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Enhancing Mindfulness-Based Cognitive Therapy in a Virtual Reality: A Prospective Interventional Study

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The increasing prevalence of depression has highlighted Mindfulness-Based Cognitive Therapy (MBCT) as an effective treatment. However, conventional MBCT has several limitations, including barriers to access, the need for trained professionals, and inconsistent levels of participant engagement. The feasibility of using Virtual Reality (VR) for MBCT has emerged as a promising solution, but further research is needed to assess its therapeutic potential. This study examines the potential of VR-based treatment as an approach for individuals with depression. We developed and evaluated introductory mindfulness exercises and a three-session VR-MBCT program and conducted a feasibility study. Using the Meta Quest Pro and the E4 wristband, we collected data from 73 participants and analyzed feasibility, engagement, and behavioral patterns. Results showed high concentration levels, distinct emotional responses, and unique interaction patterns in individuals with depression. While survey data showed no significant differences between individuals with depression and individuals without depression in terms of the usability and presence of VR, sensor data showed higher entropy in electrodermal activity for individuals with depression, suggesting better emotional confrontation. Overall, our study highlighted the user-friendly and immersive aspects of VR-MBCT and its feasibility and potential applicability for individuals with depression.

The global prevalence of depression has been steadily increasing in recent years. According to a 2023 report by the World Health Organization, approximately 280 million people, equivalent to 3.8% of the global population, suffered from depression in this year[1]. Since the COVID-19 pandemic[2], the incidence of depression has particularly increased across various age groups. This trend has highlighted the urgent need for effective mental health treatments for the general adult population[3]. Among mental health treatments, Mindfulness-Based Cognitive Therapy (MBCT) combines the principles of Cognitive Behavioral Therapy (CBT) with mindfulness meditation[4,5]. Several meta-analyses[6–8] have demonstrated its positive effects on reducing psychological stress in depressed patients. MBCT aims to prevent relapse and reduce mental stress by teaching participants to focus on the present moment and recognize and regulate negative thought patterns[9,10]. Although traditionally delivered in face-to-face group sessions, MBCT has also been adapted into a web-based format known as web-based Mindfulness-Based Cognitive Therapy (eMBCT)[11–13] to increase accessibility and cost-efficiency. eMBCT typically involves unidirectional interactions (e.g., video or audio-based lectures) and provides preset feedback as participants complete specific tasks[14].

Despite advances in MBCT, several important limitations remain. Conventional MBCT, delivered in group session formats, requires participants to follow predetermined schedules and programs, limiting flexibility[6]. High treatment costs, social stigma, and personal anxiety also pose challenges for depressed patients seeking a safer treatment environment[15,16]. These limitations, combined with long wait times for outpatient psychiatric clinics and delays in recruiting appropriate group members, can negatively impact treatment effectiveness and sustained patient adherence[17]. While eMBCT has the potential to address some of the accessibility and cost limitations[11,18], it often fails to capture subtle non-verbal cues and emotional exchanges (e.g., frequency of eye contact, changes in tone of voice) due to its web-based nature[18–20]. Moreover, both MBCT formats tend to have

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standardized program structures and limited in-depth interactions (e.g., lack of analysis of individual stressors, detailed sharing of emotional experiences). This may reduce patient engagement and sustained participation in the treatment process[7,12]. This highlights a critical gap in existing MBCT approaches and underscores the need for methods that facilitate deeper emotional engagement and address individual stressors through innovative, personalized interventions.

Virtual Reality (VR) technology offers new opportunities to address these limitations of conventional MBCT and eMBCT by providing customized interventions for depressed patients[21,22]. VR allows depressed patients to experience emotional and cognitive challenges in a realistic and repetitive manner, thereby improving their mood regulation, emotional recognition, and stress management skills[23]. Individuals who have experienced depression are more likely to have negative thought patterns formed during a depressive episode reactivated in response to minor stressors or negative emotions[24]. The core principle of MBCT is to help individuals recognize these automatic thought patterns, focus on the present moment, and practice cognitive defusion to break the cycle of rumination. This process can be effectively supported through the immersive nature of VR[5,25]. By immersing patients in controlled virtual environments, VR-based MBCT can facilitate deeper emotional engagement and provide personalized interventions tailored to individual needs[26]. For instance, VR technology can allow depressed patients to watch videos in virtual environments that align with their values and interests[27] or to select avatars and scenarios that allow them to project their emotions through self-compassion[28], thereby supporting depression relief. Providing depressed patients with VR-based MBCT can effectively offer personalized interventions tailored to their unique experiences and needs, in line with the current healthcare environment's demand for efficiency and accessibility[29].

However, the development of specific procedures and protocols for a VR-based MBCT program (VR-MBCT) that reflect the needs of clinicians and patients in understanding patient states and interactions is still in its early stages. Recent digital therapeutics, such as the mobile apps Somzz[30] and Rejoyn[31], have successfully employed mobile sensors and log data to identify significant clinical indicators, such as users' sleep patterns, reaction times, app usage frequency, and self-reported mood changes, for sleep disorders and depression, respectively. Similarly, we aim to explore the potential of VR as a representative digital environment to reflect users' states and emotions through content experience or use. Despite advancements in mobile-based digital therapeutics, there remains a research gap in understanding how immersive environments, such as VR, can enhance mindfulness-based cognitive therapy. To this end, we developed a VR system that supports MBCT, and conducted a prospective, non-randomized interventional study using VR-MBCT with 38 individuals with depression (IWD) and 35 individuals without depression (IWoD).

This study aims to propose a novel VR-based approach to address the limitations of conventional MBCT and eMBCT by supporting sustained engagement and personalized interventions, with the following objectives. First, we aim to explore the feasibility of using a VR-based program as an adjunct to the diagnosis and treatment of depression in clinical practice. Specifically, we intend to translate the conventional MBCT method for depression treatment into VR, collect and evaluate user experience data in the virtual environment, and verify the applicability of VR-MBCT as a clinical diagnostic and treatment support tool. Second, we aim to construct a digital phenotype for depression using sensor and log data collected from each participant in the VR environment. This will include the identification of behavioral and response patterns that are useful in the treatment of depression. This analysis can play a key role in understanding the behavioral characteristics of depressed patients in digital environments and improving their treatment processes.

This study aims to explore the following research questions:

- RQ1: Is VR-MBCT feasible as an adjunct tool to support clinical decision-making in the treatment of depression?
- RQ2: What are the differences in the interactions in VR-MBCT between the IWD and the IWoD?

