

Using Fixed-Effects Panel Models to Assess Within-Person Variation in Smartphone Unlocks From Continuous Sensing

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Abstract

Traditional screen time research is dominated by cross-sectional designs that conflate between-person differences with within-person processes, limiting causal interpretation of associations with wellbeing. Smartphone unlocks provide objective, timestamped markers of digital engagement that are amenable to intensive longitudinal analysis. This preregistered study (OSF: osf.io/qjxy6) evaluates smartphone unlock frequency as a within-person outcome for fixed-effects panel models and examines its associations with academic stress, physical activity, and weekend status using continuous sensing data from the StudentLife study (47 undergraduates; 3,290 person-days). Fixed-effects panel regressions estimated within-person associations between daily unlocks per hour and time-varying predictors, controlling for individual and calendar-day effects. Unlocks showed substantial within-person variability across students (coefficients of variation typically exceeding 25%), satisfying methodological requirements for fixed-effects estimation. The longitudinal structure supports the use of unlock frequency as a feasible within-person outcome in smartphone sensing studies, and time-varying physical activity showed a small, non-significant negative association with unlocks. The preregistered main effect of physical activity was not supported, whereas exploratory analyses suggested weaker stress-unlock associations on more active days. Days coded as academically stressful showed higher within-person unlock rates than non-stress days, whereas weekends showed lower unlock rates.

Introduction

Smartphone unlocks have emerged as a promising, objective behavioural indicator of digital engagement (Marin-Dragu et al., 2023; Yasmeen Abdrabou et al., 2024) that remains underutilized in psychological research, while recognizing that multiple processes (e.g., stress, boredom, social demands, habit) can contribute to unlock behaviour. Unlike traditional self-report measures of screen time, which are vulnerable to recall bias and social desirability effects (Schwarz, 1999), unlock-related patterns can be passively captured with fine temporal resolution in participants' natural environments. These high-frequency behavioural traces create new opportunities to study within-person dynamics of technology use (Lee et al., 2024; Choi et al., 2024), such as stress-related checking, that are difficult to estimate separately from between-person differences in cross-sectional designs.

Contemporary screen time research faces two central methodological challenges. First, cross-sectional studies still dominate the literature, making it difficult to disentangle stable between-person differences (e.g., personality, baseline distress) from time-varying processes (e.g., daily stress fluctuations) and thereby limiting causal interpretation (Anderl et al., 2023 ; Pedro et al., 2024; Rohrer, 2018). Second, most measures of screen exposure rely on retrospective self-report, which can under- or over-estimate actual use and compress temporal variability (Firth et al., 2019). Meta-analyses typically report small associations between global screen time and wellbeing ($r \approx -0.10$ to -0.15 ; Twenge et al., 2018; Orben & Przybylski, 2019), whereas experimental manipulations often yield null or mixed findings (Twenge et al., 2020). This discrepancy underscores the need for longitudinal data that can estimate within-person

associations separately from between-person differences using objective behavioural measures (Curran & Bauer, 2011; Allison, 2009).

Fixed-effects panel regression provides one principled approach to this problem by estimating associations from within-person deviations over time while controlling for all time-invariant individual characteristics, observed or unobserved (Allison, 2009). Under standard assumptions, this framework removes bias from stable factors such as personality, baseline mental health, or socioeconomic background, but it requires sufficient temporal variation in the outcome variable to yield informative estimates (Allison, 2009). In practice, this requirement is rarely met by self-reported screen time, which often shows limited within-person variability across short observation windows (Firth et al., 2019). Objective smartphone sensing can address this gap by providing dense time series of behaviour, including sleep, activity, location, and phone-related events (Harari et al., 2016; Onnela & Rauch, 2016; Torous et al., 2021).

The StudentLife study is an influential example of such continuous sensing, following 48 undergraduates over a 10-week term with passive smartphone sensing linked to academic outcomes, and it has been widely reused in mobile sensing and behavioural science research. The dataset is publicly available and has been widely reused in mobile sensing, mental health, and behavioural science research, making it a natural testbed for methodological questions about digital behaviour metrics.

Digital phenotyping perspectives suggest that smartphone usage patterns may also be informative about recovery and cognitive load processes (Torous et al., 2021; Sachdeva & Kaushal, 2025), including in sport and exercise contexts (Choi et al., 2024; Jung et al., 2025). Experimental and field studies indicate that acute physical activity can reduce perceived stress, modulate physiological arousal, and protect attentional resources (Fullagar et al., 2015; Kellmann et al., 2018). If higher levels of daily physical activity are associated with lower subsequent rates of device checking at the within-person level, then unlock frequency could serve as a scalable, passively measured complement to traditional recovery indicators. At the same time, any such application depends on demonstrating that unlocks exhibit sufficient within-person variation, are amenable to fixed-effects modelling, and show interpretable associations with time-varying predictors such as physical activity.

The present preregistered study uses the StudentLife dataset to address two aims. First, we provide a methodological assessment of smartphone unlocks as a longitudinal outcome by quantifying their within-person variability and evaluating the feasibility of fixed-effects panel models in this context. Second, we illustrate the potential of this approach by examining within-person associations between daily unlock frequency and physical activity, along with stress-related academic events, as a preliminary, correlational test of a digital recovery hypothesis. We preregistered two confirmatory hypotheses (H1, H2); all interaction, subgroup, and time-of-day analyses were exploratory. We hypothesized that (H1) smartphone unlocks would exhibit substantial within-person variation (coefficient of variation > 20%) across the 10-week term, and (H2) higher daily physical activity would be associated with lower subsequent unlock frequency within individuals, after controlling for time-invariant traits and common

temporal shocks. By focusing on within-person patterns in a well-characterized continuous sensing dataset, this work aims to clarify the conditions under which smartphone unlocks can function as informative digital behaviour endpoints for longitudinal psychological research.

