Capace: A Head-Mounted Haptic System for Attention Regulation in Adults with Deficit/Hyperactivity Disorder (ADHD)

ANONYMOUS AUTHOR(S)

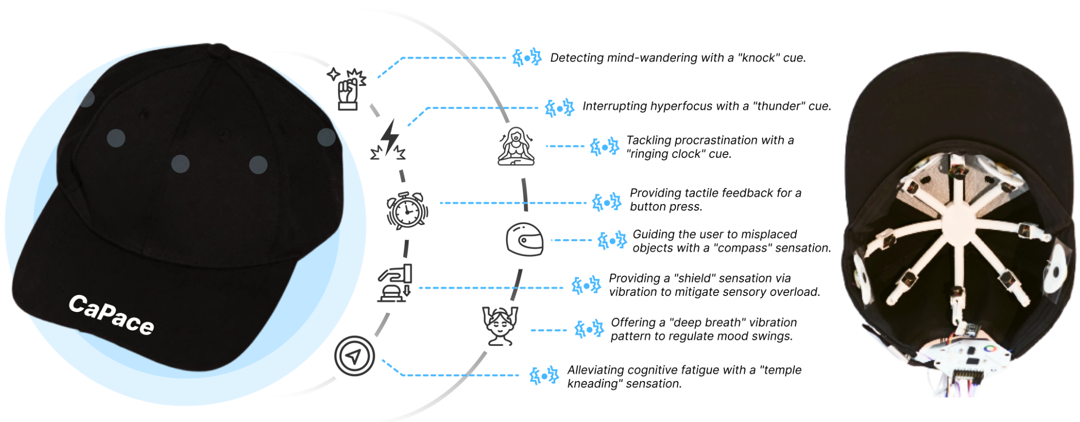


Fig. 1. The design and key features of Capace, a device for attention regulation for people with ADHD.

Regulating attention is a primary challenge for adults with Attention-Deficit/Hyperactivity Disorder (ADHD). Current technological aids, such as smartphone apps or wrist-worn wearables, often introduce visual distractions that undermine their intended purpose. Thus, we conducted formative studies involving 124 survey participants, 12 adults with ADHD, and 4 clinicians, which confirmed the need for non-visual, embodied, and in-situ interventions. Building on these insights, we present Capace, a novel head-mounted wearable device that provides real-time, context-aware vibrotactile biofeedback cues to support focus. We evaluated Capace in 2 within-group experiments with 10 adults with ADHD, assessing the comprehensibility of its haptic cues and the user experience. Our work contributes to an understanding of the design space and feasibility of using on-head haptics for attention, inspiring future explorations of embodied interfaces for cognitive support.

CCS Concepts: • **Human-centered computing → Haptic devices**; *Ubiquitous and mobile computing systems and tools*; *Accessibility systems and tools.*

Additional Key Words and Phrases: Haptic Biofeedback, Wearable Computing, Attention, ADHD

ACM Reference Format:
Anonymous Author(s). 2026. Capace: A Head-Mounted Haptic System for Attention Regulation in Adults with Deficit/Hyperactivity Disorder (ADHD). In *CHI Conference on Human Factors in Computing Systems (CHI '26), April 13 -April 17, 2025, Barcelona, Spain.* ACM, New York, NY, USA, 38 pages. https://doi.org/XXXXXXX.XXXXXXX

1 Introduction

Attention-Deficit/Hyperactivity Disorder (ADHD) affects an estimated 2–5% of adults worldwide, impairing their ability to regulate attention and sustain focus in daily life [32]. Adults with ADHD face diverse challenges, including persistent mind wandering, episodes of hyperfocus [40], procrastination [64], difficulty switching tasks [4], sensory overload [48], and cognitive fatigue [20]. Existing treatments, however, often offer partial relief. Pharmacological interventions can be effective for some but raise concerns about side effects and dependency [34]. Meanwhile, behavioral therapies often lack the immediate, in-situ support needed to manage attentional lapses in dynamic, real-world contexts [34]. These limitations motivate the exploration of Human-Computer Interaction (HCI) approaches to deliver more dynamic, context-aware interventions.

HCI researchers have explored a range of technological aids for attentional support, often delivered through smartphone apps or wearable devices [6]. Systems such as SerenSailor [76], FOQUS [33], for example, use vibrotactile wristbands or application to assist adults with ADHD in daily life or to modulate affective states through rhythmic cues or meditation. However, many existing interventions, including those implemented on smartwatches and smart applications, primarily rely on visual or auditory notifications [22]. These conventional alerts risk becoming distractions themselves, disrupting workflows and creating social awkwardness, which limits their real-world applicability [22].

While our long-term vision is to develop a fully intelligent, adaptive system that proactively supports attention, a foundational challenge must first be addressed: designing an effective and intuitive feedback mechanism [80]. Developing a non-intrusive yet comprehensible vibrotactile semantic framework for the head constitutes a substantial HCI challenge in its own right [85]. Therefore, this paper focuses on this critical initial work: the design, implementation, and validation of the core feedback device and its haptic patterns, which are essential prerequisites for future intelligent adaptation.

To address the aforementioned issues, we introduce "Capace", a smart wearable haptic system designed to help adults with Attention Deficit/Hyperactivity Disorder (ADHD) regulate their attention. As illustrated in Figure 1, the device integrates eight sets of vibration motors in an "octopus-like" layout around the head to provide targeted haptic feedback. We first conducted a formative study, which revealed a strong user need for non-visual, embodied interventions that offer in-situ support. This guided our design focus toward a head-mounted, vibration-based wearable device. The design is also inspired by prior HCI research, which has shown that vibrational stimuli can effectively convey semantic cues [86, 89] and affective signals for emotion regulation through the mechanism of proprioception [74], thus enabling attention regulation while maintaining low cognitive intrusiveness.

To evaluate Capace, we conducted a within-subjects experiment with 10 adult participants with ADHD. The study consisted of three stages: Participants first completed a task to pair vibration patterns with their corresponding semantic meanings to test for understandability. Subsequently, they experienced specific vibration patterns during a Sustained Attention to Response Task (SART) [71] and a search task to assess the system's effectiveness in specific contexts. Finally, we collected comprehensive user feedback through questionnaires and semi-structured interviews. The results indicate that Capace is effective in enhancing users' attention, its haptic language is understandable, and the overall concept is highly accepted by users.

This paper has the following contributions:

(1) The design and implementation of Capace, a novel, socially acceptable head-mounted haptic system that provides discreet, non-visual feedback for attention regulation in adults with ADHD.

(2) A systematically developed design space of head-mounted vibrotactile metaphors, mapping common attentional challenges of ADHD to a set of intuitive, embodied haptic cues.

(3) Empirical evidence of the system's efficacy and user acceptance. Findings from a study with 10 adults with ADHD demonstrate the system's effectiveness in a guided search task and its overall high usability and appeal.

2 Related Work

In this section, we review literature most relevant to our work, focusing on attentional reminders for ADHD, mind-wandering detection technique, and wearable vibration-based intervention systems.

2.1 Studies of Attentional Reminders for ADHD

In multimodal environments, individuals with ADHD primarily receive attentional cues through vision and hearing, whereas vibrotactile feedback offers a non-intrusive, private, and tactile alternative. Prior research has shown that vibrotactile feedback can support sensory regulation and attention management for individuals with ADHD [75]. However, because users often adapt quickly to repetitive stimuli, continuous or fixed vibration patterns may lose effectiveness over time. To mitigate this, studies suggest that introducing occasional and unexpected vibrations can reduce habituation and enhance the long-term impact of such interventions [70].

In addition, portability and social acceptability are critical for everyday use. Individuals with ADHD often avoid conspicuous devices—such as headbands or laboratory-grade EEG systems—that may evoke stigma or social discomfort [51]. As a result, effective vibrotactile feedback systems should take the form of everyday wearables, such as smart wristbands or embedded patches, that provide discreet sensory regulation while preserving user privacy [61]. Guided by these insights, Capace is designed as a hat that can be worn comfortably and unobtrusively in daily life.

2.2 EEG-Based Mind Wandering Detection

Electroencephalography (EEG) is a well-established modality for detecting mind wandering (MW), as it directly measures cortical activity with millisecond precision. Prior work has linked posterior alpha power (8–12 Hz) to attentional lapses [24, 58] and associated MW episodes with elevated frontal theta activity and higher theta/beta ratios [9, 81], providing a strong neurophysiological basis for EEG-based MW detection.

Traditional MW detection pipelines typically follow three stages. First, preprocessing methods such as Independent Component Analysis (ICA) or regression-based correction reduce ocular and muscular artifacts [5, 39, 46, 59, 84]. Second, features are extracted with time–frequency methods (e.g., Morlet wavelets [41]) across canonical frequency bands (delta, theta, alpha, beta, gamma)[3, 29]. Finally, classifiers such as extreme gradient boosting (XGBoost) [15] or random forests [11] are trained on spectral and entropy features, yielding reliable binary MW detection [16, 18, 56]. While effective, these approaches depend heavily on manual feature engineering and often fail to capture the complex spatio-temporal dynamics of MW.

Recent deep learning methods address these limitations by learning directly from raw EEG. Convolutional Neural Networks (CNNs) capture spatial and spectral patterns [2], while hybrid models such as CNN–LSTM networks and multi-stream spatio-temporal architectures extend this to long-range dynamics and frequency-specific representations [44, 66]. However, CNNs may underexploit temporal dependencies, and LSTM-based models are prone to overfitting and high computational cost, particularly with limited EEG data. To overcome these challenges, we adopt a multi-stream design that leverages band-specific information, while introducing a more efficient architecture for joint spatial–temporal feature extraction: our proposed multi-band EEGNet–GRU framework.

2.3 Wearable Vibration Intervention Systems

Tactile vibration feedback has become an important area of HCI research because it is non-invasive and introduces minimal cognitive load [69]. Unlike audiovisual cues, which risk sensory overload, vibrotactile signals efficiently convey information via somatosensory pathways. To expand their expressive range, researchers have explored parametric encoding (e.g., frequency, duration, waveform) and perceptual mappings. For instance, short high-frequency pulses (e.g., 200 Hz for 50 ms) are often perceived as "active," while lower-frequency, continuous vibrations (e.g., 80 Hz for 300 ms) convey a sense of "stability" [74]. Building on this, Tsinghua University developed a vibrotactile wristband that binds vibration patterns to semantic actions such as "confirm" or "cancel" [86]. Similar mappings have been applied in VR contexts, such as encoding head vibration sequences to represent vehicle acceleration or steering [87].

Despite these advances, research has focused largely on familiar form factors—such as smartwatches, wristbands, or waist belts [49, 82, 90]—leaving head-mounted tactile interaction underexplored. Early VR studies have demonstrated the potential of cranial vibrations for spatial navigation, where haptic cues complemented visual guidance in driving simulators [87]. Yet these efforts remain confined to gamified settings and have not addressed everyday cognitive support. In ADHD contexts, vibration-based interventions have begun to emerge, but they typically rely on user-triggered actions (e.g., tapping a screen) [52] or researcher-controlled schedules.

Capace directly addresses this gap by introducing a socially acceptable, head-mounted system that delivers autonomous, real-time vibrotactile cues for attention regulation in adults with ADHD. By situating haptic stimulation at the cranial level in the form of an everyday hat, Capace expands vibrotactile interaction beyond the wrist and waist, demonstrating how head-mounted feedback can unobtrusively support attention management in daily life.

3 Formative Study

To identify user needs, we conducted formative studies of questionnaires and semi-structured interviews (details shown in Appendix C). This study provided insights into their daily attentional challenges and preferences for support. In this section, we outline the study design and summarize the key requirements that directly informed the design and implementation of the Capace system.

3.1 Method

Building on prior work documenting the diverse symptoms of ADHD, we sought to examine both the contexts in which attentional difficulties occur and the types and timing of interventions that may be most effective. To this end, we conducted a multi-method formative study, including an online questionnaire with 124 participants and semi-structured interviews with 12 participants. This approach allowed us to capture both broad population-level insights and in-depth individual experiences, which directly informed the design of the Capace system. The overall study process is illustrated in Figure 2.

First, we conducted an online questionnaire (details in C.1) distributed via social media platforms (Little Red Book[1] and Weibo[2]). After excluding responses from individuals who self-reported no ADHD, we retained 124 valid responses (69 male, 55 female; average age is 28.16) from participants with confirmed or self-suspected ADHD. The questionnaire collected demographic information, explored participants' needs and preferences regarding potential assistive systems, and also served as a recruitment channel for follow-up interviews.

[1] https://www.xiaohongshu.com/explore
[2] https://weibo.com/

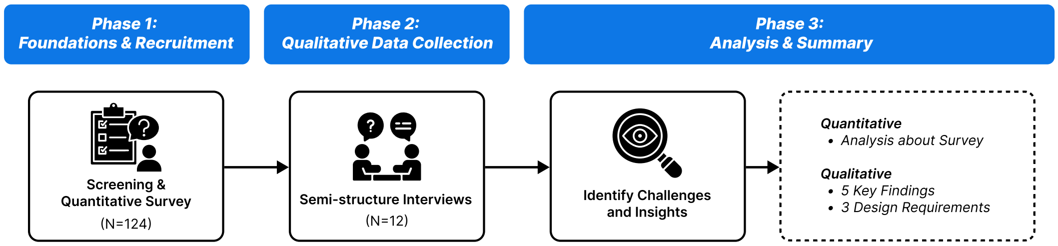


Fig. 2. Formative study workflow: use questionnaire and interviews to explore ADHD attentional contexts and intervention requirements.

Next, we conducted 60-minute semi-structured interviews (details in C.2) with 12 participants selected from the questionnaire respondents. Selection criteria included gender, occupation, and diagnostic background to ensure diversity and representativeness. The interviews explored participants' lived experiences with ADHD, coping strategies, and perspectives on technological support. Detailed demographic information is summarized in Table 1.All participants received monetary compensation for their time and contributions.

Table 1. Demographic Information of interview participants

ID	Age	Gender	Diagnosis Period	Identity	Education/Work Field
P1	19	Male	Childhood	Student	Computer Science
P2	20	Female	Childhood	Student	Journalism/Communication
P3	22	Male	Childhood	Student	Psychology
P4	24	Female	Childhood	Student	Education
P5	24	Male	Adulthood	Student	Digital Media
P6	27	Female	Adulthood	Employed	Internet Product Manager
P7	28	Female	Childhood	Employed	Public Relations
P8	30	Female	Childhood	Employed	Administrative Assistant
P9	33	Female	Adulthood	Employed	Freelancer
P10	36	Male	Childhood	Employed	Graphic Designer
P11	38	Male	Childhood	Employed	Project Manager
P12	56	Male	Adulthood	Employed	Electrical Engineer

We utilized open coding for thematic analysis[10] as outlined in grounded theory[26]. Two researchers independently coded the transcripts from the interviews. Through iterative discussion, we developed a shared codebook of all those interviews' results to ensure the consistency. The research team reviewed the coding outcomes collectively to identify high-level themes and cross-cutting insights.

3.2 Key Findings

This analysis integrates insights from both the questionnaire and interviews. These findings also reveal the users' requirements that guided the design of our system. Figure 3 shows the statistics from the questionnaire, which cover distraction situations, preferred device-wearing locations, preferred reminder methods, and concerns about daily wear.

