StreAM: An LLM-Based System for Stress-Adaptive Meditation at Work

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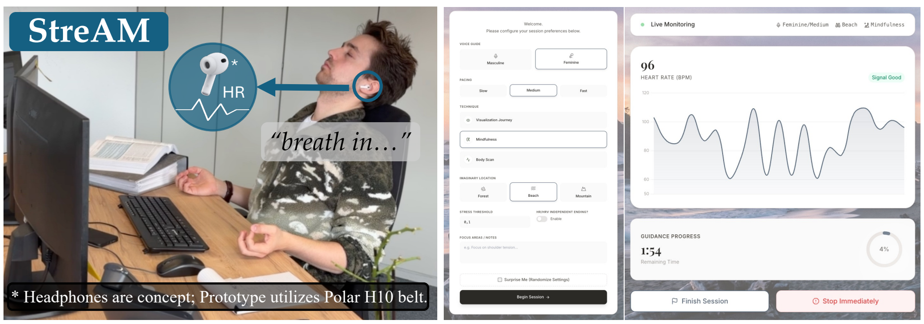

Interviewee	Industry	Meditation Experience
I1	Software Company	No
I2	Software Company	Little
I3	Aviation Company	No
I4	PhD Researcher	No
I5	PhD Researcher	No
I6	PhD Researcher	Little
I7	University	Yes
I8	Energy Supplier	Yes
I9	Energy Supplier	Yes
I10	Energy Supplier	Yes
I11	Energy Supplier	Yes

Figure 1: Overview of the *StreAM* prototype and design.

Abstract

Workplace stress is a critical factor that undermines employee performance and leads to physical ailments and mental health challenges. Although meditation is widely recognized as an effective stress-reduction strategy, traditional meditation practices are often too time-consuming or complicated to be easily incorporated into professional settings. To address this issue, we introduce *StreAM* (Stress-Adaptive Meditation), a system that combines real-time stress detection with personalized micro-meditation exercises. *StreAM* continuously monitors heart rate variability to identify heightened stress levels and initiate an adaptive meditation session guided by a large language model. These sessions are tailored to users' personal preferences and persist until physiological indicators signal stress reduction, enabling individuals to swiftly regain focus. By leveraging the growing potential of heart rate sensors in everyday devices, *StreAM* demonstrates a pathway toward scalable, accessible, and unobtrusive workplace stress management, potentially enhancing employee well-being and fostering healthier, more productive work environments.

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CCS Concepts

• **Human-centered computing** → *Interactive systems and tools*; *Human computer interaction (HCI).*

Keywords

Well-being, Adaptive, Meditation, Personalization, Workplace

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1 Introduction

Stress results from the interaction between an individual's abilities, expectations and environmental demands, with physiological, emotional, cognitive, or behavioral effects that can be harmful [19]. In a professional context, stress reduces group participation [8], impairs productivity [11], lowers job satisfaction and engagement, and increases premature turnover risk [23]. Work stress can further impact personal well-being, causing irritability and sleep disorders [3]. People use diverse coping strategies, ranging from emotional to cognitive and physical approaches [40]. Meditation in particular is recognized as an effective strategy for stress reduction [34], including in workplace settings [7]. Furthermore, it has already been shown to be effectively augmented by technology, ranging from simple notifications to breathe [28] and app-delivered meditations

[10] to immersive environments designed to further deepen the meditative state [9, 16].

While literature confirms the individual benefits of technology-aided meditation [30], most existing approaches remain non-adaptive. Existing solutions rarely respond to fluctuating stress, and require users to self-identify their stress situations. Furthermore, static meditation scripts lack personalization. Recent research has begun to explore the use of LLMs for meditation, e.g., generating tailored scripts and delivering verbal instructions [27], or supporting reflection after meditation [17, 18]. However, these approaches have not yet addressed the combined challenges of dynamically responding to fluctuating stress levels and reducing users' reliance on self-recognition of stress.

We address this gap by proposing *StreAM*, a stress-adaptive meditation system that combines physiological stress detection, established meditation principles, and LLM-based personalization. Informed by a human-centered design process that included conducting 11 interviews with potential users, the system continuously measures heart rate (HR) and heart rate variability (HRV). It also incorporates user input to generate personalized scripts and audio-based delivery enabled by text-to-speech. Participants receive a guided micro-meditation when their stress levels reach their personal predefined threshold, and the meditation continues until their stress levels drop. This creates a real-time, adaptive, and engaging stress-reduction experience. A formative evaluation with 10 university employees confirmed *StreAM*'s effectiveness and usability, providing feedback for improvement. Next, we plan to conduct a field study to evaluate *StreAM*'s practical utility and effectiveness in a broader real-world setting.

