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RainMind: Investigating Dynamic Natural Soundscape of Physiological Data to Promote Self-Reflection for Stress Management

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ABSTRACT
Metaphorical auditory displays are increasingly recognized for data presentation and self-reflection. This article presents the design and evaluation of RainMind, a web-based soundscape application that represents physiological data with dynamic natural sounds for daily stress reflection. Based on different combinations of auditory display with visualization, we identified three modes: the Visual-Aided Mode (VAM), the Audio-Aided Mode (AAM), and the Audio-Visual Mode (AVM). Through a within-subject study involving 30 participants, we conducted a mixed-methods evaluation to assess the task load, engagement, and user experience among the three modes. The findings indicated that the combination of dynamic natural soundscapes with visualization (AVM) contributes to a lower task load compared to the other two modes. Moreover, dynamic natural soundscapes as metaphors for stress data significantly enhanced engagement and user experience of self-reflection compared to static natural sounds. Based on our study, we discuss the potential of leveraging dynamic natural soundscapes as a new way of data-driven self-reflection.

KEYWORDS
Reflection for stress management; physiological data; natural soundscape; auditory display

1. Introduction

Approximately 32% of the global population suffers from psychophysiological stress (Sousa et al., 2021). Chronic stress can lead to physical illnesses such as atherosclerosis and hypertension (Baum & Posluszny, 1999), and mental illnesses like anxiety and depression (Herbert, 1997). Effective stress management can mitigate the adverse effects of stress and enhance the ability to cope with stressors through mechanisms such as increased self-efficacy (Liu et al., 2024). Therefore, prioritizing stress management is critical to improving mental health and overall well-being. For stress management, reflecting on everyday stress can help individuals gain self-insight and motivate behavior changes for healthier lifestyles (Bentvelzen et al., 2022), as well as strengthen the capacity for resilience (Crane et al., 2019). Nowadays, advancements in ubiquitous technologies allow individuals to easily collect physiological data to support stress-related self-reflection (Ding et al., 2021). A typical data-driven self-reflection method for stress coping is utilizing visualizations (Choe et al., 2017). Nevertheless, data visualizations usually provide limited value in generating desirable insights, as users are primarily passive readers of information (Baumer et al., 2014; Khot et al., 2015).

Utilizing alternative modalities, such as auditory or haptic displays, to present information for self-reflection can enhance the interactivity between users and data (Bentvelzen et al., 2023). Particularly, auditory displays have been found to be well-suited for presenting time-series data such as physiological states, with reduced mental load and enhanced pattern recognition (Kantan et al., 2022). In human-computer interaction (HCI), mapping mental health data with various types of sounds as metaphorical displays to facilitate self-reflection, such as musical sounds (Angeler et al., 2022; Nadri et al., 2023), orchestral sounds (Hinterberger & Fürnrohr, 2016), and vocal-like sounds (Borthakur et al., 2019), has been increasingly investigated. Moreover, recent studies have increasingly advocated for exploring the role of natural effects as metaphors for personal health data to improve self-reflection experiences (Jiang et al., 2023; Roo et al., 2017; Yu et al., 2017).

In fact, natural sounds have been widely proven to be effective in inducing relaxation (Song et al., 2023), facilitating attention restoration (Abbott et al., 2016), and reducing anxiety (Rejeh et al., 2016), making them valuable for everyday stress coping (Alvarsson et al., 2010). A few studies have investigated natural soundscapes as a mean of mindfulness and relaxation training (Cochrane et al., 2018, 2020; Yu et al., 2018). To the best of our knowledge, however, there is a dearth of HCI research on representing stress data with natural sounds to mediate self-reflection for mental well-being. One exception is Wagener et al. (2023) who added natural soundscapes as ambient sounds in a VR-based weather scenario to present stress data and found it worthwhile to investigate the influence of coupling natural sound elements with variables of physiological data to support self-reflection for stress management.

To mind the research gap, therefore, this article presents the design and evaluation of RainMind, a web-based

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soundscape application that represents physiological data with the dynamics of natural sounds to support users in reviewing their stress throughout a day. In this study, RainMind was utilized as a research probe to examine the role of natural sounds in representing stress data for facilitating self-reflection and was implemented into three modes. The visual-aided mode (VAM) that only visualizes physiological data into typical graphs with static natural sounds in the background; The audio-aided mode (AAM) that offers a dynamic natural soundscape based on physiological data, without presenting any visualizations; The audio-visual mode (AVM) that provides both the soundscape and the visualization. Based on the prototype of RainMind, a within-subject study with 30 participants was conducted using a mixed-methods evaluation to compare the three modes with the following research questions:

1. To what extent does the AVM of RainMind reduce the task load of mental health self-reflection compared with VAM and AAM?
2. Whether and how does the AVM of RainMind improve the engagement in self-reflection compared with VAM and AAM?
3. Whether and how does the AVM of RainMind enhance the user experience of self-reflection compared with VAM and AAM?

2. Related work

2.1. Data-driven reflection for stress management

In HCI, there is a growing effort to understand data-driven reflection, including its definitions (Baumer, 2015; Bentvelzen et al., 2022), dimensions (Baumer, 2015; Li et al., 2011), levels (Fleck & Fitzpatrick, 2010), and other components. By revisiting personal data, users could carry out self-reflection to e.g., increase self-awareness, make decisions, and change behaviors (Bentvelzen et al., 2022; Li et al., 2010). For short-term stress coping, there have been many biofeedback systems developed to enhance self-awareness of stress through real-time interactivity (Kennedy & Parker, 2019). For example, Yu et al. (2017) presented a heart rate variability (HRV) biofeedback system called StressTree, which metaphorically visualizes real-time HRV data through the growth pattern of a tree to aid relaxation training. Wang et al. (2022) developed a biofeedback VR application to complement stress management through meditation training, using users' electrocardiogram (ECG) data to adjust the virtual scenes and help them understand relaxation levels while training. MacLean et al. (2013) designed a wearable device named MoodWings to visualize the users' electrodermal activity (EDA) and ECG data through the motion of butterfly wings on the device, helping them to recognize their real-time stress levels and facilitating self-regulation.

Given the dynamic nature of stress development and different trajectories within the population, it is critical to understand individuals' variations in stress levels and their primary stressors (Liu et al., 2023). Many HCI projects have focused on helping users identify their sources of stress (González Ramírez et al., 2023) to empower stress handling and improve self-efficacy (Liu et al., 2024). For instance, AffectAura is an emotion memory application that automatically records users' emotional states and visualizes them as bubbles on the timeline to support reflective processes (McDuff et al., 2012). LifelogExplorer incorporates the visualization of personal physiological data with the digital calendar to help users understand their stress patterns (Kocielnik & Sidorova, 2015). Despite the fact that most of the long-term stress management systems were supported with screen-based data visualizations, they were found to fail to support self-reflection due to limited user interaction (Khot et al., 2015). To address this issue, alternative modalities such as auditory modality (Clark & Doryab, 2022; Mendoza et al., 2023) have been increasingly investigated as metaphorical displays for presenting historical personal health data, which is presented in detail in the next subsection.

2.2. Sounds as metaphorical displays of stress data

As an effective tool to present data, sounds can ease the way for individuals to detect temporal patterns and analyze specific features in datasets (Sawe et al., 2020). An increasing number of studies recommend incorporating metaphorical methods into auditory display design (Kantan et al., 2022; Roddy & Bridges, 2020; Roddy & Furlong, 2015). In the metaphorical auditory display design, various sound elements have been employed to represent stress data. One simple way to auditory display stress data is to map its values directly onto acoustic parameters, e.g., pitch, tempo, and volume. For instance, Bahameish (2019) used a linear parameter mapping approach to map the HRV values during mediation exercises onto sound pitch values, and used sharper and smoother tones to metaphorically represent different types of meditation exercises. Yu et al. (2015) used the timing variations of major arpeggios to represent HRV values to support breathing exercises. Their study demonstrated the effectiveness of their auditory interface, but the mapping strategy resulted in rapid fast changes in the musical rhythm which caused anxiety in some participants.

Previous study also suggests using of meaningful symbolic sound elements and metaphorical representation methods to exploit users' embodied cognition for improved data comprehension and user experience (Roddy, 2015). For example, the semantics of natural sounds have been applied to some relaxation exercises as metaphors for the physiological state of the user. Yu et al. (2018) iterated their HRV biofeedback system to foster a more relaxing experience, using the quietness and richness of a forest soundscape as a metaphor for users' HRV state. Roo et al. (2017) developed a mixed reality sandbox called Inner Garden for mindfulness practice, the sound of ocean waves was used as a metaphor for breathing, while the presence of animal sounds represented the level of cardiac coherence. For stress reflection, natural elements are often used to metaphorically visualize individuals' stress levels (Jiang et al., 2023; MacLean et al., 2013; Wagener et al., 2023). However, natural elements are less frequently applied in auditory display designs intended to review stress states for long-term stress management. Therefore, in this paper, we followed Roddy's (2015) embodied soundscape sonification framework to investigate the potential of using natural soundscape to metaphorical auditory display stress data and its impact on facilitating stress self-reflection.