KF1: Mind-wandering most frequently occurs in structured, passive contexts where internal thoughts are harder to control. Our survey data reveals that "meetings or classes" are the most common scenarios for attention loss, with an overwhelming 93.3% of respondents identifying them as challenging situations. This was followed by using electronic devices (66.7%) and engaging in conversations (62.2%). Interviews further illuminated this issue, where

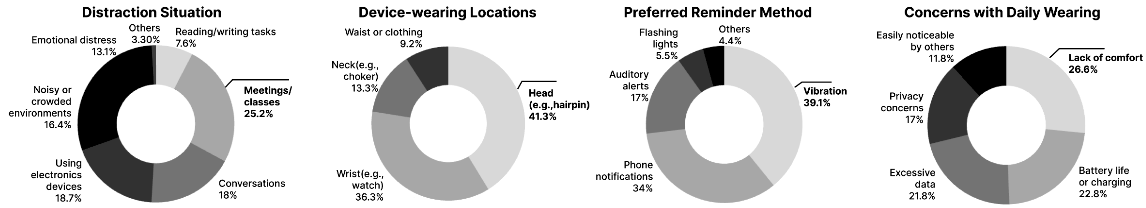


Fig. 3. Questionnaire statistics on distractions, device-wearing locations, preferred reminder method, and concerns with daily wearing.

participants described a sense of being “trapped" in low-stimulation environments. P3 explained: “In class, my brain just automatically opens ten different tabs. It’s not that I don’t want to listen; it’s just that there’s nothing to anchor my focus on, so my thoughts just drift away."

KF2: Head is a suitable location for a wearable intervention, offering a direct connection to cognitive processes while enabling discreet feedback. When asked about preferred locations for a wearable device, the head (e.g., as a headband or integrated into a hat) was the top choice for 83.7% of survey participants, higher than the wrist (75.5%). Interviewees elaborated on this preference, linking the head to the source of focus. P11 stated, “it just makes sense. My focus problem is in my brain, so a reminder on my head feels more direct, like it’s tapping me right where the problem is." Additionally, participants like P6 mentioned the potential for discreetness: “A stylish headband or something in my hat wouldn’t be obvious. A wrist device might just feel like another notification I ignore."

KF3: Haptic feedback—particularly vibration—was strongly preferred as an intervention modality due to its discreet and non-disruptive nature. Vibration was the most preferred intervention method, selected by 79.6% of survey respondents, far surpassing phone notifications (59.4%) and auditory alerts (38.8%). Light-based feedback was the least popular (10.2%). Participants in interviews consistently expressed a desire to avoid socially awkward or distracting alerts. As P8 articulated, "The last thing I need is a sound or light going off in a quiet office. It would just draw attention and make me more anxious. A silent vibration is personal; it’s just for me." This strong preference underscores the importance of designing a private feedback mechanism that avoids causing secondary anxiety related to social stigma.

KF4: Physical comfort, potential distraction, and the social visibility of the device emerged as key concerns, while users remained receptive to in-situ attentional interventions. The primary concerns voiced by survey participants were practical and social: "not comfortable enough" (81.6%), "too much data disturbing life" (71.4%), "battery life/charging issues" (69.4%), and "being easily noticed by others" (55.1%). These concerns were echoed in our interviews. P5 worried about the cognitive load of the intervention itself, asking, "What if the reminder itself breaks my focus? It needs to be gentle enough to guide me back, not jolt me out of a different thought." P9 highlighted the social barrier: "I’m trying to mask my ADHD. I wouldn’t want to wear something that screams ’I have a disability’." These findings stress that the physical design and the intervention logic of system must prioritize user comfort, subtlety, and a "low-interruption" principle to ensure adoption.

KF5: A system/device that not only provides reminders but also delivers simple, actionable insights into users’ attention patterns is desirable, supporting self-awareness and a sense of control. Beyond simple alerts, there was a clear desire for a complementary software component. 56% of survey respondents wanted the software to show "timing of triggered reminders," and 28% wanted to see "daily attention change trends." This indicates a need for more than just in-the-moment intervention. During the focus group, one participant conceptualized this as a "heat map of my mind-wandering," which would help them "observe and reflect on my own patterns." P2 added, "I don’t just want to be zapped back to reality. I want to understand when and why I lose focus. Seeing that data would give me a sense of agency, helping me to maybe make adjustments to my routine or environment." This suggests that the system should pair real-time haptic feedback with long-term data visualization to support both immediate regulation and long-term behavioral change.

3.3 Design Requirements

Based on the key findings, we summarize the following design requirements to guide the subsequent design process:

DR1: Ensure Seamless Social Integration through a Discreet Form Factor. Users expressed strong concerns about visible assistive technologies, which can evoke stigma and discourage public use. To reduce these barriers, the system should be embedded in an everyday accessory, prioritizing psychological comfort and enabling discreet integration into social contexts.

DR2: Prioritize Private Haptic Feedback for Non-Disruptive Intervention. Haptic feedback was strongly preferred over audio-visual alerts for its private and unobtrusive qualities. Interventions should be delivered exclusively through subtle haptic cues, ensuring they remain perceivable only to the user and do not disrupt surrounding activities.

DR3: Provide Nuanced Haptic Cues for Metaphorical Guidance. Simple binary alerts risk being jarring or quickly ignored through habituation. Instead, users expressed a desire for interventions that support self-awareness and gently guide focus. To achieve this, the system should employ a varied haptic vocabulary—patterns, rhythms, and intensities—that conveys nuanced, metaphorical cues rather than corrective signals.

4 The Design of Capace System

This section describes how we translated user requirements and design considerations into a tangible wearable system for attention regulation. We first present the design space that informs the creation of meaningful haptic patterns, then detail the hardware implementation, and finally introduce the deep learning model used for wandering detection based on EEG signals.

4.1 Design Space

The design space (Figure 4) is used to produce meaningful haptic patterns that address eight ADHD-related symptoms the most commonly reported by adults: (1) mind wandering, (2) hyperfocus, (3) procrastination, (4) object misplacement, (5) mood lability, (6) cognitive fatigue, (7) task-switching difficulty, and (8) sensory overload. Therefore, the space covers eight different haptic patterns.

Among the eight tactile modes, six—mind wandering, hyperfocus, procrastination, object misplacement, mood lability, and cognitive fatigue—use specific sequential activations of actuators, while two—switch task difficulty and sensory overload—involve simultaneous vibrations in design space.

are conveyed through sequential actuator activations. while two modes—task difficulty switching and sensory overload—are represented by simultaneous vibrations (Figure 4).

The haptic patterns are implemented in Capace, a wearable hat equipped with eight linear resonant actuators (LRAs) evenly distributed around the head. Within this design space, six modes—mind wandering, hyperfocus, procrastination, object misplacement, mood lability, and cognitive fatigue—are conveyed through sequential actuator activations, while two modes—task difficulty switching and sensory overload—are represented by simultaneous vibrations (Figure 4).

Metaphors were employed in designing these tactile patterns to enhance intuitiveness and memorability. Six distinct sequential vibration patterns were developed. For example, the **Mind Wandering** pattern simulates a quick, gentle

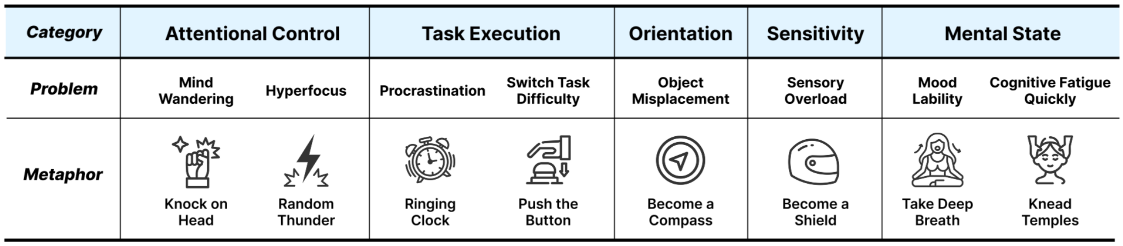


Fig. 4. Selected shortcut actions with their intended meanings.

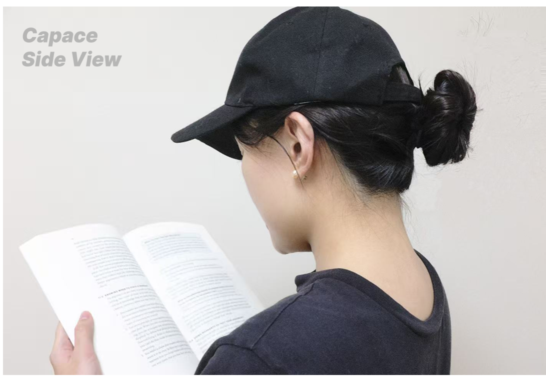
double-tap on the head, resembling a soft knock at a door, represented by two brief consecutive pulses. The **Hyperfocus** scenario, which occurs when users become excessively immersed in an activity, necessitates a sudden, random vibration resembling a startling clap of thunder to disrupt their intense focus. This is represented through rapid, strong vibrations at three randomly selected actuator points simultaneously. For **Procrastination**, the haptic feedback emulates a progressively intensifying alarm clock sensation, gradually increasing from left to right to signal that it's time to resume tasks. For **Orientation**, a compass-like vibration cue guides users by activating the actuator located in the direction of the misplaced object. In addressing "mental state" concerns, the **Mood Lability** pattern employs the 4-7-8 breathing technique[62]: actuators sequentially vibrate clockwise for 4 seconds to guide inhalation, pause silently for 7 seconds during breath retention, then reverse sequentially counterclockwise for 8 seconds during exhalation, facilitating deep relaxation. To address rapid **Cognitive Fatigue**, a gentle, rhythmic kneading sensation on both sides of the head helps alleviate tension. Additionally, two scenarios involve simultaneous activation of all eight actuators. First, the **Switch Task Difficulty** mode mimics pressing a physical button, similar to controls used in gaming to initiate, stop, or change tasks, achieved through a brief simultaneous pulse at all actuator points. Second, under conditions of high **Sensitivity** or significant environmental distraction, the entire head vibrates continuously with a gentle humming akin to white noise, aiding in blocking external stimuli and maintaining concentration.

4.2 Hardware Design

Figure 5 shows the overall hardware design of our wearable Capace, a smart attention reminder system, for adults with ADHD, which is composed of vibration modules and EEG modules. The hardware is built upon an "octopus-like" skeletal support structure, which serves a dual purpose: it ergonomically conforms to the human head while also securing all vibration modules to be seamlessly embedded within the cap. For the vibration part, it composes eight vibration units, one multiplexer, an ESP32 module, one 2000mAh rechargeable lithium battery, while they are wired together to be contained in a tailored 3D printed Thermoplastic Urethane (TPU) cover (see Figure 5a). The ESP32 module serves as the core processing module, which has the capability of retrieving and initially processing the users behaviour data from platform and could further feed the vibration data to the user device through Bluetooth transmission. For the EEG part, the OpenBCI module [14] is trained as the sensing module to record and processing the data of people's attention status. Through a sewing process, all components are physically integrated into a fabric interlayer. This results in a cap where the electronic elements are not externally visible (as shown in Figure 5b). Additionally, Figure 5c and Figure 5d illustrate authentic usage scenarios of the cap from different angles, worn by a user with ADHD.

(a) Internal Electronic Assembly.

(b) Electronics Concealed by Fabric Lining.



(c) Side View in Use.

(d) Rear View in Use.

Fig. 5. The Capace system, (a) Internal view of the modular electronics, (b) Final system with hardware integrated within a sewn lining, (c) Side view of a user wearing the cap while reading, and (d) Rear views showing the cap's when worn.

4.2.1 Spatio-Temporal Haptic Pattern Design. To ensure the vibration modules were securely and comfortably affixed to the user's head, we employed an iterative design process. We 3D-modeled and prototyped an ergonomic wearable structure, which resulted in the octopus-like form-factor shown in the Figure 7a. For material selection, we tested several 3D printing filaments, including PLA and TPU. We ultimately selected TPU over rigid alternatives like Polylactic Acid (PLA) because its flexibility and softness provided a significantly better compliance to the scalp and improved overall user comfort.

In the coding software part, the core of this system's haptic pattern design lies in leveraging the high-quality effects library built into the DRV2605 driver chip, rather than directly controlling vibration frequency. We treat the 123 professionally-tuned vibration effects in the library as indivisible "haptic primitives." Through parametric combination and orchestration of these primitives across spatial (the position of the 8 actuator units), temporal (sequence and rhythm), and qualitative (the effect itself) dimensions, we created a complex "haptic vocabulary" of 8 patterns with distinct interactive intentions. These cover a variety of interaction scenarios, from instantaneous confirmation and directional cues to rhythmic guidance. The design specification for each pattern—including its interactive intent, spatio-temporal parameters, and the effect primitive IDs used—is detailed in the Figure 8.

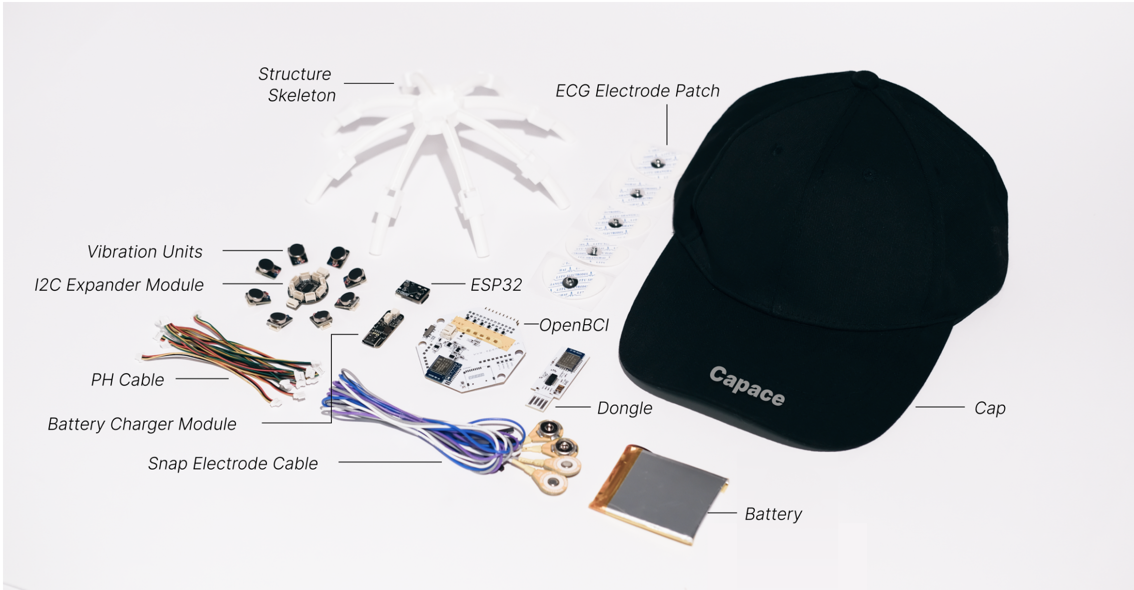
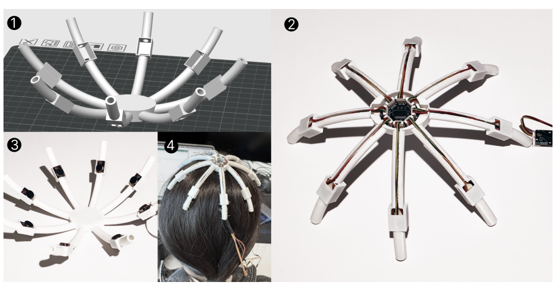
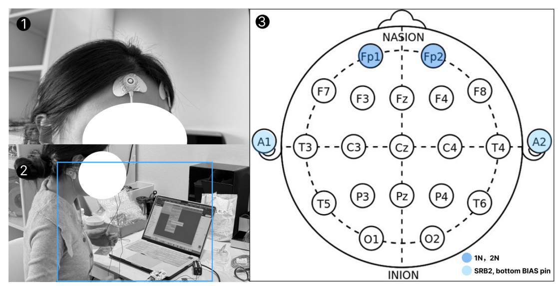


Fig. 6. Hardware overview of Capace system.



(a) Vibration Module Setup: (1) 3D model in software, (2,3) Details of setup modules in the model. (4) Wearing model skeleton in human head.



(b) EEG hardware: (1,2) The EEG patches are attached to the frontal Lobe of the human brain and the sides of the ears. (3) Four electrodes used in our design.