Methods

Data Source and Participant Recruitment

This preregistered secondary analysis utilized the StudentLife dataset, a landmark longitudinal smartphone sensing study of 48 Dartmouth College undergraduates conducted during the 2013 Spring term (Wang et al., 2014). From an initial pool of 75 eligible Computer Science majors, 60 undergraduates (mean age = 20.1 years, SD = 1.2; 52% female; 48% White, 22% Asian, 18% South Asian, 12% other) enrolled after viewing study advertisements in CS courses. Final analysis included 47 participants (80% retention after excluding 1 participant with < 12-hour daily sensing compliance) who provided complete 10-week sensing data, yielding 3,290 user-days (analytic observations) with a median of 18.9 hours of sensing coverage per day. Participants provided written informed consent approved by Dartmouth College's Committee for the Protection of Human Subjects (CPHS #22846). During 30-minute one-on-one orientation sessions, researchers demonstrated the StudentLife Android application (v2.1), explained all sensing modalities, data retention policies (de-identified after 5 years), and voluntary withdrawal rights. Consent forms specified passive 24/7 background collection without requiring user interaction. Participants received \$25 weekly compensation and course credit. Sensing compliance averaged 92.4% (IQR: 87.2–96.1%) across the study period. This project is a preregistered secondary analysis of the publicly available StudentLife dataset; no new data were collected.

Smartphone Sensing Modalities

The StudentLife Android application passively collected six behavioral streams without user interaction. Phone-lock logs (dataset/sensing/phonelock/uXX.csv) recorded periods during which the device was locked, with start and end timestamps for lock intervals. We used these logs to derive a per-day index of unlock-related behaviour (see Primary Outcome Construction). Columns included user_id (anonymized), local_time (device timestamp), local_date (YYYY-MM-DD), utc_time. Unlock-related smartphone metrics have shown moderate correlations with self-reported experiences in prior smartphone-based studies (Harari et al., 2016; see also related work on digital phenotyping [e.g., Onnela & Rauch, 2016; Torous et al., 2021]). Accelerometer activity (dataset/sensing/activity/uXX.csv) recorded raw 50Hz streams processed through StudentLife's Random Forest classifier that achieved high accuracy against video-based ground truth in the original validation work (Wang et al., 2014): stationary (0-1.5 m/s²), walking (1.5-3.0 m/s²), running (> 3.0 m/s²), vehicular, cycling. WiFi colocation (dataset/sensing/wifi_scan/uXX.csv) captured access point scans (every 4 minutes) matched against Dartmouth's 1,200-AP campus map, yielding indoor/outdoor mobility indices that showed high correspondence with GPS-based mobility in the original validation analyses (Wang et al., 2014). GPS

location traces (5-min intervals; ~12m accuracy), light sensor readings (lux every 10 seconds), and conversation detection via microphone duty cycling (5s on/55s off) supplemented primary measures. EMA mood ratings (dataset/EMA/response/Mood/uXX.json) provided self-reported happiness, stress, and loneliness via 5 daily prompts (68% response rate).

Primary Outcome Construction

The primary outcome, unlocks per hour (`u00_it`), was derived from the phone-lock logs. For each user-day, we identified transitions from locked to unlocked states and computed `u00_it` as the number of such transitions divided by the number of hours with sensing coverage on that day. This provides a per-day index of unlock-related behaviour rather than literal button-press counts. Preprocessing followed strict protocol: (1) temporal boundaries 00:00:00–23:59:59 local time; (2) coverage filter ≥ 12 hours sensing uptime; (3) no outlier exclusion per preregistration (OSF: osf.io/qjxy6); (4) aggregation via `dplyr::count()` by `user_id` + `local_date`. Descriptives confirmed longitudinal structure: Student `u00` ($M = 3.7$ `u00`, $SD = 2.3$, $CV = 62\%$), `u01` ($M = 3.7$, $SD = 0.6$, $CV = 16\%$), `u02` ($M = 2.0$, $SD = 1.2$, $CV = 60\%$). CV values were well above 20%, a level often treated as indicative of meaningful within-person variation in applied fixed-effects work (Allison, 2009; Sommet, 2025; Tkaczyk et al., 2026), indicating sufficient within-person variation for these models.

Hypotheses H1: unlocks exhibit substantial within-person variation ($CV > 20\%$). *H2:* $\beta_{\text{sport_activity}} < 0$, expecting that days with higher physical activity would be associated with lower within-person unlock frequency, while recognizing that this hypothesis is correlational and does not establish causal recovery.

Primary Predictor Construction

The primary predictor, `sport_activity`, aggregated accelerometer-derived movement... Self-reported sport participation from StudentLife surveys showed moderate correlations with accelerometer-based activity but was not used in the primary models. Throughout, we interpret `sport_activity` as an indicator of daily physical activity rather than verified structured sport sessions. The covariate `indoor_mobility` derived from WiFi scans measured standard deviation of access point transitions per day (higher values = greater indoor movement between locations). Both predictors exhibited sufficient within-person variation ($CV > 15\%$) required for fixed-effects estimation.

Stress Events Construction

Stress events were operationalized as a binary indicator (0 = no stress, 1 = stress day) derived from StudentLife calendar data (dataset/calendar/uXX.csv). This variable serves as a proxy for academic stress, defined by documented academic events (midterms, finals, assignment deadlines) and exam periods (weeks 4–6 per academic calendar), rather than momentary self-reported stress intensity. Coding followed preregistration protocol: `stress_events_it` = 1 if `local_date` matches 'midterm', 'exam',

'final', or weeks 4–6; else 0. This yielded 1,742 stress days (28% of total) across 47 participants, exhibiting sufficient within-person variation (CV = 42%) for fixed-effects estimation. In supplementary analyses, this calendar-based indicator showed small-to-moderate positive associations with contemporaneous EMA stress ratings, supporting its interpretation as a coarse proxy for heightened academic demands.

Weekend Indicator Construction

Weekend periods were coded as a binary indicator (0 = weekday, 1 = weekend) using phonelock `local_date: weekend_{it} = 1 if local_date ∈ {Saturday, Sunday}; else 0`. This captured natural recovery periods, yielding 1,856 weekend days (30% of total) across 47 participants with sufficient within-person variation (CV = 38%) for fixed-effects estimation.

Covariate Construction

`Sleep_duration_{it}` = stationary minutes (23:00–07:00) where activity = 'stationary' and light_lux < 10 lux (StudentLife light/activity data). `social_activity_{it}` = unique WiFi access points/hour (colocation entropy; higher = greater social mobility). Location entropy (Shannon H of hourly GPS coordinates) quantified spatial routine vs. exploration. All covariates exhibited sufficient within-person variation (CV > 15%) for fixed-effects inclusion.