2.3. Benefits of natural sounds as metaphors of physiological data

From an ecological perspective, it has been well-established that natural sounds can be supportive in inducing engaging experiences (Schafer, 1993; Truax, 1999), evoking memories of past feelings (Wrightson, 2000), and enhancing interpretation of data (Roddy, 2015). Previous studies have also shown that incorporating natural sound elements into auditory displays for mental health has several benefits. Firstly, natural sounds have been proven to be relaxing and pleasant (Ratcliffe, 2021), and have the function of relieving stress and anxiety (Abbott et al., 2016; Alvarsson et al., 2010; Martínez Manchón & Šimunić, 2023; Rejeh et al., 2016). Therefore, the use of natural sounds often leads to an improved listening experience. Van Kerrebroeck and Maes (2021) compared the effects of different sound stimuli in a breathing sonification system for stress reduction. They found that natural environmental sounds were perceived as the most pleasant and resulted in the most significant reduction in respiration rate. Klamet et al. (2016) incorporated bird song audio into a wearable system for relaxation and found its significant effects on creating joyfulness. Hoque et al. (2023) used natural sounds in multi-data visualizations for visually impaired people to help them concentrate on data discrimination, with a sense of relaxation and enjoyment.

Secondly, it has been observed that natural sounds might play a decisive role in enhancing the task performance of physiological data analysis. For example, Blanco et al. (2022) found that the water ambience soundscape could increase the accuracy of the ST elevation detection in ECG surveillance with a pleasant detection experience. Additionally, Wagener et al. (2023) added natural sounds to the virtual reality environment to create engaging mental health self-reflection experiences. These investigations primarily focused on applying natural sounds statically for mental health promotion. Nevertheless, how the natural sound elements could be coupled with different parameters of personal health data and their resulting effects on mental health self-reflection are still doubtful (Wagener et al., 2023).

Therefore, in this paper, we developed a research probe to investigate the data-driven natural soundscape for self-reflection on everyday stress management.

3. Design of RainMind

As shown in Figure 1, RainMind is designed as a web-based application that transforms the physiological data into a dynamic natural soundscape, supporting self-reflection throughout a day. The RainMind application comprises two steps (see Figure 2): data processing and sound synthesizing. In the data processing step, the raw physiological data is processed into stress measures. In the sound synthesizing step, the values of these stress measures are mapped to control the corresponding sound parameters.

3.1. Data processing

RainMind used HRV, EDA, and heart rate (HR) to represent a user's temporal changes in stress levels, which are generally accepted as stress indicators (Appelhans & Luecken, 2006; Babaei et al., 2021; Taelman et al., 2009). Presenting three types of data instead of just one aims to reduce the interference caused by fluctuations in single physiological data due to factors such as skin humidity and temperature changes. To collect physiological data, we applied the E4 wristband because of its suitability for daily application as a medical-certified device and its easy-to-export data storage (Empatica Inc., 2024).

Figure 3 illustrates the processing and application procedure of the original IBI, EDA, and HR data collected by the E4. These data were processed into indices over a specific time window (t_w) to represent stress data. Among them, the Standard Deviation of IBI data (SDNN) was calculated within t_w as the HRV index. The EDA data was processed into the Skin Conductance Response (SCR) data according to Taylor et al. (2015). Further, the SCR occurrences within a t_w were regarded as a data point for the Non-Specific Skin Conductance Response frequency (NS.SCR frequency), a valid stress indicator as the EDA index (Boucsein, 2012). HR was calculated as the average over t_w. As shown in Figure 4, after calculation with t_w, each of the three types of raw data yielded n data points, where $n = \frac{T_d}{t_w}$. Denoting the reflection duration provided by RainMind as T_a, and each data point's corresponding audio segment as t_i, we have $t_i = \frac{T_a}{n} = \frac{T_a t_w}{T_d}$. For the application of RainMind, T_d, t_w, and T_a can be set as required.

3.2. Sound synthesizing

For the sound synthesizing (see Figure 5), a rainy-day acoustic environment was chosen to represent users' stress levels. The choice of the rainy-day soundscape serves two purposes. First, the elements of the rainy-day soundscape are widely recognized as calming and pleasant (Nishida & Oyama-Higa, 2014), potentially positively affecting users' attention and emotional state during self-reflection. Second, rain is commonly associated with mental health, often symbolizing negative emotions in art and literature (Martín & López, 2020).

The sounds of rain, thunder, and chirping, which are commonly found in the rainy-day soundscape, were chosen to represent variations in the three physiological measures (see Table 1). We chose a concise mapping strategy (Hermann et al., 2011) to reduce the learning cost of RainMind. First, we utilized the volume of the rainy sound to represent the SDNN values to indicate the changes in HRV levels. Due to the inverse trend of SDNN with respect to stress, the SDNN inversely controls the volume of the rain sound, where an increase in volume indicates lower

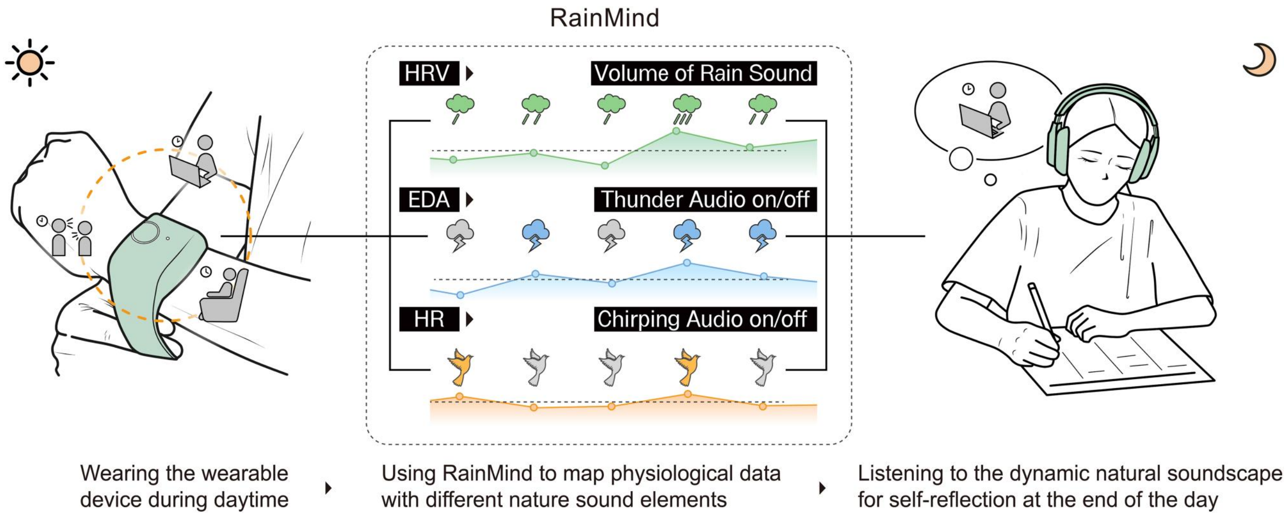

Figure 1. The concept of RainMind.

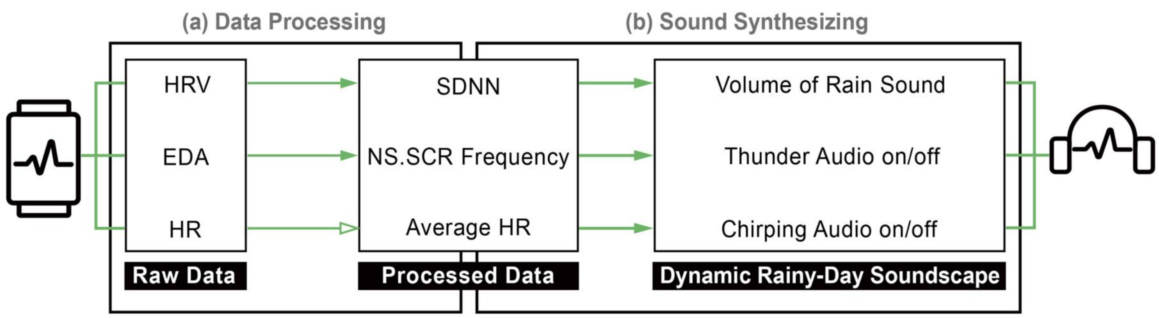

Figure 2. The structure of the RainMind application.

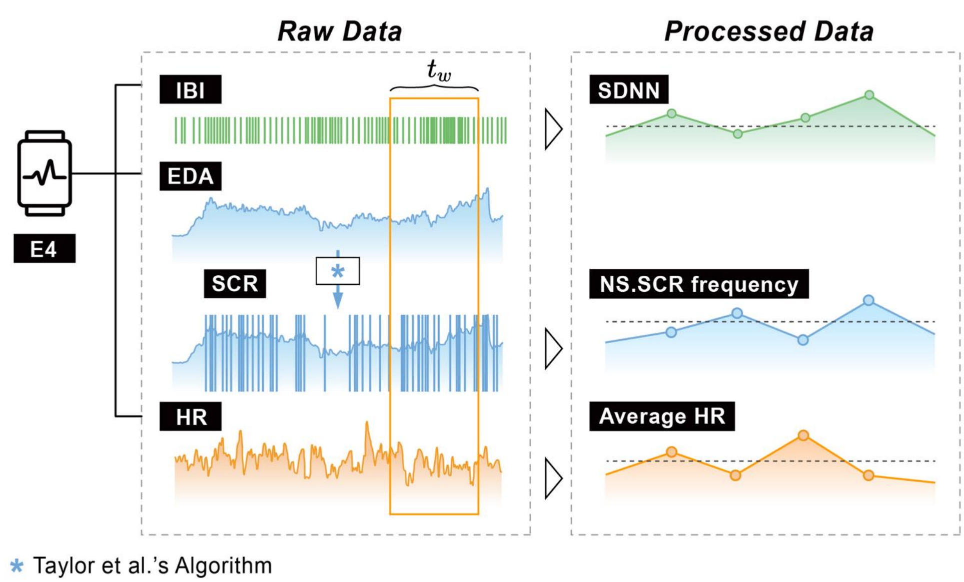

Figure 3. The data processing step of the RainMind.

