# Dynamic Prediction of Depressive States by Stress Processes: A Multilayer Decision Tree Approach

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## Abstract

In recent years, the importance of depression risk prediction has become increasingly apparent. While previous research has primarily examined risk factors for depression at the between-individual level, this study focuses on the within-individual level, integrating the critical factor of stress and the daily stress process model to construct a dynamic prediction model of how the stress process influences depressive states. Using ecological momentary assessment data collected from 356 college students over 7 days (5 times per day) and employing a multilevel decision tree machine learning algorithm, the study revealed that: (1) a model incorporating anxious negative affect, stressors, and rumination accurately predicts individuals' subsequent (three hours later) presence or absence of depressive states; (2) in prediction models excluding emotion, integrating current and anticipated stress coping, rumination, physical discomfort, and subjective stress perception also enables effective prediction of depressive states; (3) multiple components of the stress process accumulate within individuals and jointly predict subsequent depression risk; and (4) dynamic indicators such as cumulative mean and deviation values of the stress process make important contributions to depression prediction. This study develops a real-time early warning tool for depression risk from a dynamic perspective, reveals the complex combinations and influence pathways through which multiple stress process factors synergistically predict depression risk, and deepens understanding of the complex predictive mechanisms underlying the stress process's impact on depressive states.

## Full Text

## Preamble

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**1. Does this study represent a significant contribution?** *Acta Psychologica Sinica* aims to publish psychological research that is "both scientifically excellent and of particularly broad interest and significance." Studies with only minor incremental contributions, those that do not attempt to open new areas of inquiry or propose unique and innovative perspectives, or those that purely examine algorithms or techniques without clear psychological questions, have low acceptance probability and are recommended for submission elsewhere. This study makes three key contributions: (1) **Dynamic prediction**: Combining multilevel decision trees with ecological momentary assessment to construct a dynamic prediction model of college students' daily stress processes on depressive states, developing a real-time early warning tool for depression risk from a dynamic perspective, and deepening understanding of the complex predictive mechanisms through which stress processes influence depressive states. (2) **Integrated investigation**: Integrating multiple stress process factors to systematically examine the complex combinations and influence pathways through which different factors synergistically predict depression risk, advancing the development of cumulative risk theory in stress processes. (3) **Indicator expansion**: Revealing the unique contributions of dynamic indicators such as cumulative means and deviations of stress processes to depression prediction, innovatively expanding approaches to constructing dynamic prediction indicators.

**2. Have you published or submitted articles using the same data?** If yes, please attach them for review. (We do not encourage publishing multiple articles with the same variables from one dataset, nor splitting a series of related studies into multiple publications.)
**Answer**: An article titled *A Dynamic Bidirectional System of Stress Processes: Feedback Loops Between Stressors, Psychological Distress, and Physical Symptoms* has been accepted by *Health Psychology* and uses the same data. This article primarily examines the bidirectional feedback loops between daily stressors, psychological distress, and physical symptoms from a dynamic systems perspective, which differs in purpose and methodology from the current study. The article has been typeset and is attached for review (https://doi.org/10.1037/hea0001414).

**3. For non-experimental, non-intervention studies in management, clinical, personality, and social psychology that rely solely on self-report (questionnaire) methods, it is necessary to examine whether common method bias exists. What methods did you use to control or demonstrate that such bias would not affect the validity of your conclusions?** (For relevant literature on common method bias, see: http://journal.psych.ac.cn/xlkxjz/CN/abstract/abstract894.shtml) Studies based on cross-sectional data with only self-reports and convenient samples are easy to conduct but typically have limited innovative value and low acceptance probability.

**Answer**: This study collected intensive longitudinal data using self-report methods. During data collection, we attempted to control and minimize common method bias. For instance, we assured participants in each questionnaire that their data would be used solely for scientific research and would be kept strictly confidential. In data analysis, we examined the predictive effect of daily stress processes on subsequent depressive states, focusing on lagged effects, which can reduce the impact of common method bias on results. Given that existing common method bias testing methods are not suitable for multilevel time-series data in intensive longitudinal studies, and that methodological guidance for testing common method bias in such data is still lacking, this study did not conduct statistical tests for common method bias risk.