Fig. 7. Hardware details of vibration module and EEG module

4.2.2 Brain Activity Detector. Our EEG electrode placement followed the 10-20 International System [42]. We selected Fp1 and Fp2, located over the prefrontal cortex, as the primary recording electrodes, with the reference (REF) and ground (BIAS) electrodes placed on the left (A1) and right (A2) mastoids (behind the ears), respectively. This two-channel configuration targeting the prefrontal cortex was a deliberate decision guided by neuroscientific evidence and user-centered design principles. Neuroscientifically, the PFC is critically involved in executive functions like attention regulation, which are typically impaired in ADHD [4], and hallmark EEG signatures of mind wandering are robustly captured at these sites [47]. From a user-centered perspective, this minimalist approach is paramount for a device intended for everyday use. It enables a fast, gel-free setup that users can manage independently and allows for a more comfortable and socially discreet form-factor, prioritizing ecological validity over high-density recording. As detailed in

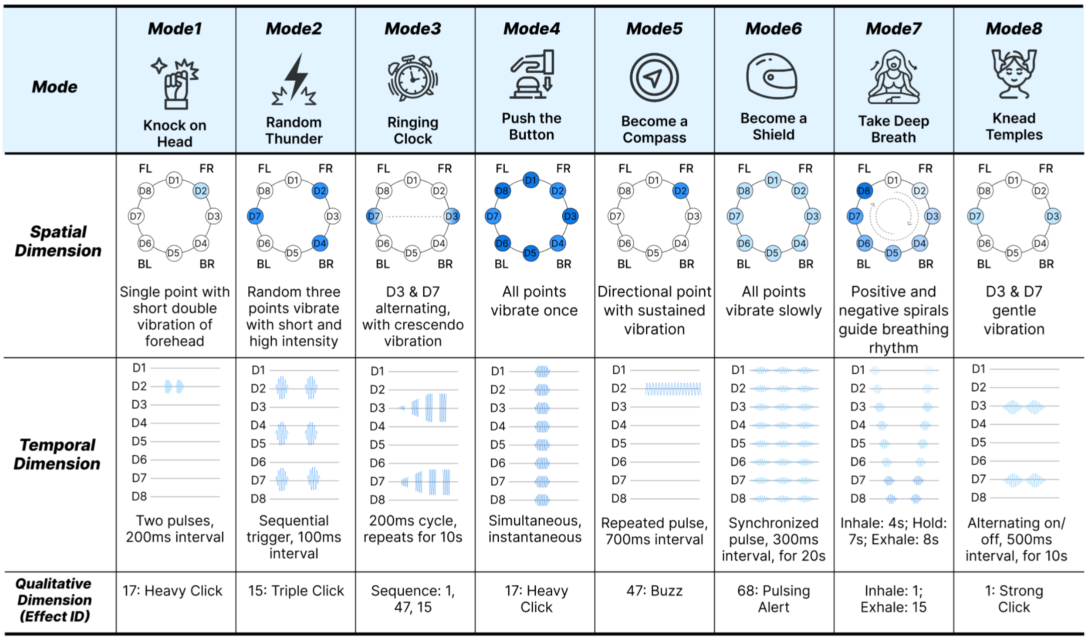


Fig. 8. Design specification of the eight spatio-temporal haptic patterns.

Figure 7b, these electrodes were connected to an OpenBCI Cyton board [60], where A1 and A2 were wired to the SRB2 (bottom SRB pin) and bottom BIAS pins, respectively, while Fp1 and Fp2 were connected to analog input channels.

4.3 Pretrained Model for EEG-based MW Detection

Although our design space addresses eight ADHD-related symptoms (Figure 4), we focus specifically on mind wandering (MW) detection. MW is the most frequently reported symptom in adults with ADHD [8, 63], making it both representative and clinically relevant. Moreover, while EEG datasets for most ADHD-related symptoms are scarce, MW benefits from comparatively well-established open-access datasets [7, 28, 31, 38, 45, 79] that support model training and validation. Finally, our system uses only the Fp1 and Fp2 channels, and data from two electrodes are insufficient for training a reliable multi-class model across all eight symptom categories. We therefore target MW detection as an initial step toward broader EEG-based symptom recognition.

To support EEG-based MW detection, we pretrained a multi-band EEGNet-GRU model (Figure 9), which demonstrated superior performance over several deep learning and traditional machine learning baselines. Below, we describe the model architecture, baseline comparisons, and experimental implementations and results.

4.3.1 Multi-band EEGNet-GRU Architecture. We propose a **multi-band EEGNet-GRU model**, a multi-branch architecture in which each branch processes one canonical EEG frequency band ($\delta, \theta, \alpha, \beta, \gamma$). This design reflects evidence that different bands are selectively associated with attention and cognitive control [9, 58]. By isolating bands, the model may improve both interpretability and sensitivity in MW detection.

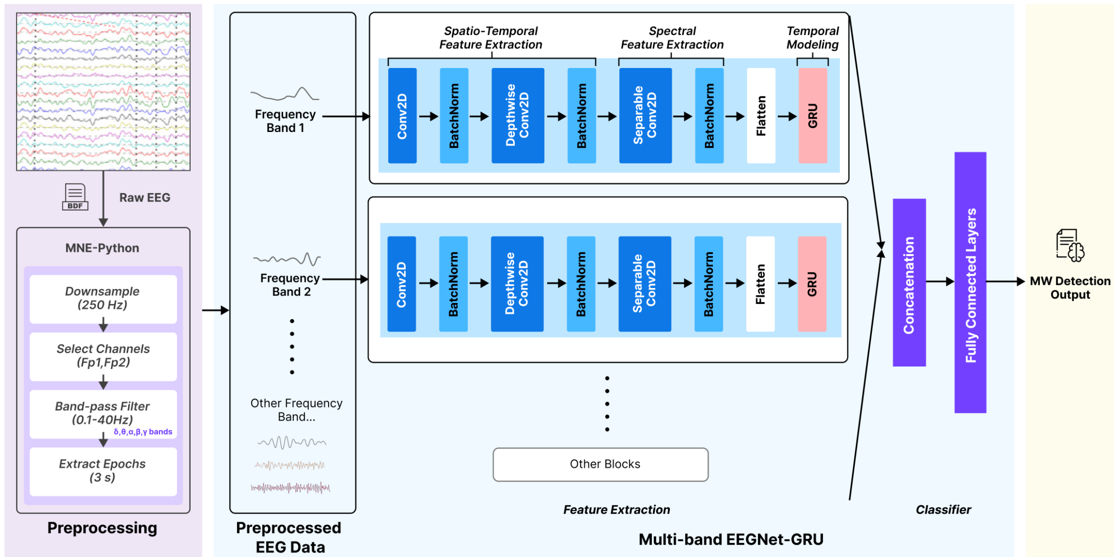


Fig. 9. Overall framework for mind wandering detection using the multi-band EEGNet-GRU model.

Each branch combines EEGNet [53]-inspired convolutional layers with a Gated Recurrent Unit (GRU) [21], enabling joint modeling of spatial–spectral and temporal dynamics. Specifically:

$$\text{Branch}_f(X_f) = \text{GRU} \circ \text{SeparableConv2D} \circ \text{DepthwiseConv2D} \circ \text{Conv2D}(X_f)$$

where X_f denotes the band-specific EEG input. Concretely, each branch applies: (1) a temporal convolution $(1, 64)$ for frequency-specific features, (2) a depthwise convolution $(2, 1)$ for electrode-wise spatial filtering, and (3) a separable convolution $(1, 16)$ for richer feature learning. Batch normalization and average pooling follow each convolution for stability and downsampling. The GRU layer then captures long-range temporal dependencies. Outputs from all branches are concatenated and passed to fully connected layers for classification.

4.3.2 Baseline Models. We evaluated both deep neural networks and traditional machine learning methods as baselines. In the deep learning category, we retained the multi-branch structure of the proposed model but varied its core components. A **multi-band EEGNet** model removed the GRU layers to test the necessity of temporal modeling. Replacing GRUs with Long Short-Term Memory (LSTM) [43] units yielded a **multi-band EEGNet-LSTM** model, allowing us to compare recurrent architectures. To examine the role of EEGNet convolutions, we substituted them with standard CNN layers [50], producing **multi-band CNN-GRU** and **multi-band CNN-LSTM** variants. A simplified **multi-band CNN** model without recurrent layers served as a lower bound.

For comparison with non-deep learning approaches, we included two traditional classifiers: **Random Forest** [11] and **Support Vector Machine (SVM)** [27]. These models relied on handcrafted power spectral density (PSD) features rather than automatic feature extraction and temporal modeling.

4.3.3 Pretrained Experiments and Results. **(1) EEG Data Preprocessing.** We trained and evaluated all models on a public EEG dataset [38] collected from two adults (1 male, 1 female) across 11 sessions each. Participants performed a breath-counting task, pressing a button to indicate MW episodes and subsequently reporting focus events. Data were recorded with a 64-channel BIOSEMI system at 1024 Hz.

Preprocessing was performed in MNE-Python (v1.9.0). The original EEG signals were downsampled to 250 Hz to align with the OpenBCI module used in our system. As the system includes only Fp1 and Fp2, we restricted analysis to these channels. Epochs for MW and focus were segmented relative to button presses, following [66], but using 3-second windows instead of 8 seconds. For deep learning models, continuous signals were band-pass filtered between 0.1–40 Hz and decomposed into five canonical frequency bands. For machine learning models, the same segmentation was applied, and PSD features (0–50 Hz) were extracted using Welch's method [83].

In total, 983 three-second epochs were obtained: 472 MW events and 511 focus events, drawn from 22 sessions across both participants.

(2) Model Training. Data were randomly split into training (80%) and test (20%) sets, with 20% of the training set held out for validation in deep learning models. Deep models were trained for up to 150 epochs (batch size = 32) using early stopping and learning rate reduction on plateau. Machine learning models used standard hyperparameters. Evaluation metrics included accuracy, sensitivity, specificity, precision, F1-score, and AUC, averaged across 3 repeated runs with standard errors reported.

(3) Results and Discussion. Table 2 shows that the multi-band EEGNet-GRU achieved the highest overall performance across most metrics, highlighting the effectiveness of combining EEGNet-based convolutions with GRUs. Deep learning models consistently outperformed traditional methods, underscoring the importance of automated feature extraction and temporal modeling. Compared to CNN variants, EEGNet convolutions provided more effective spatial–spectral feature extraction, while GRUs offered a simpler yet effective mechanism for temporal dependencies compared to LSTMs. This balance of interpretability, efficiency, and accuracy establishes multi-band EEGNet-GRU as the most robust model for MW detection in our study. Accordingly, we adopt this pretrained model for subsequent EEG recordings analysis.

Table 2. Performance metrics of multi-band EEGNet-GRU VS. baseline models (Mean ± standard deviation)

Model	**Accuracy ↑**	**Sensitivity ↑**	**Specificity ↑**	**Precision ↑**	**F1-score ↑**	**AUC ↑**
EEGNet	0.807 ± 0.015	0.763 ± 0.029	0.836 ± 0.025	0.770 ± 0.026	0.766 ± 0.026	0.863 ± 0.031
EEGNet-LSTM	0.809 ± 0.025	0.678 ± 0.123	0.894 ± 0.031	**0.824 ± 0.014**	0.738 ± 0.078	0.881 ± 0.021
CNN-GRU	0.795 ± 0.023	0.807 ± 0.042	0.784 ± 0.059	0.732 ± 0.056	0.766 ± 0.034	0.876 ± 0.026
CNN-LSTM	0.789 ± 0.023	0.705 ± 0.141	**0.837 ± 0.062**	0.766 ± 0.021	0.726 ± 0.081	0.869 ± 0.024
CNN	0.790 ± 0.013	0.766 ± 0.096	0.800 ± 0.039	0.735 ± 0.015	0.748 ± 0.054	0.862 ± 0.036
EEGNet-GRU	**0.811 ± 0.019**	**0.829 ± 0.022**	0.797 ± 0.018	0.744 ± 0.038	**0.784 ± 0.030**	**0.894 ± 0.029**
Random Forest	0.770 ± 0.016	0.664 ± 0.032	0.847 ± 0.017	0.755 ± 0.049	0.706 ± 0.031	0.847 ± 0.025
SVM	0.675 ± 0.011	0.301 ± 0.043	**0.942 ± 0.012**	0.786 ± 0.041	0.434 ± 0.047	0.708 ± 0.037

5 Experiment

The experiment was conducted with a within-subjects randomized crossover design, allowing each participant to serve as their own control and ensuring a balanced distribution of system conditions. The study was structured around two distinct tasks: a vibrotactile pattern matching task to measure the intuitive mapping and learnability of our haptic cues, and a more complex scenario-based task to simulate real-world challenges related to attention. We collected

Table 3. Demographic information of experiment participants.

ID	Gender	Age	Occupation	Diagnosis Year	Key Symptoms	Medication Intervention
M1	Male	29	Project Manager	2024	B; I; K	Yes
F1	Female	28	Student	2019	B; C; D	No
M2	Male	27	Operation Executive	2007	B; E	Yes
F2	Female	28	Teacher	2015	A; B; F	Yes
F3	Female	22	Student	2019	B; E; G;	No
M3	Male	30	Researcher	2005	A; B; C; D; H	Yes
F4	Female	21	Student	2014	B; C;	No
F5	Female	22	Unemployed	2025	A; E; F	Yes
M4	Male	22	Student	2019	B; E;	No
F6	Female	23	Student	2023	B; E; G	Yes

Key symptoms: A: Hyperfocus; B: Mind Wandering; C: Procrastination; D: Task Switching Difficulty; E: Impulsivity; F: Distractibility; G: Restlessness; H: Emotional Dysregulation; I: Executive Dysfunction

both quantitative and qualitative data—including performance metrics, EEG readings, and subjective feedback from questionnaires and interviews—to provide a robust evaluation of the Capace system.

5.1 Participants

According to targeting the core user group and ensuring consistency and representativeness, we recruited 10 people with ADHD aged 20 to 30 (6 females and 4 males) through previous formative study for the experiment (shown in Table 3). Participants had diverse backgrounds coded as follows: Gender, Age, Occupation, Diagnosis Year, Key Symptoms, Medication/Intervention. They were recruited through social media outreach, and all participants' provided informed consent. We employed a randomized within-subject experimental design, allowing each participant to interact with both a control group (using a baseline system) and an experimental group (using the Capace system).

We implemented several ethical measures to ensure the safety and comfort of adults with ADHD participants. Informed consent was obtained from them, with clear explainations of the study's purpose and procedures. Before each session, we reconfirmed the their willingness to participate and reminded them of their right to withdraw at any time. A researcher was present during all the sessions to monitor well-being and provide support if needed. We also verified with participants that they had no relevant mental health concerns and clearly communicated that the system was not harmful. Additionally, all participants received compensation for their time and contribution to the study. The study was approved by the university's Institutional Review Board (IRB).

5.2 Setup

This section describes the detailed experimental setup, including the tasks, the custom-built platform, and the physical environment used to conduct our study. We designed a methodology to evaluate the Capace system, employing a combination of standardized tasks and a custom experimental platform to ensure consistency and objective data collection. The setup was optimized to provide a controlled environment for testing the system's effectiveness in regulating attention among adults with ADHD.

5.2.1 Task. **Matching Task.** The purpose of this experiment was to examine the learnability and comprehensibility of the vibrotactile feedback set. Participants were asked to pair vibration patterns with their intended semantic meanings. The experiment consisted of two phases: (1) a *baseline phase*, where participants attempted the pairing task without being told the mappings, and (2) an *informed phase*, where the correct mappings were explained before repeating the task. After each trial, participants filled in a matching table, allowing us to record both accuracy and subjective impressions. This design enabled us to compare participants' intuitive understanding of the patterns with their learning performance after instruction.