SDNN, signifying higher stress. Second, the EDA data were processed into NS.SCR frequency to further support users in assessing their stress levels. The average value of NS.SCR frequency throughout a day was calculated and set as a threshold to trigger the occurrences of thunder, representing excessive pressure (Babaei et al., 2021).

Third, a similar mapping mechanism was also applied to the representation of HR data, where the HR value above the daily average would trigger the chirping sound to indicate the increased vitality. All audio materials were obtained from the BBC Sound Effects Archive (*BBC Sound Effects*, 2024).

3.3. Interaction modes

To facilitate the examination of our proposed sound synthetization, we designed and developed three interaction modes in the RainMind prototype: the visual-aided mode (VAM); the audio-aided mode (AAM), and the audio-visual mode (AVM). The prototype program of RainMind was developed using JavaScript, CSS, and HTML. Specifically, the visualization component was created using D3.js (Mike Bostock and Observable, Inc., 2024).

3.3.1. The visual-aided mode

In VAM, the data visualization of HRV, EDA, and HR would be simultaneously unfolded from the left side to the right side, with a static natural soundscape in background (see Figure 6). Presentations of the three types of data were color-coded into green, blue, and orange to enhance the readability of the multi-data graphs. Each area graph includes a horizontal line indicating the mean value of the physiological data over the duration of T_d. There is a vertical line that spans all three area graphs, which serves as a progress marker, and a timeline that shows the actual time of physiological data recording. Particularly, the vertical axis of the SDNN area graph is reversed, with higher values at the bottom, to align variations with stress levels. In this mode, RainMind only performs data processing to generate visualizations. Identical sound elements as described in the subsection 3.2 were chosen and edited into a steady and moderate rainy soundscape with regular presentations of thunder and chirping sounds, without any correlation with the visualizations of physiological data.

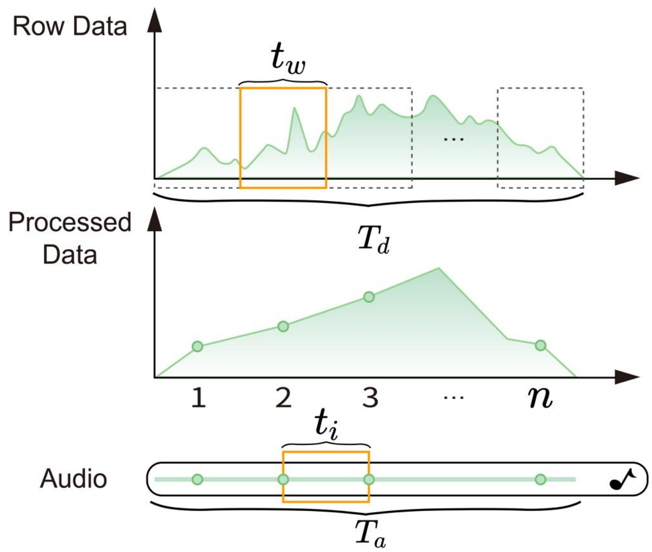

Figure 4. The temporal mapping strategy in RainMind.

3.3.2. The audio-aided mode

As shown in Figure 7, in the AAM all the data visualizations were removed, while the dynamic natural soundscape mapped with physiological data was enabled. The full detail mapping strategy has been explained in the subsection 3.2. Here, we hypothesized that users could close their eyes and immerse themselves in revisiting stress changes over a day.

3.3.3. The audio-visual mode

As shown in Figure 8, both the animated visualizations and the dynamic soundscape would be provided in AVM. According to Hermann et al. (2011) and Enge et al. (2024), the audio-visual displays of data usually improve task performances and user experiences. Therefore, with AVM we were interested in knowing whether the similar effects would be obtained in biofeedback and mental health self-reflection technologies.

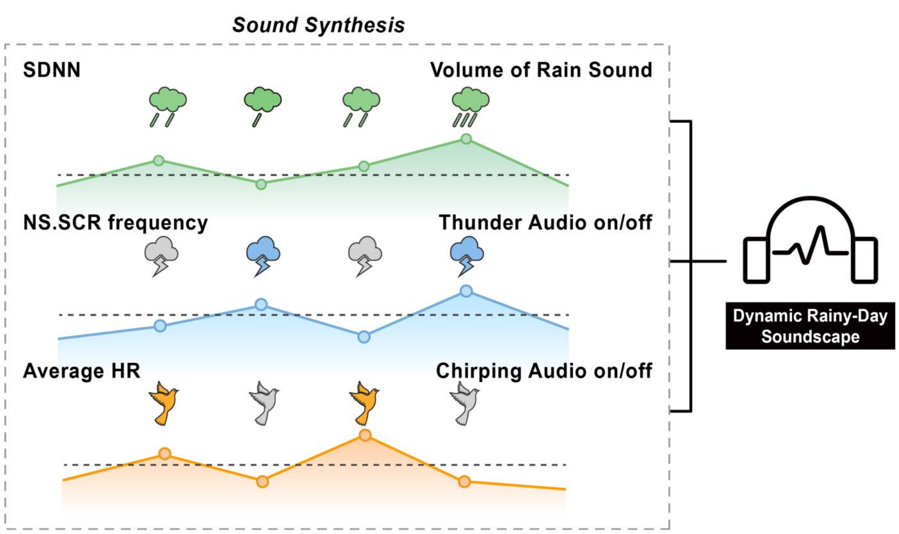

Figure 5. The sound synthesizing step of RainMind.

Table 1. The mapping strategy of RainMind.

Physiological measures	Sound elements	Sound parameters	Mapping approach
SDNN	Rain	Volume	Value increases, volume decreases
NS.SCR frequency	Thunder	On/Off	Triggered by the threshold
Average HR	Chirp	On/Off	Triggered by the threshold

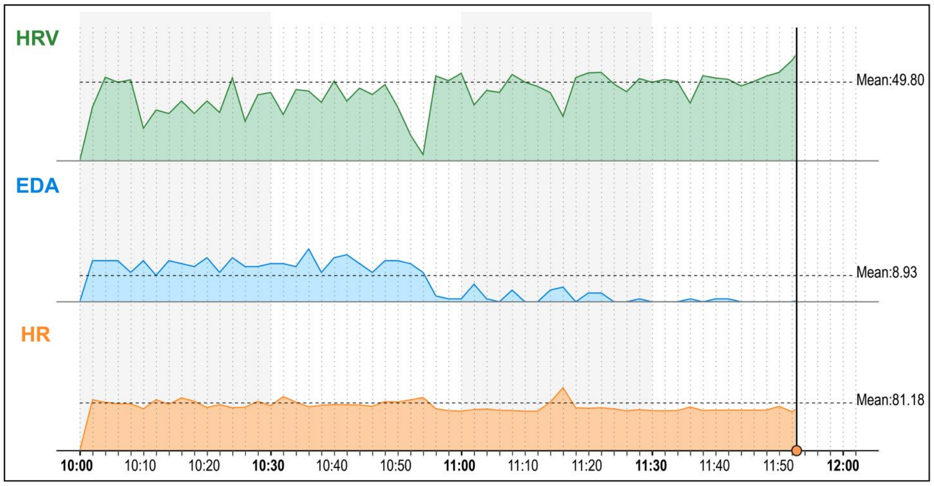

Figure 6. The interface of the visual-aided mode (VAM). Scan the QR code to access to the demo of VAM.

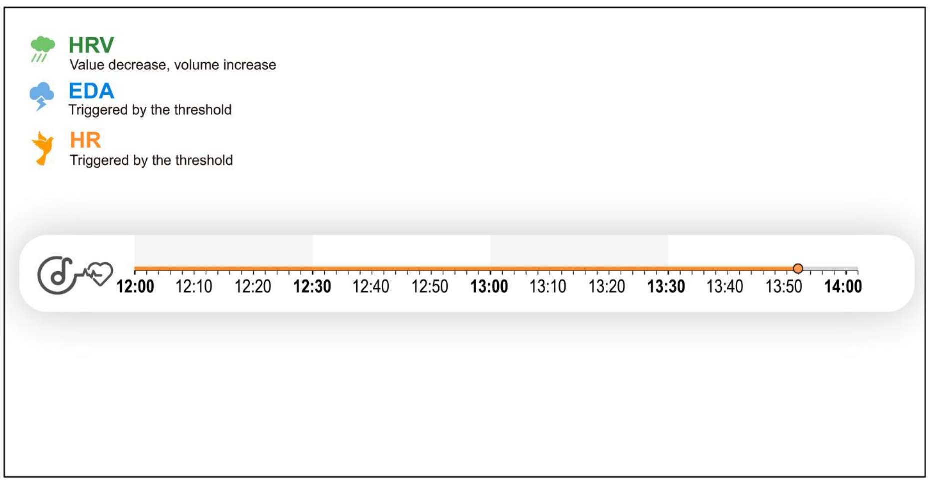

Figure 7. The interface of the audio-aided mode (AAM). Scan the QR code to access to the demo of AAM.