2 Foundations and Related Work

2.1 Reducing Stress through Meditation

Numerous papers in the HCI literature address stress management and its relationship to customer-grade technologies, even in the workplace. Howe et al. [13], for example, found that while high-effort micro-interventions are less preferred than low-effort ones, they are more effective at reducing workplace stress. Lee et al. [20] propose a system focussing on anticipating stressors to provide actionable preparation. Recent work by Neupane et al. [25, 26] demonstrates that an increase in stress awareness alone, e.g., enabled by wearable-triggered logging and subsequent reflection, is highly effective, especially when combined with context-aware, LLM-driven interventions rather than generic advice.

Meditation, a well-established psychological intervention for reducing stress and enhancing cognitive processes [4, 37], is often overlooked as stress-reducing measure. One reason for this lack of integration may be that meditation is primarily viewed as a formal practice with limitations, such as that participants must find a specific time and place to practice [22]. However, meditation is not inherently tied to formal settings; it can be understood as a flexible self-regulation practice that does not require a fixed time or place [24]. Research furthermore has shown the potential of technology to introduce non-practitioners to the psychological benefits of mindfulness meditation [38].

2.2 Large-Language-Model-Assisted Meditation

LLMs are AI systems capable of understanding, generating, and adapting language to perform tasks such as translation, summarization, question answering, and conversation at near human-like levels [39]. Past research, e.g., that of Nguyen et al. [27], has already used LLMs to generate personalized meditation scripts and found that the AI-generated content and audio quality were comparable to traditional, human-created methods. It was evaluated as more personalized, particularly when participants could choose emotional contexts, and more engaging in terms of regularity by participants. Furthermore, Kumar et al. [17, 18] demonstrate that the type of LLM used during meditation significantly affects outcomes: while both informative and self-reflection LLMs increase users' initial intention to practice mindfulness, especially compared to receiving static text descriptions, only the friendly informational agent seems to enhance engagement. However, none of these studies incorporate real-time physiological stress detection and only few utilize text-to-speech to deliver voice-based meditation content. Neupane et al. [25] are one of very few to combine wearable-triggered stress detection with LLMs for stress management, but they do not incorporate meditation. Nevertheless, their study revealed key insights into effective wearable LLM interventions, including the need to maintain contextual continuity, balance emotional and practical support, and target interventions based on stressors and user preferences.

2.3 Heart Measures for Stress Detection

Physiological signals are well-established for automated stress detection [36]. Common metrics include skin temperature [2], pupil dilation [29], as well as HR and HRV [12, 31, 35]. Physiologically, our system leverages HR and RMSSD (a time-domain HRV metric) to capture the dual-branch response of stress: sympathetic activation and parasympathetic withdrawal [14]. While HR alone is often insufficient to distinguish psychological stress from physical activity, RMSSD provides the parasympathetic context necessary to differentiate metabolic demand from emotional arousal. RMSSD is chosen because it remains reliable in 10–30 seconds windows, enabling the detection of autonomic changes required for real-time adaptive systems [6, 33]. Using heart-related data only further simplifies the hardware requirements for our prototype.

3 Contextual User Interviews

To complement these physiological metrics with user-centered insights, we conducted 11 semi-structured interviews (20–35 minutes) to derive requirements, following a pretest of the interview guide with three colleagues. The interviewees work in technical areas of business (software company, energy supplier, aviation company, $N = 7$) or academia ($N = 4$). Our sample included individuals with varying levels of experience in stress management (Figure 1, right) to capture both general system requirements and differing needs, e.g., related to usability and personalization. The interviews were conducted remotely and recorded. The responses were coded and categorized with two researchers to derive the requirements. The categories were the same as in the interview guide: users and their

Table 1: System requirements for stress recognition and meditation based on our interviews.