Scenario Task. To simulate more realistic usage, we selected two vibration modes from the eight available: *mode 1 (Mind Wandering)* and *mode 5 (Object Misplacement)*. These were embedded into two subtasks reflecting everyday ADHD-related challenges:

Subtask 1: SART. This classic paradigm from psychology is widely used to measure sustained attention and inhibitory control. Participants were presented with a random sequence of digits and instructed to press the space bar for all non-targets (any number except "3") while withholding response when the digit "3" appeared. The control condition involved no haptic cues, while in the experimental condition, vibrotactile alerts were delivered when participants made errors (misses or false alarms). This provided clear ground truth markers of attentional lapses, facilitating EEG-based analysis of mind wandering.

Subtask 2: Navigation Task. This task simulated the everyday challenge of locating misplaced items. Numbers were arranged in a circular array on the screen, and participants were asked to find a target number among distractors. In the control condition, participants searched visually without assistance. In the experimental condition, the Capace system provided directional vibrotactile cues to guide attention toward the target's location.

Both subtasks were designed with balanced trial structures across baseline and experimental conditions, enabling us to compare attentional performance with and without vibrotactile assistance.

5.2.2 Experimental Platform. We developed a custom experimental platform, as illustrated in Figure 10, based on React and Node.js architecture. The main interface integrates the two experimental tasks described above, each implemented with both a training mode and a formal testing mode. During task execution, the system automatically logs the timestamps of all stimulus onsets and records participants' behavioral responses and reaction times, thereby enabling objective comparisons between the control and experimental conditions. An administrator mode provides fine-grained control over the Capace system. Specifically, it allows researchers to test 8 vibrotactile patterns, trigger vibrations at specific actuator locations and intensities, and schedule vibration alarms by setting a time.

Communication between the web platform and Capace supports two modes: Bluetooth and serial port. Due to browser security constraints, both connection types require manual confirmation by the user before data transmission is enabled.

5.2.3 Experimental Environment. The setup consisted of a Capace device, a computer running the backend system, video and audio recording equipment for data collection, and printed task guidelines for participants. Two researchers were present throughout each session: one facilitating the experiment and another conducting behavioral observations, as shown in Figure 11.

5.3 Procedure

Each participant completed a single session under a within-subjects design. The session comprised three phases, during which behavioral, physiological, and subjective data were systematically collected. The overall workflow is illustrated in Figure 13.

Introduction and Consent (5 minutes): Participants were briefed on study objectives and reminded of their rights to withdraw at any time.

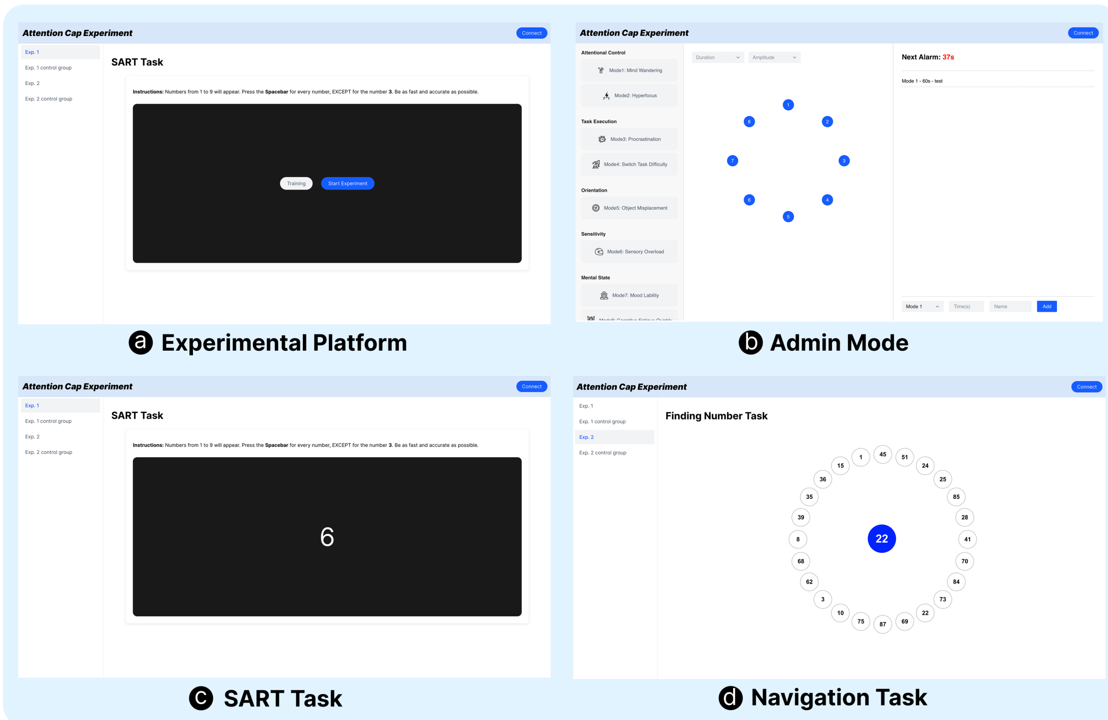


Fig. 10. Experiment platform, including (a) experimental platform. (b) admin backstage to check and control the experiment. (c) subtask 1: SART task. (d) subtask 2: navigation task.

Task 1: Vibrotactile Matching (20 minutes). Participants completed two phases (baseline and informed). In each phase, all 8 vibrotactile patterns were presented, and participants recorded semantic pairings in a response table.

Task 2: Scenario Tasks (30 minutes). Participants completed two subtasks with continuous EEG recording. After 2 Tasks, participants filled out the User Experience Questionnaire (UEQ).

Subtask 1: SART (15 minutes). Each trial contained 50 digit presentations at 1s intervals. After the training phase ensured participants understood the task, Participants completed 3 trials in the control condition and 3 trials in the experimental condition, totaling 300 stimuli. Accuracy, response times, and error rates were logged.

Subtask 2: Navigation (15 minutes). Each trial involved searching 50 numbers in a circular array. Similarly, following the training phase, Participants again completed 3 control and 3 experimental trials, for a total of 300 search instances. Performance data were collected in the same manner.

UEQ Questionnaires and Interview (10 minutes): Completed a UEQ questionnaires. After that, A semi-structured interview was conducted to gather qualitative feedback on system usability, interpretability, and social acceptability. Details can be seen in appendix D.

6 Findings

The results of our study are presented in two main parts: a quantitative analysis of task performance, EEG data, and user experience metrics, followed by a qualitative analysis of themes derived from semi-structured interviews. This

Fig. 11. Experiment environment.

mixed-methods approach allows for a robust evaluation of our findings. The quantitative data provides objective evidence of the system's impact on attention and task efficiency, while the qualitative data enriches these findings by illuminating participants' subjective experiences, mental models, and their broader reflections on the use of an embodied wearable for attention regulation.

6.1 Quantitative Results

This section presents the quantitative findings from our study, providing objective data on the Capace system's effectiveness (details shown in appendix D). We analyze three main aspects of the experiment: first, participants' task performance, including accuracy and response times in both the matching and scenario-based tasks; second, the EEG analysis, which offers a physiological perspective on the system's impact on attention and cognitive load; and third, the User Experience Questionnaire (UEQ) [72] scores(see details in D.1), which provide a quantitative measure of the system's usability and appeal. Together, these metrics offer a robust, data-driven evaluation of the Capace system's impact.

6.1.1 Task Performance and Observations. **Matching Task.** We evaluated two performance metrics for the matching task. For each participant, we calculated the overall accuracy, defined as the proportion of the 8 vibrotactile patterns they correctly matched with their semantic meanings. We also evaluated the per-pattern accuracy, which represented the mean accuracy for each individual pattern across all participants.

As shown in Figure 14a, we observed a significant improvement in overall accuracy from the baseline phase to the informed phase (p = .030, baseline: M = 0.44, SD = 0.30; informed: M = 0.64, SD = 0.31). This demonstrates the learnability of the vibrotactile patterns. Furthermore, the average accuracy for individual patterns also increased

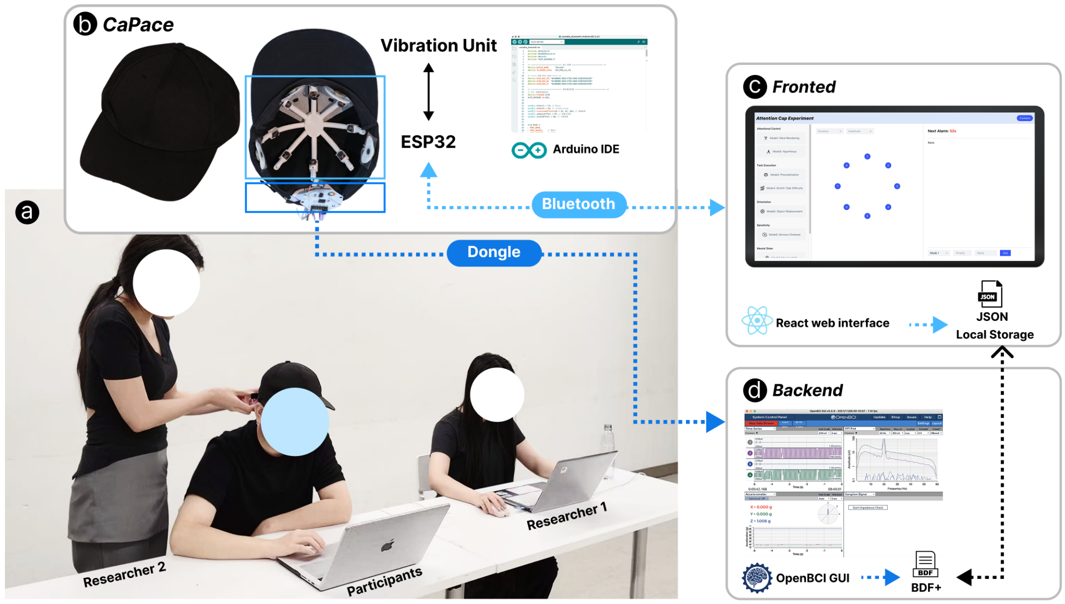


Fig. 12. Capace system architecture: (a) participant workflow: A procedural overview of the experimental process involving participants with ADHD, (b) haptic feedback module: details the vibration module's capacity for generating various haptic feedback types and metaphorical cues through bluetooth, (c) data collection and user interface: the interactive platform for user engagement and the concurrent recording of experimental data, and (d) attention monitoring: The EEG module's role in real-time attentional state monitoring and data acquisition throughout the tasks through Dongle.

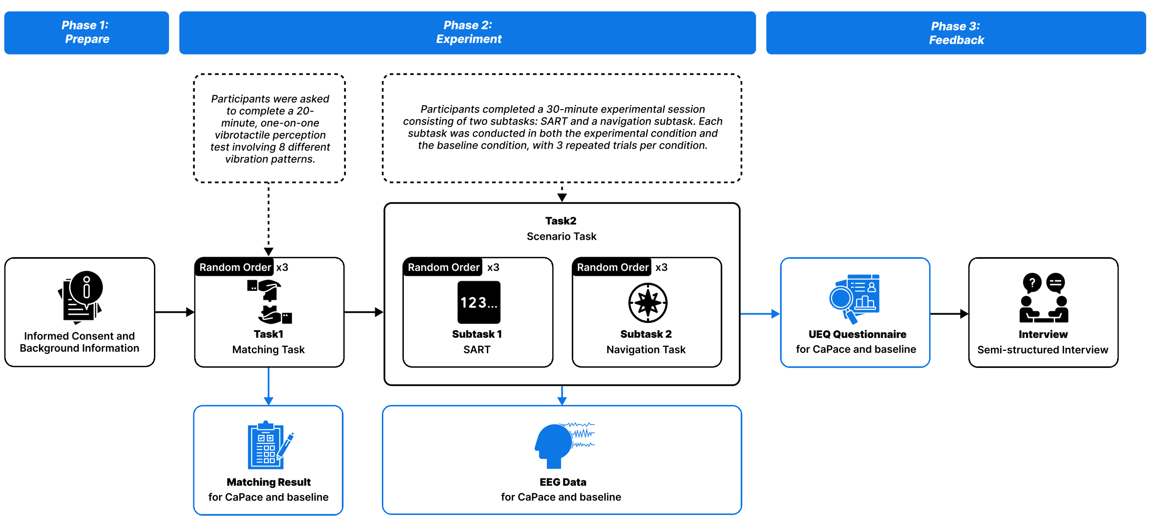
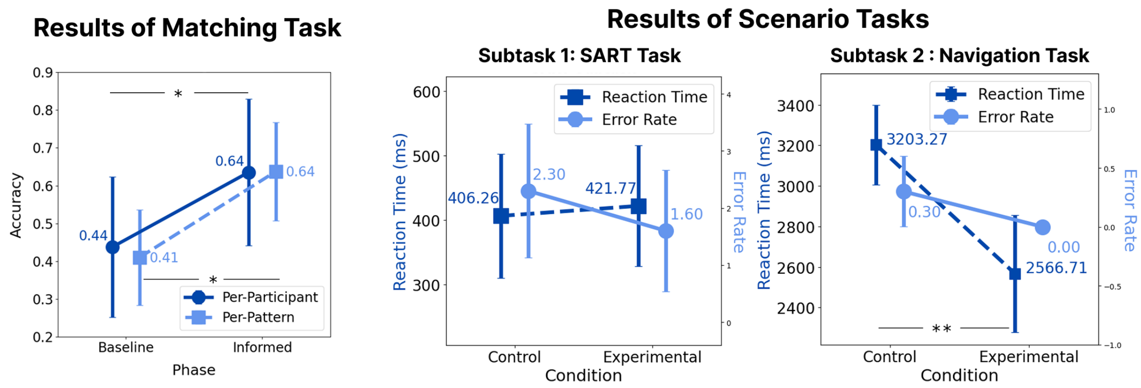


Fig. 13. **Experimental procedure: (1) Phase 1.** introduction and informed consent. **(2) Phase 2.** Task 1: vibrotactile matching task, including baseline and informed phases. Task 2: scenario-based subtasks with continuous EEG recording. **(3) Phase 3.** post-task UEQ questionnaires and semi-structured interview.



(a)

(b)

Fig. 14. Quantitative results for (a) the matching task: accuracy across participants and patterns in the baseline and informed phases; and (b) the scenario tasks: error rate and response time in the SART and navigation subtasks under control and experimental conditions. Dots and numbers denote means, and error bars denote 95% confidence intervals. $^{*}\ p < 0.05$, $^{**}\ p < 0.01$.

significantly (p = .015, baseline: $M = 0.41$, $SD = 0.18$; informed: $M = 0.64$, $SD = 0.19$). This result confirms that the instructional phase was effective in helping participants learn the entire set of patterns.

Scenario Tasks. For the scenario tasks, we evaluated two key metrics to assess the impact of vibrotactile cues on cognitive performance: error rate and response time. Error rate was measured as the number of mistakes (misses or false alarms) in the SART task and search errors in the navigation task. Response time was the average time taken to respond to a stimulus (SART) or to find a target (navigation). Results are shown in Figure 14b.

In the SART subtask, the number of errors showed a slight decrease in the experimental condition ($M = 1.60$, $SD = 1.71$) compared to the control condition ($M = 2.30$, $SD = 1.89$). The mean response time was slightly longer in the experimental condition ($M = 421.77$ ms, $SD = 150.91$ ms) than in the control condition ($M = 406.26$ ms, $SD = 155.46$ ms). While the differences were not statistically significant, the observed increase in response time coupled with a decrease in errors suggests that the vibrotactile cues may act as a "warning," making participants more cautious and attentive.

For the navigation subtask, the vibrotactile guidance had a significant impact on search efficiency. A paired samples t-test confirmed that participants were significantly faster at completing the task in the experimental condition ($M = 2566.71$ ms, $SD = 468.10$ ms) compared to the control condition ($M = 3203.27$ ms, $SD = 316.96$ ms), with a statistically significant difference ($t(9) = -4.024$, $p = .003$). Additionally, the number of errors was minimal across both conditions, and a statistical comparison showed no significant difference ($p > .050$), indicating that the haptic cues did not negatively impact accuracy while substantially improving search speed.