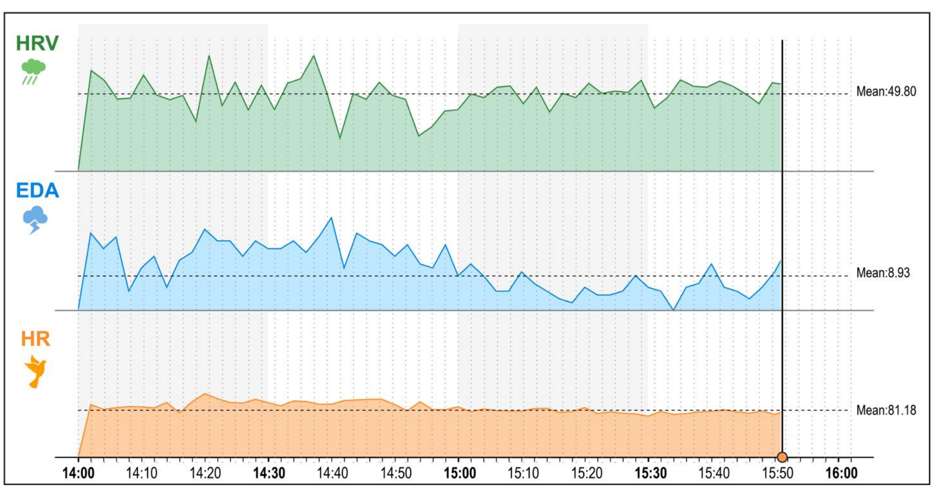

Figure 8. The interface of the audio-visual mode (AVM). Scan the QR code to access to the demo of AVM.

4. The experiment

4.1. Hypotheses

For the experiment, RainMind was used as a research probe to investigate the roles of the dynamic natural soundscape based on the multimodal physiological data in facilitating health review and self-reflection for daily stress management. We set out a within-subject study to compare the differences among the VAM, AAM, and AVM, with the following research hypotheses:

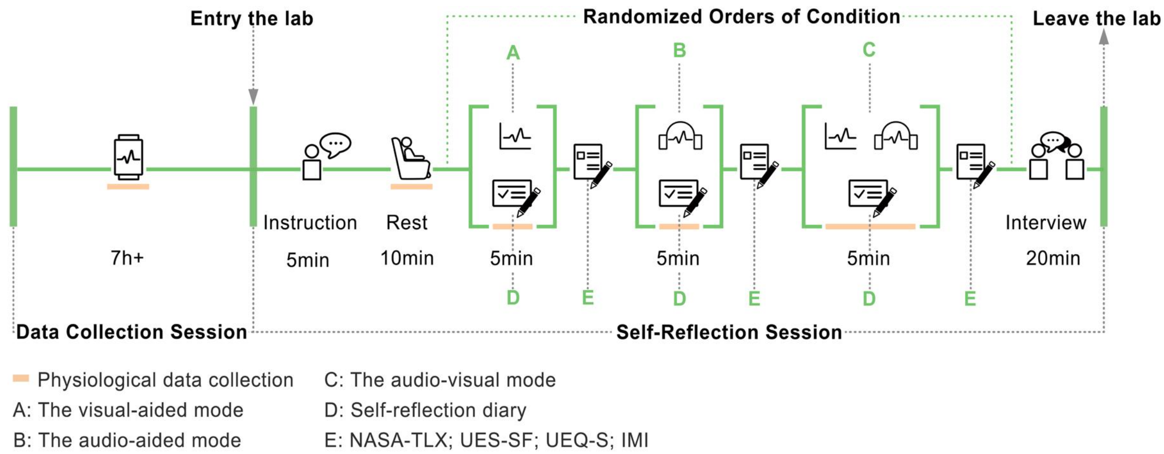

Figure 9. Experimental procedure.

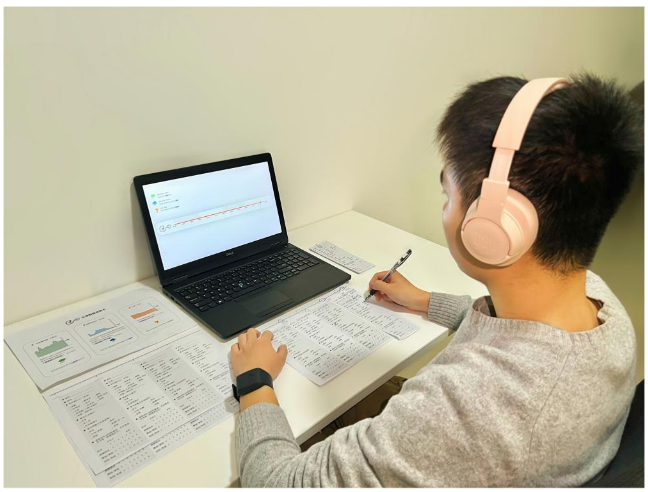

Figure 10. A participant was experiencing the AAM.

- H1: The AVM of RainMind will reduce task load in self-reflection more than the VAM and AAM.
- H2: The AVM of RainMind will improve the engagement in self-reflection more than the VAM and AAM.
- H3: The AVM of RainMind will enhance the user experience of self-reflection more than the VAM and AAM.

4.2. Participants

Thirty-four participants were recruited using an extended network and snowball sampling to enhance the recruiting efficiency. One participant withdrew from the experiment due to device malfunction and data from three participants were invalid and thus excluded. In the end, data from 30 participants (17 females and 13 males, aged between 19 and 30 years, $M = 23.1$, $SD = 2.2$) were retained for data analysis. Each participant had normal hearing, and normal vision or corrected-to-normal vision. They also reported no history of mental illness and confirmed that they were in a normal state of life on the day of the experiment. The study adhered to the Declaration of Helsinki, and the experimental procedure was approved by the Medicine and Laboratory Animals Ethics Committee of the Beijing Institute of Technology. All participants volunteered for the study and received no compensation.

4.3. Procedure

Prior to the experiment, each participant completed an informed consent form and was briefed on the basic experimental procedures and equipment usage. As shown in Figure 9, the experiment comprised two sessions: the data collection session and the self-reflection session. In the first session, participants were asked to wear an E4 wristband on their non-dominant hand continuously for at least 7 h ($M = 7.9$, $SD = 0.6$). Recording began at any time between 9:00 AM and 10:00 AM. To minimize potential data noise caused by strenuous physical activity (Stuyck et al., 2022), participants were instructed to avoid engaging in exercises during the data collection session.

After the data collection session, participants were invited to the lab for the self-reflection session between 6:00 PM and 9:00 PM on the same day. They were required to wear an acoustic noise-canceling headphone (JBL T760NC) and the E4 wristband again, and then experience the three reflection modes. During the study, the VAM, AAM, and AVM modes appeared in randomized orders and were counterbalanced across all the participants (see Figure 9). Before the experience, the participants were asked to sit quietly in a chair with their eyes closed for 10 min to achieve a resting and calm state (Figure 10).

In the experiment, data collected during daylight hours from each participant served as the data source. The first 15 min of collected data were excluded for data quality, and the remaining continuous 6-h data were extracted and divided into three equal segments. The data in these segments were presented to participants in chronological order through randomly ordered modes. Therefore, in the experiment, each mode of RainMind was provided with physiological data for one-third of the data collection duration (i.e., $T_d = 120\ minutes$). The time window t_w was set to 2 min, and the reflection duration T_a was set to 5 min. While experiencing each mode, participants were asked to fill out a self-reflection diary (see Figure 11), which was adapted from the Day Reconstruction Method (DRM; Kahneman et al., 2004). It included an unlimited number of event description notes (see Figure 11(a)) and a timeline canvas (see Figure 11(b)).

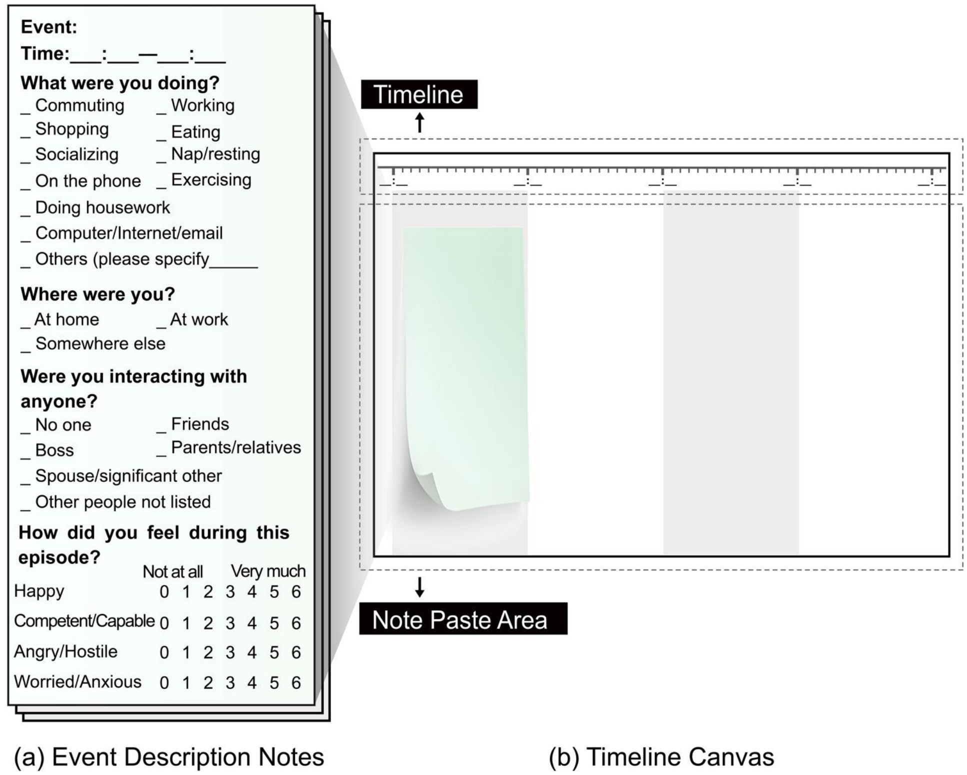

Figure 11. Self-reflection diary used during the experiment.

