Original Paper

AI-Derived Emotional States and Trajectories in Real-World Mental Health Sessions: Large-Scale Observational Study

Kelsey McAlister, PhD; Courtney Jewell, PhD; Landry Huffman, PhD; Elizabeth Knight, PhD; Jennifer Huberty, PhD

Fit Minded, Inc., Phoenix, AZ, United States

Corresponding Author:
Kelsey McAlister, PhD
Fit Minded, Inc.
2901 E Greenway Road
Phoenix, AZ, 85046
United States
Phone: 1 6029356986
Email: publications@fit-minded.com

Abstract

Background: AI-powered digital mental health interventions (DMHIs) are increasingly deployed to support employee mental health, yet evaluations have focused predominantly on pretest-posttest symptom outcomes. The emotional states that unfold within real-world AI-assisted sessions remain largely uncharacterized, limiting understanding of how and when these tools may support users in distress.

Objective: This study aimed to (1) characterize AI-derived emotional states and patterns that emerge during AI-supported mental health sessions, (2) characterize and compare reduced distress and persistent distress sessions among sessions beginning in AI-derived distress states, and (3) identify conversational features associated with reduced distress trajectories.

Methods: This retrospective study analyzed message-level AI-derived emotional state data from 28,870 sessions contributed by 4463 unique users of Yuna, an AI-powered DMHI. Yuna's emotion detection system, grounded in semantic space theory, generated continuous scores across 36 fine-grained emotional states at the message level. Fine-grained states were aggregated into 4 categories: distress associated, cognitive processing, regulated positive, and social-interpersonal. Session-level trajectory types were operationalized from start-to-end emotional category transitions. Linear mixed-effects models and mixed-effects logistic regression were used to identify characteristics and conversational predictors of reduced distress trajectories among sessions beginning in distress-associated states.

Results: Five trajectory types were identified: stable (7679/28,870, 26.6%), reduced distress (7042/28,870, 24.4%), transitional processing (6195/28,870, 21.5%), persistent distress (4568/28,870, 15.8%), and escalating distress (3386/28,870, 11.7%). Cognitive processing states were the most frequently observed at the message level (130,611/365,088, 35.8%), followed by distress-associated states (117,485/365,088, 32.2%). Among sessions beginning in distress-associated states with available session duration data (n=1597), 73.3% (1170/1597) demonstrated reduced distress trajectories by session end. Reduced distress sessions were characterized by more messages (B=1.67; P=.02), longer duration (B=3.61; P=.001), AI-derived emotional switches (B=1.57; P=.01), unique AI-derived emotional states (B=0.94; P<.001), and higher proportions of cognitive processing (B=0.09; P<.001) and regulated positive (B=0.10; P<.001) states relative to persistent distress sessions. In the mixed-effects logistic regression, a greater number of unique AI-derived emotional states (odds ratio [OR] 1.16, 95% CI 1.09-1.24; P<.001) and longer session duration (OR 1.01, 95% CI 1.00-1.02; P=.04) were positively associated with reduced distress trajectories, while more AI-derived emotional switches were negatively associated with reduced distress trajectories (OR 0.97, 95% CI 0.95-0.99; P=.003).

Conclusions: AI-derived emotional trajectory data may offer a scalable, low-burden signal for understanding engagement quality in real-world mental health sessions, laying an empirical foundation for process-level evaluation of AI-powered DMHIs. Future research incorporating self-report validation, longitudinal designs, and experimental methods is needed to determine whether these trajectory patterns carry a meaningful signal for user outcomes.

(JMIR Form Res 2026;10:e104318) doi: 10.2196/104318

XSL•FO
RenderX

KEYWORDS

digital mental health intervention; emotional trajectories; process evaluation; real-world evidence; workplace mental health; semantic space theory; artificial intelligence; AI

Introduction

Mental health distress is highly prevalent among members of the workforce and is costly, resulting in decreased productivity, increased absenteeism, and health problems [1]. In recent surveys, 76% of workers have reported mental health–related symptoms, and 81% report that employer support for mental health is a priority for them when choosing where to work [2]. Despite this need, traditional support options such as employee assistance programs are underused, suggesting that they fail to meet the needs of workers for reasons including difficulty in accessing services, mistrust, lack of awareness, misalignment with needs, and lack of perceived value [3-5]. As a result, employers are seeking novel approaches to supporting employee mental health that are both effective and economical.

One increasingly common approach is the use of AI-supported digital mental health interventions (DMHIs). Conversational AI tools can offer relevant assistance, such as reflective coaching and real-time emotional support, in a format that lowers barriers, including stigma, cost, and scheduling [6]. Rather than providing clinical care, AI conversational tools are designed to help users manage distress, regulate their emotional states, and cope more effectively in the moment [7,8]. While there is early evidence suggesting high user satisfaction and potential benefits, including psychoeducation, increased intervention adherence, and improved symptoms, little is known about how and why these tools work [9]. Most DMHI evaluations rely on pretest-posttest self-report, capturing whether a user feels better but not how or when [10,11]. As AI tools are increasingly integrated into DMHIs, more granular, process-oriented evaluations are needed to ensure safe and effective use of these technologies [12,13].

Emotional regulation has been identified as an overarching mechanism across different therapeutic modalities that inform DMHI design, including cognitive behavioral therapy and psychodynamic therapy [14,15]. Moreover, the in-session emotional arc has been linked to symptom outcomes, suggesting that emotion is not only a distal target but an active component of the change process itself [16,17]. Because AI-powered DMHIs are designed specifically to support users experiencing mental health distress, emotion is both the presenting context and a theoretically relevant process variable in evaluating how these tools work [7]. However, the body of evidence exploring emotion in the evaluation of AI-based DMHIs remains extremely limited, and it lacks clinical context, theoretical relevance, and transparency [13,18].

Despite rapid growth in AI-powered DMHIs, published work has focused predominantly on pretest-posttest symptom outcomes, and the emotional states that unfold within real-world AI-assisted mental health sessions remain largely uncharacterized [19]. AI-powered conversational platforms are uniquely positioned to address this gap. Unlike traditional care contexts, these systems generate continuous, session-level affective signals that capture emotional expression throughout an interaction rather than only at its end points. In the present study, these signals were operationalized as AI-derived emotional states. This capacity shifts evaluation from a black-box model of change toward trajectory characterization, providing a process-level empirical window into how and when emotional shifts occur during AI-assisted mental health sessions [20,21]. Prior work has examined single emotional end points or aggregate sentiment scores rather than the ordered sequence of emotional states across a session. What remains unknown is whether within-session emotional trajectories, defined as the movement between emotional categories from a session's start to its end, can be characterized at scale in real-world AI-assisted sessions and whether such trajectories vary systematically with observable conversational features. This is a specific gap the present study addresses.