6.1.2 EEG Recordings Analysis. **Model Generalization Validation.** We analyzed the EEG recordings from the SART subtask, a real-world task, using our pretrained multi-band EEGNet-GRU model to validate its effectiveness in detecting mind-wandering episodes. First, we conducted data collection and preprocessing. Following prior work [19, 88], we considered the 3-second window preceding a commission error as a mind-wandering segment. Using the timestamps from both the EEG recordings (BDF files) and our experimental platform logs, we extracted and labeled mind-wandering segments under both control and experimental conditions. These labeled segments served as the ground truth. The

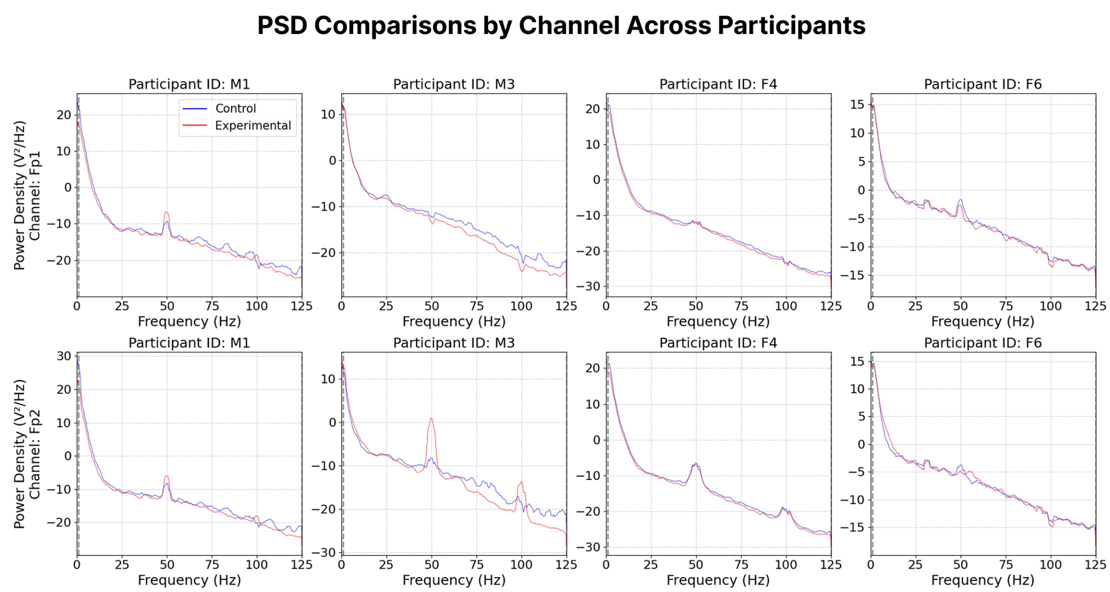


Fig. 15. PSD comparisons between control (blue) and experimental (red) conditions across Fp1 and Fp2 channels for four participants.

remaining preprocessing steps followed the same pipeline as in model pretraining, resulting in a total of 61 mind-wandering events across all participants. We then evaluated the pretrained multi-band EEGNet-GRU model on this dataset, achieving an accuracy of 0.8361, demonstrating the model's strong generalization capability for real-world attention regulation tasks.

6.1.3 EEG Visualization and Analysis. To examine the impact of vibrotactile assistance on attention regulation, we compared EEG activity during the navigation subtask under control and experimental conditions. For each participant, EEG segments were extracted from 3 to 0.5 seconds before correct identification, capturing neural activity immediately preceding decision-making. Signals were preprocessed using standard procedures, including band-pass filtering, artifact removal via Independent Component Analysis (ICA), and automatic trial rejection.

We then computed and visualized the Power Spectral Density (PSD) across channels for four randomly selected participants in both conditions (Figure 15). The PSDs consistently exhibited the expected pattern of higher power in low-frequency bands and lower power in high-frequency bands. While the overall spectral profiles of the two conditions appeared similar, notable differences emerged in most participants: the control condition generally showed elevated power in mid- to high-frequency bands relative to the experimental condition. These frequency ranges are closely associated with cognitive effort, attention, and mental workload [17].

We interpret this pattern as evidence that without vibrotactile assistance, participants needed more cognitive resources to complete the task, which led to increased power in these frequency bands. Vibrotactile assistance, on the other hand, reduced this cognitive load, thereby lowering the power. This indicates that haptic feedback may help adults with ADHD allocate their attention more efficiently, supporting them in staying focused and better regulating their attention during cognitively demanding tasks.

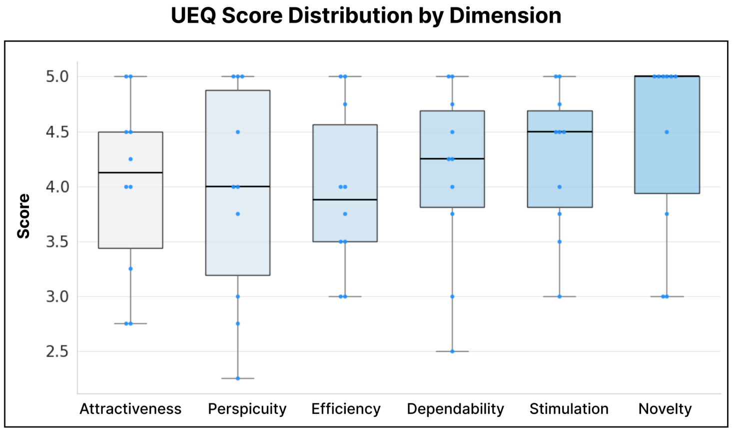


Fig. 16. User experience questionnaire (UEQ) score distribution by dimension. The box plot shows the median, quartiles, and range of scores for each of the six dimensions, with individual participant scores represented by dots.

6.1.4 System Usability: User Experience Questionnaire Analysis. The User Experience Questionnaire (UEQ) was utilized to measure participants' subjective feedback on the system's usability and overall appeal. The UEQ evaluates six dimensions: Attractiveness, Perspicuity, Efficiency, Dependability, Stimulation, and Novelty, with each dimension assessed using four questions on a 0–5 point scale. Analysis of the UEQ scores revealed an overall positive user experience, with all six dimensions receiving positive scores, as detailed in Figure 16. The system was most highly rated on Novelty ($M = 4.43$, $SD = 0.85$) and Stimulation ($M = 4.25$, $SD = 0.67$), suggesting participants found it innovative and engaging. The lowest-rated dimension was Perspicuity ($M = 3.93$, $SD = 0.99$), which still fell within the positive range.

6.2 Qualitative Results

Through thematic analysis of the interviewD.2 data, we identified four key findings regarding the user experience with Capace. These findings encompass the perceptual characteristics that determine a vibration's effectiveness, the important role of context in interpreting haptic feedback, the complex relationship between the user and the device, and a strong user desire for personalization and integration into daily life.

Perceptual characteristics for vibrations' effectiveness. First, participants clearly distinguished between effective and ineffective vibration modes. Short, distinct, and high-intensity patterns were almost unanimously preferred. For example, alarm-like pulses and knocking sensations were praised for their clarity and intuitive nature. One participant stated, "The alarm mode is definitely the most effective for getting my attention. The vibration is very strong, and the frequency feels exactly like a real alarm, so you immediately know what it means" (M1). Another participant found the knocking pattern to be highly effective and natural: "For me, the light knocking on the head works best. It simulates a real rhythm and weight, just like someone is actually tapping my head to get my attention" (M2). The semantic match was also noted: "The knocking is the most obvious signal, and it matches the meaning of a reminder very well" (F5). In contrast, diffuse, continuous, and massage-like modes were frequently dismissed as ineffective and easy to ignore. "The mode 8 (Knead Temples) is basically useless as a notification," M1 explained, "it's just a weak, continuous vibration without any gripping or urgent sensation." This sentiment was echoed by others: "The vibration for the temple massage is far too weak. Honestly, half the time I couldn't even feel it" (F1). Second, the intensity of the vibration emerged as a critical but delicate parameter. Some male participants felt the overall intensity was too low to be reliably perceived, especially for those with thick hair. M3 added, "Overall, it's just too weak, and it lacks a clear rhythm. I also think its effectiveness is related to your hair thickness; mine is quite thick." "My general feeling is that the vibrations are too weak," M2 noted similarly. Moreover, the risk of habituation was another concern. F2 remarked, "If it's too weak, when I habit to it, it actually makes me feel sleepy instead of alerting me." However, intensity needed to be carefully calibrated, as overly strong vibrations also could be disruptive. As M4 insightfully summarized, "There's a real challenge here...if it's too strong, it interrupts my train of thought completely; if it's too weak, I just ignore it. But I have to admit, those forced, strong interruption reminders are undeniably effective when you need them." This highlights a fundamental tension and points to the necessity of user-adjustable intensity settings.

Importance of context in haptic feedback. Participants emphasized that the effectiveness and appropriateness of a vibration mode were highly dependent on the specific context of use. The same vibration could be perceived as relaxing in one scenario and disruptive in another. Certain modes were deemed suitable for well-being and focus guidance. For instance, slow, rhythmic patterns were associated with relaxation. "The circular breathing guidance is very nice, it feels very relaxing and helps me calm down," described F4. M2 shared a similar experience: "When the deep breathing pattern started, I found it very soothing. It's a great feature for mindfulness." In contrast, stronger, more abrupt patterns were seen as ideal for interruption and attention-shifting. F3 valued the "thunder" pattern for this reason: "I actually think the thunder effect is great! It really jolts you and is perfect for waking me up when I'm overly focused on a task and lose track of time." However, this preference was not universal, demonstrating the subjective nature of such feedback. F1, for example, stated, "For me, the sudden thunder vibration is the least effective. It's just startling and unpleasant, not helpful." Participants also readily imagined future applications where context would be paramount, especially for safety and navigation. F2 suggested, "The compass function is a great idea. Imagine walking in a new city; you could just follow the vibration direction without constantly looking at your phone." Another participant envisioned a personal safety scenario: "This could be a game-changer for safety. If I'm walking alone at night and feel like someone is following me, the hat could give me a subtle vibration to remind me of potential danger without me having to turn around and look" (F1). These examples underscore that vibration patterns are not neutral signals; they acquire meaning and value based on the user's activity, goals, and environment.

The complex relationship between the user and the device. Participants' experiences with Capace extended beyond the perception of vibrations to more profound considerations of embodiment, personal agency, and social norms. Initial encounters with the device revealed users' feelings between curiosity and a sense of diminished agency. While some found it novel and playful, "It looks like an ordinary hat, but it has all these rich functions inside. The whole experience felt very new and futuristic" (F3). Others expressed unease about being externally controlled. As F1 recounted, "At first, I felt like I was being controlled by the hat. It was a strange sensation, I didn't feel anything, and then suddenly it buzzed, telling me what to do." This dichotomy suggests that embodied wearables are not merely tools but can trigger fundamental reflections on autonomy, with haptic feedback being interpreted as either an empowering guide or an intrusive command. Furthermore, comfort was described as both physical and cognitive. On a physical level, issues like weight and fit were raised. "For people with thick hair like me, it doesn't fit very well, and I was always worried it might shift position and I'd miss the vibration" (M2). Cognitively, the device's feedback competed for attention. While some found it easy to wear, they noted with "It's pretty comfortable and light, feels just like a normal hat" (F3). Finally, participants consistently evaluated Capace through the lens of social acceptability. The discreet design was highly praised. “The main advantage is that you don’t look strange when you go out,” M1 explained. “No one can see that you are using a special device, which is great.” This invisibility was linked to reducing potential stigma for certain user groups: “For blind people, this is so much better than a device that makes sounds. It’s private, so they won’t feel self-conscious or inferior in public” (M1). However, the form factor of a hat itself was seen as a social limitation. “The problem is, in some formal occasions like a business meeting or a nice dinner, wearing a hat feels unnatural or even rude, unlike wearing glasses or a watch” (F1). This suggests that the success of such a wearable hinges on its ability to navigate diverse social contexts, which is better being a private feedback channel than being a visible social accessory.

The desire for personalization and integration. A strong, recurring theme was the demand for a system that could be personalized and deeply integrated into the user’s existing digital and daily life. Participants wanted Capace to be an adaptive tool, not a static device with a fixed set of functions. Many expressed a desire to tailor haptic feedback to their personal needs and routines. M1 suggested, “I would want it to remind me to rest when I’ve been working for too long. Maybe a slow, cyclical vibration. It would also be amazing if it could have a navigation function for when I’m cycling.” Another participant envisioned health and wellness reminders: “It should be like the Apple Watch, reminding me to change my posture after sitting for an hour. A simple tap, like a gentle knock on the head, would be perfect for that” (M2). Participants also saw great potential in integrating Capace with other devices, particularly their smartphones. “It would be so useful for new message notifications,” F4 proposed. “If it could link with my phone, the vibration on my head would be much more noticeable than the one on my wrist, which I often miss.” Other imagined futures included applications in wellbeing, such as “guiding meditation, helping with emotional regulation, and maybe even dream detection” (F3). Ultimately, these perspectives point toward the need for an adaptable ecosystem where the meaning and utility of haptic feedback are situated within a user’s broader life. As M4 concluded, “Imagine if a company like Apple adopted this technology. If it could connect seamlessly to those bands, it could quietly collect data, display it on your phone, and provide subtle feedback throughout the day. That would be incredibly powerful.” This highlights a key design implication: the value of haptic feedback is maximized not in isolation, but when it becomes part of an integrated, context-aware, and personalized system for managing attention, mobility, safety, and self-care.

7 Discussion

Our study explored the potential of Capace, a head-mounted haptic system, for attention regulation in adults with ADHD. The qualitative feedback from our user study provides valuable insights into the design of such systems, their potential applications, and their role within the broader landscape of assistive technologies.

Our work builds upon previous studies that have explored haptics on different parts of the body. While many systems have focused on wrist-based feedback (e.g., smartwatches), we chose the head as the locus of intervention. The head is a highly sensitive area, and feedback delivered here is private and less likely to be missed than a buzz on the wrist, which is already a channel saturated with notifications. While prior research has explored head-mounted haptics for sensory substitution or spatial navigation, Capace repurposes this modality specifically for attentional regulation. We designed a unique semantic space of vibrations (e.g., "breathing guide," "thunder clap") to create distinct, intuitive cues for the user, extending the application of head-based haptics beyond mere directional information.

Compared to the numerous software-based interventions for ADHD (e.g., focus apps, timers), Capace offers a tangible, embodied alternative. For individuals who struggle with screen-based distractions, a non-visual, ambient feedback system can be a powerful tool. It allows for a gentle, in-the-moment reorientation of focus without requiring the user to interact with a screen, which could itself become a source of distraction. Our work thus presents a hardware-based approach that complements existing digital tools, contributing a novel form factor to the assistive technology ecosystem for ADHD.

7.1 Reflection on the Capace Form-Factor and Interaction

The form-factor is a critical element for any wearable technology, as it directly influences user acceptance, comfort, and the overall experience. During our post-study interviews, we learned about participants' diverse preferences for the device's appearance, which we then visualized in Figure 17. Our analysis of this feedback revealed several key considerations for the design of Capace, which can be categorized into ergonomics, aesthetics, context-specific adaptability, functional impact on perception, and psychological affordances. We used artificial intelligence (specifically, the Gemini 2.5 flash model[23]) with prompt to assist with visualizing and conceptualizing future scenarios, details could be seen in Appendix D.

Comfort and Ergonomics Practical concerns about comfort and ergonomics were prominent in the discussions. Participants raised issues such as the device potentially messing up their hairstyle, its overall weight, and the tactile sensation of the internal hardware against their scalp. These critiques highlight the crucial gap between a functional prototype and a polished, consumer-ready product. As pioneering work in wearable technology suggests, achieving true "wearability" is foundational to user acceptance [37]. Bridging this gap requires a significant focus on industrial design, material science, and human-factors engineering to create a device that is not just effective, but genuinely comfortable and unobtrusive for prolonged wear.

