Management, Sustainability, and Life Span
2025, Vol. 1, No. 1, 11 – 27
https://doi.org/10.64780/msl.v1i1.110

MANAGEMENT, SUISTAINABILTY, AND LIFE SPAN
e-ISSN: xxxx-xxxx

OPEN ACCESS | Research Article

Managing Digital Notifications and Stress: Evidence from a Hybrid Laboratory and Field Study on Cognitive Load, HRV, and Well-being

Husnain Mukhdoom*[1] and Joseph A. Villarama[2]
[1] Famous Forum of Worldwide Collaborators, Lahore, Pakistan
[2] Central Luzon State University, Philippines

ABSTRACT

Modern stress is suspected to be caused by constant digital notifications and fast task switching but causal data and applicable solutions are still in pieces. Our study is a hybrid study (A) (N=120) a laboratory experiment (randomization) comparing constant (control) and 15-minute batch notification (group) participants completing single- and dual-task blocks (2-back, Stroop, SART, email triage); and (B) a 14-day A-B-A field study (N=100) of a pragmatic bundle-system Focus/Do-Not-Disturb with a priority allow-list, batched releases, two daily 50-minute focus blocks, and scheduled email Constant notifications at the lab raised workload (NASA-TLX), decreased RMSSD, and worsened accuracy, and bigger penalties were raised in the case of the dual-task demand. Intervention, in the field, decreased the rate of notification (~50%), decreased EMA stress (~6.5 points) and enhanced morning RMSSD (~5-6 ms); all of which recovered partially on washout. Multilevel models demonstrated dose-response associations between notification rate, stress and HRV; within-person mediation was in a relationship with interruptions -cognitive load -stress pathway. There was greater higher media multitasking benefits, smaller benefits from higher self-control, and greater benefits from FoMO and trait anxiety. The results justify the use of a stratified process in form of device defaults, workflow organization and team norms to harmonize the ecology of notification with attentional boundaries of humans.

ARTICLE HISTORY
Received: 5 February 2025
Revised: 27 March 2025
Accepted: 30 May 2025

KEYWORDS
Digital Notifications; Stress Management; Cognitive Load; Heart Rate Variability; Digital Well-being

PUBLISHER'S NOTE

CORRESPONDING AUTHOR
Husnain Mukhdoom, Famous Forum of Worldwide Collaborators, Lahore, Pakistan. Email: husnainmukhdoom06@gmail.com

Cite this article:
H. Mukhdoom and J. A. Villarama, "Managing Digital Notifications and Stress: Evidence from a Hybrid Laboratory and Field Study on Cognitive Load , HRV , and Well-being," *Manag. Sustain. Life Span.*, vol. 1, no. 1, pp. 11–27, 2025.https://doi.org/10.64780/ijom.v1i1.110

Introduction

Digital notifications system-generated alerts from messaging applications, emails, social platforms, and work-related tools have become ubiquitous in modern knowledge work, often generating dozens or even hundreds of daily interruptions. At the same time, multitasking, characterized by rapid switching between competing demands, has become the default interaction mode with digital ecosystems. Together, frequent interruptions and constant task switching are consistently linked to elevated stress, attentional fragmentation, and diminished performance [1], [2]. Even seemingly trivial alerts can disrupt encoding and problem-solving processes in educational or professional contexts, with experimental evidence showing that push notifications delivered during study or lecture blocks significantly impair performance [3], [4].

While the intuitive response of "turning everything off" is increasingly advocated, empirical evidence indicates that silencing notifications may be counterproductive for individuals with high fear of missing out (FoMO) or strong affiliation needs [5], [6]. For such users, disabling notifications can exacerbate compulsive checking behaviors and preoccupation, thereby increasing stress rather than reducing it [7], [8], [9]. These findings underscore that notification management strategies cannot rely solely on blanket silencing approaches but must account for individual differences in dispositions and coping mechanisms.

Theoretically, three frameworks converge to explain how notifications drive stress. First, the transactional model of stress posits that stress arises when perceived demands exceed coping resources, with frequent and unpredictable alerts likely to bias appraisals toward loss of control, especially under time pressure [10]. Second, cognitive load theory suggests that interruptions and rapid switching impose switching costs, inflate subjective workload, and diminish executive control [11], [12]. Third, interruption science demonstrates that higher interruption frequency predicts greater workload and exhaustion, moderated by task complexity and relevance [13], [14], [15]. Collectively, these perspectives highlight notifications as a potent stressor that undermines both cognitive performance and well-being.

Despite the availability of digital well-being toolkits such as batching summaries, Focus/Do Not Disturb modes, and quiet hours empirical evidence about their comparative effectiveness remains limited and fragmented. Prior interventions have yielded mixed results, with some studies reporting negligible behavioral changes following notification disabling [6], while others show small benefits from stricter restrictions or design nudges [9]. Critically, few studies have integrated physiological indicators (e.g., heart rate variability, HRV) with subjective stress and performance metrics, nor have they systematically examined moderators such as FoMO, media multitasking orientation, or trait anxiety.

This study addresses these gaps by combining a controlled laboratory experiment with a 14-day field study, thereby triangulating causal inference with ecological validity. Specifically, we (a) quantify the causal impact of constant versus batched or silenced notifications on stress, HRV, and task performance; (b) test a pragmatic intervention bundle (batched delivery, scheduled focus blocks, and email windows) in real-world settings; and (c) explore mediating and moderating mechanisms to identify for whom and through which pathways notification management strategies are most effective. By integrating subjective, physiological, and performance outcomes across both controlled and naturalistic contexts, this work advances theoretical understanding of digital stress while offering practical guidance for organizational policy and individual coping strategies.

Methods

Research Design

This study employed a hybrid design that integrated a tightly controlled laboratory experiment with a 14-day field study to estimate both short-term causal effects and ecological validity. The two components were linked through harmonized measures, including self-report, psychophysiological indicators, digital traces, and unified constructs such as interruption rate, cognitive load, stress, and performance.