After experiencing each mode, participants completed the NASA Task Load Index (NASA-TLX) (Hart & Staveland, 1988), the short form of the User Engagement Scale (UES-SF) (O'Brien et al., 2018), the short version of the User Experience Questionnaire (UEQ-S) (Schrepp et al., 2017), and the Intrinsic Motivation Inventory (IMI) (Ryan, 1982). At the end of the experiment, a semi-structured interview was conducted for each participant. The entire second session lasted approximately 75 min.

4.4. Data collection

We collected both quantitative and qualitative data through the mixed-methods evaluation. For quantitative data, we gathered self-report data from four questionnaires (NASA-TLX, UEQ-S, UES-SF, IMI) and objective measures of stress, including physiological data (SDNN, NS.SCR frequency) from the E4 wristband. Qualitative data were collected through semi-structured interviews. Each interview was audio recorded and transformed into text for detailed analysis thereafter. These data represent the assessment content pertaining to our hypotheses.

Task load (H1) affects users' task performance and subsequent willingness to use (Born et al., 2019). The impact of different modes on subjective task load was evaluated using NASA-TLX, which comprises six subscales: *mental demand*, *physical demand*, *temporal demand*, *performance*, *effort*, and *frustration*.

User engagement (H2) enhances concentration and immersion in self-reflection tasks, thereby improving the effectiveness of the self-reflection process (Kocielnik et al., 2018; Li et al., 2011; Wagener et al., 2023). We measured user engagement using the short form of the *User Engagement Scale* (UES-SF) (O'Brien et al., 2018) with a 5-point Likert scale, which includes four subscales: *Focus Attention (FA)*, *Aesthetic Appeal (AE)*, *Reward Factor (RW)*, and *Perceived Usability (PU)*.

User experience (H3) was measured using the short version of the User Experience Questionnaire (UEQ-S; Schrepp et al., 2017) to assess the *pragmatic* and *hedonic quality* through two subscales. Each of them includes four items rated on a 7-point Likert scale, with scores scaled from -3 (fully agree with the negative term) to $+3$ (fully agree with the positive term). We also evaluated users' intrinsic motivation (Deng et al., 2010; Hornbæk & Hertzum, 2017) by choosing four related subscales from the Intrinsic Motivation Inventory (IMI) (Ryan, 1982): *interest/enjoyment*, *value/usefulness*, *perceived competence*, and *pressure/tension*, with a total of 25 items collected via a 7-point Likert scale. Additionally, participants' physiological data (SDNN, NS.SCR frequency) served as objective indicators of participants' stress states during the experiment.

4.5. Data analysis

4.5.1. Quantitative data

The physiological data from the E4 wristbands were processed using a Python toolbox for neurophysiological signal processing called NeuroKit2 (Makowski et al., 2021). The IBI data and EDA data were respectively processed into SDNN data and NS.SCR frequency data.

Physiological data and questionnaire responses were analyzed using SPSS software. Normality tests were initially conducted using the Shapiro-Wilk test. Since both the physiological data and questionnaire responses in this study did not meet the normal distribution criteria, non-parametric paired Friedman tests were employed to assess differences among the modes. Following significant Friedman results, non-parametric paired Wilcoxon tests were conducted to identify specific pairwise significance between the modes.

4.5.2. Qualitative data

We used thematic analysis (Braun & Clarke, 2006) to analyze the interview transcripts. Two authors independently conducted open coding and subsequently engaged in collaborative discussions to integrate the codes and extract themes. After several rounds of iteration, the emerging themes were defined and labeled.

5. Results

As shown in Figure 12, this section presents both quantitative and qualitative findings to address research hypotheses.

5.1. Quantitative results

The descriptive results of questionnaires and physiological measures along with the statistical analyses were organized in Table 2. Next, we explain our quantitative findings in detail.

5.1.1. Reduced task load of mental health self-reflection (H1)

Overall, the VAM received the highest scores and the AVM received the lowest scores in all the dimensions, except for the *Mental Demand* and *Temporal Demand*, where the AAM was rated slightly higher than the VAM. According to Friedman tests (see Table 2), there were significant differences among the three modes in terms of *Average workload*, *Performance*, and *Frustration*.

For *Average workload* (see Figure 13(a)), the non-parametric paired Wilcoxon tests revealed a significant difference in workload between the VAM and the AVM ($Z = 2.997$, $p = 0.003$). In terms of *Performance* (see Figure 13(f)), participants perceived their performance in the AAM ($Z = 2.130$, $p = 0.033$) and AVM ($Z = 3.006$, $p = 0.003$) as significantly better than in the VAM. For *Frustration* (see Figure 13(g)), there were significant differences between VAM and AVM ($Z = 3.260$, $p = 0.001$), as well as between AAM and AVM ($Z = 2.311$, $p = 0.021$).

To summarize, the results of NASA-TLX suggest that AVM contributes to a decreased workload in self-reflection (H1). In detail, the significant differences in the *Average, Performance*, and *Frustration* subscales between VAM and AVM, showed that the AVM of RainMind helps reduce the task load of self-reflection than VAM. AVM also demonstrated a significantly reduced level of frustration compared to AAM. Nevertheless, compared to the VAM, both the AVM and the AAM exhibited superior performance, demonstrating the effectiveness of dynamic natural sound as metaphors in enhancing reflective performance.

5.1.2. Improved user engagement of mental health self-reflection (H2)

Figure 14 shows the ratings for each subscale and the total score of the UES-SF displaying a consistent trend where VAM scores the lowest, and AVM scores the highest. As shown in Table 2, significant differences were observed among the three modes in the dimensions of *Aesthetic Appeal*, *Reward Factor*, *Perceived Usability*, and *Total* score.

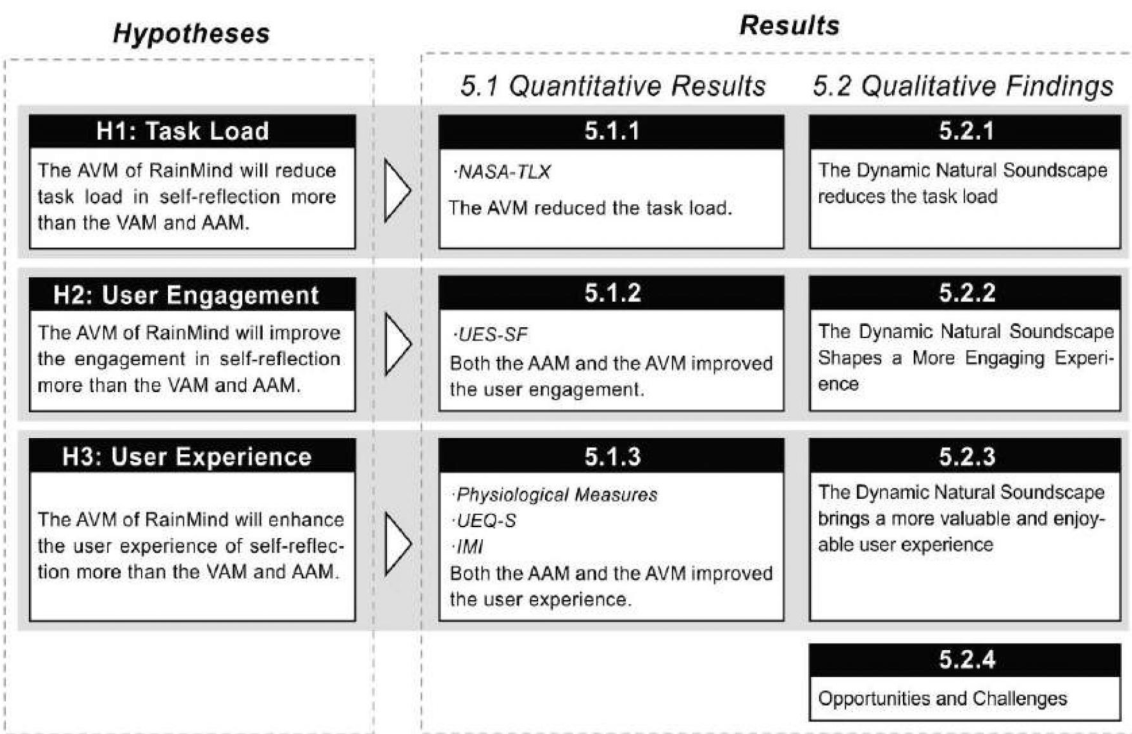

Figure 12. The structure of the results section.

Table 2. Mean and *SD* for NASA-TLX, UES-SF, physiological measures, UEQ-S, and IMI.