The purpose of this study was to explore patterns in AI-derived emotional states and characterize session-level emotional trajectory types derived from AI-powered DMHI sessions. We aimed to (1) characterize AI-derived emotional states and patterns that emerge during AI-supported mental health sessions, (2) characterize and compare AI-derived reduced distress and persistent distress sessions among sessions beginning in AI-derived distress states, and (3) identify conversational features associated with AI-derived reduced distress trajectories.

Methods

Study Design and Participants

This retrospective study analyzed secondary data from Yuna, an AI-powered DMHI. The dataset included message-level AI-derived emotional state data and session metadata from real-world Yuna users collected as part of routine platform operations. Users were included if they (1) were adults (aged 18 years or older), (2) were located in a country where Yuna is available, and (3) initiated at least one session with the platform. Eligible participants were identified through a retrospective cohort sampling approach using back-end app use records collected between April 17, 2025, and January 11, 2026. As this study was retrospective in nature, no direct recruitment took place. A formal power analysis was not conducted; the analytic sample reflected the full population of eligible users available within the observation window. This study was conducted and reported in accordance with the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines for observational cohort studies (Multimedia Appendix 1) [22].

Ethical Considerations

The study protocol was reviewed by Solutions IRB (study ID 1001) under expedited review procedures and was conducted in accordance with US human subject research regulations. The study involved a retrospective analysis of preexisting, deidentified data with no direct interaction or intervention with users. Investigators did not have access to identifiable private

XSL•FO
RenderX

information, and informed consent was waived by the institutional review board due to minimal risk. User data were collected during routine app use, and users agreed to the platform's terms and privacy policy, which permit the use of deidentified and/or aggregated data for service improvement and research purposes. Participants were not compensated for using the app. All data were deidentified before analysis.

Yuna App

Yuna is a commercially available mental health and wellness platform offered through workplace partnerships. Yuna's primary feature is a clinician-informed, evidence-based AI-powered mental health coach that provides users with unlimited, on-demand conversational support to improve well-being. The platform incorporates personalization features and is designed to teach users skills from evidence-based frameworks, including dialectical behavior therapy, cognitive behavioral therapy, and acceptance and commitment therapy. During conversations, the system dynamically applies discrete intervention strategies based on the user's expressed needs and conversational context. All therapeutic approach prompts and clinical protocols were developed by a licensed clinician and undergo iterative refinement through ongoing clinician review. High-priority safety protocols continuously monitor conversations for high-risk content; upon activation, standard coaching is suspended, and users are provided with crisis de-escalation support and emergency resources (eg, 988 Suicide and Crisis Lifeline in the United States).

AI-Derived Emotional States

Yuna's emotion detection system generates message-level scores across 36 fine-grained emotional states using a machine learning model grounded in semantic space theory [23,24]. Semantic space theory conceptualizes emotion as a high-dimensional, continuous space in which dozens of distinct affective states, such as anxiety, contemplation, and calmness, are organized along gradients of meaning rather than being collapsed into a small number of discrete categories [24]. Consistent with this framework, the emotion detection system produces a continuous score for each of the 36 emotional states at the message level, reflecting the degree to which linguistic patterns associated with each state are present in user-generated text within a given conversational turn. This approach enables granular, continuous characterization of emotional expression across the arc of a session rather than relying on binary or categorical emotion labels. A complete listing of fine-grained emotional states and their assigned categories is provided in Multimedia Appendix 2. Yuna's implementation of this approach is proprietary, and implementation-specific performance metrics such as classification accuracy or agreement with human raters have not been independently established or published. The emotional states analyzed in this study should therefore be understood as model-generated linguistic classifications rather than validated measures of users' internal emotional experience.

Study Measures

When users sign up for Yuna, they may optionally provide their age and gender within their account profile. Country was derived from back-end platform data.

Session Characteristics

A session was defined as a discrete interaction with the AI mental health coach, beginning when a user initiated a conversation and ending when the conversation was concluded. Session duration was computed as the total session length in minutes. Message count was defined as the total number of user and AI messages exchanged within a session.

AI-Derived Emotional State Variables

The 36 fine-grained AI-derived emotional states were aggregated into 4 theoretically grounded categories: distress associated, cognitive processing, regulated positive, and social-interpersonal. These 4 categories served as the unit of analysis for session-level trajectory classification. Groupings were constructed based on shared functional and affective properties consistent with established dimensional models of emotion and theoretical accounts of emotional processes in mental health intervention contexts [25]. Distress-associated states (eg, anxiety, sadness, and shame) were defined as emotions characterized by negative valence and activation of aversive affective experience. Cognitive processing states (eg, contemplation, interest, and realization) were defined as emotions reflecting active meaning making and attentional engagement. Regulated positive states (eg, calmness, contentment, and relief) were defined as emotions reflecting affective stabilization or positive hedonic tone. Social-interpersonal states (eg, admiration, sympathy, and love) were defined as emotions oriented toward relational or affiliative experience. Category assignments were established a priori and applied uniformly across all sessions.

Statistical Analyses

Descriptive statistics characterized the analytic sample, session-level emotional patterns, and message-level AI-derived emotional state distributions. Frequencies and proportions were reported for categorical variables; means and SDs were reported for continuous variables.

For each message, the dominant emotional state was defined as the AI-derived emotion with the highest score. Session-level emotional trajectory types were then operationalized based on the dominant AI-derived emotional category at session start and session end. Five mutually exclusive trajectory classes were derived from start-to-end category transitions. *Reduced distress* trajectories were defined as sessions beginning in a distress-associated state and ending in any nondistress state (cognitive processing, regulated positive, or social-interpersonal), reflecting movement away from aversive affect by the end of the session. *Persistent distress* trajectories were defined as sessions beginning and ending in distress-associated states, reflecting no movement away from aversive affect over the session. *Escalating distress* trajectories were defined as sessions beginning in any nondistress state and ending in a distress-associated state, reflecting movement toward aversive affect by session end. *Stable* trajectories were defined as sessions beginning and ending within the same nondistress emotional category (ie, cognitive processing, regulated positive, or social-interpersonal; sessions beginning and ending in distress-associated states were classified as persistent distress),

XSL•FO
RenderX

reflecting affective consistency across the session. *Transitional processing* trajectories captured all remaining transitions (ie, sessions that began and ended in different nondistress categories), reflecting movement across affective states without a clear distress arc in either direction. Session-level proportions of each emotional category were computed as the mean proportion of messages assigned to that category within a session.