In the laboratory phase, participants (≈90–110 minutes per session) were randomly assigned to one of three notification conditions. In the *constant* condition, all push notifications from email, messaging, calendar, and work applications were delivered immediately with default alerts. In the *batched* condition, notifications were silently queued and released every 15 minutes in a single bundle with vibration only. In the *silent/focus* condition, system-level Focus/Do-Not-Disturb was enabled, allowing only critical contacts and calendar alarms. Within each condition, participants completed both single-task blocks comprising a 2-back working memory task, a Stroop color-word test, and the Sustained Attention to Response Task (SART) and dual-task blocks, in which each cognitive task was paired with an email triage micro-task requiring intermittent switching. Interruption exposure was standardized through scripted notifications drawn from realistic organizational and social sources, delivered at pre-defined intervals according to condition. All devices were provisioned by the research team to ensure uniformity.

The field phase adopted a within-person A–B–A protocol spanning 14 days. Participants installed a passive logger and an ecological momentary assessment (EMA) application on their smartphones and, where applicable, laptops. During the baseline period (Days 1–5), participants used their usual notification settings while data logging and EMA sampling were conducted. During the intervention period (Days 6–10), devices were configured with Focus/Do-Not-Disturb, notifications were batched every 30–60 minutes, two 50-minute focus blocks were scheduled daily, and email windows were fixed at 10:30, 14:30, and 16:30. In the washout period (Days 11–14), participants reverted to their preferred notification settings while logging and EMA continued. Weekend days, when included, were treated descriptively and excluded from primary contrasts unless participants' work schedules regularly included weekends.

Participants and Recruitment

Adults aged 18 to 60, who self-reported using smartphones for work or study for at least 2 hours per day, and regularly engaged with email or messaging applications, were eligible for participation. Exclusion criteria included known cardiac arrhythmia (due to HRV safety concerns), dermatological conditions preventing the use of electrodermal activity (EDA) sensors, recent changes in psychotropic medication, and vision or color blindness that could interfere with the Stroop task.

Participants were recruited via university and workplace mailing lists, social media posts, and flyers. All participants provided informed consent prior to participation and were compensated according to the time committed and data completeness. In the laboratory, participants received a fixed stipend, while field participants were given a pro-rated incentive, with a performance bonus linked to their completion rate of ecological momentary assessments (EMA).

Sample Size and Statistical Power

For the laboratory experiment, the target sample size was 120 participants, with approximately 40 participants assigned to each of the three notification conditions. This sample size provides 0.80 power to detect medium effects (Cohen's $d \approx 0.4$) on primary outcomes such as changes in HRV (RMSSD) and SART commission errors. The design incorporated a 3-level between-subjects factor for notification condition and a within-subjects task demand factor ($\alpha = 0.05$, two-tailed), assuming moderate correlation between repeated measures.

In the field study, 100 participants were targeted, each completing 8–10 EMAs per day across 10 workdays, yielding over 1,000 person-days. This design powered multilevel models to detect small within-person effects ($\beta \approx 0.10$–0.15) of the intervention on EMA stress and HRV, with random slopes to account for individual variability. The study's analysis plans, primary and secondary outcomes, and stopping rules were preregistered, with recruitment ceasing once at least 120 usable laboratory sessions were completed.

Measures

Stress was assessed using the Perceived Stress Scale (PSS-10), administered before and after the laboratory session, and on Days 1, 10, and 14 in the field to gauge perceived stress over the previous week. The DASS-21 Stress Subscale was also used pre- and post-lab, and on Days 5 and 10 in the field. Ecological momentary assessment (EMA) was employed to assess real-time stress, where participants rated their current stress level on a 0–100 scale during 6–8 prompts each workday, stratified by time of day, with optional free-text responses for additional context. Cognitive load was measured with the NASA Task Load Index (NASA-TLX) after each task block in the laboratory and once per focus block in the field. This short form assesses mental demand, effort, and frustration. Mind-wandering probes were intermittently administered during tasks, asking whether participants were thinking about the task, with responses recorded as "yes/no" and a slider to rate the intensity of distraction.

Physiological measures included Heart Rate Variability (HRV), with RMSSD as the primary measure and LF/HF as an exploratory metric, collected using chest-strap or wrist sensors. In the laboratory, HRV was recorded during a 5-minute seated baseline, continuously throughout the tasks, and again during a 5-minute recovery period. In the field, HRV was recorded during a daily 5-minute morning seated reading, with additional optional 2-minute recordings before and after focus blocks. Electrodermal activity (EDA) was measured using palmar or wrist sensors in the laboratory, with field data being collected from a subsample. Salivary cortisol samples were collected from a subset of participants at pre-session, +20 minutes, and +40 minutes post-task to assess diurnal reactivity, with samples stored and assayed in batches.

Task performance was measured using several cognitive tasks. The 2-back task was used to measure accuracy and median reaction time (RT), with signal detection metrics (d' and β) calculated. The Stroop task measured interference scores (difference between incongruent and congruent RT) and errors. The Sustained Attention to Response Task (SART) assessed commission errors (failures to withhold responses) and RT variability. An email triage task was also included, measuring the number of emails processed, response latency, classification accuracy, and error types.

Digital traces were collected to quantify interruptions and task engagement. Notification counts and timing were tracked for each app/channel, including screen-on time, app opens, and operating system-level Focus/Do-Not-Disturb (DND) status, using device APIs. A desktop logger, if applicable, recorded window switches and keyboard/mouse activity, anonymizing application names without capturing content. Interruption rate was defined as the number of notifications per focused-work minute and, separately, the number of app switches per minute.

Individual differences and potential moderators were assessed using several scales, including the Media Multitasking Index (MMI), the Fear of Missing Out (FoMO) scale, trait anxiety (short STAI), and the Brief Self-Control Scale. Participants also completed the Morningness-Eveningness Questionnaire to assess chronotype. Demographic data, such as role, industry, and work context (remote/on-site, typical work hours), were recorded as part of the study.

Procedures

In the laboratory session, participants were first checked for eligibility and provided informed consent. Sensors were then fitted, and environmental conditions were standardized in a quiet room with a temperature of 21–23°C. Baseline measures were taken, including the Perceived Stress Scale (PSS-10), the DASS-Stress subscale, a 5-minute resting HRV recording, and baseline electrodermal activity (EDA). Participants were then randomly assigned to one of the three notification conditions through computerized simple randomization (1:1:1), stratified by gender and the Media Multitasking Index (MMI) tertile to balance potential moderators.

