ($F(3, 176) = 0.45, p = 0.720$). The proportion of female participants did not differ significantly across profiles ($\chi^2(3) = 3.82, p = 0.281$). Similarly, BMI values were comparable across groups, ranging from 21.2 to 22.1 kg/m² ($F(3, 176) = 0.89, p = 0.448$).

These findings indicate that the four behavioral profiles were homogeneous with respect to age, sex distribution, and BMI. Assumptions for parametric analyses were satisfied, including normality (Shapiro–Wilk tests, $p > 0.05$) and homogeneity of variances (Levene's tests, $p > 0.05$).

3.2. Objective screen-time patterns by behavioral profile

Objective screen-time patterns across behavioral profiles are summarized in Table 2. Total daily screen time differed significantly across groups ($F(3, 176) = 15.24, p < 0.001, \eta^2 = 0.21$). The fitness group reported the lowest screen time (mean [M] = 6.8 h, SD = 1.3), whereas the gaming group reported the highest (M = 9.3 h, SD = 2.3). The social media (M = 7.9 h, SD = 1.8) and streaming (M = 8.5 h, SD = 1.9) groups showed intermediate values.

Late-night screen time also differed significantly across groups ($F(3, 176) = 42.67, p < 0.001, \eta^2 = 0.42$), with the gaming (M = 2.3 h, SD = 1.1) and streaming (M = 2.1 h, SD = 0.9) groups exhibiting the highest levels, while the fitness group reported the lowest (M = 0.5 h, SD = 0.2). When expressed as a proportion of total screen time, late-night screen time accounted for 7.4% in the fitness group, 17.7% in the social media group, and 24.7% in both the gaming and streaming groups ($F(3, 176) = 48.92, p < 0.001, \eta^2 = 0.46$).

Post hoc Tukey HSD tests revealed significant differences between all groups ($p < 0.05$), except between the gaming and streaming profiles. Overall, adolescents in the gaming and streaming groups exhibited the highest levels of total and late-night screen time, whereas those in the fitness group showed the lowest.

3.3. Physical activity and sleep hygiene outcomes

Differences in physical activity and sleep hygiene across groups are presented in Table 3. ANCOVA, controlling for age and gender, revealed significant group differences in physical activity ($F(3, 174) = 86.45, p < 0.001, \eta^2 = 0.60$). The fitness group demonstrated the highest levels of physical activity, while the gaming and streaming groups

Table 1. Sample characteristics and baseline homogeneity tests

Variable	Profile groups				Test value	p-value
	Fitness (n = 38)	Social media (n = 52)	Gaming (n = 50)	Streaming (n = 40)		
Age (years)	15.1 (0.7)	15.2 (0.8)	15.3 (0.9)	15.2 (0.8)	$F(3, 176) = 0.45$	0.720
Female, n (%)	18 (47.4%)	30 (57.7%)	20 (40.0%)	19 (47.5%)	$\chi^2(3) = 3.82$	0.281
BMI (kg/m ²)	21.2 (2.8)	21.8 (3.1)	22.1 (3.4)	21.6 (2.9)	$F(3, 176) = 0.89$	0.448

Notes: Values are mean (SD) unless otherwise indicated. Continuous variables were compared using one-way ANOVA and categorical variables using chi-square tests. Assumptions for parametric analyses were satisfied, including normality (Shapiro–Wilk tests, all $p > 0.05$) and homogeneity of variances (Levene's tests, all $p > 0.05$).

Abbreviation: BMI: Body mass index.

showed the lowest.

Similarly, sleep hygiene differed significantly across groups after controlling for age and gender ($F(3, 174) = 67.33, p < 0.001, \eta^2 = 0.54$). The fitness group exhibited better sleep hygiene (lower SHI scores), whereas the gaming and streaming groups showed poorer outcomes.