Methods

We conducted a prospective interventional study to evaluate the feasibility of the VR-MBCT intervention. After confirming the usability of VR-MBCT, we compared behavioral patterns between the two groups. By analyzing behavioral patterns in both groups, this study aims to provide important insights into the feasibility and potential clinical applicability of VR-MBCT.

VR-MBCT

The two core components of MBCT are mindfulness cultivated through meditation and individual traits related to mindfulness (e.g., self-awareness, emotional acceptance)[32]. Based on these, VR-MBCT was developed through iterative discussions with mental health professionals (e.g., psychiatrists, therapists). VR-MBCT consists of an introductory mindfulness exercise and a three-session VR-MBCT program (Fig. 1). VR-MBCT is designed to be experienced in a virtual environment featuring the ocean with the goal of harnessing the positive effects of nature on mental health (e.g., stress relief, improved self-esteem)[33–35].

Introductory mindfulness exercise

The Introductory Mindfulness Exercise helps users easily adapt to meditation techniques (e.g., focusing on breathing) in a virtual environment and approach VR-MBCT comfortably and naturally. By showing visual changes from sunrise to sunset and various objects encountered at sea, users are guided to focus on the present moment and observe their experiences without critical or negative thought patterns.

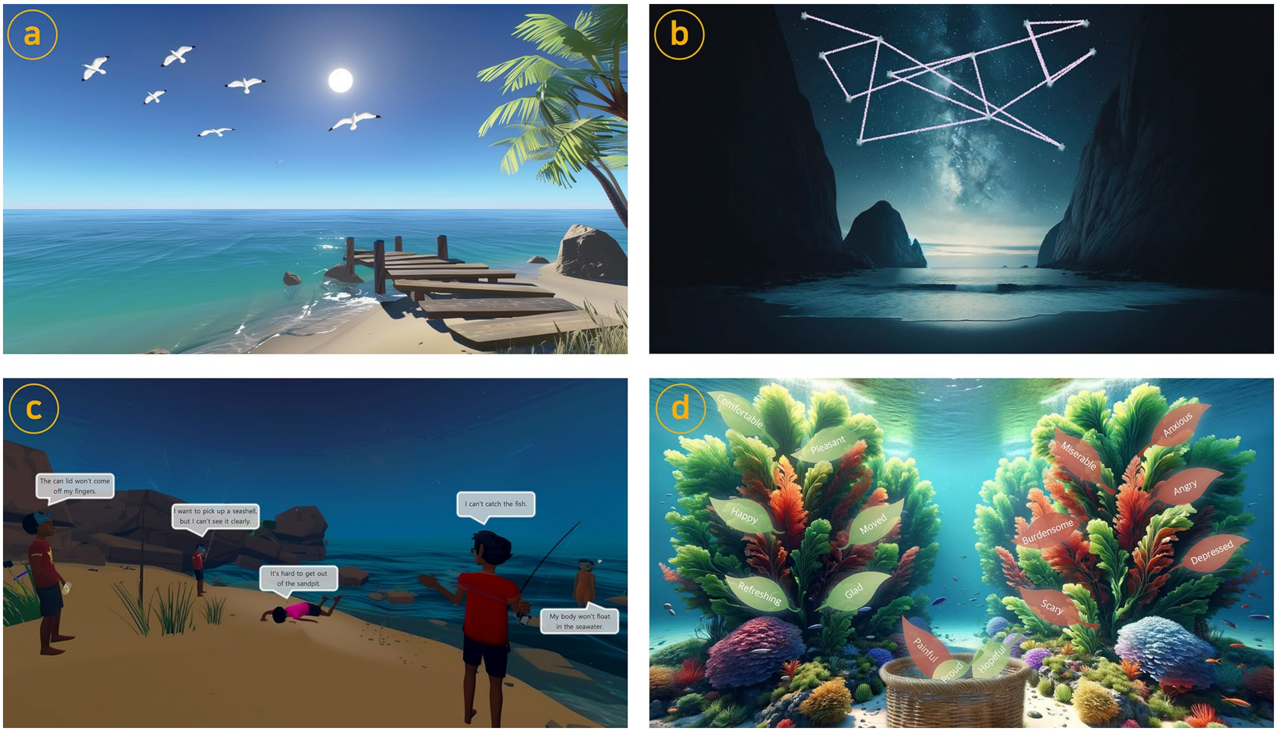

Fig. 1. Screenshots of Introductory Mindfulness Exercises and three sessions of VR-MBCT: (**a**) introductory mindfulness exercise, (**b**) starry expressions, (**c**) self as context, and (**d**) acceptance. Due to security restrictions during the Korea Food and Drug Administration (KFDA) clinical trials, we were unable to include screenshots of the actual VR content. Instead, we have used processed VR content screenshots to facilitate understanding of the paper.

Session 1: starry expressions
The Starry Expression session involves users drawing existing constellations in the night sky and then creating their own constellations through "free constellation drawing." This activity is designed based on research findings that the overload of negative emotions and thoughts experienced by depressed patients can lead to differences in information processing[36], which can increase the complexity and depth of the artwork when applied to creations[37]. Users can enhance self-expression and awareness by focusing on the present moment and their emotions.

Session 2: self as context
The Self as Context session allows users to choose an avatar that reflects their current situation, helping them view their emotions more objectively. This activity is based on the metacognitive process model of decentering[38,39], which focuses on disidentification from internal experience and self-distancing to analyze the meaning of memories and experiences, and can benefit mental health[40]. Users can practice emotional distancing and accept their emotions in a non-critical manner.

Session 3: acceptance
The Acceptance session involves users placing emotion-labeled leaves in their own baskets to understand their emotional state. This activity is based on the symbolic interaction theory[41,42], in which individuals assign meaning to symbols and objects and regulate their behaviors and responses based on these meanings. Users can reflect on and understand their recent emotional states through the emotions written on each leaf, thereby increasing their overall self-awareness and emotional clarity, and ultimately improving their mental health through clear emotional expression.

Study setting
This study was conducted from September 2023 to April 2024 in two VR laboratory units isolated from external factors. The VR laboratory was divided into a dialogue unit to explain the study, answer surveys and complete exit interviews, and a therapeutic unit for experiencing VR-MBCT. The dialogue unit was set up so that researchers and participants could face each other, which could help foster rapport and improve participant engagement and data quality[43,44]. The therapeutic unit was equipped with a swivel recliner to ensure participant comfort during the VR-MBCT experience, with all surrounding obstacles removed for safety. These units were located in the same building as the counseling center where participants were recruited, but were physically separate rooms.