The laboratory task consisted of two counterbalanced cycles of single-task and dual-task blocks. Each block included the Stroop task (6 minutes), the Sustained Attention to Response Task (SART; 8 minutes), and the 2-back working memory task (6 minutes), with brief 2–3-minute rest periods between tasks. Scripted notifications, designed to simulate realistic organizational and social interactions, were delivered at predefined intervals based on the assigned notification condition (constant, batched, or silent/focus). Following each task block, participants completed the NASA-TLX workload assessment and responded to mind-wandering probes.

A 5-minute seated recovery period was provided, during which HRV and EDA were measured. At the end of the session, participants completed the post-session PSS-10 and DASS-Stress assessments, sensors were removed, and a debriefing session was conducted to explain the purpose of the study and the notification scripts. To maintain ecological plausibility, the notification content referenced calendar invites, team chats, and personal messages; however, any personally identifiable content was fictionalized. Participants were instructed not to interact with their phones beyond the task requirements.

In the field study, participants underwent an onboarding procedure, either remotely or in person. This included the installation of the logger and EMA apps, verification of data capture, and a tutorial on the focus blocks and email window settings. A baseline survey was administered to capture participant traits. During the baseline phase (Days 1–5), participants were instructed to use their devices as usual. EMA prompts were sent at quasi-random intervals during the morning, midday, and late afternoon, and daily morning HRV readings were recorded.

During the intervention phase (Days 6–10), the researcher assisted participants in configuring their operating system's Focus/Do-Not-Disturb (DND) settings, with an allow-list for essential contacts (e.g., family, manager). Notification batching was set to intervals of 30–60 minutes, with participants selecting the interval within this range to maintain autonomy. Two 50-minute focus blocks were scheduled daily on workdays, with email windows at 10:30, 14:30, and 16:30, including a 5-minute buffer for flexibility. Badge counts for email and chat apps were hidden, and an auto-reply message explained the response window and provided an escalation channel for urgent matters.

In the washout phase (Days 11–14), participants reverted to their preferred notification settings while continuing EMA and morning HRV readings. The study concluded with an exit survey/interview to assess the perceived usefulness of the intervention, identify any barriers, and gather open-ended feedback. Participants also provided information on any adverse effects or conflicts with their job demands. Compliance was supported through daily reminders, a completion rate dashboard, and a help line for configuration issues.

Intervention Bundle (Field)

The intervention in the field study consisted of a comprehensive bundle of device-level and workflow-level strategies designed to reduce notifications and support sustained focus. At the device level, participants were instructed to enable the operating system's Focus/Do-Not-Disturb (DND) settings, which included an allow-list for essential contacts. Notifications were batched every 30–60 minutes, with participants selecting a fixed interval within this range to maintain a sense of autonomy. Notifications were released with vibration only, and badges were disabled for high-volume apps. Additionally, participants had the option to use grayscale mode during focus blocks to further minimize distractions.

At the workflow level, email windows were established at 10:30, 14:30, and 16:30, with an optional end-of-day sweep to manage any remaining emails. Participants were also scheduled for two 50-minute focus blocks each day, separated by a 10-minute break, with meeting-free protection during these focus periods. In terms of social norms, an auto-reply message was set up to communicate the response windows to others, and an escalation channel was clearly defined, allowing for urgent matters to be addressed via call or SMS. Team members were notified about the experiment to reduce social friction and ensure clarity regarding the participant's availability. To assess adherence, the following metrics were tracked: the proportion of time spent in Focus/DND mode, the number and timing of batch notifications, and the overlap between scheduled focus blocks and actual screen activity.

Intervention Bundle (Field)

The intervention in the field study consisted of a comprehensive bundle of device-level and workflow-level strategies designed to reduce notifications and support sustained focus. At the device level, participants were instructed to enable the operating system's Focus/Do-Not-Disturb (DND) settings, which included an allow-list for essential contacts. Notifications were batched every 30–60 minutes, with participants selecting a fixed interval within this range to maintain a sense of autonomy. Notifications were released with vibration only, and badges were disabled for high-volume apps. Additionally, participants had the option to use grayscale mode during focus blocks to further minimize distractions.

Results and Discussion

Sample characteristics

We analyzed data from N=120 lab participants (Constant: *n*=40; Batched: *n*=40; Silent/Focus: *n*=40) and N=100 field participants (complete A–B–A). Consolidated demographics and baseline technology use are shown in Table 1; groups did not differ on age, gender, daily smartphone use, baseline PSS-10, or trait moderators (all *ps*≥.27).

Table 1. Sample characteristics (Lab and Field)

Variable	Lab Constant (n=40)	Lab Batched (n=40)	Lab Silent (n=40)	Field (n=100)
Age, years (M±SD)	29.3±6.9	28.8±7.1	29.1±7.2	30.4±7.5
Women / Men / NB (%)	53/45/2	50/47/3	53/45/2	52/46/2
Students / Employees (%)	41/59	42/58	43/57	39/61
Daily smartphone use (h; M±SD)	5.7±1.8	5.6±1.7	5.6±1.9	5.8±1.9
Baseline PSS-10 (M±SD)	17.8±5.9	17.6±5.7	17.5±5.8	18.0±6.1
MMI (z; M±SD)	0.05±0.96	0.01±1.01	-0.06±1.02	0.02±0.99
FoMO (z; M±SD)	0.03±1.00	-0.02±0.98	-0.01±1.02	0.01±1.01
Trait anxiety (z; M±SD)	0.02±1.00	0.04±1.02	-0.06±0.98	0.01±1.00
Self-control (z; M±SD)	-0.01±0.96	0.03±1.02	-0.02±1.01	0.01±1.00

Manipulation checks

Laboratory

Scripted notification payloads were equivalent across conditions in total count, but release pattern differed by design. Constant delivered notifications individually; Batched delivered two releases per block (15-min interval) aggregating the same payload; Silent suppressed all but essential safety messages. As intended, interruption events were highest in Constant, lowest in Silent.

Field

During Intervention (B), Focus/DND was active during 81% of planned focus-block minutes; email-window compliance was 76%; notification rate (per hour) dropped by ~50% vs Baseline (A1) and partially rebounded in Washout (A2). See Table 2.