All assumptions for ANCOVA were met, including normality, homogeneity of regression slopes (verified by testing interactions between behavioral profile and each covariate: age and gender; all $p > 0.05$), and homogeneity of variances (Levene's test, $p > 0.05$)

3.3.1. Hierarchical regression analysis examining associations with sleep hygiene

Table 4 presents the full results of the hierarchical regression analysis. A hierarchical linear regression was conducted to examine the associations between behavioral profile, late-night screen time, and sleep hygiene (SHI score). In Step 1, age, gender, and behavioral profile (fitness as the reference category) were entered into the model. The model was statistically significant and explained 29% of

the variance in sleep hygiene scores ($R^2 = 0.29$, adjusted $R^2 = 0.27, F(5, 174) = 14.82, p < 0.001$). Female sex was significantly associated with poorer sleep hygiene, whereas age showed only a marginal association. Compared with the fitness profile, the social media, gaming, and streaming profiles were all significantly associated with higher SHI scores, indicating poorer sleep hygiene, with the strongest association observed for the gaming profile.

In Step 2, late-night screen time was added to the model, significantly improving the explained variance ($\Delta R^2 = 0.15, F\text{-change}(1, 173) = 45.62, p < 0.001$). The final model accounted for 44% of the variance in SHI scores ($R^2 = 0.44$, adjusted $R^2 = 0.42$). Greater late-night screen time was associated with additional variance in SHI scores after adjustment for profile membership and demographics ($\beta = 0.42, p < 0.001$). Although the associations between behavioral profiles and SHI scores remained significant after adjustment, their magnitudes were attenuated, suggesting that late-night screen exposure partially accounted for the observed differences in sleep hygiene across profiles.

Table 2. Objective screen-time patterns by behavioral profile

Screen-time measure	Fitness ($n = 38$)	Social media ($n = 52$)	Gaming ($n = 50$)	Streaming ($n = 40$)	ANOVA results
Total daily (hours)	6.8 (1.3)	7.9 (1.8)	9.3 (2.3)	8.5 (1.9)	$F(3, 176) = 15.24, p < 0.001, \eta^2 = 0.21$
Late-night (hours)	0.5 (0.2)	1.4 (0.8)	2.3 (1.1)	2.1 (0.9)	$F(3, 176) = 42.67, p < 0.001, \eta^2 = 0.42$
Late-night (% of total)	7.4% (3.2)	17.7% (8.9)	24.7% (10.3)	24.7% (9.8)	$F(3, 176) = 48.92, p < 0.001, \eta^2 = 0.46$

Notes: Values are mean (SD). Late-night screen time was defined as 23:00–06:00. Assumptions for one-way ANOVA were met (Shapiro–Wilk test and Q–Q plots for normality; Levene's test for homogeneity of variances, all $p > 0.05$). Tukey HSD post hoc tests showed significant differences for all pairwise comparisons ($p < 0.05$), except between the gaming and streaming profiles.

Table 3. ANCOVA results for physical activity and sleep hygiene outcomes by behavioral profile

Outcome measure	Fitness ($n = 38$)	Social media ($n = 52$)	Gaming ($n = 50$)	Streaming ($n = 40$)	ANCOVA results
PAQ-A score	3.44 (0.09)	2.37 (0.08)	1.83 (0.08)	1.66 (0.09)	$F(3, 174) = 86.45, p < 0.001, \eta^2 = 0.60$
SHI score	24.6 (0.8)	32.7 (0.7)	38.1 (0.7)	36.8 (0.8)	$F(3, 174) = 67.33, p < 0.001, \eta^2 = 0.54$

Notes: Values are adjusted means (SE). ANCOVA controlled for age and gender. Assumptions were met: residuals were normally distributed (Shapiro–Wilk test, $p > 0.05$), homogeneity of regression slopes confirmed (group $\times$ age interactions: PAQ-A, $F(3, 168) = 0.95, p = 0.418$; SHI, $F(3, 168) = 0.82, p = 0.484$; group $\times$ gender interactions: PAQ-A, $F(3, 168) = 0.77, p = 0.512$; SHI, $F(3, 168) = 0.69, p = 0.558$), and homogeneity of variances verified via Levene's test ($p > 0.05$).

Abbreviations: ANCOVA: Analysis of covariance; PAQ-A: Physical Activity Questionnaire for Adolescents; SHI: Sleep Hygiene Index.

