What Do Head Scans Reveal About Depression? Insights from 360° Psychomotor Assessment

Priyanka Srivastava, Rohan Lahane, Vivek R, Prudhvi Pulapa
Perception and Cognition Lab, Cognitive Science Center
Kohli Research Center on Intelligent Systems
International Institute of Information Technology, Hyderabad, India
Corresponding Authors: priyanka.srivastava@iiit.ac.in; rohan.lahane@research.iiit.ac.in

Abstract

Psychomotor changes, while crucial indicators of depression, remain underrepresented in clinical observations. We examined the relationship between depression and psychomotor behavior by analyzing head-tracking data related to yaw movements made during exploration of 360° emotional videos, alongside valence and arousal ratings on 9-point Likert scale. Symptoms of depression were recorded using the Patient Health Questionnaire (PHQ-9). While subjective ratings for valence and arousal showed no differences across depression groups, the head-tracking data revealed novel results. Individuals with moderate to severe depression exhibited significantly lower scanning speed and standard deviation in yaw movement compared to minimal to mild depression. Although preliminary, these results underscore the importance of psychomotor measures in diagnosis, risk assessment, and monitoring in psychiatric care, alongside subjective evaluations.

Keywords: Virtual Reality; Psycho-motor analysis; Depression; Head-Tracking

Introduction

Persistent sadness, accompanied by loss of ability to feel happy or satisfied, combined with somatic, cognitive, and psychomotor changes, are hallmark features of clinical depression (American Psychiatric Association, American Psychiatric Association, et al., 2013). Despite its high prevalence and incidence rates (Collins et al., 2011), as well as frequent relapses of depressive episodes (Rush, Aaronson, & Demyttenaere, 2019), psychiatric assessments continue to rely heavily on self-reported symptoms. Currently, no universally accepted biological, cognitive and/or psychomotor markers exist for the diagnosis or monitoring mental well-being. The reliance on symptom-based diagnosis, combined with the lack of objective markers, impedes not only effective diagnosis but also impairs further prognosis (Rizzo & Shilling, 2017; Freeman et al., 2017; Srivastava, 2021). These challenges underscore the urgent need for the evidence-based diagnosis and care and highlight the importance of developing effective and objective measurement techniques (Collins et al., 2011) to enhance psychiatric care and improve outcomes.

One promising way to address these gaps is the use of head-mounted virtual reality (HMD VR) as an objective, evidence-based tool for improving psychiatric care, particularly in the diagnosis and monitoring of depression. Unlike traditional interviews and psychometric tests, HMD VR offers a more ecologically valid, 360° immersive environment that fosters a vivid sense of presence within the virtual world (Slater, 2009; Srivastava, Rimzhim, Vijay, Singh, & Chandra, 2019; Goel et al., 2021). This sense of presence elicit responses similar to those experienced in the real-world situations (Srivastava, 2021), despite realizing some uncanny dissimilarities. It is akin to the experience of *Alice* in Lewis Carroll's *Alice in Wonderland* (Lewis, 1978; Goel et al., 2021), where individual is transported into an immersive environment that feels real, even if it is fantastical (Sutherland et al., 1965). The combination of an ecologically valid, immersive environment with controlled settings, helps create contextually relevant scenarios, a key element that has been missing in traditional mental health assessments, particularly during the evaluation of cognitive and/or psychomotor activities (Rizzo & Shilling, 2017; Freeman et al., 2018). In a nutshell, if validated, VR has potential to revolutionize psychiatric care by enhancing the clinical experience of patients while reducing reliance on memory, imagination, and self-reported interoceptive feeling, thoughts and behavior.

However, despite its potential, depression remains underrepresented in VR-based mental health research, with most studies focusing on other disorders like PTSD and phobia, (Freeman et al., 2017; Rizzo & Shilling, 2017), or anxiety (Baghaei et al., 2021). Additionally, most studies have continued to rely on self-reports and/or clinical observations, despite using a wide range of visually and emotionally appealing nature landscapes (such as, mountains, grass, trees, or water) for therapy as well as for relaxation and mindfulness experiences (Baghaei et al., 2021; Jingili, Oyelere, Ojwang, Agbo, & Nyström, 2023). A few exceptions include measures like eye-tracking or heart rate (Baghaei et al., 2021) and head-tracking (Jingili et al., 2023), primarily focusing on social anxiety (Jeong, Lee, Kim, & Kim, 2021).

