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GENERATIVE AI FOR JUST-IN-TIME MINDFULNESS CONTENT

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Abstracts. *The paper describes a framework for Just-in-Time Mindfulness that combines data from everyday wearables with generative artificial intelligence to offer the user a short, personalized mindfulness practice at the exact moment when the risk of stress increases. The smartphone continuously receives heart rate variability, inactivity level, accumulated sleep debt, and time-of-day context; these signals are immediately normalized against an individual baseline. A stress risk index is calculated based on these signals, and if the index exceeds a threshold, a trigger is triggered that takes into account a cooling-off period to avoid excessive intervention frequency. After the trigger is triggered, a compact language model running locally on the phone generates a meditation text lasting from thirty to ninety seconds; the text adapts to the user's current physiological state, time of day, and stylistic preferences, and a protective filter filters out potentially unwanted wording. All processing is done on the device, which eliminates cloud latency and ensures the confidentiality of personal data. The minimum requirements for a set of signals, the logic of threshold selection, the approach to content security, and the phased validation plan from simulation to pilot field study are discussed.*

Keywords: *wearable devices, stress detection, Just-in-Time interventions, generative AI, digital therapies.*

Introduction

Chronic stress is consistently linked to mental-health disorders. Large cohort studies show that high job demands, low control and job insecurity markedly raise depression risk, particularly in men [1][2][3]. In adolescence, acute and prolonged life stressors foster psychopathology, a process strongly modulated by family context [4][5]; stressful events also heighten youth suicide risk [6]. Pubertal brain plasticity amplifies sensitivity to stress [7], increasing odds of later depression [8] and bipolar-spectrum illness [9]. Boys tend to externalise stress (e.g., aggression), whereas girls show more internalising symptoms, with poverty, divorce and domestic violence posing extra hazards for males [5]. In today's always-on environment—constant alerts, sleep loss and blurred work–life boundaries—sustained HPA-axis activation erodes physiological reserves, driving burnout and mood-anxiety morbidity. Just-in-time, sensor-triggered mindfulness therefore shifts from optional self-care to a preventive buffer against chronic-stress damage.

Main text

The JIT-M system continuously ingests heart-rate, HRV, brief inactivity and accumulated sleep-debt data from a wearable, plus time-of-day context, normalises them to the user's baseline and combines them into a Stress Risk Index; when the index exceeds an adaptive threshold and the cooldown has ended, a trigger fires [10]. The phone then invokes a lightweight, on-device language model fine-tuned on meditation texts, which — within a second — creates a 30-90 s personalised script suited to the current time (energising breath in the morning, slow relaxation at night). The text passes a local safety filter that removes medical claims and negative phrasing before being pushed to the user, while all computation stays offline to protect privacy. In everyday operation the wearable streams only low-resolution data once per second, but if those "draft" signals suggest rising stress the phone temporarily switches to high-resolution capture, recomputes the index and, if the threshold is still breached, delivers support; otherwise it returns to its low-power state. Thus JIT physiology sensing and generative AI convert mindfulness from a manual option into an automatic, context-aware intervention precisely when the user is most likely to benefit.

Sensor layer and stream buffer

A low-power PPG and 3-axis accelerometer aggregate HR, R-R, steps and a motion flag every second, package the 20-byte payload, encrypt it via BLE Secure Connections and send it over a 1 Mbit PHY (≈200 ms interval), drawing ≤ 50 µA.

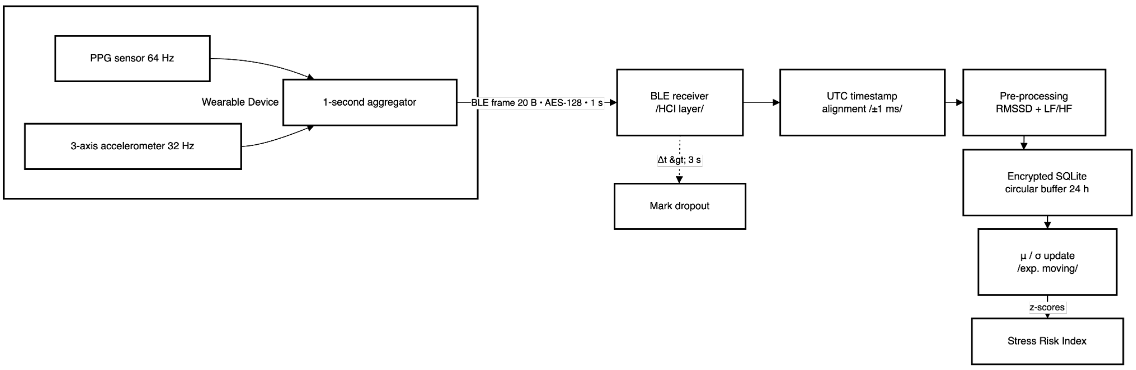

Figure 1 - Wearable-to-Stress Risk Index Pipeline

The diagram (Fig. 1) traces the biosignal flow: watch sensors aggregate PPG +

ACC once a second, encrypt the packet over Bluetooth LE and send it to the phone, where it is time-aligned to UTC, RMSSD and LF/HF are computed, then both raw and derived values land in a 24-h encrypted ring buffer. Each insert refreshes sliding μ and σ and yields z-scores for the SRI; segments missing > 3 s are flagged as dropouts and ignored. The entire process is local, encrypted and cloud-free.