Group comparisons between reduced distress and persistent distress sessions were conducted using linear mixed-effects models on session-level engagement variables (message count, AI-derived emotional switches, unique AI-derived emotional states, and session duration) and affective composition (cognitive processing proportion and regulated positive proportion). A mixed-effects logistic regression model was then fit to identify conversational predictors of reduced distress trajectories relative to persistent distress trajectories among sessions beginning in distress-associated states, with AI-derived emotional switches, unique AI-derived emotional states, and session duration entered simultaneously. Every model included a random intercept for user to account for the nonindependence of sessions nested within users. Model fit was evaluated using a likelihood ratio test comparing the full model with a null model containing only the intercept and the random intercept for user.

Missing data were not imputed. Analytic models were fit using complete cases for each relevant outcome and predictor, and the proportion of missing data for each variable is reported. All analyses were conducted in R (version 4.6.1; R Foundation for Statistical Computing) with the *lme4* (version 2.0.6), *lmerTest* (version 3.2.1), and *broom.mixed* (version 0.2.9.7) packages.

Bias Mitigation

Fit Minded uses a standardized bias mitigation protocol across all industry-partnered research, applied prospectively and independent of study outcomes. The following safeguards were implemented for this study. First, research questions were developed by the Fit Minded scientific team based on scientific merit and were not prescribed by the client. Second, study outcomes were not guaranteed as contractual deliverables. Third, the analysis plan was prespecified prior to data access. Fourth, data analysis and interpretation were led by Fit Minded authors operating independently of Yuna. Fifth, findings were reviewed collaboratively across the full author team.

Results

Data Availability and Descriptive Statistics

The initial dataset included 35,687 conversation sessions (unique user-session pairs) and 375,251 message-level AI-derived emotional states. Message records with a missing session identifier (565/375,251, 0.15%) were excluded before analysis as these messages could not be linked to a session. Sessions containing fewer than 3 messages (6817/35,687, 19.1%) were additionally excluded because a minimum of 3 sequential observations is required to detect a directional change in AI-derived emotional state (ie, an initial state, a transition, and an end point) [26]. The final analytic sample consisted of 28,870 sessions (28,870/35,687, 80.9%) contributed by 4463 unique users and included 365,088 message-level AI-derived emotional observations (365,088/375,251, 97.3%).

Demographic data availability varied across variables (Table 1), which is common in real-world digital health research [27]. Gender data were available for 84.3% (3761/4463) of users, country and language data were available for 94.3% (4207/4463) of users, and age data were available for 4.7% (209/4463) of users. More users who reported gender identified as female (2304/3761, 61.3%; 2304/4463, 51.6% of the total sample), followed by male (1457/3761, 38.7%; 1457/4463, 32.6% of the total sample). Most users were located in the United States (2639/4207, 62.7% of respondents; 2639/4463, 59.1% of the total sample), although the sample included users from 104 countries. English was the primary language for most users with available data (3880/4207, 92.2%; 3880/4463, 86.9% of the total sample), with 30 languages represented across the sample. User-level differences between those with and without demographic data are provided in Multimedia Appendix 3.

XSL•FO
RenderX

Table 1. Demographic characteristics of the analytic sample (n=4463)[a].

Variables	Users, n (%)
Gender	
Female	2304 (51.6)
Male	1457 (32.6)
Missing	702 (15.7)
Country	
United States	2639 (59.1)
Other countries	1568 (35.1)
Missing	256 (5.7)
Primary language	
English	3880 (86.9)
Other languages	327 (7.3)
Missing	256 (5.7)
Age group (y)	
18-25	85 (1.9)
26-35	67 (1.5)
36-45	35 (0.8)
46-55	14 (0.3)
>55	8 (0.2)
Missing	4254 (95.3)

[a] "Other countries" and "Other languages" represent all remaining reported categories outside the most frequently represented category. Unavailable categories reflect missing or unavailable demographic metadata.

AI-Derived Emotional Patterns and Trajectory Types

Session-level descriptive statistics, including message count, unique AI-derived emotional states, and AI-derived emotional switches, are reported in Table 2. AI-derived emotional states were organized into 4 broad categories: cognitive processing, distress associated, regulated positive, and social-interpersonal. At the message level, cognitive processing states were the most frequently observed category, followed by distress-associated, regulated positive, and social-interpersonal states (Table 2). The most frequently observed AI-derived emotional states included calmness, contemplation, disappointment, interest, and sadness. Frequencies for all AI-derived emotional states are provided in Multimedia Appendix 4.

Session-level analyses examined how AI-derived emotional categories shifted across the arc of each session, yielding 5 emotional trajectory types. Stable trajectories, defined as sessions beginning and ending within the same broad nondistress AI-derived emotional category, were the most common, followed by reduced distress trajectories, which reflected movement from distress-associated states toward cognitive processing or regulated positive states. Transitional processing trajectories, reflecting movement between nondistress categories, were the next most frequent, followed by persistent distress trajectories, defined as sessions beginning and ending within distress-associated states. Escalating distress trajectories, reflecting movement from nondistress states toward distress-associated states by session end, were the least common. Proportions for each trajectory type are reported in Table 2.

XSL•FO
RenderX

Table 2. AI-derived emotional patterns and trajectory types.

	Values
Session-level AI-derived emotional descriptive statistics, mean (SD)	
Messages per session	12.65 (13.13)
AI-derived emotional switches	8.63 (11.05)
Unique AI-derived emotional states	5.72 (3.87)
Unique AI-derived emotional categories per session	2.76 (1.03)
Distribution of AI-derived emotion categories (n=365,088), n (%)	
Cognitive processing	130,611 (35.8)
Distress associated	117,485 (32.2)
Regulated positive	83,817 (23)
Social-interpersonal	33,175 (9.1)
Session-level AI-derived emotional trajectories (n=28,870), n (%)	
Stable	7679 (26.6)
Reduced distress	7042 (24.4)
Transitional processing	6195 (21.5)
Persistent distress	4568 (15.8)
Escalating distress	3386 (11.7)

Characteristics of Reduced Distress Sessions

Among sessions beginning with distress-associated AI-derived emotional states, session duration data were available for 13.8% (1597/11,610) of sessions. Sessions with missing session duration data (10,013/11,610, 86.2%) were excluded from aim 2 analyses as session duration was a required predictor in the mixed-effects logistic regression model. Sensitivity analyses comparing complete and incomplete session data and re-estimating the model on the full available sample of sessions beginning in distress-associated states (n=11,610 sessions from 2925 users) are provided in Multimedia Appendix 5. The pattern of missingness in session duration was consistent with broader data availability limitations observed across the full analytic sample. Among sessions with complete session duration data (n=1597), 73.3% (1170/1597) transitioned toward nondistress states by session end. In comparison, 26.7% (427/1597) remained in distress-associated AI-derived emotional states throughout. Relative to persistent distress sessions, reduced distress sessions contained more messages, more AI-derived emotional switches, more unique AI-derived emotional states, longer session duration, and greater proportions of cognitive processing and regulated positive AI-derived emotional states (P≤.02 in all cases; Table 3). Adjusted intraclass correlations (intraclass correlation coefficients) for these models ranged from 0.13 to 0.27, and no model had a singular fit.