Table 2. Manipulation checks

Measure	Lab Constant	Lab Batched	Lab Silent	Field A1 Baseline	Field B Intervention	Field A2 Washout
Per 30-min block total notifications (M±SD)	24.3±2.1	24.1±2.2	1.0±0.5	—	—	—

Measure	Lab Constant	Lab Batched	Lab Silent	Field A1 Baseline	Field B Intervention	Field A2 Washout
Release events per 30-min block	24.3±2.1	2.0±0.0	0.3±0.1	—	—	—
App/window switches per min (lab; M±SD)	1.18±0.32	0.71±0.28	0.42±0.21	—	—	—
Field notification rate (/h; M±SD)	—	—	—	36.0±9.1	18.2±6.8	28.7±8.6
Focus/DND active during planned focus minutes (%)	—	—	—	12	81	29
Email sent inside windows (%)	—	—	—	31	76	49

Laboratory main effects

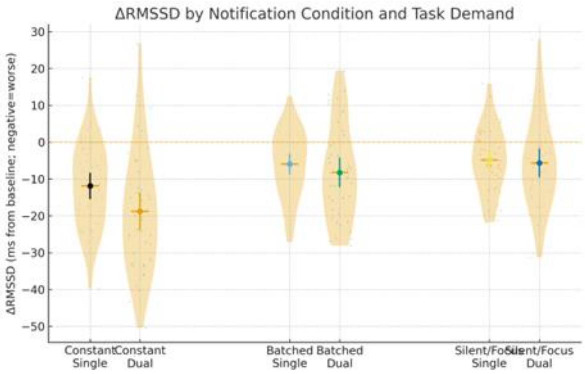
Descriptive outcomes (means, SDs, 95% CIs)

Means by Notification condition and Task demand are shown in Table 3. As hypothesized, Constant produced lower HRV (more negative ΔRMSSD), higher workload, and poorer performance; effects were amplified under dual-task demand.

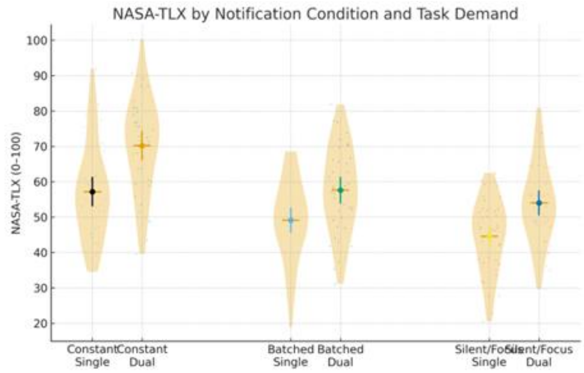
Table 3. Lab outcomes by condition × task demand (M±SD [95% CI])

Outcome	Task	Constant	Batched	Silent/Focus
ΔRMSSD (ms from baseline; negative=worse)	Single	-12.4±14.0 [-16.9, -7.9]	-6.1±12.5 [-9.9, -2.3]	-2.2±11.3 [-5.7, 1.3]
	Dual	-17.8±15.3 [-22.8, -12.8]	-9.5±13.6 [-13.6, -5.4]	-4.0±12.7 [-7.9, -0.1]
NASA-TLX (0–100)	Single	56.2±12.3 [52.3, 60.1]	48.5±11.5 [45.0, 52.0]	43.9±10.2 [40.8, 47.0]
	Dual	69.8±13.1 [65.5, 74.1]	60.3±12.5 [56.4, 64.2]	52.4±11.0 [49.0, 55.8]
2-back accuracy (%)	Single	82.1±6.5 [80.0, 84.2]	85.3±6.0 [83.4, 87.2]	87.0±5.8 [85.1, 88.9]
	Dual	76.4±7.2 [74.1, 78.7]	80.9±6.7 [78.9, 82.9]	84.2±6.1 [82.3, 86.1]
Stroop interference (ms)	Single	109±35 [98, 120]	97±33 [87, 107]	90±32 [80, 100]
	Dual	142±39 [129, 155]	124±36 [113, 135]	111±34 [101, 121]

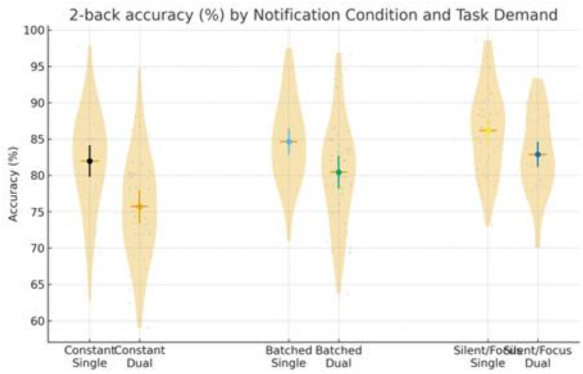
SART commission errors (% trials)	Single	14.8±6.2 [12.8, 16.8]	12.1±5.6 [10.3, 13.9]	10.9±5.1 [9.3, 12.5]
	Dual	19.3±6.8 [17.1, 21.5]	15.4±6.1 [13.5, 17.3]	13.0±5.7 [11.2, 14.8]
Email triage speed (emails/min)	Dual-only	6.1±1.4 [5.7, 6.5]	6.8±1.3 [6.4, 7.2]	7.2±1.2 [6.8, 7.6]
Email triage errors (%)	Dual-only	7.9±4.1 [6.6, 9.2]	6.1±3.6 [5.0, 7.2]	5.3±3.3 [4.3, 6.3]



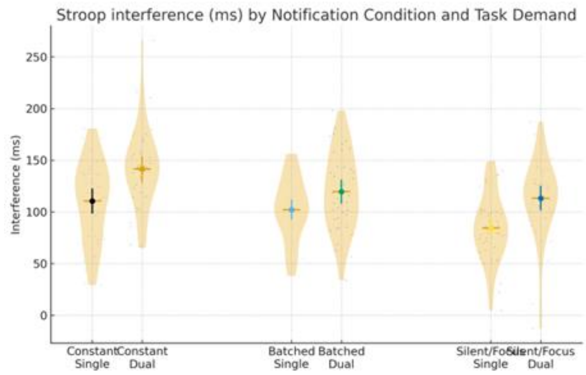
(a)