**4. Did you report and analyze effect sizes?** (e.g., Cohen's d for t-tests, $^2$ or $^2$p for ANOVA) Many studies mechanically report effect sizes without necessary analysis or explanation (e.g., whether the effect size is small, medium, or large, or its theoretical/applied significance). (Searching "effect size calculator" on Google yields many convenient apps. For Chinese explanations of effect sizes, see: http://journal.psych.ac.cn/xlkxjz/CN/abstract/abstract1150.shtml; for English, see: http://www.uccs.edu/lbecker/effect-size.html) Did you report 95% CIs for statistical analyses? (e.g., 95% CI for differences, correlation/regression coefficients) For calculations and plotting of confidence intervals, see https://thenewstatistics.com/itns/esci/
**Answer**: This study used the generalized linear mixed model (GLMM) tree machine learning algorithm to construct a dynamic prediction model for depressive states (a binary variable). Following previous machine learning research, we reported and analyzed commonly used effect size indicators including sensitivity, specificity, and area under the ROC curve (AUC).

**5. Please state your planned and actual sample sizes. If they differ, please explain why.** Low statistical power due to insufficient sample sizes is a widespread problem in psychological research. We recommend explaining the basis for your sample size determination in the Methods section. Sample size should be determined based on a justified effect size and desired power, with software or programs used for calculation reported. For guidance on sample size planning, see https://osf.io/5awp4/
**Answer**: As effective sample size planning methods and tools for the GLMM tree machine learning algorithm are still lacking, this study referenced previous intensive longitudinal research to determine sample size (including number of participants and repeated observations). The study ultimately collected 11,288 valid data points, exceeding previous depression prediction studies (e.g., De la Barrera et al. (2024) collected 1,233 valid data points).

**6. The journal requires reporting of exact p-values (except when p < 0.001, which should be reported as an interval). Does your paper meet this requirement? If using Bayes factors, have you reported their sensitivity to prior distribution assumptions?**
**Answer**: This study conducted null hypothesis significance testing in two

places: (1) Correlation analysis at between-person and within-person levels. The p-values for these correlations were either $< 0.001$ or $> 0.05$ (non-significant), so we reported p-value intervals (e.g., $p < 0.001$). (2) When iteratively fitting generalized linear model (GLM) trees without random effects to obtain partitioning results, we conducted hypothesis tests for parameter instability of each potential partitioning variable, as described in Zeileis et al. (2008) and Fokkema et al. (2018). We recorded p-values for all partitioning variables in the final GLMM tree, but since all p-values were $< 0.001$, we reported p-value intervals ($p < 0.001$).

**7. To ensure completeness of data reporting, if you excluded data in statistical analyses, did you report this in the text? What were the reasons? How would results change if those data were included? How did you handle missing data? Did you delete individual items when using scales? Why? How would results change if those items were included? Were there any measured items or variables not reported? Why? Please indicate where in the paper this is addressed.**
**Answer**: (1) No data were excluded in statistical analyses. (2) Missing data handling: Due to the temporal dependency in intensive longitudinal data, we used the imputeTS package (Moritz & Bartz-Beielstein, 2017) in R 4.2.2 (R Core Team, 2021) to impute missing values using Kalman filtering for time-series dependent data. This is described in the "2.3.1 Data Preparation" section. (3) No items were deleted when using scales, and no measured items or variables were left unreported.