ID	Category	Description
(A)	*Recognition*	Recognize stress to build awareness and distinguish physical exertion from psychological stress.
(B)	*Hardware*	Integration with existing devices (smartwatches, headphones) without requiring new hardware.
(C)	*Delivery*	Voice-based meditation only; no reading or visual engagement required.
(D)	*Environment*	Usable at a desk, home, or while walking; must be discreet enough for office use.
(E)	*Control*	Flexible usage patterns; respects "Do Not Disturb" during meetings or exercise.
(F)	*Session Start*	Adjustable stress sensitivity, including the ability to raise thresholds for high-pressure days.
(G)	*Session End*	Additional option for predefined session lengths or user-defined endings regardless of HR/HRV.
(H)	*Customization*	Choice of meditation styles (body scan, storytelling), imaginary environments, and voices.
(I)	*Modes*	Includes a "Randomization" mode for ease of use and a "Notification-only" mode for busy days.
(J)	*Individualism*	Focuses on helping the individual, filling the gap in cross-functional corporate services.

environment; stress-reduction goals, resources and methods; experience and interest in meditation; system requirements; and open comments.[1]

In the *Users* category, we asked, for example, how often stress is felt in the workplace, what the main causes are, and whether stress is recognized in time. In the *Environment/Goals* category, we asked about the effects of stress in the workplace, the measures that employees take, whether these are effective, and the reasons why or why not. Regarding *Tasks/Methods*, we asked how employees reduce stress themselves, what makes stress-reduction measures more effective and attractive, when stress-reduction methods are used, and whether meditation has been used in the workplace before; if not, we asked why and what would be the prerequisites for them to do so. We then asked specific questions about the potential nature of such a *System*, focusing on necessary functions, integration conditions, and selectable options. To avoid bias, system concepts were not disclosed, allowing participants to freely express their own ideas and requirements.

Interviewees reported that workplace stress mainly results from deadlines and time pressure (I1, I3-6, I9-11), and high self-expectations (I2, I8). Stress occurs daily (I3, I8, I10), 2-4 times a week (I1, I2, I6), or in phases (I5, I9, I11). While short-term stress can increase efficiency and motivation, all interviewees described negative long-term effects, including low mood, restless sleep, and physical deterioration, also affecting private life (I1-I11). Employer support varies from none to more overarching programs or temporary task redistribution upon request (I1, I3, I4, I6, I9), which is generally considered ineffective in the long term. Active stress management courses or well-being programs are also offered by some employers (I2, I5, I8, I10, I11). However, the interviewees all claim that they lack individualization and timeliness, i.e., they do not address specific stress-situations at a distinct moment. Individual coping strategies include breaks and physical activity (I1-I5, I10), as well as breathing, reflection, and meditation (I3, I5, I6-I11). Current meditation practitioners receive guidance outside working hours rather than during work (I6, I9, I11). Situation-dependent and individual stress management measures seem to be preferred over regular measures (I1-3, I6, I8-11), while barriers include time constraints (I1, I2, I4, I8, I9), fear of distracting colleagues (I2, I11), and self-consciousness (I1, I2, I11). Most interviewees favor audio-based meditation and emphasize personalization as key to daily use (I1-3, I5, I7-9, I11).

[1]The full interview guide is available in the supplemental materials.

4 StreAM

The aforementioned and further insights from the interviews informed the system requirements categorized in Table 1. Accordingly, *StreAM* was designed to detect stress and autonomously initiate and terminate meditation sessions based on individualized thresholds derived from heart-rate metrics (A, F, G). Upon activation, an LLM generates a personalized meditation experience (H, I) that is appropriate for office environments (D). As an audio-based system, *StreAM* naturally integrates with headphone use (B, C), supporting private, individual engagement (J). Since *StreAM* is a research prototype, we did not implement the *Do Not Disturb* requirement (E) or the *Notifications Only* mode (I), as neither was necessary to demonstrate the system's core functionality and both would have required deeper integration with the user's operating system than was feasible within the scope of this work. A video of *Stream* is available in the supplement material.

4.1 Personalization

Prior to each baseline measurement (e.g., at the start of the workday), users configure personalization settings via a start screen, which are incorporated into the LLM-generated meditation (H). Users can adjust (1) detection sensitivity, specifying how small a change in HR/HRV must be to trigger a session; (2) the meditation termination condition, based either on an indirect stress measure (i.e, heart rate) or a fixed duration (G); (3) the meditation content, including one of three predefined styles, imaginary locations, and accompanying soundscapes, all derived from the interviews; and (4) the gender of the speaker and their speaking rate (H). As all of these options can be selected with just a few clicks, personalization only takes a few seconds. Additionally (5), to increase comfort, all these options can also be randomized with a single interaction (I). Users can also enter additional preferences in a free text field such as context, story topic, or people to be involved. All of these settings (Figure 1, middle) are later passed to the LLM instructions. For example, a part of the system prompt includes the following: *"(...) the meditation should be a [chosen style] meditation style and guide*