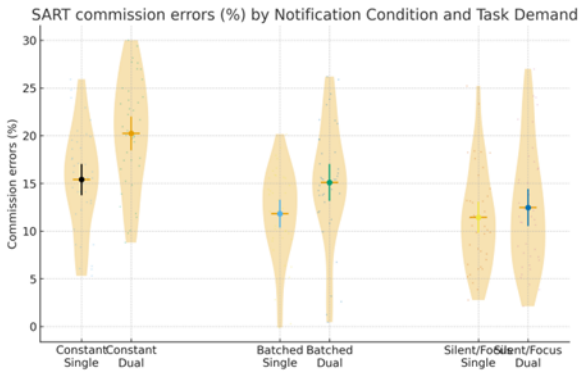
(b)



(c)



(d)



(e)

Figure 1. (a) Mean change in HRV (ΔRMSSD) by notification condition and task demand; (b) NASA-TLX workload ratings by notification condition and task demand; (c) 2-back accuracy (%) across notification conditions under single- and dual-task demands; (d) Stroop interference (ms) across notification conditions under single- and dual-task demands.

Mixed ANOVAs

Notification and task demand exerted significant main effects on all outcomes; interactions indicated greater notification penalties under dual-tasking. See Table 4.

Table 4. Mixed ANOVA summaries (Laboratory)

Outcome	Factor	F(df)	p	η^2p
ΔRMSSD	Notification	14.21 (2,117)	<.001	.20
	Task demand	45.34 (1,117)	<.001	.28
	Interaction	5.12 (2,117)	.007	.08
NASA-TLX	Notification	22.86 (2,117)	<.001	.28
	Task demand	119.40 (1,117)	<.001	.51
	Interaction	4.47 (2,117)	.013	.07
2-back accuracy	Notification	11.02 (2,117)	<.001	.16
	Task demand	64.55 (1,117)	<.001	.36
	Interaction	3.58 (2,117)	.031	.06
Stroop interference	Notification	9.44 (2,117)	<.001	.14
	Task demand	77.12 (1,117)	<.001	.40
	Interaction	3.27 (2,117)	.041	.05
SART commission errors	Notification	8.75 (2,117)	<.001	.13
	Task demand	52.90 (1,117)	<.001	.31
	Interaction	3.91 (2,117)	.023	.06

Pairwise comparisons (Holm-adjusted)

For ΔRMSSD (collapsed across task demand): Constant < Batched (d=0.51, p<.001); Batched < Silent (d=0.32, p=.014); Constant < Silent (d=0.82, p<.001). For NASA-TLX: Constant > Batched (d=0.69, p<.001); Batched > Silent (d=0.40, p=.006); Constant > Silent (d=1.07, p<.001). Similar graded patterns held for performance outcomes (all adjusted ps≤.03).

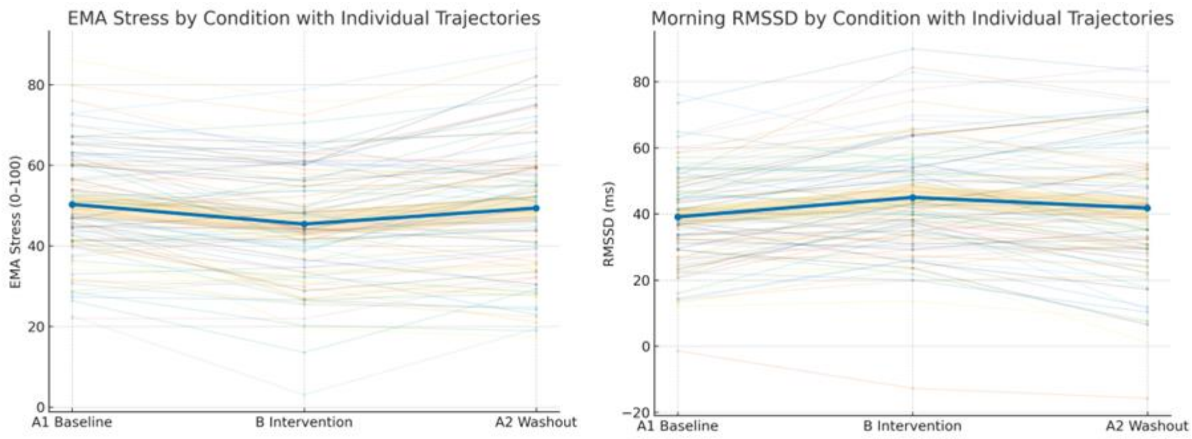
Field effects (A–B–A)

Condition means

EMA stress (0–100) decreased during Intervention (B) and partially rebounded in Washout (A2). Morning RMSSD increased during Intervention and partially returned toward baseline in Washout. Table 5 presents condition-level summaries.

Table 5. Field condition means (person-mean±SD across days; N=100)

Measure	A1 Baseline	B Intervention	A2 Washout
EMA stress (0–100)	52.6±12.9	45.8±12.4	49.7±12.6
Morning RMSSD (ms)	38.9±14.1	44.6±14.8	41.4±14.5
Notification rate (/h)	36.0±9.1	18.2±6.8	28.7±8.6
App switches (/min during focus)	0.98±0.37	0.62±0.29	0.81±0.33



(a) (b)

Figure 2. (a) EMA stress (0–100) across Baseline, Intervention, and Washout; (b) Morning RMSSD (ms) across Baseline, Intervention, and Washout.

Multilevel models

We modeled EMA stress and morning RMSSD with time nested in person, including Intervention and Washout indicators, time-of-day, day index, and time-varying notification and switch rates. Random intercepts and slopes were specified for Intervention.