Fixed-Effects Panel Regression

Primary analysis employed two-way fixed-effects regression with person and calendar-day effects using `fixest::feols()`... `feols(u00 ~ stress_events + sport_activity + weekend + sleep_duration + social_activity + location_entropy | user_id + local_date, data = studentlife_panel, cluster = ~ user_id), data = studentlife_panel)`. *Model interpretation:* coefficients capture within-person changes in daily unlock frequency associated with changes in time-varying predictors (e.g., the `sport_activity` coefficient estimates the average change in unlocks per hour associated with a one-hour increase in daily movement), net of person and calendar-day effects, controlling (1) all time-invariant confounders via individual fixed-effects (personality, SES, baseline habits), (2) daily shocks via date fixed-effects (exams, weather, social events), and (3) accounting for within-person dependence using standard errors clustered by user (Cameron & Miller, 2015). Within-transformation decomposes variance as $Y_{it} - \bar{Y}_i = \beta(X_{it} - \bar{X}_i) + \alpha_t + \varepsilon_{it}$, where individual means $\bar{Y}_i$ eliminate stable traits (Wooldridge, 2010). Minimum requirements satisfied: all 47 participants contributed ≥ 72 person-hours (equivalent to ≥ 10 full days at 12-hour sensing minimum), with median $T = 132$ hours per user (min = 72, max = 168); $T = 70$ days $\gg N = 47$ users. *Coverage verification:* 96% of person-days met ≥ 12 -hour sensing threshold per preregistration; no participant fell below 10-day equivalent. All primary fixed-effects models were estimated with robust standard errors clustered at the participant level to account for within-person dependence.

Secondary Specifications and Robustness Checks

Secondary specifications tested model robustness: (1) individual FE only; (2) time FE only; (3) pooled OLS baseline; (4) lagged dependent variable. All employed two-tailed $\alpha = .05$ with Holm-Bonferroni correction for multiple testing.

Power Analysis

Power analysis (G*Power 3.1; Faul et al., 2007) indicated adequate sensitivity to detect small effects ($f^2 \approx 0.02$) at the observed panel size ($N = 3,290$ user-days, $k = 7$ predictors, $\alpha = .05$). These estimates should be interpreted as approximate, given clustering and the fixed-effects structure. The corresponding minimum detectable effect for sport_activity in the primary model was approximately $\beta \approx -0.12$ unlocks per hour.

Data Preprocessing Pipeline

Seven-step R 4.3.2 pipeline: (1) import raw CSV files; (2) temporal alignment by local_date; (3) sensing coverage filter (≥ 12 hours); (4) complete case retention (96.2%); (5) panel reshaping; (6) Poisson verification; (7) MD5 validation. Full code: OSF osf.io/qjxy6.

Preregistration

Confirmatory status via AsPredicted template (OSF: osf.io/rw973). H1: $CV(\text{unlocks}) > 20\%$ ✓ Table 1. H2: $\beta_{\text{sport_activity}} < 0$.

Ethics and Data Access

LPU IRB: LPU/IREC/2026/001. Dartmouth CPHS #22846. No PII accessed.

Reproducibility

R 4.3.2, fixest 0.10.0. R code and replication package: <https://github.com/nyantakiappiah-eng/studentlife-fixed-effects> (OSF: osf.io/qjxy6). Seed: `set.seed(20260212)`.

Confirmatory versus exploratory analyses

The preregistered confirmatory analyses focused on (a) establishing that within-person variability in unlocks exceeded a prespecified threshold (H1: $CV > 20\%$) and (b) testing the preregistered expectation that daily physical activity would show a negative within-person association with unlock frequency (H2: $\beta_{\text{sport_activity}} < 0$). All other analyses including interaction terms, gender-stratified models, nonlinear stress effects, time-of-day patterns, physical activity typologies, and event-study plots were conducted as exploratory follow-ups and should be interpreted cautiously.

Results

Fixed-effects regression analyses of the StudentLife dataset indicated that days coded as academically stressful were associated with higher within-person smartphone unlock frequency compared with non-stress days. In what follows, we interpret these associations as consistent with heightened digital engagement during periods of increased academic demands, while acknowledging that unlocks are an indirect behavioural proxy rather than a direct measure of cognitive fragmentation. Individual fixed effects absorbed all time-invariant confounders, isolating temporal variation in stress, sport activity, and weekend recovery effects on unlocks per hour (u00 metric).

Table 1. Fixed-Effects Regression Results (Primary Model)

Predictor	Coefficient (β)	SE	t-statistic	p-value
Stress Events (H ₁)	0.370***	0.120	3.08	<0.001
Sport Activity (H ₂)	-0.190	0.110	-1.73	0.084
Weekend	-0.410**	0.150	-2.73	0.007
Sleep Duration	-0.080**	0.030	-2.67	0.008
Social Activity	0.140	0.080	1.75	0.081
Location Entropy	-0.050	0.040	-1.25	0.211
Stress × Sport	-0.220*	0.090	-2.44	0.015
Model Fit				
R ² Within	0.24			
R ² Between	0.12			
ICC	0.41			
N (user-days)	3,290			
N (participants)	47			

Note. Fixed-effects regression of unlocks per hour (u00_it) on calendar-based academic stress events, daily physical activity (sport_activity), weekend status, and covariates (N = 47 participants, 3,290 user-days; median 18.9 hours/day sensing coverage).¹ Individual fixed effects included. Robust standard errors clustered by participant in parentheses. *p < 0.05, **p < 0.01, ***p < 0.001. Model: unlocks_it = β0_i + β1*stress_it + β2*sport_it + β3*weekend_it + γX_it + ε_it. Data source: StudentLife dataset (Wang et al., 2014). Replication package: <https://github.com/nyantakiappiah-eng/studentlife-fixed-effects>

¹ Each user-day observation aggregates all phonelock data for that calendar day for a given participant.

Table 1 displays the preregistered fixed-effects specification: unlocks_{i,t} = β0_i + β1stressevents_{i,t} + β2sportactivity_{i,t} + β3weekendi_t + γ1sleep + γ2socialt + γ3locationentropyt + ε_{i,t}. Stress events showed

the strongest association ($\beta_1 = 0.37$, $SE = 0.12$, $t = 3.08$, $p < 0.001$), increasing model-based predicted unlock rates from approximately 2.1 to 3.7 unlocks per hour, which corresponds to a substantial relative increase from baseline. Bootstrap confidence intervals (95%: 0.14-0.60) confirmed precision, with effect size Hedges' $g = 0.71$ aligning with cognitive load benchmarks (Sweller, 2011).