Table 4. Hierarchical regression analysis examining associations with sleep hygiene

Variable	<i>B</i>	<i>SE</i>	β	<i>t</i>	<i>p</i>	95% CI for <i>B</i>	Tolerance	VIF
Step 1								
Age	0.18	0.09	0.08	1.98	0.049	0.001, 0.36	0.91	1.10
Gender (female)	2.14	0.88	0.18	2.43	0.016	0.40, 3.88	0.89	1.12
Social media	5.92	1.10	0.35	5.38	<0.001	3.75, 8.10	0.61	1.64
Gaming	8.44	1.21	0.48	6.98	<0.001	6.05, 10.83	0.58	1.72
Streaming	7.91	1.18	0.45	6.70	<0.001	5.58, 10.24	0.60	1.66
Model statistics	$R^2 = 0.29$	Adj. $R^2 = 0.27$		$F(5, 174) = 14.82$	<0.001			
Step 2								
Age	0.15	0.08	0.06	1.88	0.062	-0.01, 0.31	0.90	1.11
Gender (female)	1.78	0.85	0.15	2.09	0.038	0.10, 3.46	0.88	1.14
Social media	3.55	1.10	0.21	3.23	0.001	1.38, 5.72	0.59	1.69
Gaming	5.10	1.22	0.29	4.18	<0.001	2.69, 7.51	0.55	1.82
Streaming	4.57	1.19	0.26	3.84	<0.001	2.22, 6.92	0.57	1.75
Late-night screen time (%)	0.19	0.03	0.42	6.33	<0.001	0.13, 0.25	0.85	1.18
Model statistics	$R^2 = 0.44$	Adj. $R^2 = 0.42$	$\Delta R^2 = 0.15$	$\Delta F(1, 173) = 45.62$	<0.001			

Notes: The fitness profile served as the reference category. All tolerance values exceeded 0.40, and all VIF values were below 2.0, indicating no evidence of problematic multicollinearity. Assumptions of linearity, homoscedasticity, normality of residuals, and independence of errors were satisfied. The model statistics for Step 1 show the variance explained by age, gender, and behavioral profile alone. Step 2 adds late-night screen time, with ΔR^2 and ΔF -change testing its incremental contribution.

Abbreviations: *B*: Unstandardized coefficient; β : Standardized beta coefficient; VIF: variance inflation factor.

3.3.2. Post hoc pairwise comparisons

Pairwise comparisons using Tukey HSD are presented in Table 5. The fitness group demonstrated significantly higher physical activity levels than all other groups (mean differences = 1.07–1.78, $p < 0.001$) and significantly better sleep hygiene (mean differences = -13.50 to -8.10, $p < 0.001$), along with lower late-night screen use (mean differences = -17.3% to -10.3%, $p < 0.001$).

The social media group showed higher physical activity and better sleep hygiene compared with the gaming and streaming groups, although the differences were smaller. No significant differences were observed between the gaming and streaming groups across any outcomes.

Overall, the fitness profile consistently demonstrated

the most favorable behavioral profile, whereas the gaming and streaming profiles exhibited the least favorable outcomes.

The strong overall association between late-night screen time and SHI scores largely reflected differences between behavioral profiles. Specifically, the gaming and streaming groups exhibited higher levels of late-night screen time and poorer sleep hygiene, whereas the fitness group showed lower values on both measures. Nevertheless, the association remained evident within each profile, with correlation coefficients ranging from 0.76 to 0.85 (fitness: $r = 0.76$; social media: $r = 0.81$; gaming: $r = 0.85$; streaming: $r = 0.83$). For clarity of visualization, a small amount of jitter was applied to data points in Figure 2; however, all statistical analyses were performed using the original,

unmodified data. A corresponding scatterplot without jitter is provided in [Figure A1](#).

Table 5. Post-hoc pairwise comparisons (Tukey HSD) for significant main effects by behavioral profile

Comparison	PAQ-A mean difference	SHI mean difference	Late-night percentage mean difference (%)
Fitness vs. social media	1.07***	-8.10***	-10.3***
Fitness vs. gaming	1.61***	-13.50***	-17.3***
Fitness vs. streaming	1.78***	-12.20***	-17.3***
Social media vs. gaming	0.54***	-5.40***	-7.0***
Social media vs. streaming	0.71***	-4.10***	-7.0***
Gaming vs. streaming	0.17	1.30	0.0

Notes: *** $p < 0.001$. Positive PAQ-A differences indicate higher physical activity; negative SHI differences indicate better sleep hygiene; negative late-night % differences indicate less late-night usage.