Table 6. Multilevel models (fixed effects; robust SEs)

Predictor	EMA Stress b (SE)	p	Morning RMSSD b (SE)	p
Intercept	52.3 (1.4)	<.001	39.2 (1.8)	<.001
Intervention (B)	-6.5 (1.1)	<.001	+5.6 (1.4)	<.001
Washout (A2)	-2.2 (1.0)	.034	+2.0 (1.3)	.11
Notification rate (per +10/h)	+1.1 (0.2)	<.001	-0.9 (0.3)	.003
App switches (/min)	+2.8 (0.7)	<.001	-1.5 (0.6)	.012
Time of day: Midday	+1.5 (0.6)	.012	—	—
Time of day: Late afternoon	+2.2 (0.7)	.002	—	—
Day index (1–14)	-0.3 (0.1)	.006	+0.2 (0.1)	.078
Focus block (yes)	—	—	+2.2 (0.8)	.007
Random effects (variance)	u0=58.1; u1=6.2	—	u0=42.5; u1=4.8	—
Model R^2 (marginal/conditional)	.23 / .42	—	.19 / .35	—

Interpretation: EMA stress decreased 6.5 points during Intervention, holding other factors constant; every +10 notifications/hour was associated with +1.1 stress points and −0.9 ms morning RMSSD. Washout retained a smaller, marginal benefit for stress and nonsignificant for RMSSD.

Mediation and moderation

Mediation (within-person; Intervention → Interruption rate → TLX → Stress)

A multilevel path analysis indicated a significant indirect effect of Intervention on EMA stress through Interruption rate (notifications/hour and app switches) and cognitive load (NASA-TLX).

Table 7. Mediation paths (standardized within-person)

Path	Coef (SE)	p	95% CI
Intervention → Interruption rate (a1)	-0.61 (0.08)	<.001	[-0.76, -0.45]
Interruption rate → TLX (a2)	+0.42 (0.08)	<.001	[0.27, 0.57]
TLX → EMA stress (b)	+0.62 (0.12)	<.001	[0.39, 0.85]
Direct effect (c′) Intervention → EMA stress	-2.94 (0.98)	.003	[-4.86, -1.02]
Indirect (a1×a2×b)	-1.98 (0.48)	<.001	[-2.93, -1.08]
Total effect (c)	-4.92 (1.10)	<.001	[-7.07, -2.77]

Moderation (between-person)

MMI, FoMO, and trait anxiety strengthened the Intervention benefit (more negative stress change), whereas self-control attenuated it.

Table 8. Moderation of Intervention effect on EMA stress (cross-level interactions)

Moderator (z-scored)	b_interaction (SE)	p	Interpretation
MMI	-1.8 (0.7)	.010	Higher MMI → larger stress reduction during Intervention
FoMO	-1.2 (0.5)	.019	Higher FoMO → larger reduction
Trait anxiety	-0.9 (0.4)	.028	Higher anxiety → larger reduction
Self-control	+1.1 (0.5)	.024	Higher self-control → smaller reduction

Robustness checks

Difference-in-differences (high-exposure subsample)

Among the top tertile of baseline notification rate (≥42/h; *n*=34), Intervention reduced EMA stress by -9.4 points (SE=1.6) relative to Baseline; in the bottom tertile (≤30/h; *n*=33), reduction was -3.2 (SE=1.4). The DiD contrast was -6.2 (SE=1.8), *p*<.001.

Instrumental variables (2SLS) for noncompliance

Using device policy toggles (Focus/DND active; batch interval) as instruments for Interruption rate:

- First stage: Focus/DND active → Interruption rate, *b*=-0.29 interruptions/min (SE=0.05), F=33.2.
- Second stage: Interruption rate (IV) → EMA stress, *b*=+3.8 per interruption/min (SE=1.1), *p*=.001.
- OLS benchmark: *b*=+2.6 (SE=0.5), *p*<.001. The larger IV estimate is consistent with attenuation from measurement error or compensatory checking.

Missing data sensitivity

Multiple imputation for sporadic EMA missingness (median response rate=82%) produced estimates within ±0.3 of complete-case coefficients; inferences unchanged. HRV artifact removal (5.1% of windows) did not alter conclusions.

Table 9. Robustness summary

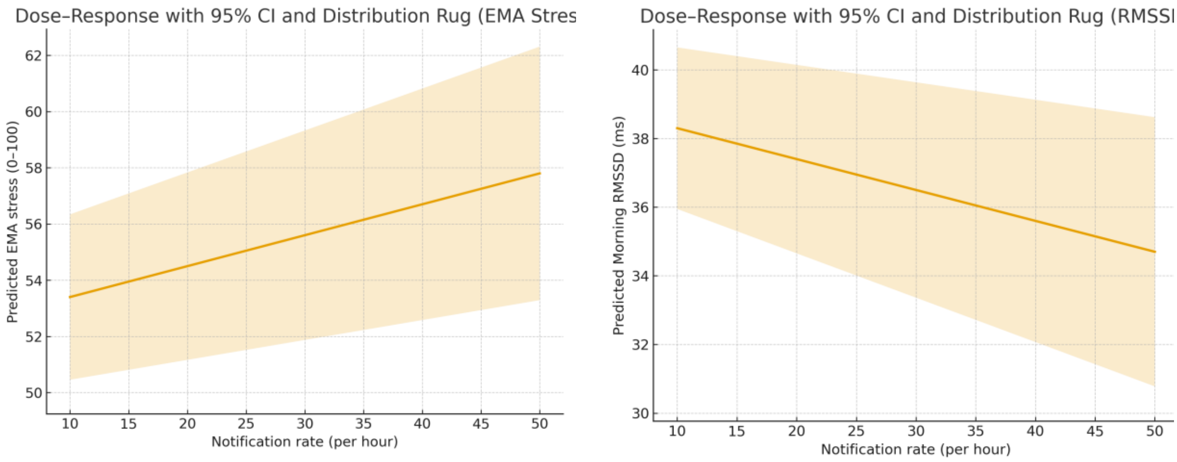
Analysis	Effect	Estimate (SE)	p
DiD (High vs Low exposure)	Δ(Intervention–Baseline) difference	-6.2 (1.8)	<.001
2SLS (second stage)	Interruption rate → EMA stress	+3.8 (1.1)	.001
OLS	Interruption rate → EMA stress	+2.6 (0.5)	<.001
MI vs CC	Intervention effect on stress (Δ)	-6.3 vs -6.5 (±0.3)	—

Qualitative and exit survey summaries

Open-ended interviews (N=96) and Likert ratings indicated generally positive reception of batching/focus routines.