In depression, anhedonia is associated with reduced emotional reactivity to positive stimuli, favoring the positive attenuation model of depression (Sheoran & Srivastava, 2022). However, persistent sadness, another hallmark feature of depression, showed a mixed result in terms of emotional reac-

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tion to negative stimuli. Some studies report increased negative emotional reaction, supporting mood congruency model (Beck, Epstein, & Harrison, 1983), while others suggest reduced negative emotional reaction, favoring emotional context insensitivity model of depression (Bylsma, Morris, & Rottenberg, 2008). These contrasting findings highlight the complexity of depression and the need for further investigation into how these models manifest in psychomotor behavior.

The current study aims to examine the impact of depression on affective processing and associated psychomotor responses in 360° immersive virtual environment, using a novel method of analyzing spatio-temporal engagement. Based on previous findings, we hypothesize that individuals with self-reported depression will exhibit decreased head-movement in response to a pleasant virtual environment, owing to a diminished appreciation for rewarding activities (Rolls, 2018), leading to anhedonic experience (Rolls, 2018, 2021). For the unpleasant stimuli, if depression leads to blunting of emotional reactions (emotional context insensitivity) (Bylsma et al., 2008), we expect reduced head-tracking for all kinds of affective stimuli, including unpleasant stimuli. However, if depression enhances the processing of unpleasant information due to mood congruency (Beck et al., 1983; Sheoran & Srivastava, 2022), we expect an increase in scanning behavior within the unpleasant virtual environment during depressive states.

Methods

Participants

Fifty participants (*M = 41, W = 9, O = 0, prefer not to say = 0*), aged between 19 to 27 years (*M=21.1 years, SD= 1.66*), were recruited using a non-probabilistic snowball sampling method. All participants reported normal or corrected-to-normal vision. They were informed about the procedure and materials to be used in the experiment and signed consent form before starting the session. The study was approved by the Institutional Review Board (IRB) committee. All participants were naive to the purpose of the experiment and had minimal or no prior experience of using HMD VR. No monetary or other incentives were provided for their participation.

Materials

The current study used 360° HMD videos, the PHQ-9 for depression, the GAD-7 for generalized anxiety, the STAI-T for trait anxiety, one question for VR immersion, and a demographic survey. Immersion and demographic responses were excluded from statistical analysis due to page limitations. Description of all the materials is provided below:

Affective 360° videos: The 360° videos were selected primarily from Stanford VR affective database (Li, Bailenson, Pines, Greenleaf, & Williams, 2017) and one video was sourced from Youtube repository. The criteria for selection was based on the above and below mean values of valence and arousal (*M* =5), ranging from 6-to-9 points for pleasant and high arousing stimuli and 1-to-4 points for unpleasant and low arousing stimuli. Since the Stanford database remarks on their lack of high arousal low valance videos in the database, hence we used a '360 Horror' video sourced from youtube as a fear stimuli. The final set comprised of 4 videos from Stanford database (Li et al., 2017) and one video from Youtube, notably low valence low arousal (LVLA), low valence high arousal (LVHA), high valence low arousal (HVLA), high valence high arousal (HVHA), and Neutral (Neu). The numbers with video names as indices are provided in Table 1.

Patient Health Questionnaire (PHQ-9): PHQ-9 is widely used nine-item self-reported instrument designed to assess an individual's state of depression. Each item corresponds to core symptoms of major depressive disorder as defined by the DSM-5 (Kroenke, Spitzer, & Williams, 2001) (American Psychiatric Association et al., 2013). Participants rate the frequency of each symptom over the past two weeks using a 4-point Likert scale (0 = "Not at all" to 3 = "Nearly every day"), yielding a total score ranging from 0 to 27. Higher scores indicate extreme severity of depression, with established clinical cutoffs categorizing depression as minimal (0–4), mild (5–9), moderate (10–14), moderately severe (15–19), and severe (20–27).