Abbreviations: HSD: Honestly significant difference; PAQ-A: Physical Activity Questionnaire for Adolescents; SHI: Sleep Hygiene Index.

4. Discussion

This study examined how predefined dominant-use smartphone-use profiles relate to sleep hygiene, physical activity, and late-night engagement among Tunisian adolescents. The findings reveal that adolescents do not exhibit a uniform pattern of PSU; instead, their behaviors can be categorized into distinct behavioral profiles: fitness, social media, gaming, and streaming, each characterized by unique risk patterns. Understanding these profiles provides new insight into potential mechanisms through which smartphone behavior may be associated with health outcomes during a developmental period marked by heightened vulnerability to digital habits.

These profile-specific associations may be interpreted through distinct cognitive, emotional, and behavioral mechanisms underlying different forms of smartphone engagement. Gaming and streaming activities are typically characterized by high levels of cognitive immersion and emotional arousal, which may prolong engagement, delay sleep onset, and increase susceptibility to late-night screen time. Social media engagement, in contrast, is often driven by anticipatory social feedback, emotional

monitoring, and fear of missing out, potentially disrupting sleep through heightened emotional reactivity rather than sustained immersion. Conversely, fitness-oriented smartphone use may support behavioral structuring, goal-setting, and self-monitoring, which could promote more regular daily routines and could be associated with healthier patterns of physical activity and sleep hygiene. However, these proposed mechanisms, including fear of missing out, emotional arousal, cognitive immersion, and behavioral displacement, were not directly assessed in the present study. Future research should incorporate validated measures of fear of missing out (FoMO), emotion regulation, anxiety/depressive symptoms, bedtime procrastination, and chronotype to empirically examine these pathways.

Across the four profiles, adolescents in the gaming and streaming groups showed the highest total daily smartphone use and, critically, the greatest concentration during late-night hours. These temporal patterns were strongly associated with poorer sleep hygiene, suggesting that the timing of smartphone engagement is closely linked to sleep-related behaviors and may be as important as overall screen-time volume. While late-night smartphone use is generally associated with poorer sleep hygiene, the relationship is nuanced and profile-dependent. In our study, adolescents in the gaming and streaming profiles exhibited the highest late-night screen time and poorest sleep, aligning with prior research showing that immersive digital engagement increases cognitive and emotional arousal and delays sleep onset.^{37,38}

Similarly, the social media group showed disrupted sleep, potentially due to anticipatory social feedback and emotional reactivity.³⁹ However, some evidence suggests that increased pre-sleep smartphone use does not always impair sleep and may, in specific contexts, be associated with longer sleep duration, such as on non-school nights.⁴⁰ These contrasting findings underscore that individual differences, behavioral motivations, and contextual factors modulate the impact of late-night smartphone use, emphasizing the importance of considering behavioral profiles rather than total screen time alone.

Comparison with recent EMA and actigraphy studies further contextualizes our findings. Tkaczyk *et al.*⁴⁰ reported that evening smartphone use did not consistently impair sleep on non-school nights, emphasizing the importance of contextual and individual differences, a pattern also reflected in our profile-dependent results. Similarly, Chen *et al.*⁴¹ found that both the timing and type of screen activity differentially predicted sleep outcomes, consistent with our observation that gaming and streaming profiles were most strongly associated with poor sleep hygiene. Unlike most