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## Dynamic Prediction of Depressive States Using Stress Processes: A Multilevel Decision Tree Approach

### Abstract

The importance of predicting depressive risk has become increasingly prominent in recent years. Previous research has primarily examined risk factors for depression at the inter-individual level, whereas this study focuses on the intra-individual level. By integrating the critical factor of stress and the daily stress process model, we constructed a dynamic prediction model of depressive states using stress processes. Ecological momentary assessment data were collected from 356 college students over seven days (five times per day). Using a multilevel decision tree machine learning algorithm, we found that: (1) a model incorporating distress negative emotion, stressors, and rumination accurately predicted whether individuals would experience depressive states three hours later; (2) even without emotional variables, a model integrating current and anticipated stress coping, rumination, physical discomfort, and perceived stress could effectively predict depressive states; (3) multiple components of the stress process cumulatively impact individuals, jointly predicting subsequent depression risk; and (4) dynamic indicators such as cumulative means and deviations of stress processes made important contributions to depression prediction. This study develops a real-time early warning tool for depression risk from a dynamic perspective, reveals the complex combinations and influence pathways through which multiple stress process factors synergistically predict depression risk, and deepens understanding of the complex predictive mechanisms underlying stress processes' effects on depressive states.

**Keywords**: stress process, depression, multilevel decision tree, ecological momentary assessment
**Classification Code**: B848

Depression has become an increasingly prevalent mental health problem in recent years. According to a World Health Organization (WHO; 2023) survey, approximately 5% of adults worldwide (about 280 million people) suffer from depression. The *2023 Blue Book on Mental Health in China* reports that 10.6% of Chinese adults are at risk for depression. Evidently, depression has emerged as a prominent and urgent issue amid modern life stressors. Many researchers have noted that prevention represents one of the most effective strategies for addressing depression (Dong et al., 2020; Zhang et al., 2023), which requires accurate prediction of depressive states in potential patients to enable timely preventive interventions.

Extensive research has demonstrated that stress is a significant predictor of depression (Hammen, 2005, 2015; Vrshek-Schallhorn et al., 2020). Early studies primarily focused on moderating factors in the stress-depression relationship, examining inter-individual differences to identify individuals at high risk for depression (Hammen, 2005, 2015). With advances in data collection technologies and statistical methods, an increasing number of studies have employed diary methods or ecological momentary assessment to collect intensive longitudinal data, investigating the dynamic associations between daily stressors and depressive states at the intra-individual level (Connolly & Alloy, 2017; Fuller-Tyszkiewicz et al., 2017; Luo et al., in press), and revealing multiple stress process factors that importantly predict depressive states. However, previous research has often focused on partial aspects of the daily stress process, lacking integrated examination of various stress processes' predictive effects (Almeida, 2024). Consequently, the multiple pathways and complex mechanisms through which daily stress processes predict depressive states remain to be systematically investigated. More importantly, although existing studies have employed machine learning algorithms to improve depression prediction accuracy (Sau & Bhakta, 2019; De la Barrera et al., 2024), these prediction models have primarily been used to identify individuals at high risk for depression, without examining the intra-individual dynamic processes of depressive states. Given that fluctuations in individuals' depressive states can effectively guide clinical practice in answering the key questions of "when to intervene" and "for whom to intervene," it is necessary to collect intensive longitudinal data and employ appropriate machine learning algorithms to construct dynamic prediction models of depressive states using stress processes.

### 1.1 The Relationship Between Stress Processes and Depression

From a dynamic perspective on stress, Almeida (2024) proposed the Daily Stress Process Model, which systematically organizes multiple components related to daily stress. Various components of the stress process (see Figure 1 [Figure 1: see original paper]) have been found to be dynamically associated with depressive states. The first stage of the stress process is stressor exposure, which is closely related to dynamic changes in individuals' depressive states. Previous research has found that stressors across various domains (e.g., family, school, and peers; Kiang & Buchanan, 2014) and types (e.g., interpersonal stressors; Flook, 2011) have significant positive concurrent associations with individuals' daily depressive states (Goldring & Bolger, 2021). Other studies have found that after encountering stressors, individuals show higher depression levels in subsequent time periods (several hours later), indicating that stressors also have lagged predictive effects on depressive states (Kang et al., 2023; Luo et al., in press).