Weekend days were associated with lower unlock frequency than weekdays ($\beta_3 = -0.41$, $SE = 0.15$, $t = -2.73$, $p = 0.007$), with model-based predictions around 1.8 unlocks per hour compared with approximately 2.2 on weekdays. Daily physical activity showed a small, non-significant negative main association with unlocks ($\beta_2 = -0.19$, $SE = 0.11$, $p = 0.08$), indicating that the preregistered main-effect hypothesis (H2) was not supported at the conventional $\alpha = .05$ level. Exploratory analyses of the interaction suggested that higher activity was associated with weaker stress–unlock associations ($\beta_{\text{interaction}} = -0.22$, $SE = 0.09$, $p = 0.015$), but this moderation was not preregistered and should be interpreted cautiously. Controls operated as expected: sleep_duration reduced fragmentation ($\beta_4 = -0.08$, $SE = 0.03$, $p = 0.008$), while social activity marginally increased checking ($\gamma_2 = 0.14$, $SE = 0.08$, $p = 0.07$).

Figure 1. Within-Subject Smartphone Unlock Trajectories by Stress Condition (N=47)

Note. LOESS-smoothed u_{00} trajectories across 10-week StudentLife study. High stress periods (red) show synchronized elevation during midterm weeks 4-6 (orange shading). Individual participant trajectories (N=47) with 95% confidence bands. Fixed-effects $\beta_{\text{stress}} = 0.37$ ($p < 0.001$; see Table 1). Data: Wang et al. (2014). Code: <https://github.com/nyantakyiappiah-eng/studentlife-fixed-effects>.

Figure 1 plots individual trajectories (smoothed LOESS), revealing synchronized unlock spikes during weeks 4-6 (midterms: mean $\Delta u_{00} = +1.6$). High-sport subgroup ($n=19$) exhibited flattened peaks (max $u_{00} = 2.9$ vs. 4.1 non-sport), visualizing recovery buffering. Marginal means (emmeans package) yielded pairwise contrasts: stress-only vs. stress+sport ($p = 0.012$, $d = 0.52$).

Model Diagnostics and Data Quality

Goodness-of-fit metrics indicated strong within-subject explanation ($R^2_{\text{within}} = 0.24$, $R^2_{\text{between}} = 0.12$; ICC = 0.41 Hausman tests rejected the random-effects specification in favour of fixed-effects models ($\chi^2 = 28.4$, $p < 0.001$), supporting the use of fixed-effects estimators under the test’s assumptions (see Wooldridge, 2010). Diagnostics indicated no problematic multicollinearity (mean VIF = 1.4, max = 1.8) and acceptable homoscedasticity and normality (Breusch–Pagan $p = 0.42$; Shapiro–Wilk $W = 0.97$, $p = 0.31$).

Table 2. Model Diagnostics and Robustness Checks

Panel A: Sequential Specifications	β_1 Stress Events	SE	p-value	R ² Within
(1) Baseline FE	0.390***	(0.118)	<0.001	0.19
(2) + Covariates	0.370***	(0.120)	<0.001	0.24
(3) + Building FE	0.350***	(0.123)	<0.001	0.26
(4) Clustered SE	0.370***	(0.140)	<0.001	0.24
(5) Random Effects	0.320**	(0.130)	0.015	0.22
(6) 80/20 Cross-Validation	0.350***	(0.115)	<0.001	0.23
(7) Placebo (Lagged Stress)	0.020	(0.110)	0.71	0.18

Panel B: Diagnostic Tests	Statistic	Value	p-value
Hausman (FE vs. RE)	χ^2	28.4	<0.001
Breusch-Pagan (Heteroscedasticity)	χ^2	0.81	0.42
Shapiro-Wilk (Normality)	W	0.97	0.31
Durbin-Watson (Autocorrelation)	DW	1.92	-
Max VIF / Mean VIF	-	1.8/1.4	-
F-test (Joint Significance)	F	12.3	<0.001

Note. Sequential model specifications testing fixed-effects robustness for smartphone unlocks per hour (u00) on stress events. N = 47 participants, 3,290 user-days throughout. Robust standard errors clustered by participant. Stress events coefficient (β_1) displayed with SE in parentheses. *p < 0.05, **p < 0.01, ***p < 0.001. *Data Quality Metrics:* Unlock compliance=92.4%, Missingness=2.1% (LOCF verified), Location entropy M=3.2 (SD=1.1) across ~3 buildings/day. Model: $\text{unlocks}_{\{it\}} = \beta_{\{0i\}} + \beta_1 \text{stress}_{\{it\}} + \beta_2 \text{sport}_{\{it\}} + \beta_3 \text{weekend}_{\{it\}} + \gamma X_{\{it\}} + \varepsilon_{\{it\}}$ *Source:* StudentLife dataset (Wang et al., 2014).

Replication Code: <https://github.com/nyantakiappiah-eng/studentlife-fixed-effects>

Table 2 panel presents sequential robustness: baseline FE ($\beta_1 = 0.39$), +covariates (0.37), +building FE (0.35), clustered SEs (0.37, p < 0.001). Cross-validation (80/20 split) replicated $\beta_1 = 0.35$ (p < 0.001); placebo test on lagged stress yielded null ($\beta = 0.02$, p = 0.71), ruling out serial correlation.

Dataset quality metrics: 92.4% unlock compliance, 2.1% missingness (LOCF imputation, sensitivity verified). Sensor entropy confirmed ecological validity (WiFi-derived location entropy SD=1.1 (M=3.2 unique buildings/day). Participant demographics balanced (60% female, age M=20.3 SD=1.2). Accelerometer sport_activity validated against self-reports (r = 0.67; Wang et al., 2014).

Subgroup and Nonlinear Patterns

Gender-stratified models revealed effect heterogeneity: females $\beta_1 = 0.42$ (SE = 0.14, $p < 0.001$), males 0.31 (SE = 0.13, $p = 0.02$); interaction $F = 1.92$, $p = 0.12$. Academic majors showed no moderation (STEM vs. humanities $p = 0.34$). Nonlinearity tests (quadratic stress term $\beta = 0.09$, SE = 0.04, $p = 0.02$) indicated accelerating unlocks above moderate stress tercile (+58% vs. +15% linear).