Aesthetics and Personalization Participants expressed a strong desire for a device that is not only functional but also aesthetically pleasing and aligned with their personal style. For instance, many female participants found the concepts of a baseball cap with customizable patterns (Figure 17, item 1) and a stylish beret (Figure 17, item 2) highly appealing. This feedback underscores the importance of personalization, allowing users to integrate Capace seamlessly into their daily wardrobe and express their individuality, thereby reducing potential stigma associated with wearing a therapeutic device. Furthermore, the symbolic meaning of worn items can influence the wearer's cognitive processes, a phenomenon known as "enclothed cognition" [1]. This suggests that a stylish, user-chosen form-factor may not only improve social acceptance but also positively impact the user's psychological state and attention.

Adaptability to Specific Contexts Participants envisioned using Capace in various scenarios, necessitating different form-factors. For example, a soft sleep cap (Figure 17, item 4) was suggested for nighttime use, while a durag (Figure 17, item 6) was proposed for physical activities. This indicates that a single design may not suffice. A successful wearable system should be context-aware, adapting to the user's changing activities and environments [30]. Therefore, a modular system or a family of products tailored to different contexts (e.g., work, sleep, exercise) could better meet diverse user needs.

Functional Impact on Vision The design's impact on the user's field of view emerged as a point of divergence. While some participants preferred a beanie-style hat (Figure 17, item 3) for its unobstructed view, others noted an unexpected benefit of the baseball cap's brim. They suggested that the partial visual occlusion could help them focus by minimizing peripheral distractions. This aligns with strategies for managing ADHD, where reducing extraneous sensory input can be an effective method for improving attention [73]. This highlights a design trade-off between an open field of view and a deliberately constrained one to aid concentration.

Psychological and Emotional Affordances Interestingly, the form-factor was also linked to psychological motivation. Several participants with ADHD were drawn to the crown-like design (Figure 17, item 5), articulating that wearing it could provide a sense of "mission" or "royalty." This powerful symbolic meaning acts as an external ritual

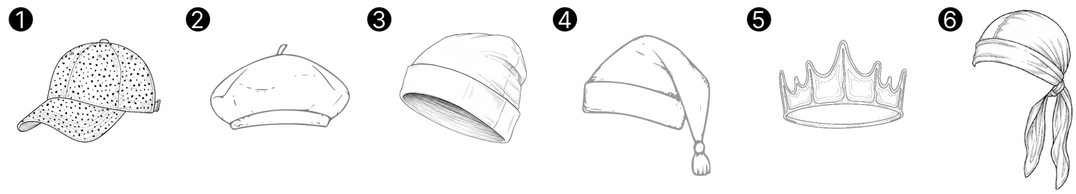


Fig. 17. Interview outcomes: a collection of potential form-factors for Capace proposed by users. The concepts shown are (1) a personalized baseball cap, (2) a beret, (3) a beanie, (4) a sleep cap, (5) a crown, and (6) a durag.

to foster internal motivation, a clear example of enclothed cognition, where the symbolism of what we wear shapes our thoughts and actions [1]. This suggests that the symbolic meaning of a wearable's form can serve as a positive psychological cue, engaging the user on a reflective, emotional level and empowering them to focus on their tasks.

7.2 Implications: A Platform for Regulation, Enrichment, and Awareness

Our study reveals that the ideal use case for the current Capace prototype is in structured, goal-oriented tasks where the user is relatively stationary, such as at a desk or commuting. Participants found the haptic feedback in these contexts to be perceptible and effective. However, they also highlighted limitations in highly stimulating or physically active scenarios, pointing to clear directions for technical improvements like context-aware intensity adjustments. Beyond these immediate refinements, our findings and participant feedback illuminate a broader future for wearable EEG-haptic systems. We conceptualize this future along four primary functional axes: enhancing cognitive focus, regulating internal states, enriching sensory experiences, and augmented situational awareness through the StoryTribe[3] to create user journey maps to visualize the insights gathered from our interviews (as shown in Figure 18).

7.2.1 Regulating Internal States for Wellness and Assistance. The core mechanism of our system is a closed-loop for regulating internal cognitive and affective states, a principle extendable to a wide range of wellness and assistance applications. Beyond this paper's focus on ADHD, this aligns with research where haptics effectively guide mindfulness and physiological rhythms like breathing [12, 78]. Furthermore, the closed-loop nature of an EEG-haptic system makes it an ideal platform for serious games for rehabilitation. Research into neurogaming demonstrates that EEG-based biofeedback can be gamified to train attention [57], while haptics can provide critical real-time feedback and guidance during therapeutic tasks in virtual environments [13, 36]. Notably, our own participants converged on these therapeutic applications, envisioning "emotional massages" for stress and "vibrating massages" to aid sleep. This latter concept is well-supported by findings that rhythmic vibrotactile stimulation can improve sleep quality [67], with wearable form-factors offering a more portable solution than environmental installations like beds [54]. The convergence of these applications—guided wellness, gamified rehabilitation, and sleep assistance—strongly validates the future of this class of systems as powerful platforms for a new generation of digital therapeutics.

7.2.2 Enriching Sensory Experiences for Leisure and Entertainment. A second key function is the ability to enrich and augment sensory experiences, transforming the system from a utilitarian tool into a medium for entertainment and relaxation. Participants frequently envisioned enhancing immersion in games and movies with synchronized haptics, a concept well-supported by research on "haptic soundtracks" and affective gaming, where vibrotactile feedback is used to increase presence and evoke emotional responses. The integration of biosensing elevates this paradigm, enabling a shift

[3] https://storytribeapp.com/

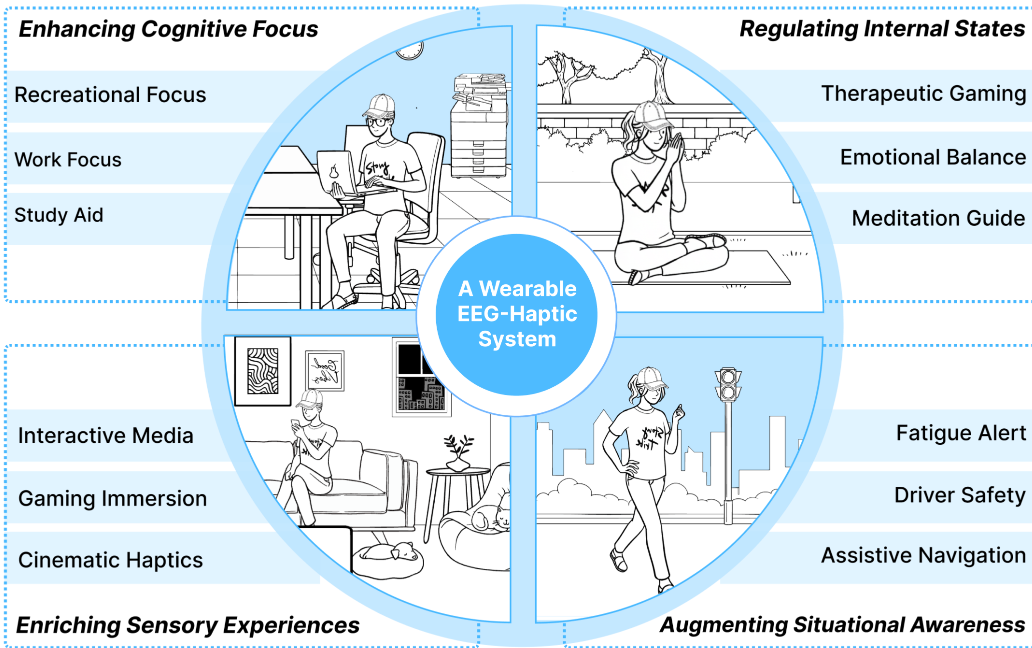


Fig. 18. A conceptual framework for future applications of wearable EEG-haptic systems.

from pre-scripted feedback to real-time experiences that adapt to a user's measured emotional state. This aligns directly with the goals of affective computing [68]. In this vein, participants imagined a multi-modal system that could infer mood and provide personalized interventions, such as playing calming music through integrated bone conduction audio. Ultimately, these directions position this class of devices not just as functional tools, but as personalizable companions that mediate our digital experiences and well-being.

7.2.3 Conveying Information for Safety and Awareness. Finally, the system serves as a powerful channel for conveying critical environmental information in a discreet and socially acceptable manner. In established applications like driver safety, it offers an integrated platform for the well-researched paradigm of EEG-based drowsiness detection and non-startling haptic alerts [55, 77]. Extending this concept, participants envisioned the system as a technological 'sixth sense' for personal safety, a direction supported by emerging research into sensory augmentation via covert haptic cues to convey information from a user's blind spots. Perhaps most critically, the system's discreet form-factor addresses a core challenge in assistive technology: the social stigma of conspicuous devices. Our user insights regarding 'hidden' navigation aids for the visually impaired underscore that a primary innovation for such technologies may lie in their potential for 'design for dignity,' a crucial principle for adoption. Thus, a head-mounted system integrated into a common accessory represents a compelling approach to bridging the gap between personal cognition and environmental hazards in a socially discreet manner.

7.3 Limitation and Future Work

We acknowledge several limitations in our current work, which in turn define promising avenues for future research.

Our evaluation, while providing foundational insights, was conducted within a controlled laboratory setting. This approach, necessary for isolating the effects of haptic feedback, does not fully capture the complexities of real-world usage. To establish the ecological validity and long-term impact of the Capace system, future work must include a longitudinal, in-the-wild study. Such a study would allow us to assess user adaptation, the device's integration into daily routines, and its efficacy across diverse, naturalistic contexts, following established methodologies for evaluating ubiquitous computing systems [25].

From a user experience perspective, the current prototype lacks features for personalization. Our findings highlighted a strong user desire to adjust vibration intensity, rhythm, and patterns to match individual sensory preferences. The absence of such customization is a significant limitation. Future iterations will incorporate a companion application, empowering users to design and assign their own haptic cues. This aligns with the principles of user-centered design [35] and is crucial for promoting long-term adoption.

On a practical level, the physical form-factor of the prototype requires further refinement. Participants noted that the coupling between the motors and the scalp could be more consistent and the integration of components more seamless. As the long-term adoption of any wearable is closely tied to its comfort and social acceptability, this is a critical step. Future work will therefore involve iterating on the industrial design to create a more durable, customized, and aesthetically pleasing device.

Looking further ahead, our ultimate vision is to evolve Capace into a closed-loop, adaptive system that can proactively respond to a user's attentional state. To achieve this, we plan to integrate a brain-computer interface (BCI) module using lightweight EEG sensors to monitor neural signals associated with attention and distraction in real-time. The collected EEG data will then be used to train a deep learning model capable of multi-class classification, distinguishing between states of focus, mind-wandering, and external distraction. This would enable Capace to deliver targeted haptic interventions automatically and pre-emptively—precisely when the user's attention begins to drift—creating a truly personalized and proactive attentional support tool.

Finally, our investigation deliberately focused on the haptic modality to establish a foundational understanding. Consequently, we did not conduct a comparative analysis against auditory or visual feedback. Future work should systematically compare the efficacy and user experience of different modalities—and their combinations—to leverage the full potential of multimodal interfaces [65] and determine which feedback types are most suitable for various situations and individuals.

8 Conclusion

In this paper, we presented the design, implementation, and evaluation of Capace, a head-mounted EEG-haptic system for regulating the attention of adults with ADHD. Our findings demonstrate the viability of this approach, showing that discreet, head-based haptic cues can be effectively used to redirect attention and support users in managing distractions during goal-oriented tasks. Beyond this primary application, our work illuminates the broader potential of wearable EEG-haptic systems as multi-faceted platforms. We identified and structured a rich design space for this class of technology along three primary axes: regulating internal states for wellness and therapy, enriching sensory experiences for entertainment and leisure, and conveying environmental information for safety and awareness. We envision that future wearable systems, following this trajectory, will evolve from single-purpose assistive tools into highly personalizable and socially-aware companions. By creating a seamless, private channel that mediates between our internal cognitive states and the external world, this line of research contributes to a future of more humane, responsive, and empowering computing.

Acknowledgments of the Use of AI

We used AI (in particular, the Gemini 2.5 fast model) for the future forms imaging in Figure 17, details can be found in the relevant section and Appendix D. Authors take responsibility for the output and use of Al in this paper.

References

[1] Hajo Adam and Adam D Galinsky. 2012. Enclothed cognition. *Journal of experimental social psychology* 48, 4 (2012), 918–925.

[2] Fred Atilla and Maryam Alimardani. 2021. EEG-based classification of drivers attention using convolutional neural network. In *2021 IEEE 2nd International Conference on Human-Machine Systems (ICHMS)*. IEEE, 1–4.

[3] Nikesh Bajaj. 2020. Wavelets for EEG analysis. *Wavelet theory* 11 (2020).

[4] Russell A Barkley. 1997. Behavioral inhibition, sustained attention, and executive functions: constructing a unifying theory of ADHD. *Psychological bulletin* 121, 1 (1997), 65.

[5] Anthony J Bell and Terrence J Sejnowski. 1995. An information-maximization approach to blind separation and blind deconvolution. *Neural computation* 7, 6 (1995), 1129–1159.

[6] S. Benyakorn, S. J. Riley, C. A. Calub, and J. B. Schweitzer. 2016. Current state and model for development of technology-based care for attention deficit hyperactivity disorder. *Telemedicine journal and e-health : the official journal of the American Telemedicine Association* 22, 9 (2016), 761–768. doi:10.1089/tmj.2015.0169

[7] Natali Bozhilova, Jonna Kuntsi, Katya Rubia, Philip Asherson, and Giorgia Michelini. 2022. Event-related brain dynamics during mind wandering in attention-deficit/hyperactivity disorder: An experience-sampling approach. *NeuroImage: Clinical* 35 (2022), 103068.

[8] Natali S Bozhilova, Giorgia Michelini, Jonna Kuntsi, and Philip Asherson. 2018. Mind wandering perspective on attention-deficit/hyperactivity disorder. *Neuroscience & Biobehavioral Reviews* 92 (2018), 464–476.

[9] Claire Braboszcz and Arnaud Delorme. 2011. Lost in thoughts: neural markers of low alertness during mind wandering. *Neuroimage* 54, 4 (2011), 3040–3047.

[10] V. Braun and V. Clarke. 2021. *Thematic Analysis: A Practical Guide.* SAGE Publications. https://books.google.com.sg/books?id=eMArEAAAQBAJ

[11] Leo Breiman. 2001. Random forests. *Machine learning* 45, 1 (2001), 5–32.

[12] Antoinette Leanna Bumatay and Jinsil Hwaryoung Seo. 2015. Investigating the role of haptic stimulation in mobile meditation tools. In *International Conference on Human-Computer Interaction*. Springer, 451–456.

[13] James William Burke, MDJ McNeill, Darryl K Charles, Philip J Morrow, Jacqui H Crosbie, and Suzanne M McDonough. 2009. Optimising engagement for stroke rehabilitation using serious games. *The Visual Computer* 25, 12 (2009), 1085–1099.

[14] Yeison Nolberto Cardona-Álvarez, Andrés Marino Álvarez-Meza, David Augusto Cárdenas-Peña, Germán Albeiro Castaño-Duque, and German Castellanos-Dominguez. 2023. A novel OpenBCI framework for EEG-based neurophysiological experiments. *Sensors* 23, 7 (2023), 3763.

[15] Tianqi Chen and Carlos Guestrin. 2016. Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*. 785–794.

[16] Yi-Ta Chen, Hsing-Hao Lee, Ching-Yen Shih, Zih-Ling Chen, Win-Ken Beh, Su-Ling Yeh, and An-Yeu Wu. 2022. An effective entropy-assisted mind-wandering detection system using EEG signals of MM-SART database. *IEEE Journal of Biomedical and Health Informatics* 26, 8 (2022), 3649–3660.

[17] Samy Chikhi, Nadine Matton, and Sophie Blanchet. 2022. EEG power spectral measures of cognitive workload: A meta-analysis. *Psychophysiology* 59, 6 (2022), e14009.