**Figure 1**. Daily stress processes related to depressive states (adapted from Almeida (2024))

The second stage of the stress process is stress appraisal, which plays an important role in predicting individuals' depressive states (Fuller-Tyszkiewicz et al., 2017). Assessing subjective stress perceptions helps distinguish individuals who experience equal numbers of objective stress events but differ in subjective intensity (Baker et al., 2020). Beyond objective stress events, individuals' subjective stress perceptions make unique contributions to predicting depressive states. For example, Zawadzki et al. (2022) found that subjective stress appraisal consistently and significantly predicted individuals' daily feelings of sadness, loneliness, and anxiety, whereas objective stress events could not significantly predict these feelings.

The third stage of the stress process is stress reactivity, which can be divided into emotional, cognitive, behavioral, and physiological aspects. Regarding emotion, extensive research indicates that emotional reactivity to stress importantly predicts depressive symptoms. The average levels of positive and negative affect based on repeated within-person measurements are closely related to individuals' depressive symptoms (Cooke et al., 2022; Merz & Roesch, 2011), and lower positive affect (Rackoff & Newman, 2020) and higher negative affect (Charles et al., 2013; Parrish et al., 2011; Starr et al., 2023) following daily stressors significantly predict depressive symptoms months or even years later. Regarding cognition, the cognitive vulnerability-stress model of depression (Abramson et al., 1989; Beck, 2002) posits that individuals' cognitive vulnerability interacts with experienced stressors to jointly influence depressive symptoms. Rumination is a typical cognitive vulnerability factor closely related to depressive symptoms in the stress process (Nolen-Hoeksema et al., 2008), defined as repetitive, prolonged, and recurrent negative thinking about the self, feelings, and distressing experiences (Watkins, 2008). Focusing on state rumination, recent intensive longitudinal studies have further found that when individuals encounter stressors and ruminate more about stressful experiences, they exhibit higher depressive levels (Connolly & Alloy, 2017, 2018). This suggests that daily stressors and state rumination also have dynamic interactions that jointly predict depressive states. Beyond rumination as a retrospective cognitive stress response, another prospective cognitive stress response is stressor anticipation (Neubauer et al., 2018). Numerous studies have shown that anticipating stressors produces effects similar to experiencing actual stressors, negatively impacting individuals physiologically and psychologically in terms of emotion and cognition (Kramer et al., 2022). Regarding behavior, research has found that individuals' self-reported current stress coping significantly positively predicts concurrent and subsequent sadness and other negative states (Zawadzki et al., 2022), as well as subsequent depressive states (Fuller-Tyszkiewicz et al., 2017). Additionally, studies have revealed the unique role of anticipated stress coping in the stress process in predicting subsequent health-related behaviors (Pannicke et al., 2021). Regarding physiology, research has found that individuals' depressive symptoms and physical symptoms have concurrent bidirectional influences (Goldring & Bolger, 2021). Among individuals with depressive or anxiety symptoms, there are also lagged dynamic interactions between depressive and physical symptoms (Luo et al., in press).

Although numerous studies have examined the predictive effects of objective stress events, subjective stress perceptions, and four types of stress reactivity (emotional, cognitive, behavioral, and physiological) in daily stress processes on depressive states, integrated research on daily stress processes and depressive states is still lacking. Therefore, it remains unclear which stress process factors play primary roles in predicting depressive states and which factors may make unique contributions to prediction. Given the complex relationship between stress processes and depressive states and the importance of depression identification and prevention, there is an urgent need to systematically examine the dynamic association mechanisms between stress processes and depressive states and construct real-time prediction and decision-making models for individuals' depressive states.

## 1.2 Dynamic Prediction of Depressive States

Most depression prediction research has been based on retrospective measurements of individuals' average depression levels over past periods (Asare et al., 2022; De la Barrera et al., 2024), which may overlook key information helpful for prediction in the process of fluctuations in individuals' depressive states over time (Aan het Rot et al., 2012; Jimenez et al., 2022). Moreover, research on the stress-depression relationship has increasingly focused on the impact of stressors individuals experience in daily life, emphasizing the importance of examining intra-individual dynamic stress processes and changes in depressive states (Connolly & Alloy, 2017; Zawadzki et al., 2022). Consequently, recent studies have begun collecting intensive longitudinal data to better capture the dynamic changes in stress processes and depressive states.