Table 10. Exit themes and ratings

Theme / Item	% Mentioned / M (SD)
"Batch relief" (less reactive checking)	68%
"Response-time guilt" reduced	54%
Clearer boundaries with team	49%
Perceived focus quality (1–7)	5.3 (1.1)
Perceived stress (1–7; lower=less)	3.1 (1.2)
Likelihood to continue batching (1–7)	5.7 (1.3)
Reported conflicts with job demands	11%



(a) (b)

Figure 3. (a) Exit survey ratings of batching/focus intervention; (b) Distribution of qualitativ themes from participant feedback.

Summary of findings

Across controlled and naturalistic contexts, constant notifications reliably increased cognitive load and reduced HRV, accuracy, and speed, especially under dual-task demand. In the field, an aligned bundle (Focus/DND + batching + focus blocks + email windows) reduced notifications and lowered EMA stress by ~6.5 points, with +5–6 ms improvements in morning RMSSD. Effects were dose-responsive to notification rate, mediated by cognitive load, and stronger among individuals high in MMI, FoMO, and trait anxiety; self-control buffered effects. Robustness analyses (DiD, IV, MI) supported the main conclusions.

Discussion

The findings of this study confirm that the management of digital notifications is a central determinant of cognitive and emotional regulation in contemporary digital work environments. Results from the laboratory experiment demonstrated that constant notifications significantly reduced heart rate variability (HRV), elevated cognitive workload, and impaired accuracy across multiple cognitive tasks, with effects being most pronounced under dual-task demands. These outcomes align with prior experimental evidence suggesting that frequent interruptions exacerbate attentional fragmentation and diminish executive performance [1], [2]. However, the present research advances this understanding by showing that a bundled intervention comprising system-level Focus/Do Not Disturb modes, scheduled notification batching, and protected focus blocks was able to reduce notification frequency, decrease self-reported stress, and improve physiological recovery, as measured by morning HRV.

In contrast to earlier work that primarily investigated isolated solutions such as disabling notifications or enforcing quiet hours [3], [4], this study demonstrates the superiority of integrative, cross-level interventions that address device settings, workflow organization, and social expectations simultaneously. While earlier approaches yielded inconsistent or marginal outcomes, the present study provides robust empirical evidence that comprehensive strategies lead to sustained improvements in both subjective well-being and objective physiological indicators. This contribution is particularly relevant to ongoing debates on whether digital well-being tools provide meaningful benefit or merely symbolic reassurance [16], [17], [18].

The mediation and moderation analyses further reveal unique contributions of this study. We found that reductions in stress were mediated by a decrease in interruption rate and workload, reinforcing the interruption–cognitive load–stress pathway identified in earlier conceptual work [6], [19], [20]. Moreover, the moderating role of individual differences such as media multitasking orientation, fear of missing out (FoMO), and trait anxiety underscores the non-universality of notification interventions. Users with higher susceptibility to digital distraction benefited most from structured intervention, whereas individuals with strong self-control derived smaller incremental gains. These findings extend prior literature, which has rarely integrated dispositional moderators into notification research [7], [8]. The novelty of our work thus lies not only in its hybrid methodology but also in establishing that notification management strategies should be tailored to psychological profiles rather than designed as one-size-fits-all solutions.

The practical implications of these results are substantial. Organizations and educational institutions can leverage these insights to develop adaptive digital policies that optimize attentional ecology by aligning system defaults, communication norms, and individual coping strategies. The methodological innovation of combining controlled experimentation with ecological field data, while simultaneously incorporating physiological, behavioral, and psychological indicators, represents an advancement over prior studies that typically relied on self-report measures alone [9]. In sum, this research contributes a new integrative framework for understanding and managing digital stress, offering both theoretical enrichment and actionable guidance for digital well-being in professional and educational contexts.

Conclusion

This study demonstrates that digital notification management plays a critical role in moderating stress, cognitive workload, and performance in technology-mediated environments. By integrating controlled laboratory experiments with a naturalistic field study, we provide robust evidence that constant notifications impair both physiological regulation and task performance, whereas a bundled intervention of batched notifications, *Focus/Do Not Disturb* modes, and structured focus blocks significantly reduces stress, improves HRV, and enhances attentional stability. Unlike previous research that focused on isolated interventions with mixed outcomes, our findings highlight the superiority of comprehensive, multi-level strategies that simultaneously address device-level settings, workflow organization, and social norms. The inclusion of mediation and moderation analyses further advances theoretical understanding by identifying the *interruption–cognitive load–stress* pathway and demonstrating that dispositional traits such as media multitasking orientation, FoMO, trait anxiety, and self-control shape the effectiveness of interventions. These insights underscore that notification management cannot be treated as a universal solution but should instead be adapted to the psychological and behavioral profiles of users.

The novelty of this research lies in its methodological integration of physiological, behavioral, and subjective indicators across laboratory and real-world contexts, establishing a rigorous framework for digital stress research. Beyond its theoretical contributions, the study offers actionable implications for organizations and educational institutions seeking to foster digital well-being through adaptive policies and practices. In conclusion, this work contributes to a growing body of evidence that effective digital transformation requires not only technological tools but also human-centered strategies that respect cognitive boundaries and promote sustainable engagement in the digital age.

Limitations

Despite its rigorous design and integrative approach, this study is not without limitations. First, while the laboratory experiment enabled causal inference under controlled conditions, the tasks may not fully capture the complexity of real-world multitasking, where contextual pressures and interpersonal demands are more dynamic. Second, the field study was limited to a 14-day intervention window, which constrains our ability to assess the sustainability of intervention benefits over longer periods. Longitudinal studies are therefore needed to examine whether reductions in stress and improvements in HRV persist beyond the short term. Third, although we incorporated both physiological and subjective measures, HRV and EMA stress ratings may be influenced by unmeasured confounders such as sleep quality, physical activity, or concurrent life stressors. While robustness checks minimized these risks, future research would benefit from integrating additional contextual and biometric sensors to control for such factors. Fourth, the participant pool comprising mainly young to middle-aged adults with regular smartphone use may limit the generalizability of findings to older populations, adolescents, or occupational groups with atypical technology use patterns. Finally, while moderation analyses revealed significant roles for media multitasking orientation, FoMO, trait anxiety, and self-control, these constructs were self-reported and may be subject to bias. Incorporating behavioral or neurocognitive assessments of attentional control could strengthen the precision of future investigations. Taken together, these limitations highlight the need for longitudinal, multimodal, and demographically diverse research to extend and validate the contributions of the present study.