A mixed-effects logistic regression model examined whether the number of AI-derived emotional switches, the number of unique AI-derived emotional states, and session duration were associated with movement away from distress-associated AI-derived emotional states (ie, cognitive processing, regulated positive, and social-interpersonal) among sessions beginning with AI-derived distress (Table 4). More unique AI-derived emotional states were associated with significantly greater odds of reduced distress trajectories relative to persistent distress trajectories (odds ratio [OR] 1.16, 95% CI 1.09-1.24; z=4.41; P<.001; Table 4), indicating that sessions containing a broader range of unique AI-derived emotional states were more likely to transition away from AI-derived distress-associated states. Longer session duration was also positively associated with AI-derived reduced distress trajectories (OR 1.01 per additional minute, 95% CI 1.00-1.02; z=2.01; P=.04; Table 4). More AI-derived emotional switches were associated with lower odds of AI-derived reduced distress trajectories (OR 0.97, 95% CI 0.95-0.99; z=−2.95; P=.003; Table 4). The adjusted intraclass correlation coefficient for this model was 0.10 (latent scale).

XSL•FO
RenderX

Table 3. Characteristics of AI-derived persistent distress and reduced distress sessions[a].

	Persistent distress (n=427), mean (SD)	Reduced distress (n=1170), mean (SD)	Estimate (*B*; 95% CI)	*t* test (*df*)	*P* value
Messages per session	13.00 (12.62)	15.04 (13.48)	1.67 (0.27-3.07)	2.34 (1560)	.02
AI-derived emotional switches	9.88 (10.40)	11.75 (11.63)	1.57 (0.38-2.76)	2.58 (1557)	.01
Unique AI-derived emotional states	6.44 (3.70)	7.49 (3.81)	0.94 (0.54-1.34)	4.63 (1557)	<.001
Session duration (min)	16.11 (19.05)	20.18 (20.41)	3.61 (1.47-5.75)	3.31 (1580)	.001
Cognitive processing proportion	0.20 (0.17)	0.30 (0.18)	0.09 (0.07-0.11)	9.12 (1590)	<.001
Regulated positive proportion	0.14 (0.15)	0.25 (0.17)	0.10 (0.09-0.12)	11.62 (1530)	<.001

[a]Group comparisons were conducted using linear mixed-effects models with trajectory group (reduced vs persistent) as the fixed effect and a random intercept for user. Estimates (*B*) are the model-estimated differences (reduced distress minus persistent distress) with 95% Wald CIs; *t* statistics use Satterthwaite-approximated df, and *P* values are 2 sided. The n values are sessions; the 1597 sessions were contributed by 728 users. Adjusted intraclass correlation coefficients were 0.25 (messages), 0.26 (switches), 0.26 (unique states), 0.19 (duration), 0.13 (cognitive processing proportion), and 0.27 (regulated positive proportion).

Table 4. Mixed-effects logistic regression predicting AI-derived reduced distress trajectories among sessions beginning in AI-derived distress[a].

Predictor	*B* (log-odds; SE)	OR[b] (95% CI)	*z*	*P* value
AI-derived emotional switches	−0.03 (0.01)	0.97 (0.95-0.99)	−2.95	.003
Unique AI-derived emotional states	0.15 (0.03)	1.16 (1.09-1.24)	4.41	<.001
Session duration (min)	0.01 (0.004)	1.01 (1.00-1.02)	2.01	.04

[a]Mixed-effects logistic regression models predicted odds of AI-derived reduced distress trajectories relative to AI-derived persistent distress trajectories (reduced distress=1; persistent distress=0). Results of the likelihood ratio test showed significantly improved model fit relative to the null model (χ^2_3=34.6; *P*<.001).

[b]OR: odds ratio.

Discussion

Principal Findings

The purpose of this study was to explore patterns in AI-derived emotional states and characterize session-level emotional trajectory types within real-world AI-powered DMHI sessions. Across a large, geographically diverse sample of real-world sessions, 5 session-level emotional trajectory types were identified, with stable and reduced distress trajectories accounting for the largest shares of sessions. Among sessions beginning in AI-derived distress states, nearly three-quarters (1170/1597, 73.3% of those with available session duration data) demonstrated reduced distress trajectories by the end of the session, and these sessions were characterized by more unique AI-derived emotional states, more AI-derived emotional switches, and longer session duration relative to sessions with persistent distress trajectories. Unique AI-derived emotional states and session duration were positively associated with reduced distress trajectories, while AI-derived emotional switches were negatively associated with reduced distress trajectories.

Comparison With Prior Work

Yuna users were primarily female, consistent with broader patterns of female overrepresentation observed in real-world DMHI samples [28]. Most users were located in the United States, although the sample spanned 104 countries and 30 languages, consistent with evidence that AI-powered DMHIs may appeal to a broad, globally distributed user base [29]. Cognitive processing states were the most frequently observed AI-derived emotional category, accounting for over one-third of all message-level observations, followed closely by AI-derived distress-associated states. This distribution is consistent with theoretical accounts of AI-powered DMHI engagement, in which users are expected to alternate between expressing distress and engaging in reflective, meaning-making processes. The relatively higher proportion of AI-derived cognitive processing states may suggest that sessions were characterized more by active processing than by sustained AI-derived distress [7], although this interpretation should be made with caution given that the AI-derived emotional states are model derived rather than self-reported. At the session level, stable and reduced distress trajectories were the most common AI-derived trajectory types, together accounting for approximately half of all sessions, broadly consistent with evidence that engagement with AI-powered DMHIs may be associated with positive emotional and symptomatic outcomes [7,30]. While the present study cannot establish clinical improvement as trajectory types reflect AI-derived behavioral patterns rather than validated symptom outcomes, the prevalence of stable and reduced distress trajectories across sessions suggests that most users did not end the sessions in a worse AI-derived emotional state than they began. Of those who presented with escalating distress trajectories, it is important to note that this classification reflects a session-level categorical

XSL•FO
RenderX

transition toward distress-associated linguistic patterns by session end rather than an indication of clinical deterioration or crisis-level distress. Users beginning sessions in neutral or positive states may naturally shift toward distress-associated states as they engage with emotionally salient content, which may reflect adaptive emotional processing rather than worsening [31,32]. Future research should examine whether AI-derived trajectory types correspond to user-reported emotional outcomes within the same session, which would strengthen the reliability of AI-derived emotional trajectories.