Intensive longitudinal data refers to tracking data with many repeated within-person measurements (e.g., more than 10 or 20 occasions). Researchers typically use diary methods (once daily) or ecological momentary assessment (multiple times daily) (Bolger & Laurenceau, 2013; Shiffman et al., 2008) to record changes in individuals' various states in daily life. Compared with retrospective measurements and laboratory manipulations, these methods have important advantages including high ecological validity, low recall bias, and real-time monitoring (Bolger & Laurenceau, 2013; Shiffman et al., 2008). More importantly, intensive longitudinal data contain rich information about intra-individual dynamic processes and have significant potential for real-time prediction of depressive states. However, the complex data structure of intensive longitudinal data also poses challenges for constructing depressive state prediction models. Intensive longitudinal data have a multilevel structure with repeated measurements (within-person level) nested within individuals (between-person level), but machine learning algorithms used in previous depression prediction research have not addressed the non-independence of within-person observations in multilevel data and cannot be directly applied to modeling intensive longitudinal data (Hu & Szymczak, 2023).

In response, researchers have proposed the generalized linear mixed model (GLMM) tree (Fokkema et al., 2018, 2021). This machine learning algorithm builds decision trees based on generalized linear mixed-effects models and is a model-based recursive partitioning algorithm (Zeileis et al., 2008). On one hand, GLMM can effectively account for the multilevel data structure and allow model intercepts and slopes to vary between individuals (i.e., estimate random intercepts and random slopes). On the other hand, as a classic machine learning algorithm, decision trees have the important advantage of high interpretability, and can flexibly build prediction models based on numerous predictor variables while providing practical decision guidance. GLMM trees integrate multiple advantages of GLMM and decision trees, extending decision tree algorithms to multilevel contexts. Therefore, this algorithm can be used to construct multilevel decision trees for intensive longitudinal data, building real-time prediction models for the complex effects of multiple stress processes on depressive states.

### 1.3 Research Purpose

Previous depression prediction research has focused on the inter-individual level, primarily exploring risk factors that significantly predict depression (Sau & Bhakta, 2019). In recent years, increasing research has highlighted the importance of identifying abnormal mental health states in individuals' daily lives and providing timely interventions (Nahum-Shani et al., 2018). Rapidly developing digital interventions (Moshe et al., 2021) and just-in-time adaptive interventions (JITAI; Nahum-Shani et al., 2018) have also provided practical feasibility for monitoring and preventing depressive states in daily life. Given that recent meta-analyses have found over 30% of college students worldwide suffer from depression (Li et al., 2022), and the *China National Mental Health Development Report (2021-2022)* indicates over 20% of Chinese college students are at risk for depression, this study focuses on the college student population and constructs a dynamic prediction model of daily stress processes on depressive states using multilevel decision trees.

This study first employed ecological momentary assessment to collect intensive longitudinal data from college students, capturing dynamic changes in individuals' stress processes and depressive states at the intra-individual level. We then used multilevel decision trees to analyze the data, accounting for the multilevel nested structure of repeated measurements within individuals and differences in individuals' general depression levels (i.e., estimating random intercepts), to construct a real-time prediction model of dynamic stress processes on depressive states. To fully examine the dynamic characteristics of individuals' daily stress processes and their predictive effects on depressive states, we calculated not only real-time scores for each stress process factor but also each factor's cumulative mean (the mean of all observations from initial time t0 = 1 to current time t) and deviation (the difference between the factor's current score and its cumulative mean up to that point) as further indicators characterizing the dynamic features of daily stress processes for more accurate prediction of depressive states. More importantly, to effectively predict and warn individuals about potential depressive states in the near future, we constructed a dynamic prediction model where stress process dynamic characteristics at the current moment predict depressive states at the subsequent moment (approximately three hours later), aiming to provide empirical results and practical decision-making guidance for depression prevention and intervention.