Measures	*M* (*SD*) VAM	AAM	AVM	Friedman
NASA-TLX				
Average	11.40 (3.89)	10.08 (4.01)	8.66 (3.76)	6.780, 0.034*
Mental Demand	12.17 (5.02)	12.30 (5.38)	10.60 (4.45)	1.676, 0.433
Temporal Demand	10.63 (5.60)	11.47 (4.95)	8.87 (5.22)	1.477, 0.478
Physical Demand	7.73 (5.31)	6.97 (5.36)	5.83 (3.72)	3.146, 0.207
Effort	12.00 (5.35)	10.39 (5.42)	9.97 (5.04)	1.733, 0.420
Performance	10.97 (4.76)	8.57 (4.40)	7.20 (4.15)	9.415, 0.009**
Frustration	10.47 (5.07)	8.50 (4.90)	6.87 (4.72)	13.872, 0.001***
UES-SF				
Focused Attention	2.75 (0.79)	3.29 (1.03)	3.42 (0.96)	4.294, 0.117
Aesthetic Appeal	3.21 (1.02)	3.94 (0.95)	4.13 (0.93)	8.096, 0.017*
Reward Factor	3.24 (1.10)	3.98 (0.91)	4.22 (0.85)	13.96, 0.001***
Perceived Usability	3.14 (1.19)	3.66 (0.85)	4.06 (0.88)	9.34, 0.009**
Total	3.09 (0.79)	3.72 (0.75)	3.96 (0.76)	11.175, 0.004**
Physiological measures				
SDNN	51.33 (18.02)	52.29 (19.76)	52.68 (21.87)	1.231, 0.540
NS.SCR frequency	3.04 (4.43)	1.84 (4.11)	3.80 (6.11)	7.848, 0.020*
UEQ-S				
Pragmatic Quality	0.30 (1.56)	1.14 (1.35)	1.74 (1.10)	11.028, 0.004**
Hedonic Quality	0.66 (1.48)	1.73 (1.18)	1.73 (1.11)	12.369, 0.002**
Overall	0.48 (1.40)	1.43 (1.14)	1.73 (1.04)	15.027, 0.001***
IMI				
Interest/enjoyment	4.24 (1.43)	5.17 (1.20)	5.46 (1.13)	6.018, 0.049*
Value/usefulness	4.42 (1.60)	5.40 (1.33)	5.74 (1.16)	15.907, <0.001***
Perceived competence	4.19 (1.45)	4.71 (1.41)	5.26 (1.28)	7.207, 0.027*
Pressure/tension	3.56 (1.52)	3.08 (1.28)	2.73 (1.52)	8.220, 0.016*

Results of Friedman tests among the VAM, the AAM, and the AVM. Significance levels are indicated with * for $p \leq 0.05$, ** for $p \leq 0.01$, and *** for $p \leq 0.001$.

For *Aesthetic Appeal* (see Figure 14(b)), non-parametric paired Wilcoxon tests revealed significant differences between the VAM and the AAM ($Z = 3.098$, $p = 0.002$), as well as between the VAM and the AVM ($Z = 2.988$, $p = 0.003$). For *Reward Factor* (see Figure 14(c)). The reward factor was significantly higher in the AAM ($Z = 3.351$, $p = 0.001$) and the AVM ($Z = 3.205$, $p = 0.001$) compared to the VAM. In *Perceived Usability* (see Figure 14(d)), only the rating of the AVM was significantly higher than that of the VAM, with $Z = 3.395$, $p = 0.01$. Finally, for *Total* score (see Figure 14(e)), both the AAM ($Z = 3.268$, $p = 0.004$) and the AVM ($Z = 3.364$, $p = 0.001$) received significantly higher ratings than the VAM.

The H2 received partial support, as indicated by the UES-SF results, which demonstrated that the AVM and AAM both effectively improved user engagement compared to the VAM. This is supported by significantly higher ratings in AVM compared to the VAM in the *Aesthetic Appeal*, *Reward Factor*, and *Perceived Usability* subscales, as well as the *Total Score*. And the results for the AAM significantly surpassed those of the VAM in terms of *Aesthetic Appeal*, *Reward Factor*, and *Total* score. There were no significant differences observed between AAM and VAM. In summary, the dynamic natural soundscapes as metaphors can enhance user engagement in self-reflection, whether combined with data visualization or not.

5.1.3. Enhanced user experience of mental health self-reflection (H3)

5.1.3.1. Physiological measures. We removed data with excessive fluctuations, resulting in the retention of data from 25 participants for subsequent physiological data analysis. We calculated SDNN and NS.SCR frequency to measure participants' stress states while experiencing the three modes.

As shown in Figure 15, the *SDNN* values in the three modes were similar, while the *NS.SCR frequency* values exhibited a decreasing trend. The Friedman test revealed no significant difference in SDNN among the three modes ($X^2(2) = 1.231$, $p = 0.540$).

However, significant differences were observed in *NS.SCR frequency* ($X^2(2) = 7.848$, $p = 0.020$). Subsequent non-parametric paired Wilcoxon tests revealed a significant difference in *NS.SCR frequency* between the VAM and the AVM ($Z = 2.427$, $p = 0.015$).

5.1.3.2. UEQ-S. As illustrated in Figure 16, participants indicated that VAM has the lowest *Pragmatic Quality* (see Figure 16(a)) compared to AAM ($Z = 2.418$, $p = 0.016$) and AVM ($Z = 3.644$, $p < 0.001$). Similarly, participants reported the lowest *Hedonic Quality* (see Figure 16(b)) during the VAM than AAM ($Z = 3.691$, $p < 0.001$) and the AVM ($Z = 3.033$, $p = 0.002$). However, the *Hedonic Quality* scores for both the AAM and the AVM are nearly identical. Overall, the user experience with both the AAM ($Z = 3.486$, $p < 0.001$) and the AVM ($Z = 3.591$, $p < 0.001$) was perceived to be significantly superior to the VAM (see Figure 16(c)).

5.1.3.3. IMI. As depicted in Figure 17, participants perceived that the AVM, compared to the VAM and the AAM, resulted in higher levels of *interest/enjoyment*, *value/usefulness*, and *perceived competence*, along with lower levels of *pressure/tension*. According to Friedman tests, all the dimensions in the IMI show statistical significance.

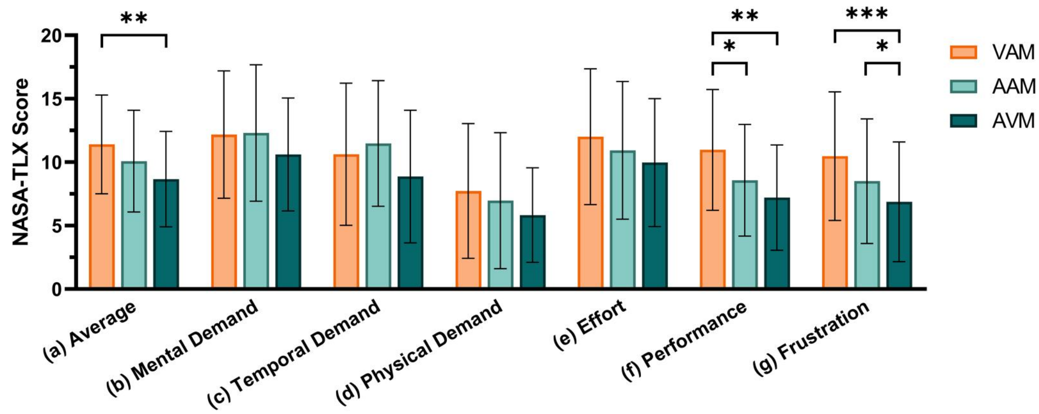

Figure 13. The results of the NASA Task Load Index (NASA-TLX) among the VAM, the AAM, and the AVM.

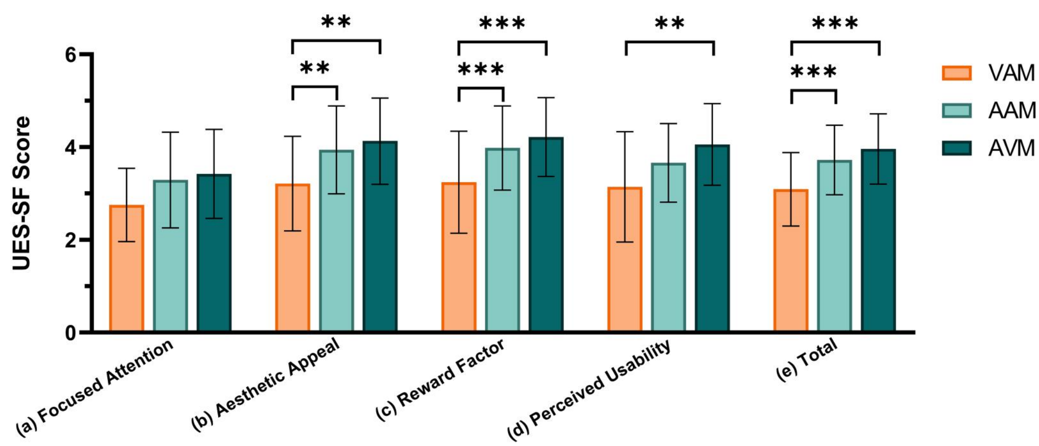

Figure 14. The results of the short form of the User Engagement Scale (UES-SF) among the VAM, the AAM, and the AVM.

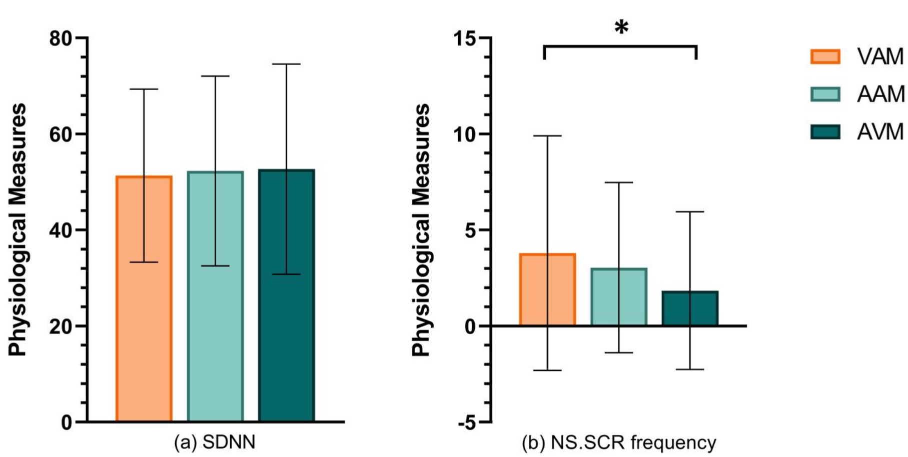

Figure 15. The results of participants' SDNN and NS.SCR frequency during the VAM, the AAM, and the AVM experiences.