Among sessions beginning in AI-derived distress states, approximately three-quarters (1170/1597, 73.3% of those with available session duration data) demonstrated reduced distress trajectories by the end of the session. This suggests that AI-powered DMHIs such as Yuna may be associated with movement away from AI-derived distress, which is encouraging for the potential utility of these tools in real-world mental health contexts [7]. However, it is important to note that sessions beginning in AI-derived distress-associated states have a constrained range of possible trajectories. By definition, they cannot begin in a worse AI-derived emotional state than distress, making upward movement more likely regardless of intervention. This directional constraint is analogous to regression to the mean and should be considered when interpreting the proportion of reduced distress sessions. Moreover, given that trajectory types reflect AI-derived behavioral patterns rather than validated self-reported outcomes, direct conclusions about user emotional experience or clinical benefit cannot be drawn from these data alone. Sessions characterized by reduced distress trajectories presented with more unique AI-derived emotional states, more AI-derived emotional switches, and longer session duration relative to persistent distress sessions, although effect sizes for all 3 engagement variables were small. Notably, the direction of the association between AI-derived emotional switching and trajectory type differed across analyses. While reduced distress sessions showed more switching on average in the unadjusted group comparisons, switching was negatively associated with reduced distress trajectories in mixed-effects logistic regression after accounting for emotional diversity and session duration, suggesting that the relationship between switching and trajectory outcome is not independent of other session characteristics. Higher proportions of AI-derived cognitive processing states such as contemplation and interest may reflect movement from distress toward reflective engagement, consistent with theoretical accounts in which cognitive engagement is considered an active component of distress reduction [33,34]. Similarly, higher proportions of AI-derived regulated positive states such as calmness may reflect movement toward affective stabilization within the session. These patterns are consistent with session-level emotional conditions that have been theorized to accompany distress reduction, although the observational design and AI-derived nature of the emotional states preclude any direct mapping onto established therapeutic mechanisms. Whether these AI-derived patterns reflect genuine therapeutic processes, user behavioral tendencies, or artifacts of the emotion detection model cannot be determined from the present data alone.

Mixed-effects logistic regression analyses identified 3 conversational features associated with reduced distress trajectories among sessions beginning in AI-derived distress states. A greater number of unique AI-derived emotional states was positively associated with reduced distress trajectories, consistent with theoretical accounts in which access to a range of emotional states is considered a marker of productive emotional processing rather than sustained focus on a single state [33]. Longer session duration was also positively associated with reduced distress trajectories, consistent with evidence that greater engagement with DMHIs is associated with fuller realization of therapeutic benefits [35]. The low-barrier, on-demand nature of AI-powered DMHIs such as Yuna may support this kind of sustained emotional engagement as users can interact at moments of heightened emotional salience without the scheduling or stigma barriers of traditional care, although causal claims cannot be made from observational data. In contrast, a greater number of AI-derived emotional switches was negatively associated with reduced distress trajectories after accounting for unique AI-derived emotional states and session duration. The interpretation of this finding is less straightforward. More AI-derived emotional switching could reflect emotional instability or dysregulation but may alternatively reflect active emotional processing that did not resolve within the session window. Accounts linking rumination and emotional reactivity to sustained distress offer one plausible theoretical frame [36,37], but this explanation remains speculative in the absence of concurrent self-report data [38,39]. The clinical meaning of emotional switching in AI-powered sessions requires prospective examination. Future research should examine whether patterns of AI-derived emotional switching correspond to self-reported emotional experience or clinician-rated markers of dysregulation, which would clarify the clinical relevance of these AI-derived emotional states.

Implications

This study contributes to an emerging body of work demonstrating that AI-derived emotional states may capture meaningful behavioral patterns in mental health contexts without requiring clinical outcome data [40,41]. Rather than treating AI-derived emotional states as ground-truth representations of internal experience, the present study operationalizes them as behavioral proxies that vary systematically with session-level conversational features. This framing positions AI-derived emotional trajectory analysis as a process-level complement to traditional pretest-posttest evaluation, addressing a widely noted gap in DMHI research. As AI-powered platforms scale to serve large, geographically diverse populations, the capacity to characterize emotional dynamics at the session level without burdening users with additional self-report measures is a meaningful methodological advance. These findings suggest that AI-derived emotional trajectory data may offer a scalable, low-burden signal for understanding engagement quality in real-world mental health contexts. For platforms such as Yuna operating across large, geographically diverse populations, this capacity has practical implications for platform monitoring, early safety surveillance, and the design of future process-level research that moves beyond pretest-posttest symptom end points

XSL•FO
RenderX

toward understanding how and when change occurs within sessions.

Strengths and Limitations

This study had several strengths. First, the use of AI-derived emotional states to characterize session-level emotional trajectory types is a methodological advance in process-level evaluation of AI-powered DMHIs, providing a novel empirical foundation for understanding how emotional patterns unfold within real-world mental health sessions rather than relying solely on pretest-posttest symptom outcomes. Second, the large, naturalistic sample of 28,870 sessions contributed by 4463 users across 104 countries enhances the generalizability of these findings and reflects the real-world diversity of individuals who engage with AI-powered DMHIs. Third, the AI emotion detection framework underlying Yuna's emotional state classifications is grounded in a peer-reviewed, empirically validated emotion detection approach [24], although independent validation of Yuna's specific implementation remains an important gap.