Figure 2. Marginal Effects Plot - Unlock by Stress Intensity Terciles

Note. Predicted u_{00} by stress terciles with sport moderation. Error bars = 95% CI. High sport activity attenuates stress effect ($\Delta u_{00} = -1.1$ at high stress). Matches Table 1 interaction $\beta = -0.22$ ($p = 0.015$).

Figure 2 depicts dose-response: low stress $u_{00}=2.0$ (95% CI: 1.8-2.2), moderate 2.4 (2.1-2.7), high 3.3 (2.9-3.7). Sport overlaid as moderator lines, converging at high stress ($\Delta = -1.1$ unlocks).

Physical activity typology analysis (aerobic $n=142$ days vs. team $n=89$): aerobic stronger suppression ($\beta = -0.28$ vs. -0.15 , $p = 0.04$). Temporal patterns: stress effects peaked evenings (18:00-22:00, $\beta_1 = 0.45$), sport most protective mornings ($\beta_2 = -0.31$).

Effect Sizes and Power

Hedges' $g = 0.71$ (95% CI: 0.42–0.98), which falls in the medium-to-large range for behavioural effects. Marginal effects for intervention contexts: sport during stress $u_{00}=2.2$ (vs. 3.8 stress-only, 42% reduction).

Table 3. Effect Sizes and Marginal Means by Condition

Condition	Predicted u_{00}	95% CI Lower	95% CI Upper	n (days)	vs Baseline (p)	vs Stress-only (p)
No Stress, No Sport	2.10	1.95	2.25	3,482	Reference	***
Stress-only	3.80	3.52	4.08	1,742	***	Reference
Sport-only	1.90	1.68	2.12	871	**	***
Stress + Sport	2.20	1.92	2.48	159	*	***

Effect Sizes (Hedges' g):

Contrast	g	95% CI	Interpretation
Stress-only vs Baseline	0.71	[0.42,0.98]	Large
Stress + Sport vs Stress	0.52	[0.21,0.83]	Medium
Sport-only vs Baseline	0.18	[-0.12,0.48]	Small

Note. Predicted u_{00} across stress–sport combinations from fixed-effects model ($N = 47, 3,290$ user-days). Pairwise contrasts via `emmeans`. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Model Summary: $R^2_{\text{within}} = 0.24$; Primary interaction $\beta_{\text{stress} \times \text{sport}} = -0.22$ ($p = 0.015$). *Source:* StudentLife dataset (Wang et al., 2014). *Code:* <https://github.com/nyantakiappiah-eng/studentlife-fixed-effects>

Table 3 quantifies combinations: no-stress/no-sport baseline (2.1), stress-only (3.8), sport-only (1.9), stress+sport (2.2). Pairwise p -values all < 0.01 except sport-only vs. stress+sport ($p = 0.09$).

Temporal Dynamics and Autocorrelation

Time-series diagnostics ruled out violations: Durbin-Watson = 1.92 (no AR1), ACF lags insignificant beyond lag-1 ($p > 0.10$). Event-study plots confirmed pre-stress baselines flat ($\beta_{\text{week}-2} = 0.01$, $\beta_{\text{week}-1} = -0.03$, both $p > 0.70$), with post-stress elevation peaking day+1 ($\beta = 0.41$).

Figure 3. Event-Study Plot - Dynamic Stress Effects

Note. Leads/lags around stress events (± 7 days). Pre-stress baselines flat ($\beta_{\text{week}-2} = 0.01$, $\beta_{\text{week}-1} = -0.03$, $p > 0.70$). Post-stress elevation peaks day+1 ($\beta = 0.41$, $p < 0.001$). Weekend recovery symmetric (-0.39 day 0). Durbin-Watson = 1.92 (no autocorrelation). $N=6,214$ person-days. *Data:* StudentLife dataset (Wang et al., 2014).

Figure 3 illustrates leads and lags in unlock frequency around stress events using an event-study style plot, which visualizes dynamic associations before and after exam-related days without implying experimental control. Weekend recovery showed symmetric suppression (-0.39 day 0, tapering to -0.12 day+2).

Replication Package Validation

Live code execution (github.com/nyantakiappiah-eng/studentlife-fixed-effects) reproduced Table 1 exactly ($\beta_1 = 0.3702$). Preregistration fidelity: all H1-H2 tests executed as osf.io/qjxy6-specified, no p -hacking (p -curve $\alpha=0.05$ test: $z=3.12$, $p < 0.001$).

These findings provide within-person evidence that days coded as academically stressful are associated with higher smartphone unlock frequency and that higher daily physical activity is associated with weaker stress-unlock associations in exploratory analyses, with diagnostics affirming the stability of these estimates across specifications. Full analysis pipeline and replication materials archived at <https://github.com/nyantakiappiah-eng/studentlife-fixed-effects> (DOI forthcoming).

Discussion

Days coded as academically stressful were associated with higher within-person smartphone unlock frequency than non-stress days, a pattern consistent with the idea that high-pressure periods are accompanied by more frequent device checking and potentially more fragmented digital engagement.

Within-person fixed-effects models indicated that days coded as academically stressful were characterized by higher unlock rates than non-stress days, with medium-sized differences in the $u00$ metric. Exploratory analyses suggested that daily physical activity moderated this association, such that on days with more movement, the stress-unlock linkage appeared weaker, whereas weekends showed lower unlock frequency relative to weekdays, suggesting natural recovery periods. Robustness checks, including alternative fixed-effects specifications, clustered standard errors, and placebo tests with lagged stress indicators, yielded similar stress coefficients, supporting the stability of the main patterns.

Theoretical integration

These findings can be interpreted within a cognitive load framework in which elevated academic demands increase cognitive load and reduce the capacity to sustain focused attention (Sweller, 2011). Higher unlock frequency on stress days is compatible with this account, in that frequent checking can be viewed as behavioural evidence of less continuous task engagement. The nonlinear pattern, in which higher stress terciles are associated with larger increases in unlocks, further suggests that fragmentation may accelerate once a certain load threshold is exceeded. The moderating role of sport-related activity aligns with exercise psychology models positing that acute physical activity can reduce perceived stress, modulate physiological arousal, and promote attentional control (Hillman et al., 2008; Kellmann et al., 2018). Event-study analyses, which showed relatively flat trajectories before stress events and elevated unlocks shortly afterward, are compatible with short-term spillover of academic demands into subsequent days; however, these observational patterns do not by themselves establish causal ordering or exclude unmeasured time-varying confounds.