For of *Interest/Enjoyment* (see Figure 17(a)), the AAM ($Z = 2.479$, $p = 0.013$) and the AVM ($Z = 2.877$, $p = 0.004$) received significantly higher ratings than the VAM. For *Value/Usefulness* (see Figure 17(b)), participants perceived both the AAM ($Z = 3.266$, $p = 0.001$) and the AVM ($Z = 3.630$, $p < 0.001$) to be significantly more valuable and useful than the VAM. For *Perceived Competence* (see Figure 17(c)), there was a significant increase in ratings between VAM and AVM ($Z = 2.897$, $p = 0.004$). For *Pressure/Tension*, the tests showed that the AVM rating was significantly lower than the VAM ($Z = 2.395$, $p = 0.017$).

Overall, the results partially support H3, indicating that the AVM and AAM can both enhance the user experience of self-reflection. There were no significant differences between AAM and AVM, and they both exhibited a tendency to outperform VAM, regardless of the outcomes in physiological data, UEQ-S, or IMI. This indicates that dynamic natural soundscape had the capability to enhance both pragmatic and hedonic quality, as well as perceived

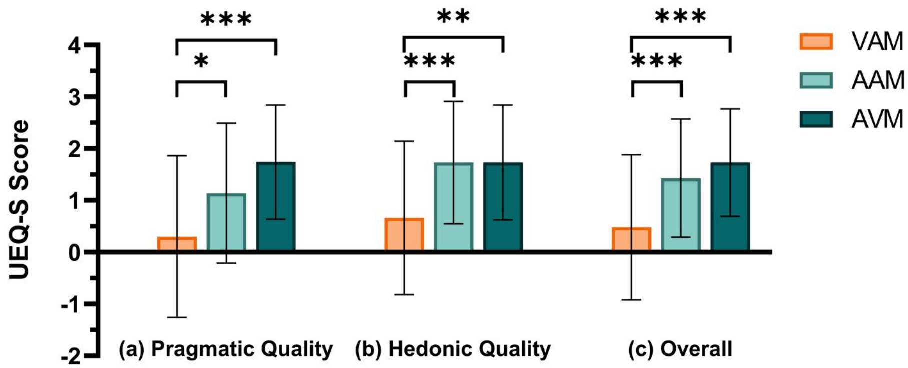

Figure 16. The results of the short version of the User Experience Questionnaire (UEQ-S) among the VAM, the AAM, and the AVM.

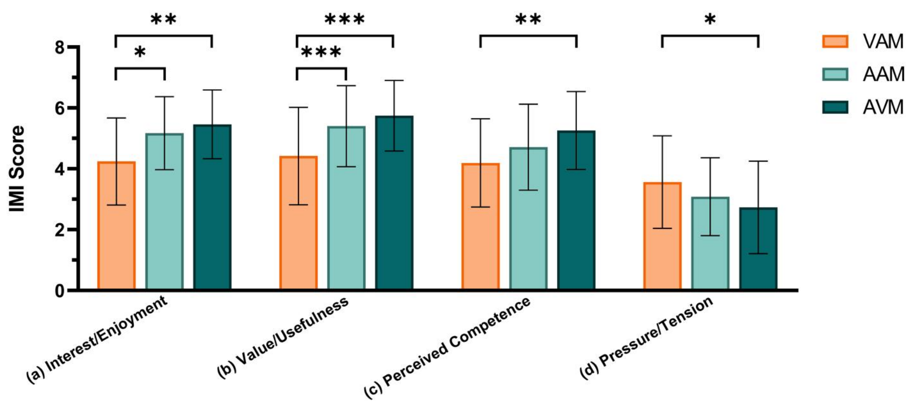

Figure 17. The results of the Intrinsic Motivation Inventory (IMI) among the VAM, the AAM, and the AVM.

enjoyment and value in stress self-reflection, whether combined with data visualization or not. However, only the comparison between the VAM and AVM showed significant differences in the *Perceived Competence* and *Pressure/Tension* dimensions, and there were no significant differences between VAM and AAM in these two subscales. A similar situation was also observed in the physiological data results. These might be attributed to the higher learning cost associated with solely auditory displays.

5.2. Qualitative analysis

In this section, we summarized user feedback into four main themes, including 5.2.1 about task load (H1), 5.2.2 emphasizing user engagement (H2), 5.2.3 highlighting user experience (H3), and 5.2.4 emphasizing opportunities and challenges.

5.2.1. The dynamic natural soundscape reduces the task load

Generally, participants reported that they were able to effectively identify data cues from the dynamic natural soundscape to support their self-reflection. Relative to solely visual data acquisition, they perceived the addition of auditory signals as beneficial in reducing the burden of information identification. As P7 described, "*I can identify periods of significant sound changes. It (the dynamic natural soundscape) can selectively alert me to periods where something has happened.*" P6 also mentioned that "*Maybe it's because important things are always signaled to the user through sound, I find it less taxing for me to get information through audio.*" Relying only on auditory information could also lead to concerns about missing critical data, as indicated by P10, who stated," *I have to keep listening (in the AAM). It's like I'm taking a listening test.*" And P11 mentioned that "*I keep worrying about missing some important data points (in the AAM).*" P9 said, "*I can find the start time of a particular event, but often struggle to locate the end time. And I can't overview my data to identify outliers.*"

In contrast, the AVM, as opposed to the VAM and AAM, offers a synergistic blend of visual and auditory elements, thereby enhancing information identification through multimodal channels and potentially reducing task load. It was observed that participants adjusted their attention between the two methods based on their habits and needs in the AVM. Some participants primarily focused on data visualization, considering the auditory display as a supplementary enhancement. For instance, P28 stated," *I prefer to get information primarily through visualization, and I see the audio as an experiential enhancement.*" Another group of participants relied more on the auditory display for information and turned their attention to the graphs when additional details were needed. P21 explained," *I get information primarily through the audio, and only when I hear something special do I look at the graphs to see what's happened to the data there.*"

5.2.2. The dynamic natural soundscape shapes a more engaging experience

Participants described their self-reflection experience within the AAM and AVM as "*immersive*" (P7) and "*absorbing*" (P2). Two key factors contributed to this deep engagement in the self-reflection experience. Firstly, participants found it fascinating to transform their physiological data into natural soundscape audio. Their curiosity kept them engaged in it. For example, P10 explained," *I'm curious about what sound effect is going to come up next, which keeps me focused on the audio*." Secondly, the virtual nature scene created by the natural sound elements provided a sense of immersion. For instance, some participants mentioned that "*The sound of the rain (in the AAM and the AVM) was soothing and tense at times, making me feel immersed in the raining environment*" (P2), and "*It (the AAM) allowed me to just focus on the sound and close my eyes to fully experience the natural environment created by the natural sounds*" (P25).

5.2.3. The dynamic natural soundscape brings a more valuable and enjoyable user experience

In the interviews, participants expressed greater pleasure and enjoyment in the AAM and the AVM. The main factor behind this was the efficacy of metaphorical auditory displays in stimulating their rapid comprehension. Additionally, participants' subconscious responses to natural sounds contribute to emotional arousal, leading to subsequent reflective behavior. We provide detailed explanations for the two reasons.

First, prior knowledge enhanced the comprehension of complex physiological data through metaphorical associations with audio symbols. Participants mentioned that their existing knowledge of natural sounds made it easier to understand the characteristics of the physiological data. For example, P1 explained, "*Thunder is a sudden natural occurrence that helps me understand that this physiological data (NS.SCR frequency) indicates a sudden increase in my stress level.*" P6 mentioned, "*I see the thunder sounds as a warning signal, telling me that the data during that time means I'm dealing with a higher stress level.*"

However, it is worth noting the direction of data metaphors, which necessitates adjustment based on individual cognition. During the interviews, all 30 participants conveyed an understanding that heavier rain metaphorically represented increased stress. Still, 3 participants found the selection of thunder peculiar, and 8 participants deemed the use of chirping sound inappropriate. For example, P4 mentioned, "*Thunder has a strong sense of warning, but I don't see my change in stress as something that needs to be warned about*", and P30 expressed confusion about the use of chirping sound, "*I thought the birds songs represented a positive intention, but they were triggered when I was stressed, which made me feel confused.*"

Second, the natural soundscape evoked new emotions that facilitated participants' self-reflection. Some participants mentioned that listening to thunderstorms or chirping created a sense of tension, causing them to re-experience their stress and gain a new awareness of their previous states of stress. For example, P2 mentioned, "*When I hear the sound of thunder and rain, I become slightly nervous. It's as if I am directly sensing the stress from my past experiences*", and "*The heavy rain sounds really stressed me out, and it made me realize I was under a lot of pressure during that moment (public speaking). I think I need to practice my public speaking skills more*" (P20). However, not everyone is receptive to such emotional arousal. Two participants found the new negative emotions uncomforting, who expressed a preference for a more relaxing self-reflection process.