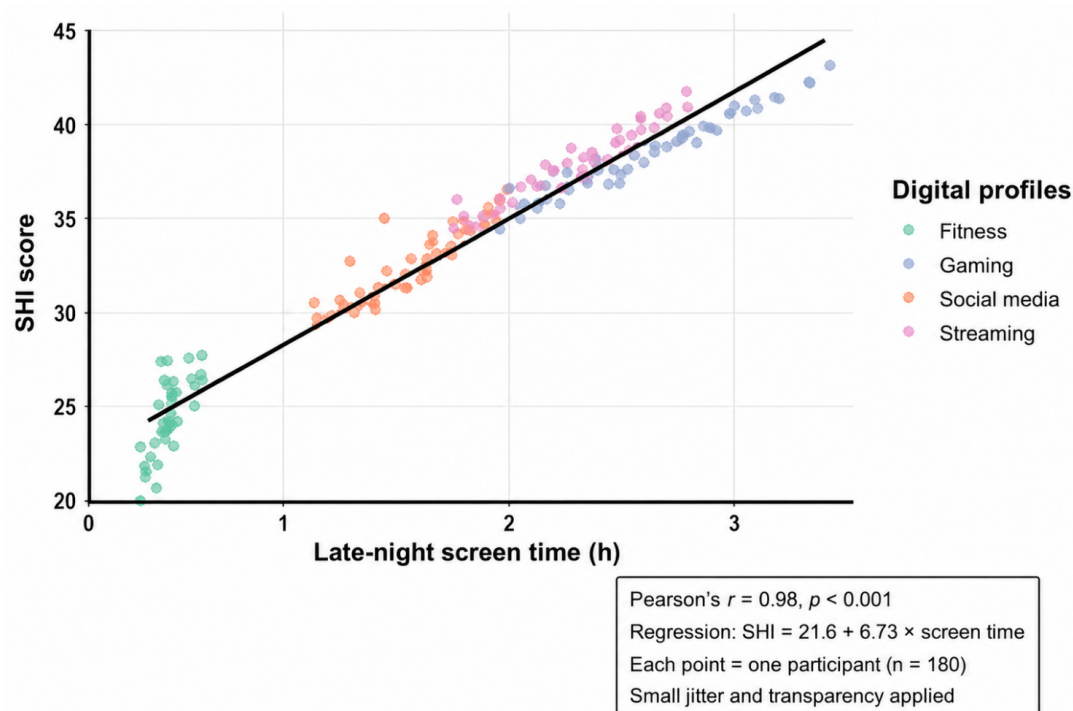


Figure 2. Association between late-night screen time and Sleep Hygiene Index (SHI) scores

Notes: Point colors denote participants' predominant late-night digital activity profile (fitness, social media, gaming, or streaming). The solid black line represents the fitted linear regression model, and the shaded area indicates the 95% confidence interval. Jitter was applied only for visualization; the correlation and regression were calculated on raw, unfiltered data.

EMA studies, which are limited to 7–14 days, our one-month objective monitoring period might captured more stable behavioral patterns. Nevertheless, wake-up times and bedtime variability were not assessed using actigraphy, which should be addressed in future research.

Physical activity also varied systematically by profile. Adolescents in the fitness profile demonstrated higher physical activity levels compared to peers engaged in gaming and video streaming. This aligns with typological frameworks that distinguish “active” adolescents, who combine high physical activity with low screen use, from “sedentary gamers,” who engage in high screen use and low activity.⁴² The Environmental Determinants of Dietary Behaviors among Adolescents study also supports this pattern, showing that gaming is particularly associated with lower physical activity levels.⁴³

Notably, the fitness profile was the smallest subgroup in our sample, highlighting that adolescents with PSU infrequently utilize smartphones for health-promoting behaviors. This aligns with research showing that while fitness apps and digital interventions have the potential to improve physical activity and sleep quality among adolescents, actual engagement is limited and effects are often inconsistent.^{44,45} Thus, high smartphone engagement

is rarely directed toward productive health-oriented activities in adolescents with PSU, revealing a critical reality for intervention design.

Sedentary screen-based behaviors, such as gaming and prolonged video streaming, have consistently been linked to reduced movement, supporting the displacement hypothesis, which posits that time spent on media competes with time available for physical activity.^{46,47} In contrast, social media engagement did not show the same degree of inactivity, and some evidence suggests that certain social applications may even promote light-intensity physical activity, particularly among female adolescents.^{48,49} These findings indicate that the type of digital activity, rather than total digital engagement, is a key determinant of physical activity patterns.

The finding that late-night smartphone use explained additional variance in sleep hygiene beyond behavioral profile highlights a robust association between nocturnal digital engagement and sleep-related behaviors. The exceptionally strong association observed between late-night screen time and SHI scores ($r = 0.98$) may be explained by both methodological and behavioral factors. The late-night interval examined in the present study (23:00–06:00) corresponds to a critical circadian window

characterized by increased susceptibility to melatonin suppression and sleep disruption. Consistent with this interpretation, longitudinal evidence has shown that nighttime screen exposure predicts poorer sleep quality and greater insomnia severity in adolescents.⁴¹ Similarly, previous studies^{50,51} have reported that smartphone use after lights-off and prolonged social media engagement were associated with increased sleep disturbance, sleep latency, and daytime dysfunction.