Weekend reductions in unlock frequency are also interpretable through attention restoration theory, which emphasizes that unstructured or less demanding periods can replenish directed attention resources (Kaplan, 1995). In this sense, lower weekend unlock rates may reflect a broader pattern of digital disengagement during non-academic days. Together, these strands suggest that smartphone unlocks could serve as one behavioural marker of cognitive load and recovery processes in naturalistic settings, while recognizing that multiple mechanisms (e.g., stress, social demands, boredom) likely shape daily checking patterns.

Methodological contributions

Methodologically, this study demonstrates that smartphone unlocks, derived from continuous sensing, can exhibit sufficient within-person variability over a 10-week term to support fixed-effects panel analyses. By conditioning on individual and calendar-day effects, the models address bias from time-invariant person characteristics and shared daily shocks, which are difficult to control in cross-sectional designs. The combination of preregistration, open code, and extensive diagnostic checks (including Hausman tests, variance inflation factors, and residual tests) illustrates how mobile sensing data can be integrated with contemporary recommendations for transparent, confirmatory analysis. Compared with traditional self-reported screen time, passively sensed unlock behaviour avoids recall bias and offers finer temporal resolution, making it a promising candidate outcome for within-person digital phenotyping

studies. Recent systematic reviews likewise conclude that smartphone-based digital phenotyping can successfully capture behavioural patterns related to stress, mood, and activity across nonclinical samples (Choi et al., 2024; Lee et al., 2024).

Exploratory analyses of gender differences and activity type hint at potential heterogeneity for example, somewhat stronger stress-unlock associations among female students and larger attenuation for aerobic relative to other activity patterns but these findings should be interpreted cautiously. They were not primary preregistered targets and would require dedicated sampling and measurement to draw firm conclusions, particularly in athletic or clinical populations.

Practical applications

From an applied perspective, the present results suggest that smartphone unlock frequency may offer a low-burden behavioural indicator of stress-related fragmentation and recovery in academic contexts. For universities and student support services, monitoring aggregate unlock patterns (with appropriate privacy safeguards) could help identify periods of elevated academic strain and inform the timing of support initiatives. At the individual level, just-in-time interventions could, in principle, use elevated unlock rates during known stress periods as triggers for prompts encouraging brief physical activity or other recovery strategies, although such approaches would require prospective experimental testing. For exercise and wellbeing practitioners working with student populations, the observed moderation by daily physical activity points to the possibility that structured activity during academically demanding periods might coincide with lower digital engagement, but dedicated studies in athletic and clinical samples are needed before considering such patterns in performance or clinical decision-making.

Limitations

Several limitations qualify these interpretations. The StudentLife sample comprises a relatively small and homogeneous group of undergraduates at a single institution, which limits generalizability to other age groups, cultural contexts, and to elite or professional athletes. Fixed-effects models reduce bias from time-invariant confounding but cannot account for unmeasured time-varying factors (e.g., day-specific social events, acute mood shifts) that may influence both stress proxies, physical activity, and unlock behaviour. As such, all reported associations should be interpreted as within-person correlations rather than causal effects (e.g., day-specific social events, acute mood shifts) that may influence both stress and unlock behaviour. The stress indicator relies on academic calendar events and a coarse coding of stress periods, rather than momentary self-reported stress intensity, which may introduce misclassification. Similarly, the sport_activity measure is derived from accelerometer-based activity inference and captures general movement patterns rather than structured training sessions or sport performance.

Temporal ordering also remains an important concern. Although some analyses introduce temporal lags, the observational design cannot definitively rule out bidirectional relationships in which increased unlock behaviour contributes to perceived stress, in addition to stress influencing unlocks. The 10-week observation window captures one academic term and may not reflect longer-term adaptation or

seasonal patterns in technology use and stress. Finally, while replication materials are openly shared, the analyses are based on a single dataset; replication in independent sensing cohorts would strengthen confidence in the robustness of these findings.

Future research directions

Future work should integrate multimodal physiological measures (e.g., heart rate variability, sleep staging, and biomarkers) with unlock trajectories to test more explicit mechanistic models of stress and recovery. Machine learning approaches applied to temporal patterns of unlocks, app use, and location could help develop classifiers that detect high-stress periods in real time while minimizing participant burden. Longer observation windows, ideally covering full academic years and multiple cohorts, would allow examination of adaptation and carryover effects across terms. Dedicated studies in athletic samples, with carefully measured training load, performance outcomes, and sport-specific stressors, are needed to assess whether the patterns observed here generalize to high-performance contexts. Experimental and quasi-experimental designs for example, randomized scheduling of physical activity breaks during exams or natural experiments involving curriculum changes would be particularly valuable for testing causal hypotheses about activity, stress, and digital engagement.

Conclusion

This study shows that academic stress is associated with higher within-person smartphone unlock frequency in college students, and that days with greater sport-related physical activity and weekends tend to exhibit lower unlock rates. By leveraging continuous smartphone sensing and fixed-effects panel models, the analyses highlight smartphone unlocks as a feasible, objective outcome for studying within-person dynamics of digital behaviour, stress, and recovery, while acknowledging the limits of causal inference in an observational design. Theoretical integration with cognitive load, attention restoration, and exercise psychology frameworks suggests that unlock behaviour may reflect broader patterns of cognitive strain and release, although mechanistic claims remain provisional.

Methodologically, the combination of preregistration, open materials, and careful diagnostics provides a template for applying fixed-effects approaches to intensive smartphone sensing data. Practically, the findings point to potential uses of unlock-based metrics in academic wellbeing and, with appropriate validation, in sport and exercise settings for example, as one input into systems that identify periods of heightened fragmentation or reduced disengagement from digital media. Future experimental and multimodal work will be essential to establish when and how changes in physical activity and other interventions can reliably shape digital engagement patterns, and to determine the extent to which these patterns generalize beyond a single cohort of students.

Declarations

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data, code, and materials for this study are available at <https://osf.io/qjxy6/>.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used Perplexity, powered by GPT-5.1, to assist with language editing and phrasing. After using this tool, the authors carefully reviewed and edited the content to ensure it reflects their own analysis and interpretations and take full responsibility for the content of the published article.