Enhanced collection and calculation of SRI

In basic mode the phone just tracks z-scores; when HRV and activity drift toward sympathetic load it enters a 30 s high-resolution phase, raising R-R sampling to 250 Hz and streaming raw accelerometer data, while also retrieving the stored sleep-debt value.

Figure 2 - State Machine for StressAlert Trigger

After a 30-second high-frequency window, the phone combines the z-scores of HRV, immobility, and sleep "debt" into a scalar Stress Risk Index, giving the highest weight to HRV, less weight to inactivity, and the lowest weight to sleep deprivation (Fig. 2).[11][12] Every night, a personal threshold is calculated as the average of a three-day history with a small margin; an hourly "cooling down" is also supported. If the new index does not exceed the threshold or the interval is still ongoing, the system returns to basic logging; otherwise, it generates a StressAlert and blocks repetitions for an hour. All calculations are local, so the solution is obtained in a few seconds, even before the user is consciously aware of the stress [13].

Generation of micro-interventions

After the StressAlert event, the phone generates a compressed prompt - SRI [14], time of day, and user style - and sends it to the local LoRA-T5 model (≈ 230 MB, INT8), which creates a 30-90-second script with breathing or relaxation in ≈ 250 ms, consistent with the current context. The text undergoes a two-stage check: the regex removes medical statements, the classifier removes negative tone; if it is rejected, "4-

7-8” is inserted. After push delivery (with offline TTS, if necessary), a one-hour cooling timer starts, blocking new interventions.

Delivery and adaptation

After the text is approved, the app sends a push from the deep-link to the practice screen; when the user opens it, they see the timer and script, and, if desired, offline TTS sound. At the end of the session, the user marks “helped” or “not”; the score and the fact of completion, along with the SRI and time, are recorded in the local log. Next, a one-hour cool-down starts, blocking any new StressAlerts during this period, even if the index exceeds the threshold again.

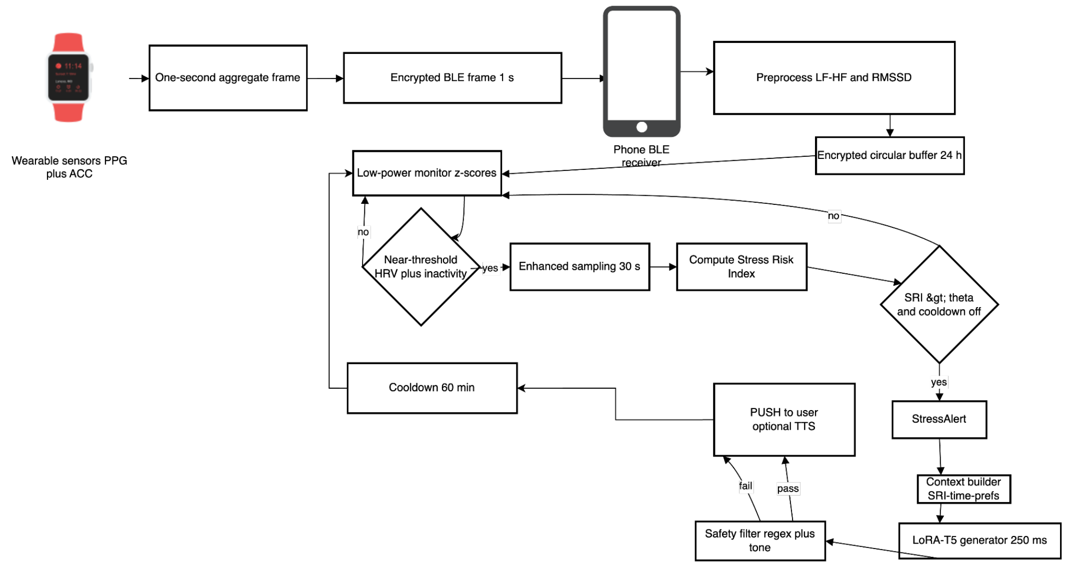

Figure 2 - End-to-End JIT-Mindfulness Data Flow

Every night, the app analyzes feedback: when most sessions are marked “useful,” the SRI threshold is slightly lowered to catch smaller spikes; if reminders are ignored, the threshold is raised and scripts are shortened. In this way, the delivery channel is self-adjusting, matching the frequency and tone of interventions to the reactions of a particular user (Fig. 3).

Summary and conclusions

The system links a wearable, phone and compact LoRA model into an autonomous measure-assess-act loop. One-second baseline streaming builds a secure 24-h history; short, event-triggered high-rate sampling refines it only during suspected stress. An adaptive Stress Risk Index fires the trigger, the on-device model drafts a personalised script in milliseconds, and push delivery plus binary feedback close the loop. All computation stays local, ensuring low latency and full data privacy. This validates Just-in-Time Mindfulness as a practical, self-learning digital therapy ready for large-scale evaluation.

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