Generalized Anxiety Disorder (GAD-7): GAD-7 is a self-report questionnaire, used for measuring the severity of generalized anxiety symptoms. The GAD-7 consists of seven items that align with the core criteria for generalized anxiety disorder as outlined in the DSM-5 (American Psychiatric Association et al., 2013) (Spitzer, Kroenke, Williams, & Löwe, 2006). Participants rated the frequency of each symptom over the past two weeks using a 4-point Likert scale (0 = "Not at all" to 3 = "Nearly every day"), resulting in a total score ranging from 0 to 21 (0–4), mild (5–9), moderate (10–14), and severe (15–21).

State-Trait Anxiety Inventory-Trait scale (STAI-T): State-Trait Anxiety Inventory-Trait scale (STAI-T) is a self-report instrument designed to assess stable, long-term tendencies toward experiencing anxiety. The STAI-T consists of 20 items that capture how individuals generally feel in anxiety-provoking situations. Participants responded using a 4-point Likert scale (1 = "Almost never" to 4 = "Almost always"), with a total score ranging from 20 to 80. Higher scores indicate greater levels of trait anxiety, with higher levels being associated with a heightened tendency to experience anxiety across various contexts.

Equipment

The videos were shown using HTC Vive pro HMD. It consisted of 1,080 × 1,200 pixel resolution per eye, and 2,160 ×1,200 for both eyes with 90Hz refresh rate for a smooth visual rendering experience, and 360° positional tracking.

Unity 3D game engine running on NVIDIA GeForce GTX 1060 graphics card, was used as a platform to transform the 360° videos into 3D scenes on the VR headset. The engine's capabilities were leveraged to calculate real-time head movements data including both rotational and positional data. These measurements were subsequently used to calculate angular velocities and spatiotemporal exploration patterns, providing quantitative metrics for analyzing participants' viewing behavior.

Procedure

The session began with welcoming the participants and preparing them for the experiment. Once ready, participants were given a consent form to read, which outlined the duration, materials to be used, privacy notice, and their right to withdraw at any point during the session. Upon obtaining consent, participants were instructed about the task, including the HMD experience, and detailed description of valence and arousal ratings using the 9-points Likert self-assessment manikin (SAM) scale. After completing the demographic survey, participants were presented with 360° videos in HMD VR in a pseudo-randomized order. Each video from a specific category was played only once throughout the session. After completing the session, participants were asked to provide feedback regarding their affective experience in the environment. The HMD was adjusted for clear vision, and participants were instructed to explore the environment as naturally as possible. Finally, participants completed the PHQ-9, GAD, and the STAI-T questionnaire to record their self reported levels of depression, state and trait anxiety (Figure 1).

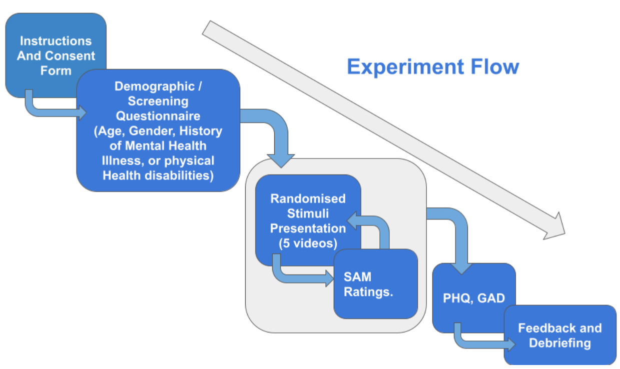

Figure 1: Schematic representation of flow of a session

Measures of Performance

In addition to self-reported psychological health responses, the study comprised a self-reported measure of affective response and head-tracking data recorded while participants explored the 360° immersive videos. A detailed description of these measures is given below:

Self-Reported Affective State: Participants' affective responses were measured using the Self-Assessment Manikin (SAM) scale, a validated non-verbal pictorial assessment tool (Russell, 1980). The SAM scale was administered immediately following each video stimulus to evaluate two fundamental dimensions of emotional experience: valence, and arousal. The scale utilized a 9-point rating system for each dimension, where 1 referred to extremely unpleasant or completely calm, and 9 referred to extremely pleasant or highly excited.