[18] Swati Chowdhuri, Satadip Saha, Samadrita Karmakar, and Ankur Chanda. 2024. Real-time classification of EEG signals using Machine Learning deployment. *arXiv preprint arXiv:2412.19515* (2024).

[19] Kalina Christoff, Alan M Gordon, Jonathan Smallwood, Rachelle Smith, and Jonathan W Schooler. 2009. Experience sampling during fMRI reveals default network and executive system contributions to mind wandering. *Proceedings of the National Academy of Sciences* 106, 21 (2009), 8719–8724.

[20] Andrea Chronis-Tuscano, Anil Chacko, and Russell Barkley. 2013. Key issues relevant to the efficacy of behavioral treatment for ADHD. *American Journal of Psychiatry* 170, 7 (2013), 799–799.

[21] Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555* (2014).

[22] Franceli L Cibrian, Kimberley D Lakes, Arya Tavakoulnia, Kayla Guzman, Sabrina Schuck, and Gillian R Hayes. 2020. Supporting self-regulation of children with ADHD using wearables: tensions and design challenges. In *Proceedings of the 2020 CHI conference on human factors in computing systems*. 1–13.

[23] Gheorghe Comanici, Eric Bieber, Mike Schaekermann, Ice Pasupat, Noveen Sachdeva, Inderjit Dhillon, Marcel Blistein, Ori Ram, Dan Zhang, Evan Rosen, et al. 2025. Gemini 2.5: Pushing the frontier with advanced reasoning, multimodality, long context, and next generation agentic capabilities. *arXiv preprint arXiv:2507.06261* (2025).

[24] Rebecca J Compton, Dylan Gearinger, and Hannah Wild. 2019. The wandering mind oscillates: EEG alpha power is enhanced during moments of mind-wandering. *Cognitive, Affective, & Behavioral Neuroscience* 19, 5 (2019), 1184–1191.

[25] Sunny Consolvo and Miriam Walker. 2003. Using the experience sampling method to evaluate ubicomp applications. *IEEE pervasive computing* 2, 2 (2003), 24–31.

[26] Juliet Corbin and Anselm Strauss. 2014. *Basics of qualitative research: Techniques and procedures for developing grounded theory.* Sage publications.

[27] Corinna Cortes and Vladimir Vapnik. 1995. Support-vector networks. *Machine learning* 20, 3 (1995), 273–297.

[28] Jonathan Tourney (data, curation), Greg Apker (data), Brent Lance (data), Scott Kerick (data), Anthony Ries (data), Justin Brooks (data), Kaleb McDowell (data), Tony Johnson (curation), and Kay Robbins (curation). 2022. *BCIT Mind Wandering.* doi:10.18112/openneuro.ds004121.v1.0.0

[29] Costanza Davanzo, Vincenza Tarantino, Patrizia Bisiacchi, Giovanni Sparacino, et al. 2009. A wavelet methodology for EEG time-frequency analysis in a time discrimination task. *International Journal of Bioelectromagnetism* 11 (2009), 185–188.

[30] Anind K Dey. 2001. Understanding and using context. *Personal and ubiquitous computing* 5, 1 (2001), 4–7.

[31] Kiret Dhindsa, Anita Acai, Natalie Wagner, Dan Bosynak, Stephen Kelly, Mohit Bhandari, Brad Petrisor, and Ranil R Sonnadara. 2019. Individualized pattern recognition for detecting mind wandering from EEG during live lectures. *PloS one* 14, 9 (2019), e0222276.

[32] Adele Diamond. 2005. Attention-deficit disorder (attention-deficit/hyperactivity disorder without hyperactivity): A neurobiologically and behaviorally distinct disorder from attention-deficit/hyperactivity disorder (with hyperactivity). *Development and psychopathology* 17, 3 (2005), 807–825.

[33] Victor Dibia. 2016. FOQUS. In *Proceedings of the 18th International ACM SIGACCESS Conference on Computers and Accessibility* (Reno Nevada USA). ACM, New York, NY, USA.

[34] Stephen V Faraone, Tobias Banaschewski, David Coghill, Yi Zheng, Joseph Biederman, Mark A Bellgrove, Jeffrey H Newcorn, Martin Gignac, Nouf M Al Saud, Iris Manor, et al. 2021. The world federation of ADHD international consensus statement: 208 evidence-based conclusions about the disorder. *Neuroscience & biobehavioral reviews* 128 (2021), 789–818.

[35] Gerhard Fischer. 2001. User modeling in human–computer interaction. *User modeling and user-adapted interaction* 11, 1 (2001), 65–86.

[36] Roger Gassert and Volker Dietz. 2018. Rehabilitation robots for the treatment of sensorimotor deficits: a neurophysiological perspective. *Journal of neuroengineering and rehabilitation* 15, 1 (2018), 46.

[37] Francine Gemperle, Chris Kasabach, John Stivoric, Malcolm Bauer, and Richard Martin. 1998. Design for wearability. In *digest of papers. Second international symposium on wearable computers (cat. No. 98EX215)*. IEEE, 116–122.

[38] Romain Grandchamp, Claire Braboszcz, and Arnaud Delorme. 2014. Oculometric variations during mind wandering. *Frontiers in psychology* 5 (2014), 31.

[39] Gabriele Gratton, Michael GH Coles, and Emanuel Donchin. 1983. A new method for off-line removal of ocular artifact. *Electroencephalography and clinical neurophysiology* 55, 4 (1983), 468–484.

[40] Yvonne Groen, Ulrike Priegnitz, Anselm BM Fuermaier, Lara Tucha, Oliver Tucha, Steffen Aschenbrenner, Matthias Weisbrod, and Miguel Garcia Pimenta. 2020. Testing the relation between ADHD and hyperfocus experiences. *Research in Developmental Disabilities* 107 (2020), 103789.

[41] Alexander Grossmann and Jean Morlet. 1984. Decomposition of Hardy functions into square integrable wavelets of constant shape. *SIAM journal on mathematical analysis* 15, 4 (1984), 723–736.

[42] JASPER HH. 1958. The ten-twenty electrode system of the international federation. *Electroenceph clin Neurophysiol* 10 (1958), 367–380.

[43] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation* 9, 8 (1997), 1735–1780.

[44] Seyedroohollah Hosseini and Xuan Guo. 2019. Deep convolutional neural network for automated detection of mind wandering using EEG signals. In *Proceedings of the 10th ACM international conference on bioinformatics, computational biology and health informatics*. 314–319.

[45] Christina Yi Jin, Jelmer P Borst, and Marieke K Van Vugt. 2019. Predicting task-general mind-wandering with EEG. *Cognitive, Affective, & Behavioral Neuroscience* 19, 4 (2019), 1059–1073.

[46] Tzyy-Ping Jung, Scott Makeig, Colin Humphries, Te-Won Lee, Martin J Mckeown, Vicente Iragui, and Terrence J Sejnowski. 2000. Removing electroencephalographic artifacts by blind source separation. *Psychophysiology* 37, 2 (2000), 163–178.

[47] Julia WY Kam, Elizabeth Dao, James Farley, Kevin Fitzpatrick, Jonathan Smallwood, Jonathan W Schooler, and Todd C Handy. 2011. Slow fluctuations in attentional control of sensory cortex. *Journal of cognitive neuroscience* 23, 2 (2011), 460–470.

[48] MS Kamath, CR Dahm, JR Tucker, CL Huang-Pollock, NM Etter, and KA Neely. 2020. Sensory profiles in adults with and without ADHD. *Research in developmental disabilities* 104 (2020), 103696.

[49] Eunseong Kim, Jeongyun Heo, and Jeongmin Han. 2021. Attention to breathing in response to vibrational and verbal cues in mindfulness meditation mediated by wearable devices. In *International Conference on Human-Computer Interaction*. Springer, 415–431.

[50] Yoon Kim. 2014. Convolutional neural networks for sentence classification. *arXiv preprint arXiv:1408.5882* (2014).

[51] Kesavan Krishnan, Nazean Jomhari, Ramesh Kumar Ayyasamy, Sameem Abdul Kareem, and Sathis Krishnan. 2024. Haptic feedback: an experimental evaluation of vibrations as tactile sense in autistic people. *IEEE Access* 12 (2024), 81088–81104.

[52] Man-Chi Lai, Ming-Shan Chiang, Ching-Tien Shih, and Ching-Hsiang Shih. 2018. Applying a vibration reminder to ameliorate the hyperactive behavior of students with attention deficit hyperactivity disorder in class. *Journal of Developmental and Physical Disabilities* 30, 6 (2018), 835–844.

[53] Vernon J Lawhern, Amelia J Solon, Nicholas R Waytowich, Stephen M Gordon, Chou P Hung, and Brent J Lance. 2018. EEGNet: a compact convolutional neural network for EEG-based brain–computer interfaces. *Journal of neural engineering* 15, 5 (2018), 056013.

[54] Jueun Lee, Dennis Moschina, Supraja Ramesh, Tobias Röddiger, Kai Kunze, and Michael Beigl. 2025. Closed-Loop Rhythmic Haptic Biofeedback via Smartwatch for Relaxation and Sleep Onset. *arXiv preprint arXiv:2507.02432* (2025).

[55] Chin-Teng Lin, Yu-Chieh Chen, Teng-Yi Huang, Tien-Ting Chiu, Li-Wei Ko, Sheng-Fu Liang, Hung-Yi Hsieh, Shang-Hwa Hsu, and Jeng-Ren Duann. 2008. Development of wireless brain computer interface with embedded multitask scheduling and its application on real-time driver's drowsiness detection and warning. *IEEE Transactions on Biomedical Engineering* 55, 5 (2008), 1582–1591.

[56] Ruixue Liu, Erin Walker, Leah Friedman, Catherine M Arrington, and Erin T Solovey. 2021. fNIRS-based classification of mind-wandering with personalized window selection for multimodal learning interfaces. *Journal on multimodal user interfaces* 15 (2021), 257–272.

[57] Nicholas Lofthouse, L Eugene Arnold, Sarah Hersch, Elizabeth Hurt, and Roger DeBeus. 2012. A review of neurofeedback treatment for pediatric ADHD. *Journal of attention disorders* 16, 5 (2012), 351–372.

[58] James SP Macdonald, Santosh Mathan, and Nick Yeung. 2011. Trial-by-trial variations in subjective attentional state are reflected in ongoing prestimulus EEG alpha oscillations. *Frontiers in psychology* 2 (2011), 82.

[59] Scott Makeig, Anthony Bell, Tzyy-Ping Jung, and Terrence J Sejnowski. 1995. Independent component analysis of electroencephalographic data. *Advances in neural information processing systems* 8 (1995).

[60] Melinda Melinda, Prima Dewi Purnamasari, Fahmi Fahmi, Emerson Sinulingga, Muliyadi Muliyadi, and Imam Ashabul Yamin. 2024. Innovative Portable Quantitative EEG Data Acquisition Based Cyton Biosensing Board using PSD Analysis. In *2024 10th International Conference on Smart Computing and Communication (ICSCC)*. IEEE, 631–636.

[61] Pardis Miri, Mehul Arora, Aman Malhotra, Robert Flory, Stephanie Hu, Ashley Lowber, Ishan Goyal, Jacqueline Nguyen, John P Hegarty, Marlo D Kohn, et al. 2022. FAR: end-to-end vibrotactile distributed system designed to facilitate affect regulation in children diagnosed with autism spectrum disorder through slow breathing. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–20.

[62] Eleni Mitsea, Athanasios Drigas, and Charalampos Skianis. 2022. Breathing, attention & consciousness in sync: The role of breathing training, metacognition & virtual reality. *Technium Soc. Sci. J.* 29 (2022), 79.

[63] Florence D Mowlem, Jessica Agnew-Blais, Jean-Baptiste Pingault, and Philip Asherson. 2019. Evaluating a scale of excessive mind wandering among males and females with and without attention-deficit/hyperactivity disorder from a population sample. *Scientific reports* 9, 1 (2019), 3071.

[64] Hannah CM Niermann and Anouk Scheres. 2014. The relation between procrastination and symptoms of attention-deficit hyperactivity disorder (ADHD) in undergraduate students. *International journal of methods in psychiatric research* 23, 4 (2014), 411–421.

[65] Sharon Oviatt. 2007. Multimodal interfaces. *The human-computer interaction handbook* (2007), 439–458.

[66] Subrata Pain, Subhrasankar Chatterjee, Monalisa Sarma, and Debasis Samanta. 2025. MSSTNet: A multi-stream time-distributed spatio-temporal deep learning model to detect mind wandering from electroencephalogram signals. *Computers and Electrical Engineering* 122 (2025), 110005.

[67] Aurore A Perrault, Abbas Khani, Charles Quairiaux, Konstantinos Kompotis, Paul Franken, Michel Muhlethaler, Sophie Schwartz, and Laurence Bayer. 2019. Whole-night continuous rocking entrains spontaneous neural oscillations with benefits for sleep and memory. *Current biology* 29, 3 (2019), 402–411.

[68] Rosalind W Picard. 2000. *Affective computing*. MIT press.

[69] Jenny Preece, Yvonne Rogers, Helen Sharp, David Benyon, Simon Holland, and Tom Carey. 1994. *Human-computer interaction*. Addison-Wesley Longman Ltd.

[70] GS Rajshekar Reddy and GM Lingaraju. 2020. A brain-computer interface and augmented reality neurofeedback to treat ADHD: A virtual telekinesis approach. In *2020 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct)*. IEEE, 123–128.

[71] Ian H Robertson, Tom Manly, Jackie Andrade, Bart T Baddeley, and Jenny Yiend. 1997. 'Oops!': Performance correlates of everyday attentional failures in traumatic brain injured and normal subjects. *Neuropsychologia* 35, 6 (May 1997), 747–758.

[72] Martin Schrepp, Andreas Hinderks, and Jörg Thomaschewski. 2017. Construction of a benchmark for the user experience questionnaire (UEQ). *Int. J. Interact. Multimed. Artif. Intell.* 4, 4 (2017), 40.

[73] Marcel Schulze, Silke Lux, and Alexandra Philipsen. 2020. Sensory processing in adult ADHD–a systematic review. (2020).

[74] Hasti Seifi, Mattew Chun, and Karon E Maclean. 2018. Toward affective handles for tuning vibrations. *ACM Transactions on Applied Perception (TAP)* 15, 3 (2018), 1–23.

[75] Farhad Shabani, Sajid Nisar, Hemma Philamore, and Fumitoshi Matsuno. 2021. Haptic vs. visual neurofeedback for brain training: A proof-of-concept study. *IEEE Transactions on Haptics* 14, 2 (2021), 297–302.

[76] Jorge Luis Siesquén Deza. 2025. Bridging therapy and daily life: A blended CBT-biofeedback intervention for emotional self-regulation in adults with ADHD. In *Adjunct Proceedings of the 4th Annual Symposium on Human-Computer Interaction for Work* (Amsterdam Netherlands). ACM, New York, NY, USA, 1–5.

[77] Jaka Sodnik, Christina Dicke, Sašo Tomažič, and Mark Billinghurst. 2008. A user study of auditory versus visual interfaces for use while driving. *International journal of human-computer studies* 66, 5 (2008), 318–332.

[78] Benjamin Tag, Takuya Goto, Kouta Minamizawa, Ryan Mannschreck, Haruna Fushimi, and Kai Kunze. 2017. atmoSphere: mindfulness over haptic-audio cross modal correspondence. In *Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers*. 289–292.

[79] shaohua tang, Yutong Liang, and Zheng Li. 2023. Mind wandering state detection during video-based learning via EEG. doi:10.17605/OSF.IO/7MJ5E

[80] Jan B. F. van Erp. 2002. Guidelines for the use of vibro-tactile displays in human computer interaction. In *Proceedings of Eurohaptics 2002*. Edinburgh, UK, 18–22.

[81] Dana Van Son, Frances M De Blasio, Jack S Fogarty, Angelos Angelidis, Robert J Barry, and Peter Putman. 2019. Frontal EEG theta/beta ratio during mind wandering episodes. *Biological psychology* 140 (2019), 19–27.