Hardware
We chose the Meta Quest Pro standalone VR Head-Mounted Display (HMD) and the Empatica E4 wristband. The Quest Pro has a customizable fit to accommodate a variety of head sizes and shapes, and its built-in sensors track the user's eye movements, head movements, and facial expressions. The VR content was designed to provide a fully immersive 3D experience through the HMD by placing the user in a 360-degree environment with 4K resolution and a 60 Hz refresh rate to ensure a high level of user immersion. The E4 wristband non-invasively collects electrodermal activity (EDA) data without compromising the user's immersion during the VR experience.

Software (VR interface tutorial)
Minimizing researcher intervention is crucial to allow participants to explore and resolve their emotions and issues independently through VR-MBCT. To support this goal, we developed a VR interface tutorial (mean = 36 s, min = 25 s, max = 40 s) to familiarize participants with the VR interface prior to performing VR-MBCT. This tutorial was essential to effectively control for exogenous variables, such as behavioral delays due to unfamiliarity with the VR interface during tasks in VR-MBCT. The tutorial demonstrated the appearance of the actual controller within the virtual environment, allowing participants to intuitively understand trigger positions and interact with VR-MBCT through scripts and narration (e.g., pressing the "next" button, selecting objects).

Study procedure
Screened participants completed three sessions in the experiment: (1) an introductory session that included an explanation of the study and the VR interface tutorial experience, (2) an intervention session in which they experienced VR-MBCT, and (3) a review session that included post-experience surveys. In the introductory session, the researchers introduced the purpose of the study, explained the equipment, allowed sufficient time to become familiar with the virtual environment (e.g., personalized gaze calibration) and equipment, and guided participants through the VR interface tutorial. The intervention session took place in a therapeutic unit, starting with participants wearing the HMD and E4 wristband, followed by the VR-MBCT experience (*mean*=9.45 minutes, *min*=6.83 minutes, *max*=12.72 minutes). The researchers did not intervene during the VR experience, but were always available in case of emergencies. Finally, in the review session, we collected responses to the System Usability Scale (SUS)[45], the Igroup Presence Questionnaire (IPQ)[46], and the NASA Task Load Index (NASA-TLX)[47] to assess the immersion and usability of VR-MBCT (See Supplementary Tables S1, S2, and S3).

Recruitment
Considering the potential for difficulties of using VR technology to act as an exogenous variable influencing experimental results, we restricted the age of participants to between 18 and 40 years to minimize the impact of these factors. This step was taken to more accurately assess the feasibility of VR-MBCT. Initially, we recruited 48 young adults with depression and 49 young adults without depression in the same age range who were screened according to the eligibility criteria for participation in the study. The required sample size was calculated using G*Power (version 3.1). For a two-tailed independent samples t-test, with an effect size of d=0.8, an alpha level of 0.05, and a power of 0.95, the analysis indicated a total sample size of 70 participants (35 per group). The sample size recruited for this study significantly exceeded this requirement, ensuring sufficient statistical power for reliable interpretation of the results.

Exclusion criteria included age outside the specified range, failure of the Northstar Digital Literacy Assessment (NDLA)[48], which assesses basic digital skills (e.g., using document software), comorbid psychiatric conditions (e.g., bipolar disorder, schizophrenia) that affect the ability of decision-making, and refusal to participate in the experiment (n = 18). We also collected responses to the Patient Health Questionnaire-9 (PHQ-9), developed by Kroenke et al. (2001)[49]. The PHQ-9 is a validated self-report measure consisting of 9 items that contain the frequency of depressive symptoms over the past two weeks on a 4-point Likert scale (0 ="Not at all" to 3 ="Nearly every day"). Scores range from 0 to 27, with higher scores indicating greater depressive severity. Among participants with PHQ-9 scores of 20 or higher (n = 3, indicating severe depressive symptoms), two were excluded following consultation with the clinical team, as their symptoms were considered unsuitable for cognitive therapy. Most participants with depression (33 out of 38; 86.84%) had mild to moderate depressive symptoms based on PHQ-9 scores (See Table 1).

Although depressive symptoms can fluctuate episodically[50,51], PHQ-9 was used as a screening tool before the VR-MBCT experience to identify participants currently experiencing depressive symptoms. Participants with a score of 5 or higher (indicating mild depression or above) were grouped as individuals with depression. Applying these exclusion criteria resulted in a final sample of 38 individuals with depression and 35 without depression. Figure 2 shows the flow of study participants from recruitment to analysis.

Demographics
The baseline demographic and clinical characteristics of the study participants are summarized in Table 1. The study included 73 participants who were divided into two groups: the IWD (n = 38) and the IWoD (n = 35). The mean age was similar between groups, with the IWD at 25.36 years (SD = 3.61) and the IWoD at 25.17 years (SD = 4.11). Gender distribution showed 21 females and 17 males in the IWD, and 18 females and 17 males in the IWoD. Depression severity reassessed using the PHQ-9 prior to conducting the study, showed a range of severity within the IWD: 21 with mild, 17 with moderate, 5 with moderately severe, and 1 with severe depression.

Characteristics	Individuals with depression (IWD; n=38)	Individuals without depression (IWoD; n=35)
Age (years), mean (SD)	25.36 (3.61)	25.17 (4.11)
Gender, n (%)		
Female	21 (55.26)	18 (51.43)
Male	17 (44.74)	17 (48.57)
PHQ-9, n (%)		
None-minimal	–	35 (100)
Mild	20 (52.63)	–
Moderate	13 (34.21)	–
Moderately Severe	4 (10.53)	–
Severe	1 (2.63)	–

Table 1. Demographics and clinical characteristics for all participants.