Head Tracking: We recorded participants' head orientation (pitch, yaw, roll) at 90 Hz during 360° video exploration, using the calibrated starting camera positionthat matched the center of the video stimuli as a reference point to calculate all other angles.This high sampling rate captured both rapid head movements and subtle positional adjustments, providing detailed data on exploratory behavior.

Standard deviation of head-movement: Psychomotor engagement was quantified by calculating the mean angular head orientation across the three rotational axes (pitch, yaw, roll). Given the circular nature of 360° data, circular mean was used to address the inherent wrapping effect, where, for example, 359° and 1° represent nearly identical orientations despite their numerical difference. The dispersion of head movements was then evaluated by computing the standard deviation (SD) of angular positions relative to these circular means. This metric provides a measure of exploratory behavior, quantifying the extent to which participants deviated from their mean orientation during stimulus presentation. SD analysis was performed independently for each rotational axis for a comprehensive assessment of viewing patterns in the immersive environment.

Scanning speed: This measure represents the rate of change of angular movement at which the scene was explored. The scanning speed was calculated by taking the total angular distance covered per unit time. Angular distance is the total degree of angle covered by the participant while exploring the video. For example, distance covered by yaw movements was calculated by summing up the differences between two consecutive time stamp logged values in 'Y' direction. Similar calculations were performed along 'X' and 'Z' axes for pitch and roll movements, respectively. The total angular distance traveled was calculated as $\sqrt{dx^2 + dy^2 + dz^2}$.

Results and Discussion

The results are presented in three major subsections: the first outlines the population description, the second examines the emotional reactivity to the 360° affective videos, and the third reports head-movement as a measure of psychomotor activity. We used JASP statistical software to conduct statistical tests and plots. For head-tracking, we used unity to log raw data and Python for data visualization.

Demographics: Consistent with previous findings (Cherian et al., 2024), the current study revealed high number of self-

Table 1: List of 360° videos with descriptions, and mean SAM emotional ratings (Valance; Arousal) across depression and anxiety groups. Sourced from Stanford database ((Li et al., 2017) and Youtube

Index	Video	Description	PHQ None	PHQ Mild	PHQ Moderate-Severe	GAD None	GAD Mild	GAD Moderate-Severe
1	The Nun 360 Experience	A horror-themed VR experience featuring dark and unsettling environments.	4.3; 4.9	3.7; 6.5	4.5; 6.4	4.3; 5.8	4.0; 6.1	4.3; 6.3
2	Tahiti Surf	In this video, the viewer experiences snorkeling and surfing on a beach with bright, vivid colors.	6.7; 6.5	6.5; 5.5	6.6; 5.5	7.1; 6.5	6.4; 5.2	6.2; 5.4
3	Abandoned Buildings	An exploration of abandoned buildings with a dark atmosphere.	4.0; 3.8	5.0; 4.1	5.3; 4.9	4.3; 4.2	5.0; 4.2	5.3; 4.7
4	Evening at the Beach	A peaceful beach scene at sunset.	6.5; 3.5	6.5; 4.4	6.0; 4.7	6.3; 3.8	6.1; 4.5	6.0; 4.7
5	Campus	A walk through a university campus.	5.6; 4.5	5.1; 4.0	6.0; 4.4	5.5; 4.5	5.4; 4.1	6.0; 4.3

reported moderate or severe depression among participants. Descriptive statistics indicated that 40% of participants reported moderate or severe symptoms of depression, 36% reported mild symptoms, and 24% reported minimal or no depression. Similarly, for anxiety, 26% of participants reported moderate or severe symptoms, 38% reported mild, and 36% reported minimal or no symptoms of anxiety (Table 2).

Further analysis of co-occurring symptoms of depression and anxiety, labeled as *psychological distress* revealed 26% of participants reported moderate symptoms of both, 24% reported mild depression and anxiety, and only fewer than 13% reported either mild or moderate symptoms of one disorder. These results support previous research (Cherian et al., 2024) indicating a high prevalence of moderate to severe symptoms of depression in college young adults.