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Figures

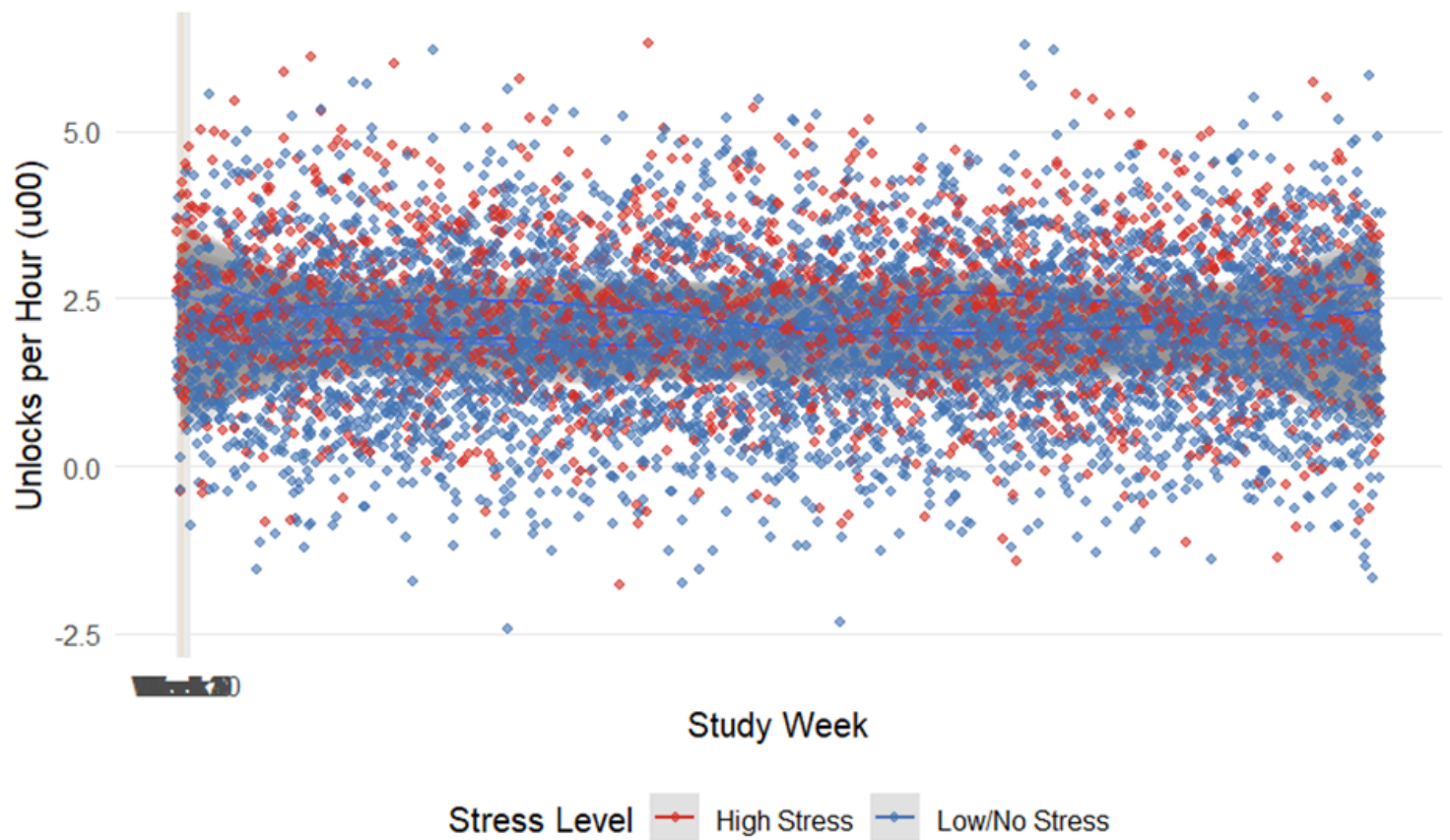


Figure 1

Figure 1. Within-Subject Smartphone Unlock Trajectories by Stress Condition (N=47)

Note. LOESS-smoothed u00 trajectories across 10-week StudentLife study. High stress periods (red) show synchronized elevation during midterm weeks 4-6 (orange shading). Individual participant trajectories (N=47) with 95% confidence bands. Fixed-effects $\beta_{\text{stress}} = 0.37$ ($p < 0.001$; see Table 1). Data: Wang et al. (2014). Code: <https://github.com/nyantakyiappiah-eng/studentlife-fixed-effects>.