Participants appeared to cluster into distinct nocturnal digital engagement profiles (i.e., Fitness, Social Media, Gaming, and Streaming), characterized by markedly different levels of nighttime screen exposure and sleep hygiene scores. This interpretation aligns with findings suggesting that the effects of screen exposure on sleep vary according to both the timing and type of digital activity.⁴¹ Furthermore, the use of relative screen exposure (percentage of total daily screen time) may have reduced interindividual variability by standardizing exposure across participants, thereby amplifying the observed linear association. Across behavioral profiles, adolescents reporting higher levels of nighttime smartphone use also reported poorer sleep hygiene. The observed association between late-night screen time and sleep hygiene is consistent with neurobiological models indicating that nighttime digital exposure disrupts melatonin secretion, delays sleep onset, and causes compensatory sleep loss.^{52,53} The present study contributes novel evidence by showing that this mechanism operates across behavioral profiles, underscoring the universal association between nocturnal smartphone use.

These results also carry relevance for the Tunisian adolescent context, where increasing digital connectivity has occurred alongside limited digital literacy and insufficient school-based awareness programs.^{54,55} The elevated nighttime use observed in gaming and streaming profiles may reflect limited parental monitoring during evening hours,⁵⁶ cultural norms surrounding late-night activity among youth, and the widespread availability of low-cost entertainment platforms.⁵⁷ The current findings suggest that Tunisian adolescents may be particularly susceptible to sleep disruption due to contextual factors associated with unregulated smartphone engagement. It is important to emphasize that these contextual factors, including digital literacy, parental monitoring, cultural norms, and access to low-cost entertainment, were not directly assessed in the present study. Accordingly, they should be considered exploratory hypotheses for future investigation rather than definitive conclusions regarding Tunisian adolescents.

The identification of distinct profiles further advances

the theoretical understanding of PSU. Traditional models often conceptualize PSU as a single construct defined by excessive duration or addiction-like symptoms. In contrast, the profile-based approach demonstrates that risk is multidimensional, shaped by motivational drivers, temporal patterns of use, and behavior-specific tendencies.⁵⁸⁻⁶⁰ This perspective aligns with emerging digital behavior frameworks that emphasize heterogeneity and the need to differentiate harmful patterns from neutral or beneficial ones.^{19,61} The identification of a fitness profile indicates that not all smartphone engagement among adolescents with PSU is uniformly sedentary or health-adverse. However, this subgroup represented the smallest proportion of the sample and was defined by relatively modest fitness-application engagement criteria. Therefore, this profile should not be interpreted as evidence that smartphone use directly promotes physical activity, but rather as suggesting that some adolescents with lower-risk digital profiles may integrate limited health-oriented app use into broader behavioral routines.

The consistency of the results with international findings supports the generalizability of the profile-based approach while also emphasizing the importance of cultural context.^{61,62} Although the behavioral profiles mirror patterns observed in other regions, the magnitude of nighttime use and sleep disruption appears heightened in this sample. This suggests that digital health interventions in Tunisia may need to prioritize nighttime use regulation, sleep education, and youth-specific digital guidelines.

Overall, this study contributes to the literature by demonstrating that behavioral profiles offer a more nuanced and meaningful framework for understanding PSU among adolescents. By integrating usage patterns, timing, and health outcomes, the findings highlight the need for precision-oriented models that could better capture the diversity of adolescent digital behavior.

This study enhances understanding of PSU by incorporating objective smartphone usage data, temporal usage patterns, and health-related outcomes within a profile-based framework, thereby characterizing PSU as a multidimensional and behavior-specific phenomenon. The results indicate that the health-related associations of smartphone usage are influenced not only by the frequency of use but also by the nature and timing of digital activities, highlighting the significance of profile-based methodologies in adolescent digital health research.

Several limitations should be acknowledged. First, the cross-sectional design precludes causal inference and does not allow determination of the direction or potential bidirectional nature of the associations between smartphone-use profiles, sleep hygiene, and physical

activity. Longitudinal or experimental studies are required to clarify whether changes in smartphone behaviors are associated with health alterations or whether existing health behaviors influence smartphone use patterns.