Table 2: Psychological health score distribution of participants. Min=minimal, and Mod= moderate

Category	Min (0-4)	Mild (5-9)	$\geq$ *mod* (10-27)
Depression (PHQ-9)	12	18	20
Anxiety (GAD-7)	18	19	13

Emotional Reactivity: Emotional reactivity was measured through self-reported valence and arousal ratings for emotional stimuli that ranged from low to high levels of both valence and arousal dimensions. A Shapiro-Wilk test indicated a violation of normality ($p < .05$), and led us to choose a non-parametric analysis to examine emotional reactivity across the three depression groups. We couldn't perform the analysis of co-variance (ANCOVA) to treat anxiety as a covariate of depression and hence conducted a Kruskal-Wallis test to compare valence and arousal ratings across five different video stimuli, separately for depression and anxiety groups. No significant differences were observed for either dimension of emotional reactivity, indicating no significant effect of depression and anxiety on valence and arousal ratings ($p > .05$) (Table 1).

The current results are inconsistent with previous findings (Sheoran & Srivastava, 2022; Beck et al., 1983; Bylsma et al., 2008). The lack of significant difference in self-reported emotional reactivity highlights the limitations of 9-points Likert scale in measuring emotional reactivity. Participants rated their experience for most videos as closer to neutral affective response (Table 1), suggesting that three groups of depression and anxiety found the videos equally emotionally engaging. Given the concrete nature of Likert scales, it also limits the participants' ability to fully express the real nature of their engagement with the stimuli.

Head-movement as a psychomotor activity This section presents multiple analyses. We will first outline the analysis scheme and then report the statistical results.

Analysis scheme: Shapiro-Wilk test results indicated no significant violation of normality for yaw, pitch, and roll, and the associated scanning speed and standard deviation of head-tracking data across the three groups of depression and anxiety. However, the scanning speed and standard deviation of yaw (SDY) data associated with emotional video explorations violated the assumption of normality. Based on the charateristics of the data, we chose appropriate parametric and non-parametric statistical tests. For this manuscript, we chose to report results related to the yaw movement due to the design of the videos, and limitation of the pages.

First, we conducted Pearson's correlation to examine the relationship between head-tracking data related to yaw movement and psychological health scores. Next, we performed a set of analyses to evaluate the impact of depression on head-movement. An analysis of co-variance (ANCOVA) was conducted to evaluate the impact of depression on SDY and scanning speed, while controlling for state and trait anxiety scores, as obtained from the GAD-7 and STAI-T, respectively.

Additionally, we performed an analysis of variance (ANOVA) to assess the effect of distress on scanning speed and SDY behavior. Distress was a conditional analysis that emerged due to significant strong correlation (r = .752, p < .001)between depression and anxiety. We operationalized five categories of distress, namely, BD, BMD, ED, EMD, and none. BD (both distress) comprised scores moderate or above scores from both depression and anxiety (PHQ-9 and GAD-7 score $\geq$ 15); BMD (both mild distress) referred to mild distress, with scores between $\geq$ 5 but <10 on both questionnaires; while ED (either distress) and EMD (Either mild distress) referred to either distress or mild distress conditions, respectively. In these conditions, participants reported varying levels of severity for either disorders; and None referred to minimal scores obtained on both the PHQ-9 and GAD-7.

Finally, a Kruskal Wallis test was conducted on scanning speed and SDY across five emotional video conditions (emotional videos: LVHA, LVLA, HVHA, HVLA, and Neutral as within group) separately, due to violation of normality assumption. Bonferroni corrections were applied to post-hoc comparisons between three groups of depression, and only Bonferroni's corrected values were considered for final reporting.

Correlation between head-movement and psychological health scores: Pearson's correlation between the psychological health scores (PHQ-9, GAD-7, and STAI-T) and head-tracking data (SDY and scanning speed) revealed significant negative correlations. Specifically, the SDY showed a significant (p = <.05), though weak, negative correlation with depression and anxiety scores (Figure 2). While scanning speed exhibited a moderately strong negative correlation with all psychological health scores (p <.001), including trait anxiety (Figure 2). Additionally, a strong, significant correlation was observed between the three psychological health scores (p <.001) (Figure 2).