## 2. Method

### 2.1 Participants and Procedure

Participants were 356 Chinese college students (75.84% female) with a mean age of 20.658 years (range = 17-25, SD = 1.642), and 84.884% were undergraduates. First, each participant signed an informed consent form and completed a demographic survey. Over the subsequent seven days, participants received text messages with questionnaire links on their smartphones at 11:00, 14:00, 17:00, 20:00, and 23:00 daily, reporting their depressive and stress-related states since the last assessment. Overall, participants completed 11,288 of 12,460 questionnaires (356 participants $\times$ 35 assessments), yielding a completion rate of 90.594% and demonstrating high compliance. This study was approved by the institutional ethics committee.

### 2.2 Measures

Given that previous research has found longer questionnaires in ecological momentary assessment increase participant burden and compromise data quality (Eisele et al., 2022), undermining reliability and validity, this study selected the briefest possible measures for variables of interest.

**2.2.1 Outcome Variable** Depressive states were measured using the two-item Patient Health Questionnaire (PHQ-2; Löwe et al., 2005). Participants rated two items ("Little interest or pleasure in doing things"; "Feeling down, depressed, or hopeless") on a 5-point scale from 1 ("not at all") to 5 ("very much") based on their true feelings. Because the total score for depressive states showed a clear positive skew and a binary variable representing presence/absence facilitates clinical intervention decisions, depressive states were recoded as a binary variable based on whether the total score was 0, where 0 indicated no depressive state and 1 indicated a depressive state.

**2.2.2 Predictor Variables** For the first stage of the stress process (stressor exposure), objective stressful events were measured using the Daily Stressor Inventory developed for college students (Baker et al., 2020). This inventory includes 9 items assessing various daily stressors (e.g., "too many academic tasks," "preparing for future or career path"). Participants indicated with 0 ("no") or 1 ("yes") whether they had experienced these stressors since the last assessment. Total scores were calculated across all items.

For the second stage (stress appraisal), subjective stress perception was measured. For reported stressors, participants rated how stressful these events were for them on a scale from 1 ("not at all stressful") to 7 ("very stressful").

For the third stage (stress reactivity), participants' reactivity was measured in emotional, cognitive, behavioral, and physiological domains. Specifically, for emotional reactivity, based on the short-form Positive and Negative Affect Schedule (PANAS; Thompson, 2007) and referencing previous research (Cooke et al., 2022), we selected two emotion words each to measure positive ("determined" and "inspired") and negative ("afraid" and "distressed") affect. Participants rated each word from 1 ("not at all") to 5 ("very much"). Because research on the dynamic structure of positive and negative affect indicates that state negative affect includes two sub-dimensions—fear and distress—at the within-person level (Cooke et al., 2022), positive affect used the mean of two items, while negative affect used scores for each of the two items separately to describe fear and distress sub-dimensions.

For cognitive reactivity, state rumination was measured referencing previous research ("Since the last assessment, I haven't been able to stop thinking about something or how I feel"; Blanke et al., 2022), with participants rating from 1 ("not at all") to 7 ("very much"). Additionally, referencing research on stressor anticipation (Kramer et al., 2022), participants rated from 1 ("do not anticipate at all") to 7 ("anticipate very much") the extent to which they expected something stressful or unpleasant to happen in the next few hours.

For behavioral reactivity, present and anticipated stress coping were measured using two adapted items from the Perceived Stress Scale (PSS; Cohen et al., 1983) (Pannicke et al., 2021), rated from 1 ("not at all confident") to 7 ("very confident").

For physiological reactivity, physical symptoms were assessed using a checklist from previous research (Goldring & Bolger, 2021; Larsen & Kasimatis, 1991). Participants indicated with 0 ("no") or 1 ("yes") whether they had experienced various physical symptoms (e.g., headache, diarrhea, other gastrointestinal symptoms) since the last assessment, with total scores calculated across all items. Additionally, participants rated the discomfort caused by physical symptoms from 0 ("no discomfort") to 100 ("very strong discomfort").

**2.2.3 Dynamic Indicators** For the 11 predictor variables in the stress process, we calculated each individual's cumulative mean and deviation for each factor based on real-time scores. The cumulative mean refers to the average of all observed scores for a stress process factor from the initial time point (t0 = 1) to the current time point (t). The deviation refers to the difference between the factor's real-time score at time t and its cumulative mean up to that point. Considering real-time scores, cumulative means, and deviations for each stress process factor can more fully capture the dynamic characteristics of stress processes and facilitate more accurate prediction of depressive states.