Although smartphone use was assessed using objective screen-time data, physical activity and sleep hygiene relied on self-reported measures, which may be subject to recall and social desirability biases; future studies would benefit from wearable or actigraphy-based assessments. Furthermore, objective monitoring may have induced reactivity, leading participants to modify or reduce their smartphone use when they were aware of being observed, potentially resulting in an underestimation of typical usage patterns. Nevertheless, the one-month monitoring period potentially mitigated this effect relative to shorter assessment durations.

The single-region Tunisian sample may limit generalizability to other sociocultural contexts characterized by different digital norms and parental monitoring practices. Moreover, several exclusion criteria (including elite sport participation and health conditions affecting sleep or activity) were applied to reduce heterogeneity but may limit the external validity.

The study did not include a non-PSU comparison group; therefore, we cannot determine whether the observed association patterns are specific to adolescents with PSU or generalizable to the broader adolescent population. The recall period for the PAQ-A (seven days) differs from the one-month smartphone monitoring period; this temporal mismatch should be considered when interpreting the associations. Participants were recruited from multiple schools and classes, but we did not adjust for potential clustering due to the exploratory nature of the study and the relatively small number of schools. The fitness profile definition ($\geq 50\%$ of daily app time on fitness apps) may overestimate health-promoting use; future studies should validate more realistic thresholds. While the profile-based approach offers greater behavioral specificity, the identified clusters may not capture the full spectrum of adolescent smartphone-use profiles, warranting replication in larger and more diverse populations. Excluding participants with mixed usage patterns may introduce selection bias and limit the generalizability of our findings. Future studies should retain such participants to characterize their health profiles.

The identification of distinct smartphone-use profiles allows a precision-prevention strategy for adolescent digital health, in which interventions are customized to predominant usage patterns rather than uniformly aiming at overall screen-time reduction. This approach may be more effective, as it involves the specific behavioral

and temporal risks associated with different types of smartphone use.

The phenotypic model provides actionable guidance for health professionals, educators, and policymakers addressing adolescent PSU. Findings indicate that the type of digital activity, rather than total screen time, critically shapes physical activity and sleep patterns. Adolescents in the gaming and streaming profiles may benefit from structured sleep-hygiene programs, digital curfews, and guidance on managing pre-sleep arousal. For social media users, interventions focusing on emotional regulation, digital self-esteem, and healthy online social practices may be more effective.

Conversely, the fitness profile demonstrates that smartphones can support healthy routines. School- and community-based programs could leverage digital fitness applications or peer-led activity challenges. Overall, these findings endorse digital harm-reduction strategies that minimize specific risks, such as late-night screen time, while promoting goal-oriented engagement. Implementing curricula on digital hygiene and establishing family guidelines for evening smartphone use may support healthier adolescent digital habits.

5. Conclusion

This study demonstrates that smartphone-use behaviors among adolescents can be categorized into predefined dominant-use profiles that meaningfully relate to sleep hygiene, physical activity, and late-night digital engagement. Gaming and streaming profiles were characterized by high screen-time exposure and frequent nocturnal use, both of which were associated with poorer sleep quality and lower activity levels. In contrast, the fitness profile showed healthier behavioral patterns and was associated with better sleep hygiene and higher physical activity. Importantly, late-night smartphone use showed a strong and consistent association with poorer sleep hygiene across all profiles.

These findings highlight the need to move beyond uniform measures of PSU and adopt more differentiated frameworks that account for behavioral diversity. By identifying how specific usage styles relate to health outcomes, this study may inform more targeted, contextually sensitive interventions tailored to adolescents' digital behavior patterns.

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Conflict of interest

The authors declare they have no competing interests.