5.2.4. Opportunities and challenges

5.2.4.1. Opportunities. It was observed that RainMind enhanced participants' willingness to share and exchange data. Some participants mentioned that using audio as a data presentation method and employing a metaphorical approach made them less reluctant to share their personal data with others. At the same time, they expressed curiosity about the audio generated from others' physiological data. Participants believed that sharing the audio generated by RainMind in close relationships and on social media platforms could serve as a form of self-disclosure, providing a means of stress release and evoking empathy from others. For instance, P14 mentioned that "*I would really like to share this audio with my parents and my supervisor so that they can understand the stress I am under during the exam preparation.*"

5.2.4.2. Challenges. During the interviews, participants discussed the challenges they encountered while using the three modes of RainMind. About the reflection function, they expressed a desire for RainMind to incorporate audio control functions (pause, play, progress adjustment, etc.) as well as features that support self-reflection, such as making annotations, recording thoughts, and reviewing specific periods. They also expressed the necessity for personalization in RainMind. They suggested that data presentation methods could be personalized, enabling them to switch between data visualization and auditory display based on their individual states and needs. For example, P21 mentioned that "*When I have a normal day, I prefer to quickly review my physiological data (through visualization). On days with more stressors, I like to listen attentively to the gradual changes in my stress levels (through the dynamic natural soundscape).*" In terms of auditory display design, participants expressed the need for personalized adjustments to the soundscape, sound elements, physiological data parameters, and mapping strategy in RainMind. For example, "*I really don't like the rain sound. Can I change it to the wind sound?*" (P5), and "*Some of my stress, like the stress from working out, is not a bad thing for me. I want to express that part of my stress in a more positive sound, like fire*" (P9).

6. Discussion

Our study investigated the usage of dynamics of natural sounds to metaphorically present the changes in stress-related physiological data, and evaluated its applications of

RainMind in supporting self-reflection in a daily stress management setting for mental health promotion. By comparing the visual-aided mode (VAM), the audio-aided mode (AAM), and the audio-visual mode (AVM), this paper revealed the potential values of the physiological data-driven dynamic natural soundscape in the following aspects. First, quantitative and qualitative findings indicated that the AVM contributed to a lower task load compared to both the AAM and the VAM (H1). This could be attributed to the auditory displays of natural sound clips for significant vital signals (i.e., increased NS.SCR frequency and HR) efficiently supported users to memorize unique moments of the day, whereas the animated visualization of physiological data provided a mental health overview of the day. This finding is in line with earlier studies on multisensory integration, which can be valuable to diminish the split of attention (Latif et al., 2022) and enhance the information processing capabilities (Enge et al., 2024). Second, both AAM and AVM equally contributed to significantly increased user engagement compared to the VAM (H2). This is primarily due to the curiosity fostered by the metaphorical auditory display and the immersion provided by the natural soundscape, as suggested by Hoque et al. (2023) and Roddy (2015). Third, both RainMind's AAM and AVM enhanced user experience more significantly than VAM (H3), whereas no differences were produced between AAM and AVM. Consistent with previous research (Blanco et al., 2022; Van Kerrebroeck & Maes, 2021), the inclusion of natural sounds in the auditory display design could be decisive in creating relaxing and pleasurable experiences. Moreover, we summarize a set of design implications for the next HCI developments of mental health self-reflection tools empowered by data-driven natural soundscapes.

6.1. Design implications

6.1.1. Sonifying remarkable physiological states with natural sound clips to support data reading at ease

The results of our study indicated that integrating data visualization with dynamic natural soundscapes to present various physiological data reduced task load during self-reflection. Particularly, our design used sound clips of natural elements in the soundscapes to sonify significant physiological states, which might be useful in reducing task load by allowing users to manage their attention. This effect was similar to the multisensory integration (Ren et al., 2021). In qualitative analysis, we observed distinct patterns of attention allocation among participants engaging with AVM. While participants generally focused on self-reflection, they shifted their attention to data visualizations for detailed insights when encountering thunder and chirping sounds. For example, P14 mentioned that *"I was relaxed during AVM, but when I heard thunder and birds chirping, I started paying closer attention to the data fluctuations in that area."* Therefore, we recommend sonifying remarkable physiological states with natural sound clips to support data reading at ease in the reflection-support applications. This approach can promote the formation of long-term reflective habits by reducing the task load of self-reflection. Dedicated machine learning algorithms can be incorporated into this process (Vos et al., 2023), enabling accurate detection of noteworthy vital states from the physiological data.

6.1.2. Shaping immersive reflection experiences with dynamic natural sounds through representing multimodal psychophysiological data

In our study, both AAM and AVM significantly enhanced user engagement, underscoring the pivotal role of dynamic natural soundscapes. In RainMind, dynamic natural soundscapes shaped virtual nature scenes to bring about a more immersive self-reflection experience, sparking curiosity and encouraging users to slow down the pace of reflection (Bentvelzen et al., 2022). During interviews, we found that the utilized multimodal data were no longer read separately, but were intertwined through auditory displays to formulate a soundscape that was perceived as a whole. For example, P12 mentioned that *"I focused on one-fold and disregarded the other two when looking at visualizations, using auditory cues makes overall judgments easier."* This not only deepens understanding of stress-induced physiological changes but also facilitates the exploration of data relationships. In future designs, a variety of psychophysiological data such as EEG (Norata et al., 2023), behavioral data (Clark & Doryab, 2022), and subjective reporting data (Angeler et al., 2022) could be incorporated to form a more vivid and meaningful dynamic natural soundscape. However, unlike our findings, Du et al. (2018) did not observe a significant increase in user engagement when presenting multimodal data from sports competitions using both auditory display and visualization. They attributed this to inappropriate sonic cues that caused confusion in the interpretation of the sounds. In the design of RainMind's auditory display, we employed metaphorical techniques to create effective mapping strategies, as recommended by Roddy and Bridges (2020). Therefore, we suggest selecting meaningful sound elements and designing mapping strategies that enhance meaning-making to create authentic natural soundscapes, thereby enhancing mental health self-reflection experiences.

6.1.3. Re-experiencing emotions in self-reflection support systems with personalized natural soundscapes

Our study results suggested that dynamic natural soundscapes facilitated enjoyable and effective self-reflection experiences. During interviews, participants reported sensations of previous emotions, particularly in response to the rainy ambience, which is consistent with Hoque et al. (2023) findings that natural sounds evoke emotions and provide listeners with a sense of realism. Participants noted that these emotions enabled them to re-experience stress and gain insights into their past stress levels in an embodied way, fostering deeper insights and motivating behavioral changes. Sonification has been seen as an emotionalizing carrier that could effectively convey both information and emotions (Rönnberg, 2021). In addition, compared to the other prevalent methods for enhancing user-data interactions, such as physicalization (Bentvelzen et al., 2023; Sauvé et al., 2020;

Thudt et al., 2018) and virtual reality (Jiang & Ahmadpour, 2021; Wagener et al., 2023), auditory displays require low-level setups that maximize the accessibility for users (Ha & Kim, 2020). Therefore, incorporating dynamic natural soundscapes into existing visual-based self-reflection applications, such as digital apps or wearable devices could foster long-term self-reflection habits in a lightweight manner.

Besides, from interviews, we observed that participants had distinct preferences for soundscapes and sound elements, as well as the mechanism of data mapping. As suggested by Yu et al. (2018), individual preferences over specific sound elements could significantly influence their overall experiences of the auditory biofeedback. Additionally, participants indicated the potential needs to adapt data presentation methods based on individual states in a long run. Hence, we recommend enabling personalization in a wide variety of the parameters in natural soundscapes to satisfy individual differences and changes in personal status. For example, considering factors such as perceived stress, stress trajectory class, sleep duration, and family background (Ekuni et al., 2022; Liu et al., 2023, 2024), adaptive natural soundscapes could be generated through machine learning integrated into the self-reflection system (Oyebode et al., 2023).

6.2. Limitations and future work

There are several limitations to this study that require discussion. First, similar to the studies by Yu et al. (2018) and Wagener et al. (2023), our participants consisted of young adults from the same cultural background, which may limit the generalizability of perspectives.

Therefore, the effectiveness of RainMind in other age groups is not guaranteed and should be further explored. Future study could be conducted with a larger number of participants from a diversity of age groups to improve the representativeness of the results. Second, in this study, every participant experienced each reflection mode in RainMind once in a laboratory setting, which might cause the novelty effects (Kjærup et al., 2021) to our design. The real-world applicability of RainMind in daily situations, along with its potential to cultivate long-term habits of self-reflection, has not been validated. To obtain insights into long-term stress coping assisted with RainMind, in the future we plan to carry out a longitudinal study with updated prototypes to understand daily adoptions of data-enabled mental health self-reflection with data-driven natural soundscapes. Third, another limitation is the reliance on subjective reports for evaluating RainMind's effectiveness. Objective evaluations, such as the number, type, and depth of the participants' insights, are crucial for future research.

In our future work, we will further design the audio-aided mode and audio-visual mode of RainMind to meet users' everyday self-reflection and personalized needs in different contexts. For instance, the shared stress-related reflection might be incorporated into RainMind, which has been proven to be effective for curing overstress (Jiang et al., 2023) and such mechanisms have been increasingly applied in a variety of health promotion contexts, such as healthy eating (Lukoff et al., 2018), physical activity (Ren et al., 2018), and so on. This exploration may provide additional insights into shared data representation methods.

7. Conclusion

In this article, we present RainMind, a soundscape that represents physiological data with dynamics of natural sounds to support users reviewing their stress throughout a day. Through a within-subject study involving 30 participants, we evaluated the effectiveness of RainMind in facilitating self-reflection by comparing its three data presentation modes (VAM, AAM, and AVM) in task load, user engagement, and enhancing user experience. Qualitative and quantitative findings suggested that the integration of dynamic natural soundscape and visualization contributes to a lower task load in self-reflection. Furthermore, whether combined with visual elements or not, the use of dynamic natural soundscape as metaphors for stress data can help enhance user engagement and user experience. We further propose design implications for using dynamic natural soundscape as a new way of data-driven self-reflection for mental health promotion in the daily setup. This article aims to inspire the use of metaphorical auditory displays in presenting physiological data and encourages their application in a broader range of health-related contexts.

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