Impact of depression on head-movement: ANCOVA results indicated a significant effect of depression symptoms on scanning speed, after controlling for state and trait anxiety (GAD-7 scores and STAI-T scores, respectively) (p <.001, η^2 = .295) (Figure 3). Post hoc comparisons revealed that individuals with severe symptoms of depression demonstrated significantly slowest scanning speed (M = 3.88, SD = 0.88) compared to those with mild depression (M = 4.94, SD = 1.07) and no-depression (M = 5.29, SD = 0.88), (p = .028, d = -1.22; and p = .021, d = 1.64, respectively) (Figure 3). However, no significant interaction effects were observed between depression and state and trait anxiety for scanning behavior. Depression scores did not significantly influence the yaw and standard deviation of yaw movement. Figure 4, depicts an example of head-movement data visualization in a 360° virtual environment by four participants, representing varying severity of depression and anxiety. The visualization demonstrates consistency in change in head-movement in individuals with severe depression and anxiety, suggesting that head-tracking data in VR videos exploration could be considered a reliable psychomotor assessment for depression.

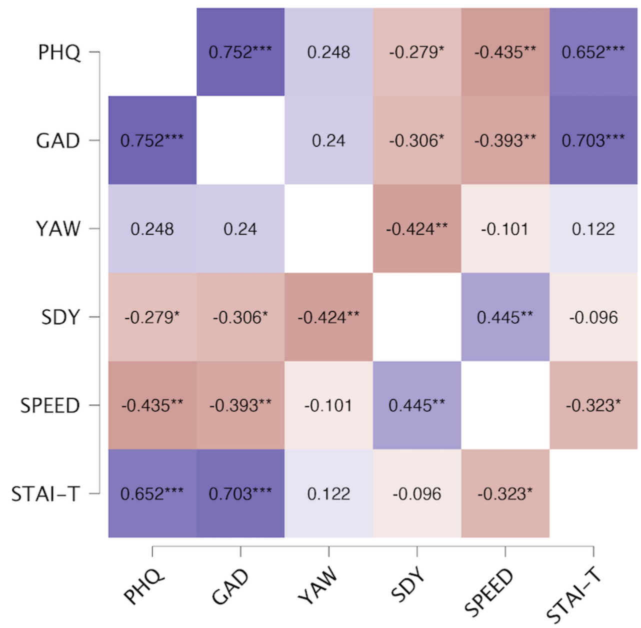

Figure 2: Correlation heatmap representing Pearson's correlation coefficient between psychological health scores and head-tracking data focusing on yaw and related measures. PHQ-9: Patient Health Questionnaire, GAD-7: Genralized Anixety Disorder, STAI-T: State Trait Anxiety Inventory - Trait, SDY: standard deviation of yaw movement.
* $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

The Kruskal Wallis test for SDY movement indicated no significant effect of depression on SDY movement across five emotional conditions. However, the analysis revealed an impact of depression on scanning speed, with significant differences observed in LVHA, HVLA, and Neutral emotional conditions. Specifically, individuals with severe depression demonstrated significantly slower scanning speed (*M* = 3.18, *SD* = 1.46) than those with no-depression (*M* = 5.0, *SD* = 1.98) during exploration of the LVHA (*p* = .032, *d* = -.96). Similar trends were observed with Neutral videos (*p* = <.001, *d* = -1.46, *M* = 3.54, *SD* = 1.75; *M* = 5.98, *SD* = 1.43, receptively for severe and no-depression groups). For HVLA video exploration, a difference was observed between the severe (*M* = 4.13, *SD* = 2.13) and the mild (*M* = 5.82, *SD* = 2.31) depression groups (*p* = .045, *d* = -.822).

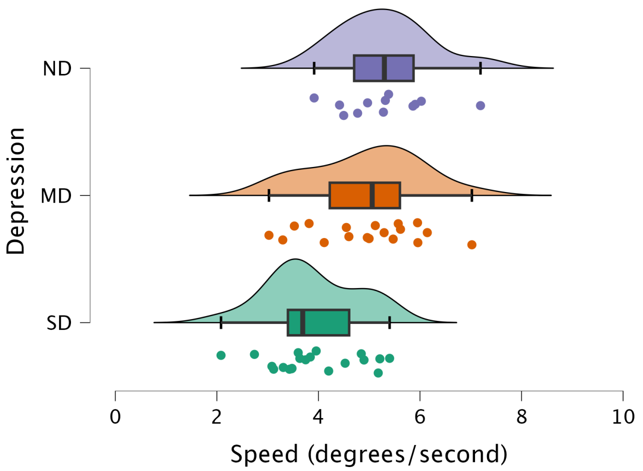

Figure 3: Raincloud plot depicting comparison between scanning speed while exploring 360° affective virtual environments across depression groups. SD = severe depression, MD = mild depression, and ND = no depression.