[82] Zhikai Wei, Aiguo Song, Ye Yan, Erwei Yin, Xuhui Hu, Fengkai Guo, and Ziyi Zhao. 2024. An Electro-Vibration Feedback Armband for a Prosthetic Hand. In *Proceedings of the 2024 4th International Conference on Robotics and Control Engineering*. 83–89.

[83] Peter D Welch. 1967. The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms. *IEEE Transactions on audio and electroacoustics* 15, 2 (1967), 70–73.

[84] Irene Winkler, Stefan Haufe, and Michael Tangermann. 2011. Automatic classification of artifactual ICA-components for artifact removal in EEG signals. *Behavioral and brain functions* 7, 1 (2011), 30.

[85] Dennis Wolf, Michael Rietzler, Leo Hnatek, and Enrico Rukzio. 2019. Face/On: Multi-Modal Haptic Feedback for Head-Mounted Displays in Virtual Reality. *IEEE Transactions on Visualization and Computer Graphics* 25, 11 (2019), 3169–3178. doi:10.1109/TVCG.2019.2932215

[86] Shan Xu, Sarah Sykes, Parastoo Abtahi, Tovi Grossman, Daylon Walden, Michael Glueck, and Carine Rognon. 2024. Designing haptic feedback for sequential gestural inputs. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*. 1–17.

[87] Neng-Hao Yu, Shih-Yu Ma, Cong-Min Lin, Chi-Aan Fan, Luca E Taglialatela, Tsai-Yuan Huang, Carolyn Yu, Yun-Ting Cheng, Ya-Chi Liao, and Mike Y Chen. 2023. DrivingVibe: Enhancing VR driving experience using inertia-based vibrotactile feedback around the head. *Proceedings of the ACM on Human-Computer Interaction* 7, MHCI (2023), 1–22.

[88] Anthony P Zanesco, Ekaterina Denkova, and Amishi P Jha. 2021. Self-reported mind wandering and response time variability differentiate prestimulus electroencephalogram microstate dynamics during a sustained attention task. *Journal of cognitive neuroscience* 33, 1 (2021), 28–45.

[89] Rui Zhang, Yixuan Li, Zihuang Wu, Yong Zhang, Jie Zhao, and Yang Jiao. 2024. SemanticTap: A Haptic Toolkit for Vibration Semantic Design of Smartphone. In *Proceedings of the 26th International Conference on Multimodal Interaction*. 264–273.

[90] Lingfei Zhu, Qi Cao, and Yiyu Cai. 2020. Development of augmented reality serious games with a vibrotactile feedback jacket. *Virtual Reality & Intelligent Hardware* 2, 5 (2020), 454–470.

A Design Space

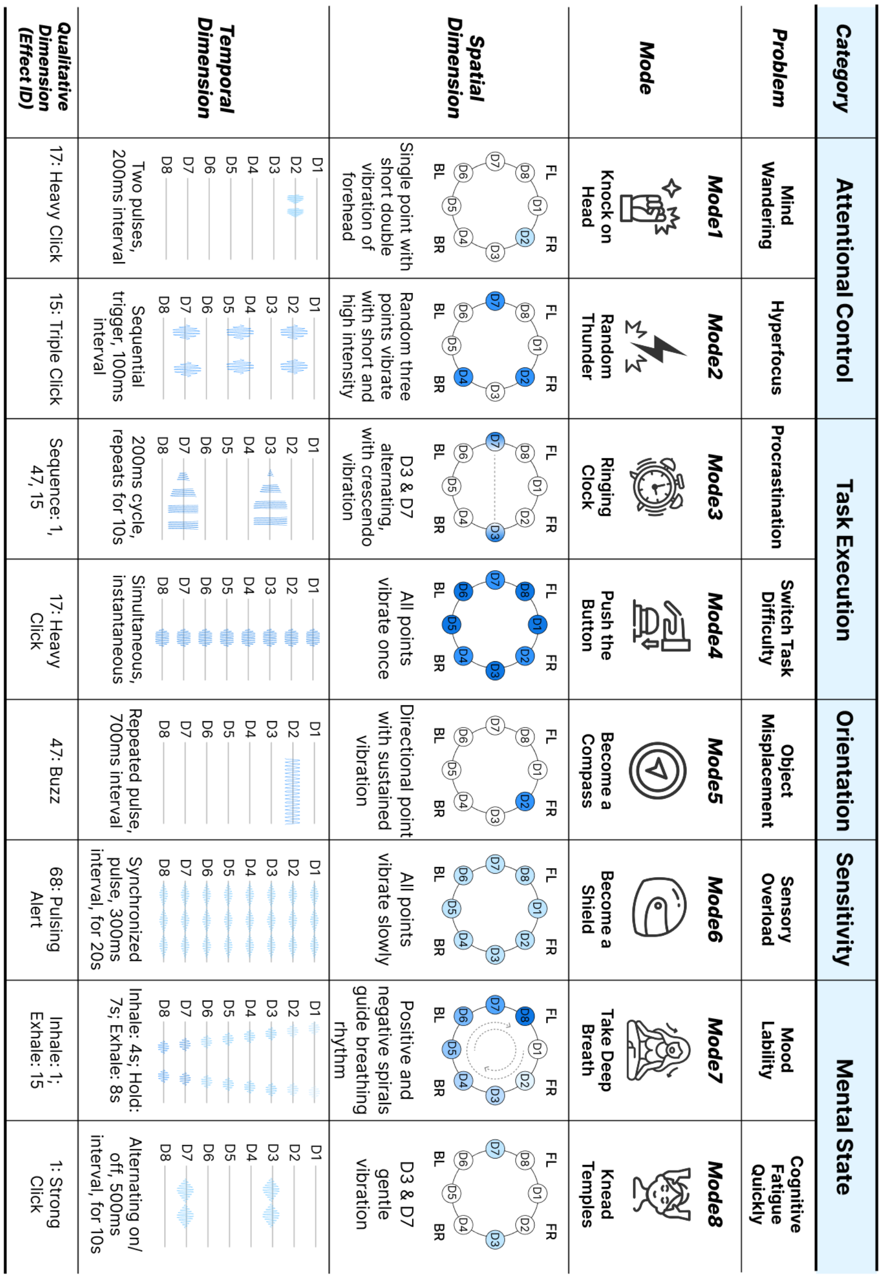


Fig. 19. Design Space: Related Vibration Modes, Frequencies, and Semantic Information.

B AI Image Usage Supplement

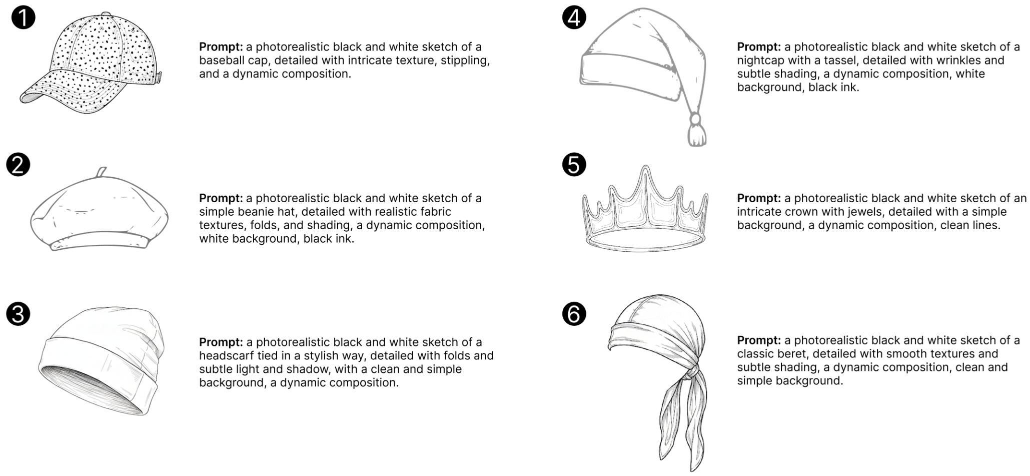


Fig. 20. Prompts of AI usage in caps generating in the Gemini 2.5 flash model.

C Formative Study Materials

C.1 Questionnaire

(1) What is your age range?
- 18-25
- 26-30
- 31-35
- 36-40
- Over 40

(2) What is your gender?
- Female
- Male
- Prefer not to disclose

(3) Have you been formally diagnosed with ADHD? If so, when were you diagnosed?
- Formally diagnosed in childhood
- Formally diagnosed in adulthood
- No formal diagnosis but suspect I have ADHD
- I do not have ADHD

(4) What specific problems have you experienced due to attention difficulties? (Multiple choices)
- Low work efficiency
- Missing important matters
- Problems with communication
- Affecting academic performance

- Feeling down or irritable
- Other

(5) In which daily situations are you most easily distracted? (Multiple choices)
- Reading or writing
- Meetings or classes
- Conversations
- Using electronic devices
- Noisy or crowded environments
- During large mood swings
- Other

(6) Facing attention problems or other ADHD-related difficulties, what self-regulation or improvement methods have you tried? (Multiple choices)
- Regularly keeping a diary or self-reflecting
- Trying cognitive behavioral therapy, meditation, or mindfulness exercises
- Taking medication
- Participating in ADHD support groups
- Asking friends or family for supervision and encouragement
- Have not tried any
- Other

(7) If a system could help you detect attention fluctuations and provide reminders, when would you want it to intervene? (Multiple choices)
- The moment my attention starts to fluctuate
- When I am completely distracted
- Within a time frame I set
- Anytime
- I do not want automatic intervention
- Other

(8) Which device-wearing locations are more acceptable to you? (Multiple choices)
- Head (e.g., headband, hat)
- Wrist (e.g., watch)
- Neck (e.g., necklace)
- Patch on the waist or under clothing
- I do not want to wear any device

(9) Which intervention reminder methods do you prefer? (Multiple choices)
- Vibration
- Flashing lights
- Sound alerts or ringtones
- Mobile phone notifications
- Other

(10) If the device needs to be worn daily, what are your main concerns? (Multiple choices)
- Lack of comfort

- Being easily noticed by others
- Battery life or charging issues
- Privacy leakage
- Too much data disrupting daily life
- No particular concerns

(11) If the device has accompanying software, what information would you like it to provide? (Multiple choices)
- Current focus level
- Daily attention trend
- Time points when reminders are triggered
- The system provides no feedback
- Other

(12) Please briefly describe: What functions or features should your ideal "attention-assistive system" have?

(13) We will be conducting in-depth interviews and co-design activities in the future. Would you be willing to participate?
- Willing
- Unsure
- Unwilling

(14) If willing, please leave your contact information (Email):

C.2 Semi-structure Interview Questions for Formative Study

Part 1: Opening and Background.

(1) First, could you please briefly introduce yourself? For example, your profession, daily routine, etc.

(2) When were you diagnosed with ADHD? Or when did you start suspecting you might have it? Could you share what that experience was like?

Part 2: Challenges in Daily Life. app:appendix C.2

(1) In your daily work or studies, how do inattention or hyperactivity-impulsivity primarily manifest? Could you give some specific examples?
- **Follow-up:** Do these situations happen frequently? In what contexts are they more likely to occur?

(2) Besides work and studies, have these symptoms caused any difficulties in other aspects of your life (e.g., social interactions, chores, personal hobbies)?
- **Follow-up:** Could you describe that in more detail?

Part 3: Coping Strategies and Tool Usage.

(1) To cope with these challenges, what methods or strategies have you tried? For instance, time management techniques, environmental modifications, or seeking help from others.
- **Follow-up:** How effective were these methods? Which ones worked well, and which were less than ideal?

(2) Have you used any digital tools (apps, wearable devices, etc.) to help you manage your attention or improve your efficiency?
- **Follow-up (if yes):** Could you share your experience using them? What features did you find most and least useful?

- **Follow-up (if no):** What do you think are the reasons you haven't tried them?

Part 4: Concepts for a Future Assistive System.

(1) Imagine if there were an assistive system specifically designed for adults with ADHD. What core features would you want it to have to help you?
   - **Follow-up:** What form would you want this system to take (e.g., a mobile app, a smartwatch, a standalone device)?

(2) In terms of reminders or interventions, which type would you prefer (e.g., vibration, sound, visual cues), and why?

(3) Regarding privacy and data, what concerns would you have? How would you want to control your own data?

Part 5: Closing.

(1) Thank you for sharing your valuable experiences. Before we conclude, is there anything else you would like to add, or any questions you have for me?

D Experiment Materials

D.1 User Experience Questionnaire (UEQ)

(1) Your Experiment ID
(2) Gender
(3) Age Group
(4) Profession
Please rate the following aspects of the system on a 5-point scale.
(5) **Attractiveness:** The overall impression of the system. Do you like or dislike it? Is the system attractive, pleasant, or comfortable?

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
The system is pleasant.	○	○	○	○	○
I like the system.	○	○	○	○	○
The system is attractive.	○	○	○	○	○
The system is friendly.	○	○	○	○	○

(6) **Perspicuity (Clarity):** Is the system easy to get familiar with? Is it easy to learn, understand, and clear?

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
The system is easy to understand.	○	○	○	○	○
The system is easy to learn.	○	○	○	○	○
The system is simple.	○	○	○	○	○
The system is clear.	○	○	○	○	○

(7) **Efficiency:** Can you complete tasks without unnecessary effort? Is the interaction efficient and fast? Does the system react quickly to your input?

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
The system is fast.	○	○	○	○	○
The system is efficient.	○	○	○	○	○
The system is practical.	○	○	○	○	○
The system is well-organized.	○	○	○	○	○

(8) **Dependability:** Do you feel in control of the interaction? Can you predict the system's behavior? Do you feel secure while using the system?

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
The system's behavior is predictable.	○	○	○	○	○
The system is supportive.	○	○	○	○	○
I feel secure using the system.	○	○	○	○	○
The system meets my expectations.	○	○	○	○	○

(9) **Stimulation:** Is it exciting and motivating to use the system? Is it fun to use?

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Using the system is valuable.	○	○	○	○	○
Using the system is exciting.	○	○	○	○	○
Using the system is fun.	○	○	○	○	○
The system is motivating.	○	○	○	○	○

(10) **Novelty:** Is the system innovative and creative? Does it capture your attention?

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
The system is creative.	○	○	○	○	○
The system is inventive.	○	○	○	○	○
The system is leading-edge.	○	○	○	○	○
The system is innovative.	○	○	○	○	○

(11) Do you have any suggestions or ideas for Capace?

D.2 Semi-structure Interview Question for Experiment

Part 1: Product Impression and Ergonomics.

(1) What was your first impression when you saw "Capace"? What did you think of it initially (e.g., practical, interesting, novel, strange)?

(2) During the process of wearing and using "Capace," did you find it comfortable? Was there anything that made you feel uneasy (e.g., weight, material, wearing style)?

Part 2: Core Functionality and Vibration Patterns.

(3) "Capace's" vibration patterns are designed to help you refocus your attention. Did you find these patterns (e.g., single-point, multi-point, crescendo) to be effective?
(4) Can you describe a specific situation where you received a vibration reminder? What type of vibration was it, how did you feel at that moment, and what was your reaction to it?
(5) Which vibration pattern did you find most effective? Which one was the most uncomfortable or least effective, and why?
(6) Did you find the intensity and rhythm of the vibration reminders appropriate? Did you ever feel they were too weak to notice, or too strong to the point of discomfort?
(7) If you could customize them, what new vibration patterns would you like to have? Or, based on what situations would you want the device to trigger a vibration reminder?

Part 3: Social Acceptance and Future Outlook.

(8) Compared to other wearable products that are obviously smart devices (e.g., smartwatches, AR glasses), what do you think are the advantages and disadvantages of "Capace's" "invisible design"?
(9) In which situations do you think this product is most suitable to be worn, and why? In which situations might you feel uncomfortable wearing it?
(10) Besides attention reminders, what other features would you hope for "Capace" to offer in the future (e.g., meditation assistance, stress relief, sleep aid)?