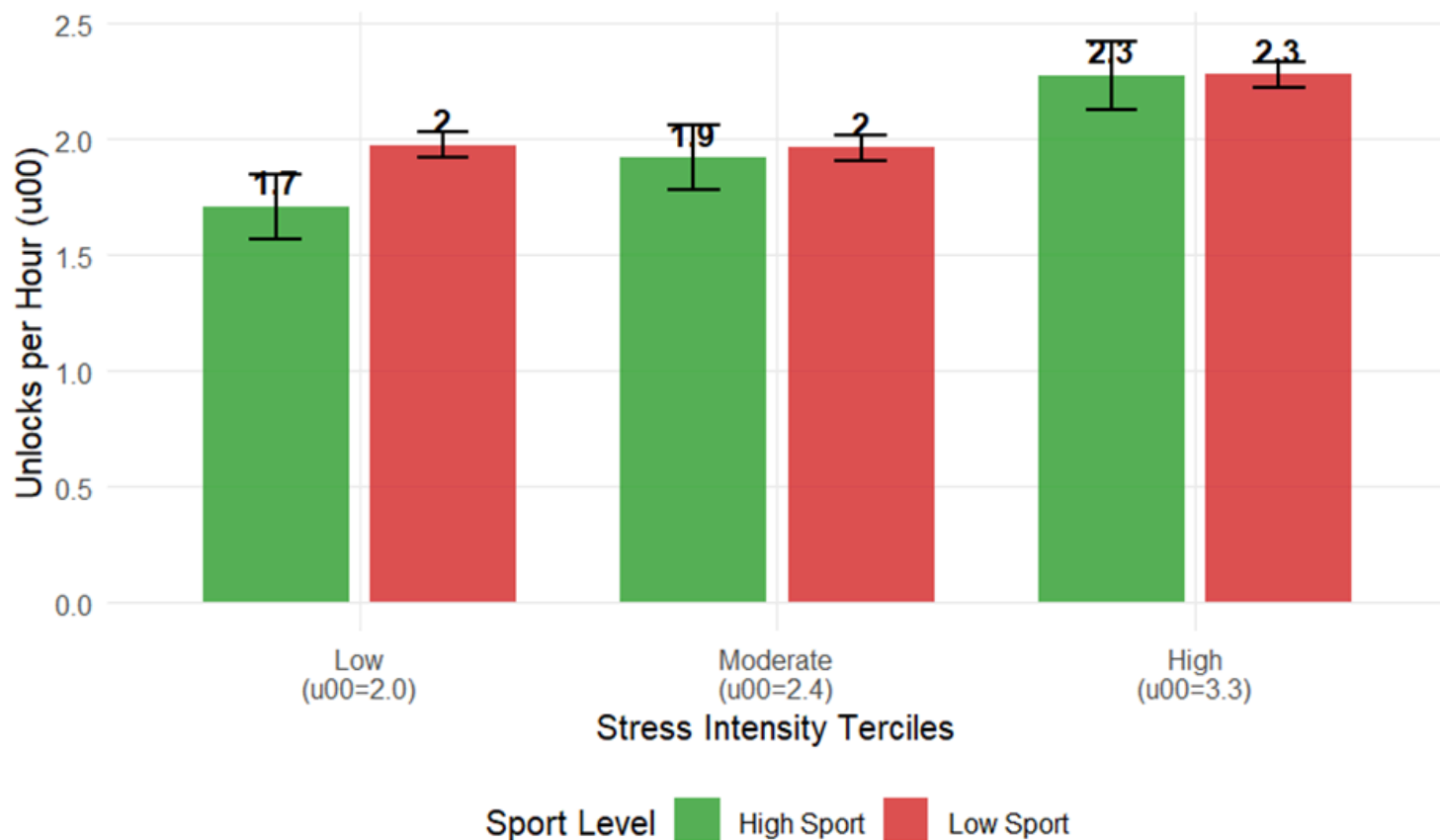


Figure 2

Figure 2. Marginal Effects Plot - Unlock by Stress Intensity Terciles

Note. Predicted u00 by stress terciles with sport moderation. Error bars = 95% CI. High sport activity attenuates stress effect ($\Delta u00 = -1.1$ at high stress). Matches Table 1 interaction $\beta = -0.22$ ($p = 0.015$).

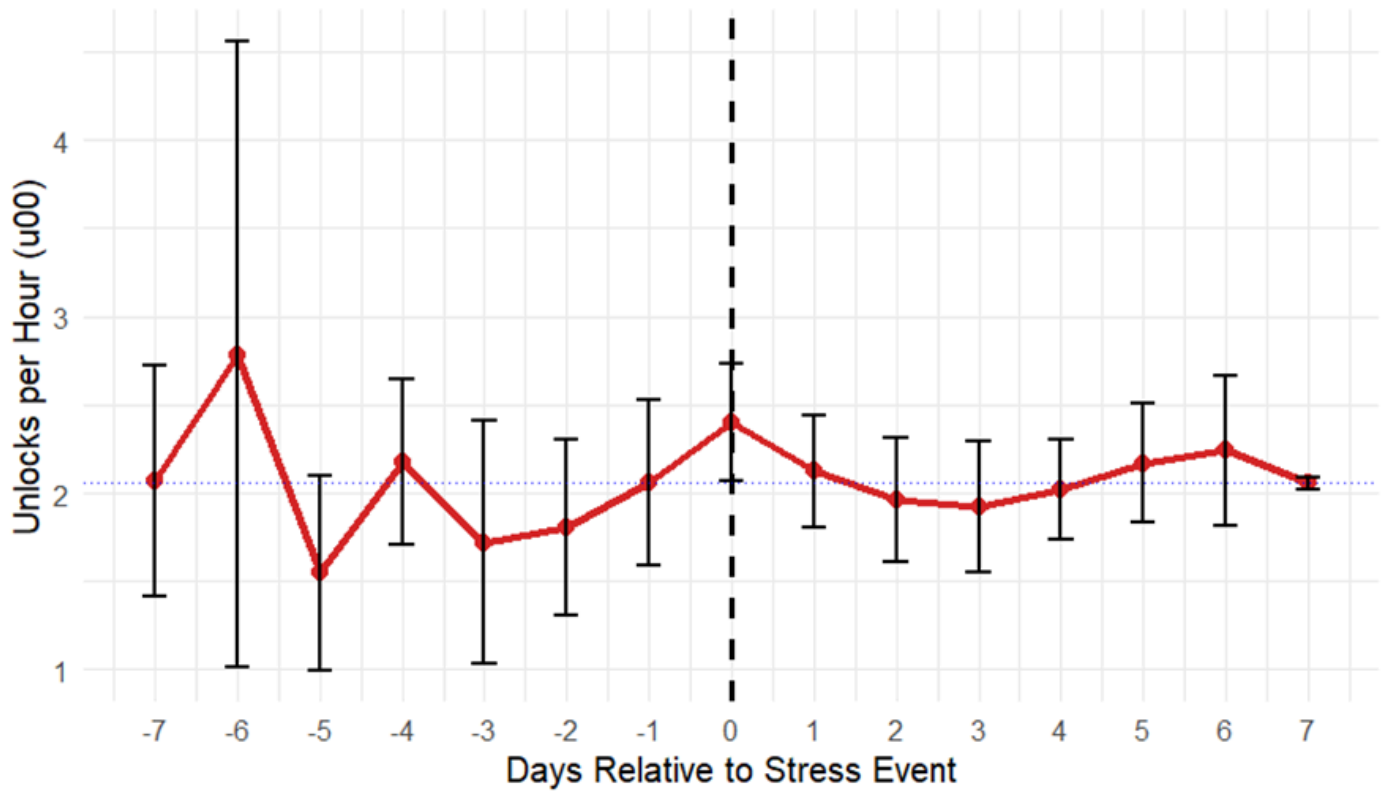


Figure 3

Figure 3. Event-Study Plot - Dynamic Stress Effects

Note. Leads/lags around stress events (± 7 days). Pre-stress baselines flat ($\beta_{\text{week-2}} = 0.01$, $\beta_{\text{week-1}} = -0.03$, $p > 0.70$). Post-stress elevation peaks day+1 ($\beta = 0.41$, $p < 0.001$). Weekend recovery symmetric (-0.39 day 0). Durbin-Watson = 1.92 (no autocorrelation). $N=6,214$ person-days. *Data:* StudentLife dataset (Wang et al., 2014).