Unlike self-reported emotional reactivity, the head movement data provided new insights, revealing unique findings. The negative correlations between the psychological health scores and head movement data, particularly with the scanning speed, suggest that the higher levels of depression and anxiety are associated with reduced motor engagement, i.e. scanning behavior. Further, ANCOVA results reinforced understanding of the role of depression in modulating psychomotor behavior, including head-movement, during a 360° video exploration. The slowest scanning speed by individuals with severe depression, even after controlling for state and trait anxiety, supports previous findings on psychomotor disturbances (American Psychiatric Association et al., 2013) and offers a novel criterion for more objective assessment of psychomotor behavior in depression. Such results not only support the DSM-V (American Psychiatric Association et al., 2013) criteria for psychomotor disturbance in depression, but also suggest that VR-based measurements could serve as an objective tool for screening and monitoring depression, especially as an outcome of therapeutic intervention.

Furthermore, in contrast to self-reported emotional reactivity, which showed no significant difference between the depression groups across the five affective videos, the head-movement data revealed significantly slower scanning speed in individuals with severe depression compared to those with mild-depression for LVHA, Neutral, and HVLA stimuli. Although the data are not entirely consistent with varying levels of arousal and valence, they inclined towards supporting the emotional context insensitivity (ECI) model (Bylsma et al., 2008; Sheoran & Srivastava, 2022) over Beck's model of depression (Beck et al., 1983).

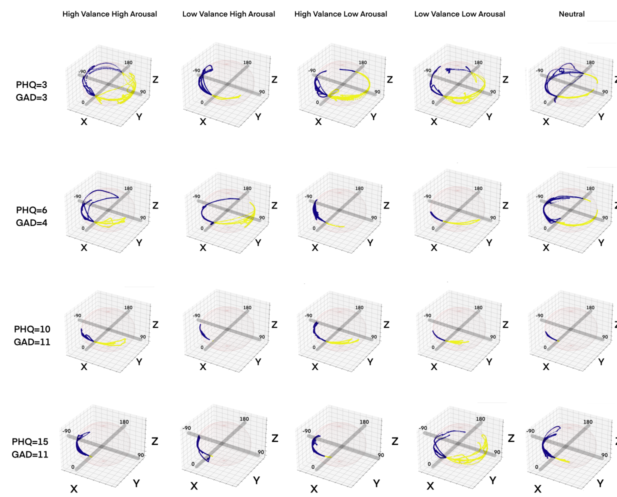

Figure 4: Head-tracking coordinates sample for participants representing varying severity of depression while exploring 360° affective videos. PHQ-9 (range: 0-27) and GAD-7 (range: 0-21) categorization, 0-4 = minimal, 5-9 = mild, 10-14 = moderate and $\geq$ 15 moderate severe or severe category.

Head-movement to emotional stimuli in VR appear as reliable indicators of propensity to depression, especially when self-report measures for emotional reactivity fail to distinguish between individuals with and without depression. The finding is critically relevant in light of rising cases of moderate to severe depression among young adults. Future studies require to examine such responses with standardized video, MDD population as gold standard for better understanding of depression.

Conclusion

The current study highlights the potential of VR-based affective psychomotor responses to reliably indicate depression, even when self-reports do not distinguish healthy and depressed groups. In light of rising moderate-to-severe depression among youth, such objective measures are critical. Despite promising results, the findings should be interpreted with caution due to lack of standardized affective VR databases and gold-standard clinical MDD samples. Future work should integrate eye tracking to provide a more nuanced understanding of the spatio-temporal attentional dynamics involved in affective VR exploration. These advances lay the foundation for the use of attention and psychomotor metrics as objective tools in affective and clinical VR research.

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