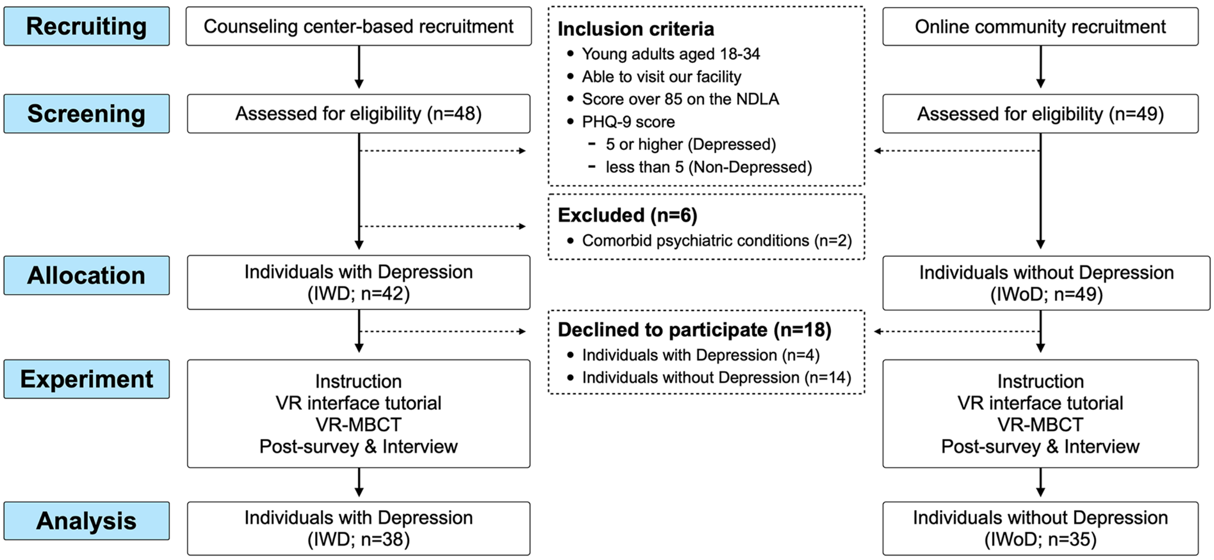

Fig. 2. Flowchart of study participants from recruitment to analysis. Participants were recruited from university counseling center-based or online community sources, screened based on inclusion criteria, and assigned to either the IWD or the IWoD.

Data collection

Measures of user experience and usability

All scales were assessed after the completion of VR-MBCT. These measures were chosen because they comprehensively reflect aspects of the user experience and represent the usability of VR-MBCT. We used SUS to assess the usability of VR-MBCT. This survey consists of 10 items, scored on a 5-point Likert scale ranging from 1 ("Strongly disagree") to 5 ("Strongly agree"). Scores below 68 are considered inadequate, scores between 68 and 84 are considered acceptable, and scores above 85 are considered excellent (Brooke et al., 1996). To measure the presence experienced by users in the virtual environment, we used the IPQ, which includes one general item and three subscales (spatial presence, involvement, and realness) considered as independent factors. It consists of 14 items using a 7-point Likert scale, with higher scores indicating greater presence in a VR environment (Schubert et al., 2001). To assess the cognitive load of users in VR-MBCT-guided activities, we used the NASA-TLX, which consists of six subscales (mental demand, physical demand, temporal demand, performance, effort, and frustration) with a 7-point Likert scale. Higher scores on mental demand, physical demand, temporal demand, effort, and frustration indicate higher cognitive load, while higher scores on performance reflect better task performance (Hart, 2006). Table 2 shows the types and features of the surveys, sensor data, and user interaction log data used in our study.

Sensor data

Sensor data are passive data collected continuously by sensors that reflect physiological responses or behavior patterns of the user without direct manipulation or conscious input from the user. Sensor data were collected non-invasively and in real-time during the VR-MBCT experience to avoid disrupting the user experience. We used the eye-tracking technology of Meta Quest Pro to collect users' eye movement data. By projecting a laser from the gaze origin in the direction of the gaze, we confirmed interactions with objects in the virtual

Data type	Data features
Survey data	System usability scale (SUS) Igroup presence questionnaire (IPQ) NASA task load index (NASA-TLX)
Sensor data	
HMD	Gaze origin Gaze direction
E4 wristband	Electrodermal activity (EDA)
User interaction log data	
Session 1	Sequence of connected stars
Session 2	Latency to select an avatar A type of selected avatar
Session 3	Types of emotions of the selected leaves Total number of leaves selected

Table 2. Summary of data types and their features.

environment. When the laser collided with an object, the system recorded the object name and the conflict signal, allowing us to identify the region of interest (ROI) where the user's gaze was focused. Additionally, we used the E4 wristband to collect EDA data. The E4 wristband detects the user's autonomic nervous response to stress, emotional changes, and physiological arousal. EDA is widely recognized as a potential digital biomarker for reflecting various mental and emotional states and predicting depression[52–54].

User interaction log
We collected user interaction logs during the three VR-MBCT sessions. In the first session, we recorded the sequence of stars drawn by users based on 13 fixed star coordinates. In the second session, we collected the latency and the type of avatar chosen by users among five avatars with different concerns. In the final session, we collected the emotion labels written on the leaves chosen by users (e.g., relaxed, confused) and the number of positive or negative emotion leaves placed in their baskets.

Exit interview
We conducted 10-minute exit interviews to identify participants' usability experiences and any discomfort during each VR-MBCT session. The interview questions, detailed in Supplementary Table S4, were designed to align with the survey and provide comprehensive qualitative feedback on VR-MBCT. Three authors of this paper independently coded interview transcripts, repeatedly discussing the coding results to categorize themes until the coders reached a consensus. Cohen's Kappa measurement verified the inter-coder reliability. The scores for each category were higher than 0.70 (mean=0.82, max=0.90), indicating that the inter-coder reliability lies between "substantial" and "perfect"[55].

Ethics approval
Ethical approval was granted by the Institutional Review Board (IRB) of the authors' institution (HYUIRB-202308-006). All procedures and methods were explicitly conducted in accordance with the relevant guidelines and regulations as approved by the institution. All participants provided written informed consent and could voluntarily withdraw from the VR-MBCT session at any time without giving a reason. Patients who were considered high risk required hospitalization, or showed other signs that the use of VR-MBCT might be harmful were not offered the use of VR-MBCT. All personally identifiable information was removed from the collected data to protect the privacy of the participants, and code names were assigned prior to analysis.

Statistical analysis
To evaluate VR-MBCT and to investigate unique behavioral patterns in the IWD, we conducted descriptive statistics and statistical tests on post-evaluation results for several measures, including SUS, IPQ, NASA-TLX, ROI-based level of attention, emotional variability from EDA, and session-by-session log data.

Our analysis aimed to identify significant differences between the IWD and the IWoD. To control for potential confounding variables, we included gender, age, VR experience (categorized as 0 times, 1-2 times, 3-5 times, more than 5 times), and the time spent experiencing VR-MBCT as covariates in our statistical model. We used Analysis of Covariance (ANCOVA) to adjust for these covariates and ensure robust comparisons between groups. Before running ANCOVA, we confirmed that all necessary conditions were met, including independence, linearity, homoscedasticity, normality of covariates, and the absence of interaction effects between covariates and treatments. In addition, we used partial eta squared η_p^2 to estimate the effect sizes of our results, interpreting values around 0.01 as small, 0.06 as medium, and 0.14 as large effects.