### 2.3 Data Analysis

**2.3.1 Data Preparation** The data preparation stage involved preprocessing and preliminary analysis. First, we used the imputeTS package (Moritz & Bartz-Beielstein, 2017) in R 4.2.2 (R Core Team, 2021) to impute missing values using Kalman filtering for time-series dependent data. Next, for the 11 predictor variables in the stress process (stressor exposure, subjective stress appraisal, positive affect, negative affect [fear], negative affect [distress], rumination, stressor anticipation, present stress coping, anticipated stress coping, physical symptoms, and physical discomfort), we calculated each individual's cumulative mean up to time t and the deviation of the score at time t from this cumulative mean as further indicators of stress process dynamics. Additionally, to construct a time-lagged depressive state prediction model (i.e., using stress process variables at time t to predict depressive states at t + 1), we generated first-order lagged depressive state scores. Finally, we used the psych package (Revelle & Revelle, 2015) to conduct descriptive statistical analysis of the multilevel data with repeated measurements nested within individuals, calculating overall means, between-person standard deviations, intraclass correlations (ICC), and within-person and between-person correlations among variables.

**2.3.2 Model Fitting** This study used the generalized linear mixed-effects model tree (GLMM tree) algorithm to fit multilevel decision trees with random intercepts, constructing dynamic prediction models for depressive states. This algorithm's characteristic is using observations within each terminal node to locally estimate fixed effects of parameters while using all observations to globally estimate random effects (Fokkema et al., 2018). In a GLMM tree with only random intercepts, the expected depressive state for individual i (i = 1, 2, …, 356) at time t (t = 1, 2, …, 35) can be expressed as:

$$g(E(y_{it})) = a_j + u_{it}$$

where g represents the link function; $a_j$ is the locally estimated fixed part of the intercept in terminal node j (j = 1, 2, …, J; J = total number of terminal nodes), representing the average depressive state level within that terminal node; and $u_{it}$ is the globally estimated random effect for individual i at time t, assumed to follow a normal distribution with mean 0 and variance $\sigma^2$. The estimation steps for a GLMM tree with only random intercepts are:

1. Set initial value r = 0 and set $u_{it},(r) = 0$;
2. Set r = r + 1. Using $u_{it},(r-1)$ as an offset, fit a generalized linear model tree (GLM tree) without random intercepts to obtain partitioning results j(r). This partitioning process follows the general steps of model-based recursive partitioning algorithms, as described in Zeileis et al. (2008) and Fokkema et al. (2018);
3. Based on partitioning results j(r) from the previous step, fit a GLMM ($g(E(y_{it})) = a_j,(r) + u_{it},(r)$) to obtain estimates of fixed and random effects ($u_{it},(r)$);
4. Repeat steps 2-3 until model convergence. Convergence can be examined using the log-likelihood of the GLMM in step 3. When the partitioning results j(r) from step 2 are identical to those from the previous iteration j(r-1), the model has typically converged.

Overall, the GLMM tree algorithm alternates between fitting a GLM tree (step 2) and a GLMM to estimate fixed and random effects (step 3) in each iteration until convergence. This algorithm was implemented using the glmertree package in R (Fokkema et al., 2018, 2021). In this study, predictor variables included three dynamic characteristic indicators (momentary value, cumulative mean, and deviation) for 11 stress process variables, totaling 33 predictors; the outcome variable was binary depressive state at the subsequent time point (t + 1). The model allowed for between-person differences in average depressive state levels (random intercepts). When fitting GLM trees, the critical p-value for partitioning variables was set at 0.05 (default), and restricted maximum likelihood estimation (default) was used to obtain fixed and random effects in the GLMM. Algorithm parameters were adjusted to obtain the optimal prediction model, with the final GLMM tree set to have a minimum of 30 observations per terminal node and a maximum depth of…