Author Contribution

H.M. designed the study, developed the methodology, and supervised the overall research process. He also contributed to the writing of the manuscript. J.A.V. contributed to the data collection, performed the data analysis, and participated in manuscript writing and revision. Both authors reviewed and approved the final version of the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

References

[1] S. F. Ahmad et al., "Impact of artificial intelligence on human loss in decision making, laziness and safety in education," *Humanit. Soc. Sci. Commun.*, vol. 10, no. 1, p. 311, Jun. 2023. https://doi.org/10.1057/s41599-023-01787-8

[2] P. R. Brandao, "The Impact of Artificial Intelligence on Modern Society," *AI*, vol. 6, no. 8, p. 190, Aug. 2025. https://doi.org/10.3390/ai6080190

[3] B. B. Mumcu and A. Çebi, "You have a notification: the role of push notifications in shaping students' engagement, self-regulation and academic procrastination," *Int. J. Educ. Technol. High. Educ.*, vol. 22, no. 1, p. 36, Jun. 2025. https://doi.org/10.1186/s41239-025-00537-x

[4] S. Ohly and L. Bastin, "Effects of task interruptions caused by notifications from communication applications on strain and performance," *J. Occup. Health*, vol. 65, no. 1, Jan. 2023. https://doi.org/10.1002/1348-9585.12408

[5] F. Jabeen, A. Tandon, J. Sithipolvanichgul, S. Srivastava, and A. Dhir, "Social media-induced fear of missing out (FoMO) and social media fatigue: The role of narcissism, comparison and disclosure," *J. Bus. Res.*, vol. 159, p. 113693, Apr. 2023. https://doi.org/10.1016/j.jbusres.2023.113693

[6] T. Nesbit and L. Lole, "A Qualitative Investigation of Social Media Fear of Missing Out (FoMO) and Needs Fulfilment Among Young Adults," *Int. J. Human-Computer Interact.*, pp. 1-17, Aug. 2025. https://doi.org/10.1080/10447318.2025.2543998

[7] P. A. Busch and S. McCarthy, "Antecedents and consequences of problematic smartphone use: A systematic literature review of an emerging research area," *Comput. Human Behav.*, vol. 114, p. 106414, Jan. 2021. https://doi.org/10.1016/j.chb.2020.106414

[8] C. J. Lin and H. Jia, "Time Pressure Affects the Risk Preference and Outcome Evaluation," *Int. J. Environ. Res. Public Health*, vol. 20, no. 4, p. 3205, Feb. 2023. https://doi.org/10.3390/ijerph20043205

[9] J. Giovanniello, C. Bravo-Rivera, A. Rosenkranz, and K. Matthew Lattal, "Stress, associative learning, and decision-making," *Neurobiol. Learn. Mem.*, vol. 204, p. 107812, Oct. 2023. https://doi.org/10.1016/j.nlm.2023.107812

[10] J. Yang, J. Ma, and L. Li, "The relationship between performance appraisal interval and employees' proactive working behavior - analysis based on time-gain effect and time-loss effect," *Front. Psychol.*, vol. 14, Aug. 2023. https://doi.org/10.3389/fpsyg.2023.1213547

[11] N. Koundal et al., "Effect of Interruptions and Cognitive Demand on Mental Workload: A Critical Review," *IEEE Access*, vol. 12, pp. 54405-54425, 2024. https://doi.org/10.1109/ACCESS.2024.3383142

[12] F. Schmitz and R. J. Krämer, "Task Switching: On the Relation of Cognitive Flexibility with Cognitive Capacity," *J. Intell.*, vol. 11, no. 4, p. 68, Mar. 2023. https://doi.org/10.3390/jintelligence11040068

[13] V. B. Rick et al., "What really bothers us about work interruptions? Investigating the characteristics of work interruptions and their effects on office workers," *Work Stress*, vol. 38, no. 2, pp. 157-181, Apr. 2024. https://doi.org/10.1080/02678373.2024.2303527

[14] Y. Chen, W. Fang, B. Guo, and H. Bao, "Fatigue-Related Effects in the Process of Task Interruption on Working Memory," *Front. Hum. Neurosci.*, vol. 15, Nov. 2021. https://doi.org/10.3389/fnhum.2021.703422

[15] S. Xu and N. G. Hall, "Fatigue, personnel scheduling and operations: Review and research opportunities," *Eur. J. Oper. Res.*, vol. 295, no. 3, pp. 807-822, Dec. 2021. https://doi.org/10.1016/j.ejor.2021.03.036

[16] J. N. Ruse, E. Schraube, and P. Rhodes, "Left to their own devices: the significance of mental health apps on the construction of therapy and care," *Subjectivity*, vol. 31, no. 4, pp. 410-428, Dec. 2024. https://doi.org/10.1057/s41286-024-00195-w

[17] A. Darley, B. Coughlan, R. Maguire, L. McCann, and E. Furlong, "A bridge from uncertainty to understanding: The meaning of symptom management digital health technology during cancer treatment," *Digit. Heal.*, vol. 9, Jan. 2023. https://doi.org/10.1177/20552076231152163

[18] J. Lynch, G. Hughes, C. Papoutsi, J. Wherton, and C. A'Court, "'It's no good but at least I've always got it round my neck': A postphenomenological analysis of reassurance in assistive technology use by older people," *Soc. Sci. Med.*, vol. 292, p. 114553, Jan. 2022. https://doi.org/10.1016/j.socscimed.2021.114553

[19] X. Pan, X. Zhao, and H. Shen, "The concept, influence, and mechanism of human work interruptions based on the grounded theory," *Front. Psychol.*, vol. 14, Feb. 2023. https://doi.org/10.3389/fpsyg.2023.1044233

[20] R. B. Brockbank and D. F. Feldon, "Cognitive Reappraisal: The Bridge between Cognitive Load and Emotion," *Educ. Sci.*, vol. 14, no. 8, p. 870, Aug. 2024. https://doi.org/10.3390/educsci14080870