To evaluate the emotional variability from EDA, we compared pre- and post-session measures (i.e., emotional state, stress levels) across three sessions without controlling for pre-measures as covariates. Since the EDA data did not follow a normal distribution, we used the Wilcoxon Signed-Rank Test. We also compared the entropy-based variability across three sessions by group. We conducted Shapiro-Wilk tests for normality, and when outliers, skewed, or multimodal distributions were detected, we applied the non-parametric Mann-Whitney U test. For the effect size of both tests, we used the coefficient *r*, interpreting values around 0.1 as small, 0.3 as medium, and 0.5 as large effects.

Results

This section consists of two parts, each corresponding to RQ1 and RQ2. The first section presents the results of the perception of VR-MBCT, based on passive data such as eye-tracking data for ROI and EDA analysis collected continuously during the VR experience. Surveys and exit interviews after the VR experience highlight the overall satisfaction with VR-MBCT regarding usability. The second section presents the analysis results of behavioral pattern differences between the IWD and the IWoD, based on interactive log data collected during the three sessions of VR-MBCT.

Effective usability and engagement (RQ1)

Survey data

We analyzed the survey results of SUS, IPQ, and NASA-TLX to evaluate the participants' user experience with VR-MBCT (Table 3; see Supplementary Tables S5-S7 for details). First, the overall average score on SUS was 77.33, above the general average of 68, with no statistically significant difference between the two groups ($F(1,65)=3.79$, $p=0.06$, $\eta_p^2=0.06$). Second, on the IPQ, both groups showed high immersion in VR-MBCT with no statistically significant difference in the general item ($F(1,65)=0.97$, $p=0.33$, $\eta_p^2=0.01$). There were statistically significant differences in the spatial presence ($F(1,65)=4.94$, $p=0.03$, $\eta_p^2=0.07$) and realism ($F(1,65)=5.29$, $p=0.02$, $\eta_p^2=0.08$) subscales, but no significant difference in involvement ($F(1,65)=0.93$, $p=0.34$, $\eta_p^2=0.01$). Lastly, NASA-TLX indicated that participants effectively managed the demands of VR-MBCT, with no statistically significant differences in all subscales except frustration (mental demand: $F(1,65)=3.00$, $p=0.09$, $\eta_p^2=0.04$; physical demand: $F(1,65)=1.52$, $p=0.22$, $\eta_p^2=0.02$; temporal demand: $F(1,65)=2.94$, $p=0.09$, $\eta_p^2=0.04$; effort: $F(1,65)=0.003$, $p=0.95$, $\eta_p^2=0.00005$; performance: $F(1,65)=0.39$, $p=0.53$, $\eta_p^2=0.01$; frustration: $F(1,65)=14.95$, $p=0.0002$, $\eta_p^2=0.19$).

Exit interview

We examined how VR-MBCT supported users' experiences in terms of usability and engagement through the analysis of the exit interview (Supplementary Table S4). Two main themes emerged from the analysis: self-emotion management and self-reflection.

Self-emotion management

Participants reported that visual and auditory elements in the VR environment were immediately noticeable and contributed to their emotional engagement during the session. Several participants noted that specific types of interaction were associated with shifts in their emotional states. Participant described experiencing gradual emotional changes while performing a drawing task.

> "*I felt my emotions gradually shift as I drew each line-drawing upwards made me feel more agitated, while drawing downwards felt calming, so I ended up drawing in a wave-like motion (P01).*"
>
> "*I was feeling withdrawn at the time, but I chose the word 'confident' because I wanted to cheer myself up (P06).*"
>
> Participants also indicated that receiving real-time feedback during interactions supported their sense of emotional involvement. Some participants noted that such feedback, including sound effects and narration, allowed them to stay emotionally engaged and occasionally facilitated a sense of emotional release. Certain interaction features can promote emotional awareness and support self-motion management in the VR context."*When I drew stars and heard the popping sound, it felt like my stress was being released. I wanted to see the stars pop quickly, so I started drawing faster (P18).*"
>
> "*I chose an avatar that I felt connected to and told it to stay still. It felt like the answer I had found for myself after going through confusing times. Even if I had been asked to answer freely, I would have said 'Stay still.' I was already feeling emotional before the narration started, so the narration resonated even more (P08).*"

Scale	Individuals with depression (IWD; n = 38)	Individuals without depression (IWoD; n = 35)
SUS, mean (SD)	75.53 (10.45)	79.29 (12.01)
IPQ (1–7 Likert scale), mean (SD)		
General item	5.29 (1.37)	5.54 (1.20)
Spatial presence	4.43 (0.93)	4.88 (1.01)
Involvement	4.10 (1.09)	4.34 (1.26)
Realism	3.45 (1.34)	4.03 (1.01)
NASA-TLX (1–7 Likert scale), mean (SD)		
Mental demand	2.55 (1.62)	1.97 (1.22)
Physical demand	2.45 (1.67)	2.06 (1.59)
Temporal demand	3.29 (1.77)	2.60 (1.58)
Effort	4.63 (2.15)	4.80 (2.14)
Performance	4.71 (2.04)	4.57 (2.24)
Frustration	2.92 (1.79)	1.66 (1.00)

Table 3. Results of each survey by group.

In contrast, some participants expressed that it was more difficult to remain emotionally engaged when interactions were perceived as overly constrained or predetermined. These perspectives underscore the importance of designing for user autonomy and flexibility to better support emotional engagement in VR environments.*"I was supposed to draw my constellation, but the stars were fixed in place, so I felt like I was being controlled (P38)."*

"Being told to draw the constellation suddenly felt annoying. When I'm tired or struggling, I usually just want to stay still, so being told to do something felt bothersome. I would have preferred just to move around freely (P42)."

Self-reflection
We found that the VR environment can support users in self-reflection as they explore and organize their internal states. One participant reported that the process of identifying and expressing emotional states provided a sense of accomplishment.

"The act of capturing my emotions gave me a sense of achievement. I've been going through a lot and feeling overwhelmed lately, but the words that stood out to me were all positive ones (P06)."