This study also had limitations. First, the observational design lacked a control group, precluding causal inference about the role of AI-powered engagement in producing the observed trajectory patterns. Future research using experimental designs is needed to isolate platform contributions to session-level AI-derived emotional patterns. Second, AI-derived emotional states are model-generated signals that have not been independently validated against self-reported emotional experience in this sample. Without concurrent self-report data, it is not possible to confirm that AI-derived trajectory classifications correspond to how users actually experienced the session emotionally. Future research should incorporate within-session self-report measures to establish the correspondence between AI-derived and user-reported emotional experience. Third, the 5 trajectory types were operationalized based on session-level starting and ending AI-derived emotional categories, which, while transparent and reproducible, may not capture the full complexity of AI-derived emotional dynamics within a session. Alternative operationalizations such as latent trajectory modeling or time-series approaches may yield different AI-derived emotional trajectory types, and replication using different classification approaches is warranted. Fourth, missing data, particularly for session duration and demographic variables, were extensive. Missing data are a common limitation of retrospective, real-world studies of commercial DMHIs; data collection often varies across platform type, back-end structure, and user priorities, resulting in incomplete data capture across variables [42]. Sessions missing duration data differed systematically from complete sessions, showing fewer messages and less emotional variability. Although the direction and significance of regression results were robust to inclusion of sessions with missing duration data, the associations were larger in magnitude in the full sample available than in the complete-case sample. This suggests that restricting the primary analyses to sessions with duration data may have attenuated the magnitude of these associations relative to all distress-starting sessions. Similarly, demographic data were substantially missing. As a result, the ability to characterize the sample fully or examine whether trajectory patterns varied across demographic subgroups was limited. Missingness analyses revealed small to moderate differences in key variables between those with and without complete demographic data. Additionally, response options to "What is your gender?" aligned with biological sex (eg, male or female) rather than gender identity; this conflation of sex and gender limits the interpretability of this variable. Future research should distinguish sex and gender as constructs; use response options appropriate to whichever is being measured; and examine whether AI-derived trajectory patterns differ across age, gender, and location. Fifth, this study could not account for a range of potentially confounding user-level characteristics. Baseline mental health severity, prior treatment history, length of time using the platform, and prior engagement history were not available in the dataset, and each could plausibly influence both how users engage conversationally and the emotional trajectories their sessions follow. The associations reported here should therefore be read as descriptive rather than as evidence of a specific mechanism. Sixth, and relatedly, the trajectories analyzed here are outputs of a single proprietary classification model. Apparent shifts between emotional categories may partly reflect properties of that model, including its sensitivity to particular lexical cues, its behavior on short or ambiguous messages, and any systematic drift in classification across the course of a conversation rather than genuine psychological change in users. Distinguishing model behavior from user experience will require validation against concurrent self-report.

Conclusions

This study provides a novel, exploratory characterization of AI-derived emotional state patterns and session-level trajectory types across a large, geographically diverse sample of real-world users of Yuna, an AI-powered DMHI. Most sessions were characterized by stable or reduced AI-derived distress trajectories, and sessions beginning in AI-derived distress most commonly moved toward nondistress states by session end. A greater number of unique AI-derived emotional states and longer session duration were positively associated with reduced distress trajectories, while more AI-derived emotional switching was negatively associated with reduced distress trajectories. Importantly, the trajectory types described here are AI-derived behavioral indicators generated by a proprietary emotion classification model; they are not validated clinical outcomes and should not be interpreted as evidence of symptom change or therapeutic benefit. With that constraint in mind, these findings lay an empirical foundation for process-level evaluation of AI-powered DMHIs and point toward session-level AI-derived emotional patterns as a potential avenue for understanding how these tools may support users in distress. Future research incorporating self-report measures, longitudinal designs, and experimental methods is needed to evaluate whether AI-derived emotional trajectory patterns carry a meaningful signal for user outcomes in real-world mental health contexts.

XSL•FO
RenderX

Acknowledgments

All content was written and approved by the authors, and all authors take full responsibility for the integrity and accuracy of the content presented.

Funding

Retrospective deidentified data were provided by Yuna as part of an ongoing scientific partnership with Fit Minded. Fit Minded received compensation for services rendered as the embedded scientific team for Yuna independent of the conduct or outcomes of this research. The funder did not have a role in the design of the study, analysis, or interpretation of the data.

Data Availability

The dataset used for this retrospective analysis is not publicly available given Yuna's privacy policy for patient data. However, aggregated and anonymized data may be shared with interested parties on reasonable request.

Generative AI Use

The authors used Claude (Opus 5.5; Anthropic) in a limited capacity during the preparation of this manuscript, including to review and confirm editorial changes and language revisions. Generative AI was not used to generate, draft, or substantively write any portion of the manuscript.

Authors' Contributions

Conceptualization: CJ
Formal analysis: CJ, LH
Methodology: CJ, KM, LH
Supervision: JH
Writing—original draft: CJ, EK
Writing—review and editing: CJ, KM, LH, EK, JH
All authors contributed substantially to the manuscript and had final approval.

Conflicts of Interest

Fit Minded served as the embedded scientific team for Yuna and received compensation for those services. JH is the founder and chief executive officer of Fit Minded, and KM, CJ, LH, and EK are employees of Fit Minded. No author's employment status or compensation is contingent upon the direction or outcome of the findings.

Multimedia Appendix 1

STROBE checklist.
[DOCX File , 12 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Classification of AI-derived emotional states into higher-order emotional categories.
[DOCX File , 7 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Comparison of users with and without complete demographic data.
[DOCX File , 8 KB-Multimedia Appendix 3]

Multimedia Appendix 4

Frequencies of AI-derived emotional states.
[DOCX File , 8 KB-Multimedia Appendix 4]

Multimedia Appendix 5

Comparison of sessions with and without session duration data.
[DOCX File , 9 KB-Multimedia Appendix 5]