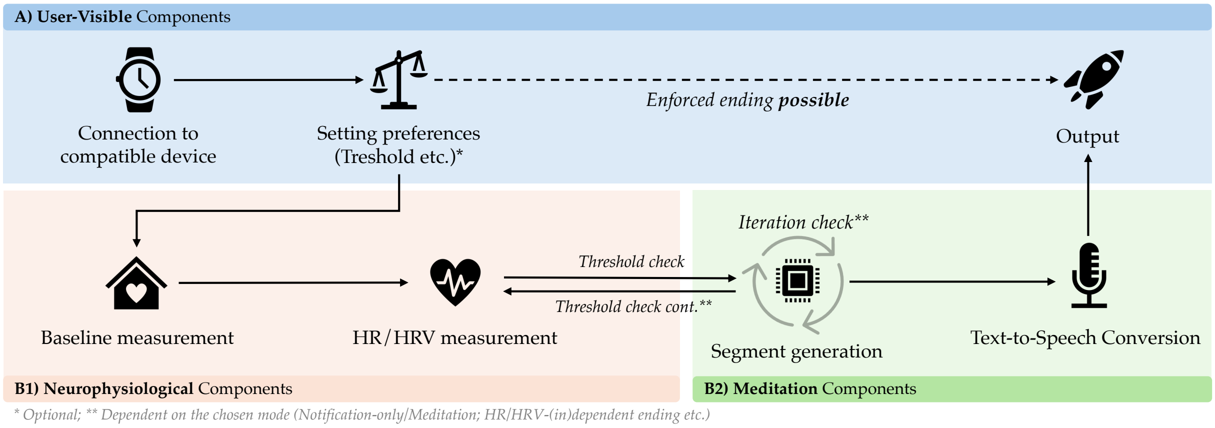

Figure 2: System architecture of *StreAM*.

through an imaginary [chosen environment and soundscape] environment. The user has provided these personal notes to incorporate: [notes] (...)" [2].

After configuration and initialization of the background processes, users can resume their usual activities while heart-rate metrics are monitored. When the defined stress threshold is exceeded, a meditation session is triggered (F). The interface allows users to view their current heart rate at any time and, during meditation, see the remaining session duration until the next measurement (Figure 1, middle). Users may terminate a session either at the end of the current segment (soft exit) or immediately (hard exit) if they do not wish to wait until the ending threshold is reached (G).

4.2 Technical Implementation

Neurophysiological Components. To detect stress, we used the metrics explained in Section 2.3 and measured them with a Polar H10 belt (A, F). To distinguish between psychological and physical stress, we incorporate both HRV and HR into the determination of the stress threshold [14, 15]. Both are measured continuously, and the meditation session only begins (or ends) if both exceed the set threshold. This threshold is a predefined percentage deviation from the baseline measurements and is set by the user. The default is 10%, which aligns well with theory [6]. With this setting, the session only begins (ends) when the HR increases (decreases) and the RMSSD decreases (increases) by 10%.

Meditation Components. We configure the LLM via a system prompt that specifies its role, task, and user preferences provided through the front end. Based on this information, the LLM, we used Gemini 2.5 Flash-Lite as fast and cost-effective model, generates a meditation script, which is converted to audio using the Google Cloud Text-to-Speech API, providing access to human-like voices (C). To ensure consistent and concise session lengths, we constrain each segment to a predefined word count, resulting in segments of approximately 90-120 seconds. This duration has already been shown to be effective in micro break research [1, 5], allows sufficient time to compute reliable RMSSD values, and was perceived as natural during pilot testing. The LLM additionally receives the meditation iteration number to maintain continuity across segments and to enforce termination when users specify a fixed session length. The final segment is played only when the user manually ends the session or when stress falls below the predefined threshold. The overall prototype architecture is presented in Figure 2.

4.3 Formative Evaluation

Ten university staff and research assistants participated in a formative evaluation, using the system for up to one hour following a five-minute baseline measurement, after which they provided quantitative and qualitative feedback.[3] If no stress threshold was met within the hour, meditation was automatically triggered to ensure that all participants could evaluate the session. Quantitative results on a 1–7 Likert scale were positive: the meditation sessions were rated as sufficiently short for work (M = 5.6, SD = 1.4), well-personalized (M = 5.7, SD = 1.2), effective at reducing stress (M = 5.8, SD = 0.8), easy to understand (M = 6.5, SD = 0.5), and easy to use (M = 6.4, SD = 1.0). The system was also rated slightly better than other meditation systems (M = 4.6, SD = 2.1). The lowest rating concerned stress detection timing (M = 4.3, SD = 2.2), skewed by two immediate triggers and one automatic one-hour trigger, which were also noted qualitatively. The variance in ratings underscores that sensitivity is individual. To address this and optimize trigger timing, integrating more sophisticated algorithms and stronger personalization via long-term monitoring is essential.