Several participants indicated that the visual representation of emotions helped them explore and define their emotional states more clearly. The interactions that support emotional exploration may play an important role in facilitating self-reflection and contribute to emotional acceptance.*"I usually just think of my mood as either positive or negative. But seeing all those different emotions listed helped me figure out exactly how I was feeling (P02)."*

"I usually have a strong tendency to avoid negative feelings, but I tried to include them because they were mine. It wasn't easy to accept those emotions, but the act of placing them in the tank helped me focus on the process of exploring them, and that helped me face myself more honestly (P38)."

However, some participants felt that, despite the options available, the content did not fully reflect their circumstances or emotional needs. This reflects an expectation of greater variability in how users can engage with and interpret their states through VR, highlighting the need for user-tailored interaction.*"I completed the content sincerely, but I'm not sure whether the advice was appropriate for my situation. I think it would be more helpful if the content were personalized (P44)."*

HMD comfort and VR sickness experience
Several participants noted that the comfort and usability of the headset influenced their sense of immersion. Some described challenges related to partial exposure to the real-world environment, which disrupted their concentration. In contrast, others found the device to be lightweight and easy to use.

"I wish the headset completely blocked my view. When I looked down, I could see my legs and the floor, which made it hard to concentrate (P05)."

In terms of physical discomfort, only two participants reported experiencing mild symptoms of VR sickness that occurred during certain parts of the content. Importantly, both participants stated that these symptoms did not significantly interfere with their ability to continue the interaction.*"The emotion shells were placed too close together, and it made me feel dizzy (P44)."*

"When I looked around the space at the beginning, I felt dizzy (P01)."

Level of attention
We employed eye-tracking technology to monitor the region of interest (ROI) and evaluate users' level of attention during VR-MBCT. Since the tasks required by VR-MBCT are explicitly defined, ROI data during specific tasks can effectively assess users' focus and acceptance of the content. To quantitatively evaluate this, a conflict signal (1) was sent whenever the gaze intersected with objects that required attention during the sessions. The formula is as follows:

$$CS(e) = \begin{cases} 0 & \text{if, } e \neq \text{ROI} \\ 1 & \text{if, } e = \text{ROI} \end{cases} \tag{1}$$

where $CS(e)$ is a conflict signal function, and e is the eye gaze of a user. ROI is the object in VR-MBCT. Based on the collected conflict signals, the group's level of attention for each session is calculated using the following formula:

$$A_s = \frac{1}{N_s}\sum_{i=1}^{N_s}\left(\frac{T_{S_i}}{D_{S_i}} \times 100\right) \tag{2}$$

where A_s is the average level of attention (%) for session s from the participants in the same group. N_s is the number of participants in session s, $T_{(S_i)}$ is the time participant i spent focusing on objects during session s, and $D_{(S_i)}$ is the duration of session s for participant i.

Table 4 shows the levels of attention for the IWD and the IWoD for each VR-MBCT session. Individuals with depression often have difficulty participating in specific activities due to symptoms such as decreased concentration[56]. However, in VR-MBCT, the IWD showed high levels of attention at 83.09%, 93.65%, and

Session number	Individuals with depression (IWD; n = 38) (%)	Individuals without depression (IWoD; n = 35) (%)
1	83.09	84.50
2	93.65	93.95
3	88.96	86.52

Table 4. Attention by group in each session, with attention rates presented as percentages, indicating the level of participant attention relative to a maximum of 100% for each session.

88.96% in Sessions 1, 2, and 3, respectively, similar to the levels of attention for the IWoD: 84.50%, 93.95%, and 86.52%. Statistical analysis showed no significant differences in attention across sessions: Session 1 (F(1,65)=0.88, p=0.35, η_p^2=0.01), Session 2 (F(1,65)=0.0008, p=0.98, η_p^2=1.31), and Session 3 (F(1,65)=3.50, p=0.07, η_p^2=0.05). Supplementary Table S8 provides detailed statistics on each session.

Emotional variability

We calculated the entropy of EDA to analyze the emotional changes experienced by participants during VR-MBCT, using this metric to measure the randomness and irregularity of the time series data. Entropy, a widely validated metric in fields such as information science and mental health, quantifies the dispersion of data[57–59]. High entropy indicates sporadic data distribution, while low entropy indicates data concentration. In the entropy formula, *pi* represents the probability of a specific value occurring.

$$Entropy = -\sum(p_i)log(p_i) \tag{3}$$

The mean entropy for the IWD was 5.77, higher than the IWoD (5.02), with a statistically significant difference as indicated by the Mann-Whitney U test (U = 849.5, p = 0.04, r = 0.24) during VR-MBCT experience. Additionally, we defined the mean of EDA measured before the VR-MBCT intervention as the baseline and the mean measured after three VR-MBCT sessions as the post-intervention value. The Wilcoxon Signed-Rank test revealed statistically significant differences between the pre- and post-intervention measures in both the IWD (W=447.0, p=0.015, r=0.16) and the IWoD (W=542.0, p=0.006, r=0.01).

Distinctive behavioral patterns in IWD (RQ2)

Findings from Session 1

In Session 1, we aimed to determine whether the IWD expressed more complexity in free constellation drawing compared to the IWoD. We analyzed the sequence and coordinate log data of the stars freely drawn by the participants and derived the number of revisited stars (R) and the total number of revisits (T) to quantitatively evaluate the complexity of the final constellation's complexity, as presented in the rationale in Method Section (Session 1: Starry Expressions). The formulas for R and T are as follows:

$$R = |\{x_i \in S : f(x_i) \geq 2\}| \tag{4}$$

$$T = \sum_{x_i \in S} max(f(x_i) - 1, 0) \tag{5}$$

where R is the number of stars revisited at least twice, and T is the total number of revisits excluding the first visit for stars. In these formulas, S represents the set of all stars, x_i is an individual star within the set S, $f(x_i)$ is the function that returns the number of times a star x_i has been visited, and $\max(f(x_i) - 1, 0)$ calculates the additional visits by subtracting one (i.e., first visit) from the total visits to account only for revisits.

As shown in Fig. 3a, the results of the analysis showed that the average number of revisited stars R in the IWD was 3.62 (SD = 3.53), significantly higher than 0.81 (SD = 1.67) in the IWoD (F(1,65) = 14.77, p = 0.0003, η_p^2 = 0.19). Additionally, the total number of revisits in the IWD was 7.78 (SD =7.39), significantly higher than 0.89 (SD = 2.11) in the IWoD (F(1,65) = 29.66, $p < 0.001$, η_p^2 = 0.31). Supplementary Table S9 provides detailed statistics on the number of revisited stars and the total number of revisits.