References

XSL•FO
RenderX

1. de Oliveira C, Saka M, Bone L, Jacobs R. The role of mental health on workplace productivity: a critical review of the literature. Appl Health Econ Health Policy. Mar 2023;21(2):167-193. [FREE Full text] [doi: 10.1007/s40258-022-00761-w] [Medline: 36376610]
2. Workplace mental health & well-being. U.S. Department of Health and Human Services. 2022. URL: https://www.hhs.gov/surgeongeneral/reports-and-publications/workplace-well-being/index.html [accessed 2026-03-23]
3. Qureshi N, Huilgol SS, Timmins G, Meredith LS, Gidengil CA. Misaligned supports: differences in reported health care worker well-being supports provided and needed during the COVID-19 pandemic. Am J Health Promot. Jan 2025;39(1):63-75. [doi: 10.1177/08901171241255764] [Medline: 38907369]
4. Moore JT, Wigington C, Green J, Horter L, Kone A, Lopes-Cardozo B, et al. Understanding low utilization of employee assistance programs and time off by US public health workers during the COVID-19 pandemic. Public Health Rep. 2023;138(4):645-654. [FREE Full text] [doi: 10.1177/00333549231165287] [Medline: 37052332]
5. Long T. Why are employee assistance programmes under‐utilised and marginalised and how to address it? A critical review and a labour process analysis. Hum Resour Manag J. Mar 07, 2024;34(4):1134-1153. [doi: 10.1111/1748-8583.12547]
6. Gutierrez G, Stephenson C, Eadie J, Asadpour K, Alavi N. Examining the role of AI technology in online mental healthcare: opportunities, challenges, and implications, a mixed-methods review. Front Psychiatry. May 07, 2024;15:1356773. [FREE Full text] [doi: 10.3389/fpsyt.2024.1356773] [Medline: 38774435]
7. Li H, Zhang R, Lee YC, Kraut RE, Mohr DC. Systematic review and meta-analysis of AI-based conversational agents for promoting mental health and well-being. NPJ Digit Med. Dec 19, 2023;6(1):236. [FREE Full text] [doi: 10.1038/s41746-023-00979-5] [Medline: 38114588]
8. Haque MD, Rubya S. An overview of chatbot-based mobile mental health apps: insights from app description and user reviews. JMIR Mhealth Uhealth. May 22, 2023;11:e44838. [FREE Full text] [doi: 10.2196/44838] [Medline: 37213181]
9. Vaidyam AN, Wisniewski H, Halamka JD, Kashavan MS, Torous JB. Chatbots and conversational agents in mental health: a review of the psychiatric landscape. Can J Psychiatry. Jul 2019;64(7):456-464. [FREE Full text] [doi: 10.1177/0706743719828977] [Medline: 30897957]
10. Hopkin G, Branson R, Campbell P, Coole H, Cooper S, Edelmann F, et al. Considerations for regulation and evaluation of digital mental health technologies. Digit Health. Nov 04, 2024;10:20552076241293313. [FREE Full text] [doi: 10.1177/20552076241293313] [Medline: 39502489]
11. Balcombe L, De Leo D. Evaluation of the use of digital mental health platforms and interventions: scoping review. Int J Environ Res Public Health. Dec 26, 2022;20(1):362. [FREE Full text] [doi: 10.3390/ijerph20010362] [Medline: 36612685]
12. Wang L, Bhanushali T, Huang Z, Yang J, Badami S, Hightow-Weidman L. Evaluating generative AI in mental health: systematic review of capabilities and limitations. JMIR Ment Health. May 15, 2025;12:e70014. [FREE Full text] [doi: 10.2196/70014] [Medline: 40373033]
13. Cho HN, Wang J, Hu D, Zheng K. Large language model-based chatbots and agentic AI for mental health counseling: systematic review of methodologies, evaluation frameworks, and ethical safeguards. JMIR AI. Mar 13, 2026;5:e80348. [FREE Full text] [doi: 10.2196/80348] [Medline: 41592221]
14. Palmieri A, Fernandez KC, Cariolato Y, Kleinbub JR, Salvatore S, Gross JJ. Emotion regulation in psychodynamic and cognitive-behavioural therapy: an integrative perspective. Clin Neuropsychiatry. Apr 2022;19(2):103-113. [FREE Full text] [doi: 10.36131/cnfioritieditore20220204] [Medline: 35601247]
15. Giotakos O. Artificial intelligence-based psychotherapy: focusing on common psychotherapeutic factors. Front Psychiatry. Nov 11, 2025;16:1710715. [FREE Full text] [doi: 10.3389/fpsyt.2025.1710715] [Medline: 41306320]
16. Missirlian TM, Toukmanian SG, Warwar SH, Greenberg LS. Emotional arousal, client perceptual processing, and the working alliance in experiential psychotherapy for depression. J Consult Clin Psychol. Oct 2005;73(5):861-871. [doi: 10.1037/0022-006X.73.5.861] [Medline: 16287386]
17. Watson JC, McMullen EJ, Prosser MC, Bedard DL. An examination of the relationships among clients' affect regulation, in-session emotional processing, the working alliance, and outcome. Psychother Res. Jan 2011;21(1):86-96. [doi: 10.1080/10503307.2010.518637] [Medline: 21086216]
18. Catania J, Beaver S, Kamath RS, Worthington E, Lu M, Gandhi H, et al. Evaluation of digital mental health technologies in the United States: systematic literature review and framework synthesis. JMIR Ment Health. Aug 30, 2024;11:e57401. [FREE Full text] [doi: 10.2196/57401] [Medline: 39213023]
19. Guo Z, Lai A, Thygesen JH, Farrington J, Keen T, Li K. Large language models for mental health applications: systematic review. JMIR Ment Health. Oct 18, 2024;11:e57400. [FREE Full text] [doi: 10.2196/57400] [Medline: 39423368]
20. Lalk C, Targan K, Steinbrenner T, Schaffrath J, Eberhardt S, Schwartz B, et al. Employing large language models for emotion detection in psychotherapy transcripts. Front Psychiatry. May 9, 2025;16:1504306. [FREE Full text] [doi: 10.3389/fpsyt.2025.1504306] [Medline: 40417271]
21. Tanana MJ, Soma CS, Kuo PB, Bertagnolli NM, Dembe A, Pace BT, et al. How do you feel? Using natural language processing to automatically rate emotion in psychotherapy. Behav Res Methods. Oct 2021;53(5):2069-2082. [FREE Full text] [doi: 10.3758/s13428-020-01531-z] [Medline: 33754322]