Author contributions

Conceptualization: Mohamed Yaakoubi, Omar Trabelsi, Luca Paolo Ardigo

Data curation: Mohamed Yaakoubi, Ahmed Ghorbel

Formal analysis: Mohamed Yaakoubi, Georgian Badicu

Investigation: Mohamed Yaakoubi, Ghada Regaieg, Adnene Gharbi

Methodology: Mohamed Yaakoubi, Mustapha Bouchiba, Ahmed Ghorbel

Project administration: Omar Trabelsi

Supervision: Omar Trabelsi, Luca Paolo Ardigo

Validation: Mustapha Bouchiba, Georgian Badicu, Luca Paolo Ardigo

Writing—original draft: Mohamed Yaakoubi

Writing—review & editing: Omar Trabelsi, Luca Paolo Ardigo, Mustapha Bouchiba, Georgian Badicu

Ethics approval and consent to participate

This study received ethical approval from the local Committee for the Protection of Persons (CPP SUD; Approval No. 0554/2023). The research was conducted in full compliance with the ethical standards outlined in the Declaration of Helsinki (2013), ensuring the protection, dignity, and rights of all participants. Written informed consent was obtained from parents or guardians, and assent was obtained from all participants. Data were anonymized using coded identifiers, with personal information stored separately from research responses.

Consent for publication

Written informed consent was obtained from the parents or legal guardians of all participants, and assent was obtained from the participants prior to participation. All data were anonymized, and no identifying information or images are included in this manuscript. Therefore, additional consent for publication of identifiable data was not required.

Availability of data

Due to ethical restrictions, the study data are not publicly available. Anonymized data may be requested from the corresponding author, pending approval from the Tunisian Ministry of Education and CPP SUD.

Further disclosure

This article was drafted to assess English language fluency with the assistance of ChatGPT Version 1.2026.104 (OpenAI, San Francisco, CA), in keeping with established best practices (Biondi-Zoccai G, editor. ChatGPT for Medical Research. Torino: Edizioni Minerva Medica; 2024). The final content, including all conclusions and opinions, has been thoroughly revised, edited and approved by the authors. The authors take full responsibility for the integrity and accuracy of the work and retain full credit for all intellectual contributions. Compliance with ethical standards and guidelines for the use of artificial intelligence in research has been ensured.

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Appendix

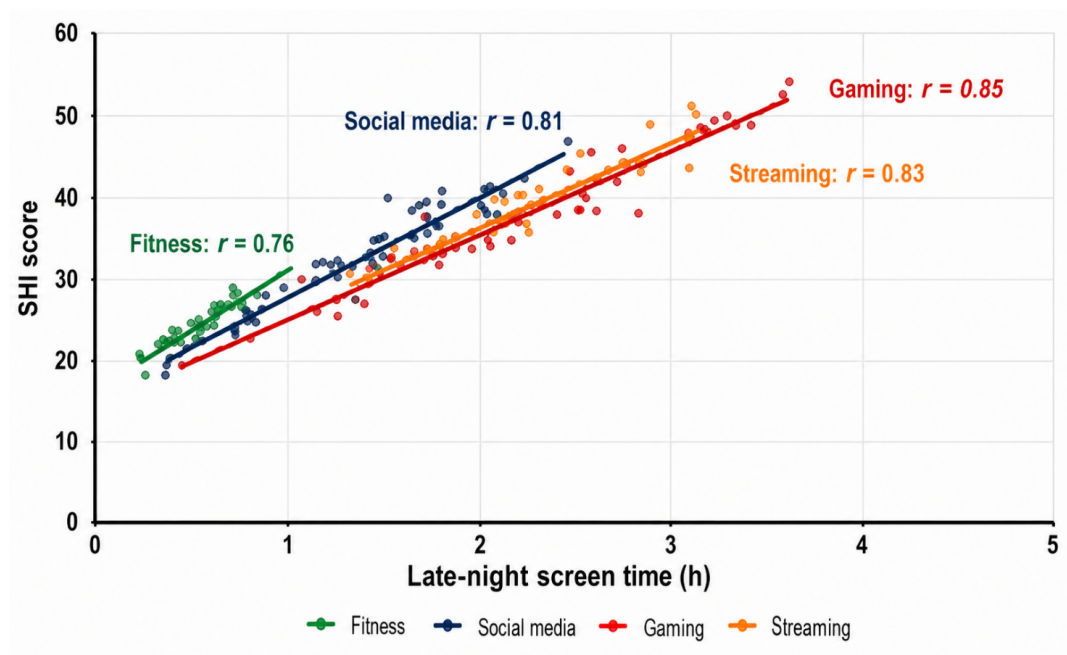


Figure A1. Relationship between late-night screen time and Sleep Hygiene Index (SHI) across behavioral profiles