Findings from Session 2

In Session 2, we examined the time taken by each group to select an avatar that reflected their current situation or concern. ANCOVA results showed that the IWD took significantly more time than the IWoD to select an avatar (F(1,65) = 24.53, $p < 0.001$, η_p^2 = 0.27). Supplementary Table S10 provides detailed statistics on avatar selection latency. Specifically, the IWD spent an average of 80.83 seconds (min = 51.88, max = 187.90, SD = 27.08), while the IWoD spent an average of 55.29 s (min = 26.46, max = 74.43, SD = 10.49). As shown in Fig. 3b, the IWD showed a broader and more skewed distribution, indicating a tendency for longer response times. In contrast, the IWoD exhibited a more clustered and symmetrical distribution, indicating relatively consistent and shorter response times. This indicates that the IWD took more time to select an avatar.

Findings from Session 3

In the final session, we investigated the participants' recent positive or negative emotions and the differences between the two groups. Results showed significant differences in the number of emotions selected between the two groups (See Fig. 3c). For positive emotions, the IWD selected an average of 2.22 positive emotions

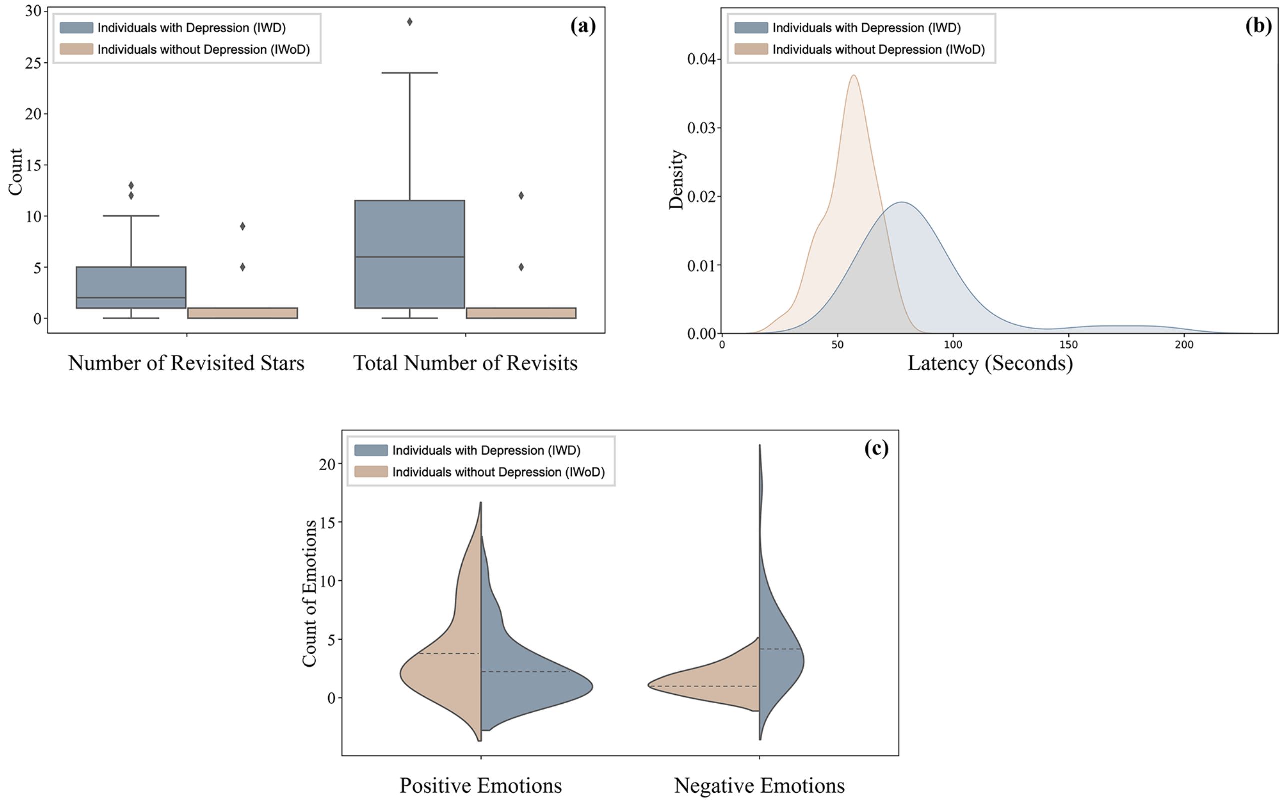

Fig. 3. Patterns of behavior in IWD across three sessions. (**a**) Box plot showing the group differences in the number of revisited stars and the total number of revisits during Session 1, with the line inside the box representing the median value. (**b**) Density plot showing the group differences in avatar selection latency during Session 2. (**c**) Violin plot illustrating the number of positive/negative emotions selected by each group during Session 3, with dashed lines indicating the mean values.

(*SD*=2.58) out of 25, while the IWoD selected 4.17 (*SD*=3.66) ($F(1,65)=4.01$, $p=0.05$, $\eta_p^2=0.06$). For negative emotions, the IWD and the IWoD selected an average of 4.38 (*SD*=3.29) and 1.33 (*SD*=1.17) out of 25, respectively ($F(1,65)=29.39$, $p<0.001$, $\eta_p^2=0.31$). Supplementary Table S11 provides detailed statistics on the number of selected positive and negative emotions.

Discussion
Principal findings
To the best of our knowledge, no prospective interventional study has yet been conducted using VR-MBCT for individuals with depression. The usability evaluation based on SUS showed that both groups had average scores above the benchmark of 68 (IWD: 75.53, IWoD: 79.29), indicating the high usability of VR-MBCT. High general item scores on IPQ indicated high immersion in VR for both groups. However, statistical significance was found between the two groups regarding spatial presence and realism. The IWD scored lower on both subscales. This lower score is consistent with our intentional design to prevent emotional overload by avoiding excessive realism in the VR environment[60,61]. This approach allows individuals with depression to safely explore and process their emotions and thoughts without emotional overload, which is essential for maintaining psychological stability[26,62]. The user experience workload evaluation using NASA-TLX showed that all participants found VR-MBCT easy to understand, navigate, and engage with. Although the IWD had statistically significantly higher frustration scores than the IWoD, the average score of 2.92 was relatively low. This may be due to the gradually increasing task load[63,64] during participation in VR-MBCT as the participants in the IWD were directly confronted with their emotions. Qualitative analysis of the exit interviews suggests that the VR environment can positively support self-emotion management and self-reflection. Participants reported that visual and auditory elements that evoked emotional responses enhanced their sense of immersion and supported emotional management, especially when real-time feedback was provided. The process of visually expressing and organizing emotions was also described as helpful in exploring and accepting one's feelings. This indicates the potential of VR as a tool for emotional exploration and self-reflection. However, some participants noted that limited personalization of the content could hinder deeper self-reflection. To address this, a personalized feedback system can be considered. This system would detect users' emotional states in real-time through voice or biosignal analysis. Based on the detected state, the VR experience could be adjusted by changing elements such as background color, voice guidance, or some elements in the content (after expert approval). Although a few participants mentioned discomfort related to headset fit or dizziness during certain interactions, most reported that these

issues did not significantly affect their ability to remain immersed. Nevertheless, it may be necessary to design experimental settings that take into account the usability limitations of current hardware. Researchers can set an appropriate session length or adjust the content to minimize visual elements that may cause discomfort, such as rapid screen transitions or sudden movements.