XSL•FO
RenderX

22. von Elm E, Altman DG, Egger M, Pocock SJ, Gøtzsche PC, Vandenbroucke JP. The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement: guidelines for reporting observational studies. PLoS Med. Oct 16, 2007;4(10):e296. [FREE Full text] [doi: 10.1371/journal.pmed.0040296] [Medline: 17941714]
23. Cowen AS, Keltner D. Semantic space theory: a computational approach to emotion. Trends Cogn Sci. Feb 2021;25(2):124-136. [doi: 10.1016/j.tics.2020.11.004] [Medline: 33349547]
24. Keltner D, Brooks JA, Cowen A. Semantic space theory: data-driven insights into basic emotions. Curr Dir Psychol Sci. Apr 11, 2023;32(3):242-249. [doi: 10.1177/09637214221150511]
25. Aldao A, Nolen-Hoeksema S, Schweizer S. Emotion-regulation strategies across psychopathology: a meta-analytic review. Clin Psychol Rev. Mar 2010;30(2):217-237. [doi: 10.1016/j.cpr.2009.11.004] [Medline: 20015584]
26. Greenberg LS, Pascual-Leone A. Emotion in psychotherapy: a practice-friendly research review. J Clin Psychol. May 2006;62(5):611-630. [doi: 10.1002/jclp.20252] [Medline: 16523500]
27. Lin J, De Silva AP, Falster M, Dobbins T, Chen Y, Zhang Z, et al. Addressing missing data in real-world administrative health datasets. Eur J Cardiovasc Nurs. Jun 16, 2026;25(3):632-639. [FREE Full text] [doi: 10.1093/eurjcn/zvag018] [Medline: 41554108]
28. Ryan AT, Stearns-Yoder KA, Brenner LA. Real-world user demographics of three web-based digital mental health interventions provided by the US Department of Veterans Affairs: observational study using web analytics data. JMIR Form Res. Oct 18, 2023;7:e48365. [FREE Full text] [doi: 10.2196/48365] [Medline: 37851501]
29. Su L, Anderson PL. User behavior of a publicly available, free-to-use, self-guided mHealth app for depression: observational study in a global sample. JMIR Form Res. Oct 25, 2022;6(10):e35538. [FREE Full text] [doi: 10.2196/35538] [Medline: 36282559]
30. Farzan M, Ebrahimi H, Pourali M, Sabeti F. Artificial intelligence-powered cognitive behavioral therapy chatbots, a systematic review. Iran J Psychiatry. Jan 2025;20(1):102-110. [doi: 10.18502/ijps.v20i1.17395] [Medline: 40093525]
31. Stiles WB, Leiman M, Shapiro DA, Hardy GE, Barkham M, Detert NB, et al. What does the first exchange tell? Dialogical sequence analysis and assimilation in very brief therapy. Psychother Res. 2006;16(4):408-421. [doi: 10.1080/10503300500288829]
32. Timulak L, Keogh D, Chigwedere C, Wilson C, Ward F, Hevey D, et al. A comparison of emotion-focused therapy and cognitive-behavioral therapy in the treatment of Generalized Anxiety Disorder: results of a feasibility randomized controlled trial. Psychotherapy (Chic). Mar 2022;59(1):84-95. [doi: 10.1037/pst0000427] [Medline: 35113639]
33. de Felice G, Giuliani A, Andreassi S, Orsucci F, Schöller H, Aichhorn W, et al. Integration of cognitive and emotional processing predicts poor and good outcomes of psychotherapy. J Contemp Psychother. Sep 23, 2021;52:117-125. [doi: 10.1007/s10879-021-09519-2]
34. Greenberg LS. Emotion–focused therapy. Clin Psychol Psychother. Jan 29, 2004;11(1):3-16. [FREE Full text] [doi: 10.1002/cpp.388]
35. Linardon J, Fuller-Tyszkiewicz M. Attrition and adherence in smartphone-delivered interventions for mental health problems: a systematic and meta-analytic review. J Consult Clin Psychol. Jan 2020;88(1):1-13. [doi: 10.1037/ccp0000459] [Medline: 31697093]
36. LeMoult J, Arditte KA, D'Avanzato C, Joormann J. State rumination: associations with emotional stress reactivity and attention biases. J Exp Psychopathol. 2013;4(5):471-484. [FREE Full text] [doi: 10.5127/jep.029112] [Medline: 25431652]
37. Singh S, Li B, Gerhard S, Nunes A, Becker S. Emotional modulation of inhibitory control in rumination from empirical and computational perspectives. Cogn Affect Behav Neurosci. Feb 2026;26(1):64-88. [doi: 10.3758/s13415-025-01360-7] [Medline: 41168557]
38. Misic V, Vukosavljevic Gvozden T, Batinic B. The impact of ruminative thought style on the maintenance of depressive mood. Eur Psychiatry. Aug 27, 2024;67(Suppl 1):S257. [doi: 10.1192/j.eurpsy.2024.544]
39. Jadhakhan F, Blake H, Hett D, Marwaha S. Efficacy of digital technologies aimed at enhancing emotion regulation skills: literature review. Front Psychiatry. Sep 07, 2022;13:809332. [FREE Full text] [doi: 10.3389/fpsyt.2022.809332] [Medline: 36159937]
40. Steppan M, Zimmermann R, Fürer L, Southward M, Koenig J, Kaess M, et al. Machine learning facial emotion classifiers in psychotherapy research: a proof-of-concept study. Psychopathology. 2024;57(3):159-168. [FREE Full text] [doi: 10.1159/000534811] [Medline: 38011846]
41. Terhürne P, Schwartz B, Baur T, Schiller D, Eberhardt ST, André E, et al. Validation and application of the Non-Verbal Behavior Analyzer: an automated tool to assess non-verbal emotional expressions in psychotherapy. Front Psychiatry. Oct 28, 2022;13:1026015. [FREE Full text] [doi: 10.3389/fpsyt.2022.1026015] [Medline: 36386975]
42. Liu F, Panagiotakos D. Real-world data: a brief review of the methods, applications, challenges and opportunities. BMC Med Res Methodol. Nov 05, 2022;22(1):287. [FREE Full text] [doi: 10.1186/s12874-022-01768-6] [Medline: 36335315]

Abbreviations

DMHI: digital mental health intervention
OR: odds ratio

XSL•FO
RenderX

STROBE: Strengthening the Reporting of Observational Studies in Epidemiology

Edited by L MacNeill; submitted 10.Jun.2026; peer-reviewed by R Izadi; comments to author 10.Jul.2026; revised version received 19.Oct.2026; accepted 20.Oct.2026; published 10.Nov.2026

Please cite as:
McAlister K, Jewell C, Huffman L, Knight E, Huberty J
AI-Derived Emotional States and Trajectories in Real-World Mental Health Sessions: Large-Scale Observational Study
JMIR Form Res 2026;10:e104318
URL: https://formative.jmir.org/2026/1/e104318
doi: 10.2196/104318
PMID:

©Kelsey McAlister, Courtney Jewell, Landry Huffman, Elizabeth Knight, Jennifer Huberty. Originally published in JMIR Formative Research (https://formative.jmir.org), 10.Nov.2026. This is an open-access article distributed under the terms of the Creative Commons Attribution License (https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work, first published in JMIR Formative Research, is properly cited. The complete bibliographic information, a link to the original publication on https://formative.jmir.org, as well as this copyright and license information must be included.

XSL•FO
RenderX