Qualitative feedback focused on system shortcomings, desired adaptations, and long-term use potential. Besides the two early triggers, the shortcomings mentioned were that the meditation sessions were too short (twice) and that the Polar belt caused ergonomic discomfort (four times). Furthermore, participants stated that they would like the personalization components to be used more extensively and noted that the sedentary baseline measurement might not accurately reflect no-stress working levels. Participants wished for different voices or sound/music options (four times), integration with more common devices, such as smartwatches (four times), a skipping option, softer fading in and out of the meditation, and

[2]The used prompt and system instructions to the meditation LLM are available in the supplement materials.

[3]The questionnaire is available in the supplement materials.

the ability to determine session lengths themselves (all mentioned once). Three participants would use the system immediately; six others would do so pending everyday device integration (3) or improved detection accuracy (3). One participant expressed general disinterest in meditation, even though they like the idea.

5 Limitations and Outlook

StreAM is not yet fully integrated into users' work ecosystems. For example, it does not recognize calendar data or keyboard activity, nor does it report ongoing meditation sessions to other systems. Consequently, high-focus work sessions, appointments, and deadlines are not recognized in order to adjust meditation timing, and notifications are not suppressed during meditation sessions. The systems also does not yet automatically adjusts sensitivity levels when meditations are triggered too frequently, which could result in users blocking sessions, nor increase sensitivity if no triggers occur for an extended period. Moreover, the formative evaluation suggests that the stress threshold needs to be individualized Furthermore, stress detection relied on the Polar H10 belt because it was easier to integrate, which limited usability. Our vision is that stress detection in the field could use consumer-grade devices like the AirPods Pro, OpenEarable 2.0 [32], or smartwatches to monitor HR/HRV metrics, eliminating the need for specialized hardware and increasing comfort.

In the future, we plan to address the aforementioned limitations by switching to more common hardware, integrating a broader variety of modes (e.g., notifications-only or background music-only modes) to make *StreAM* more accessible to different types of workers, and further analyzing and integrating better stress-detection mechanisms. Additionally, a few interviews recommended integrating movement detection to enhance customization. This would allow the system to recognize the user's context (e.g., sitting or walking) and adjust the meditation experience accordingly. The formative evaluation did not reveal any issues or dissatisfaction regarding the system's latency, as we employed a rather efficient model. However, we will conduct further evaluations of this aspect, along with potential trade-offs between quality and speed. Additionally, we will address concerns about system noise under heavy locomotion, clothing, and different body characteristics before testing it in the field. To sufficiently detect stress, we may also need to integrate additional signals, such as electrodermal activity, respiration patterns, and motion. We also plan to analyze the LLM component by benchmarking the Off-the-Shelf Gemini API used against proprietary models and models fine-tuned especially for our context. We will compare perceived quality, response latency, and other factors. We will furthermore validate *StreAM* in a field study to evaluate its usability and effectiveness in reducing stress and adjust its thresholds. We plan to integrate more usability metrics, such as the System Usability Scale [21], to derive more meaningful results. We will especially analyze whether frequent triggers create general disinterest in meditation. To identify the specific components that contribute to stress reduction, we plan to compare *StreAM* to a non-adaptive control group and to a treatment in which the stress recognition component remains adaptive but triggers a standardized stimulus, such as relaxing music, rather than a personalized meditation.

6 Conclusion

In this work, we presented *StreAM*, an LLM-based system that detects stress in the moment and performs personalized micro-meditation exercises in a work environment. We conducted 11 interviews to identify user requirements for the system, which served as the basis for developing our prototype. Stress is measured using heart metrics, triggering a personalized LLM-based meditation when a threshold value is reached. The meditation session ends automatically when the stress level falls below the threshold or when the user ends the session manually. The prototype fulfills all but two of the user requirements described in Table 1 and has already been tested as part of a formative evaluation. The results showed that the system was generally easy to use and effective at reducing users' perceived stress. The stress detection function worked but needs to be customized for better situational use.

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