VR offers an attractive method to enhance concentration and treatment participation in a safe environment for depressed individuals. We confirmed that all participants showed high ROI-based levels of attention in all interactions required by VR-MBCT. This is particularly meaningful considering that individuals with depression often experience decreased concentration due to lethargy[65]. Moreover, this result suggests that the VR-MBCT design may include elements that support improved concentration and participation in the therapeutic process for individuals with depression. Furthermore, the entropy of EDA decreased significantly in both the IWD and the IWoD. Research[66,67] indicates that lower EDA variability is correlated with less stress and greater emotional regulation. Therefore, our results suggest that the VR-MBCT intervention was perceived as promoting psychological stability and calmness in participants from both groups. Specifically, the significant reduction in EDA variability in the IWD implies that VR-MBCT may promote emotional balance and stress management. This is consistent with existing research[68,69] suggesting that VR-based meditation therapy can be effective in improving mental health. However, it is noteworthy that while the variability of EDA signals in depressed patients is generally lower than that in individuals without depression[53], our study results showed the opposite. The IWD showed significantly increased EDA variability during the VR-MBCT experience. A study[70] has shown that EDA variability increased in depressed patients when they were placed in an environment that induces cognitive and emotional stress. In other words, the high EDA variability in the IWD indicates that VR-MBCT effectively guided participants to appropriately confront their emotions and thoughts.

Each session of VR-MBCT was co-designed through iterative discussions with mental health professionals (e.g., psychiatrists, therapists), and our study demonstrated that the design successfully elicited distinctive behavioral patterns based on interaction logs in the IWD. Specifically, the more complex and repetitive constellation drawings observed in the IWD during the first session are consistent with previous research suggesting that the overload of negative emotions and thoughts may lead to differences in information processing, increasing the complexity and depth of creations[36,37]. In the second session, the participants in the IWD took a statistically significantly longer time to select an avatar that reflected their emotions and situation among the five avatars, indicating that the IWD approached the avatars' concerns more deeply and empathetically. In the final session, the IWD selected statistically significantly fewer positive emotions and more negative emotions than the IWoD. This is consistent with the findings in previous neuroscience research showing that depressed individuals often experience fewer positive emotions[71].

Conventional MBCT, delivered primarily through face-to-face therapy and group sessions, has limitations in providing personalized treatment tailored to individual traits and needs[15]. These limitations fail to address critical considerations for the effective treatment of depressed individuals, such as high treatment costs, social stigma, and personal anxiety[16]. Additionally, the effectiveness of conventional MBCT has mostly been evaluated based on self-reports[7,8]. While self-reports have been a valuable tool due to their ease of administration and ability to capture subjective experiences, answering questions about one's mental habits or behaviors is a complex cognitive task[72]. Participants may lack the insight to accurately recall or communicate all related behaviors to clinicians. As a result, subjective self-reports may reflect participants' perceptions rather than objective measures of their self-compassion and mindfulness, relying heavily on their memory and self-reflection skills[72–75]. VR-MBCT explores a potential approach to overcoming these limitations by collecting sensor and log data from each task with clinicians in the virtual environment, allowing for an objective and accurate assessment of the individual's state. Additionally, clinicians can efficiently and accurately adjust treatment plans based on these objective and quantitative evaluation metrics[76], significantly improving the monitoring of patient conditions during the treatment process.

Limitations and future research

Despite the demonstrated applicability of VR-MBCT through various metrics, there are two main limitations. The first limitation is that the study participants were young adults between the ages of 18 and 40 and were not clinically diagnosed individuals but were experiencing the early stage of depression. Future research should expand the range of participants to include clinically diagnosed individuals to analyze the characteristics of various age groups, and identify and address different challenges for each age group to increase the accessibility and generalizability of VR-MBCT. The second limitation is that the distinctive behavioral patterns identified in the IWD were derived from a single experience with VR-MBCT. Although these patterns provide important initial insights into understanding depression response patterns and offering initial treatment methods for better emotion recognition and regulation, there are limitations in assessing long-term effects and changes. While this study confirmed the feasibility of VR-MBCT as an adjunct tool, future research will focus on evaluating its effectiveness through more extensive, multi-session studies. These studies will aim to assess the long-term effects of VR-MBCT and allow for more in-depth analyses based on data from participants with diverse demographics and clinical characteristics. This will allow us to evaluate the effectiveness of VR-MBCT as an adjunct tool for assisting clinical decision-making in the treatment of depression. We also plan to integrate core elements of MBCT, CBT, and Acceptance and Commitment Therapy (ACT) into a digital transformation within the VR environment and develop additional sessions. Through this process, we expect to identify key indicators during the alleviation or exacerbation of depression by analyzing data-driven behavioral characteristics that may vary depending on the severity or symptoms of depression in patients.

Conclusions

We developed and evaluated VR-MBCT to improve the mental health of depressed patients. Results from three scales (SUS, IPQ, and NASA-TLX) and exit interviews completed by a total of 73 participants indicated that VR-MBCT is user-friendly and highly immersive. The ROI-based level of attention, as measured by eye-tracking, remained high across all sessions for both groups, and entropy analysis of EDA collected by the E4 wristband showed emotional stability in both groups during the VR-MBCT experience. Additionally, interaction logs from the IWD revealed distinctive behavioral patterns, including complex and repetitive interactions, and unique approaches to processing emotions and situations. We expect that our findings and insights will be helpful to researchers who seek to adapt VR environments for mental health treatments.

Data availability

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

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Declarations

Competing interests
The authors declare no competing interests.

Additional information
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