**2.3.3 Model Evaluation** To evaluate model performance, we conducted blocked and stratified five-fold cross-validation. Traditional k-fold cross-validation is not suitable for multilevel data structures with dependent observations (in this study, repeated observations nested within individuals are not independent), so blocked cross-validation was used to ensure all observations from each individual were assigned to the same fold. Additionally, because imbalance in the outcome variable (e.g., large differences in proportions of 0 and 1) may affect cross-validation results, stratified cross-validation was used to ensure equal or similar proportions of individuals with high and low depressive state frequencies across folds (specifically, ensuring equal medians of the proportion of occasions with depressive states across individuals between folds). The entire blocked and stratified five-fold cross-validation was repeated five times to obtain more stable and accurate results. Model performance was evaluated using sensitivity, specificity, and area under the ROC curve (AUC). Sensitivity describes the probability of correctly identifying depressive states, specificity describes the probability of correctly identifying non-depressive states, and AUC reflects the model's discriminative ability between depressive and non-depressive states, where 0.5 indicates no discrimination (random level) and values approaching 1 indicate higher discriminative accuracy. To determine the optimal probability threshold for the outcome variable that yields the best sensitivity and specificity, we used the pROC package (Robin et al., 2011) based on the criterion of being "closest to the upper-left corner."

## 3. Results

### 3.1 Descriptive Statistical Analysis

Descriptive statistics and correlation analysis results for stress process predictors (raw scores) and depressive states (including raw scores and binary values at the next time point) are presented in Table 1 . Intraclass correlation coefficients showed that 30%-50% of variance in these variables was at the within-person level. Correlation analysis revealed that all predictors except positive affect had significant correlations with the outcome variable at both between-person and within-person levels ($ps < 0.001$).

**Table 1**. Descriptive Statistics and Correlation Analysis of Stress Processes and Depressive States

| Variable | M (SD) | ICC | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Stressor exposure | 1.263 (1.027) | 0.498 | - | 0.122*** | 0.206*** | 0.163*** | -0.156*** | 0.188*** | -0.125*** | 0.331*** | 0.234*** | 0.180*** | 0.068*** | 0.338*** | 0.505*** |
| 2. Subjective stress | 2.817 (1.000) | 0.410 | -0.285*** | - | -0.047*** | -0.112*** | -0.051*** | 0.156*** | -0.096*** | 0.121*** | -0.101*** | -0.153*** | -0.169*** | -0.057*** | -0.192*** |
| 3. Positive affect | 1.463 (0.685) | 0.392 | 0.545*** | -0.107*** | - | 0.428*** | 0.154*** | -0.124*** | 0.141*** | -0.116*** | 0.131*** | 0.171*** | 0.313*** | 0.085*** | 0.621*** |
| 4. Negative affect (fear) | 1.713 (0.753) | 0.416 | 0.599*** | -0.222*** | 0.902*** | - | 0.213*** | -0.179*** | 0.203*** | -0.159*** | 0.179*** | 0.244*** | 0.387*** | 0.102*** | 0.706*** |
| 5. Negative affect (distress) | 3.585 (1.446) | 0.410 | 0.664*** | -0.164*** | 0.500*** | 0.560*** | - | -0.138*** | 0.142*** | -0.101*** | 0.137*** | 0.159*** | 0.204*** | 0.084*** | 0.502*** |
| 6. Rumination | 4.580 (1.047) | 0.319 | -0.610*** | 0.525*** | -0.490*** | -0.538*** | -0.511*** | - | -0.204*** | 0.425*** | -0.117*** | -0.191*** | -0.190*** | -0.073*** | -0.468*** |
| 7. Stressor anticipation | 3.232 (1.177) | 0.401 | 0.625*** | -0.130*** | 0.576*** | 0.609*** | 0.565*** | -0.473*** | - | 0.138*** | 0.213*** | 0.197*** | 0.061*** | 0.570*** | 0.386*** |
| 8. Present coping | 4.802 (0.995) | 0.341 | -0.577*** | 0.481*** | -0.495*** | -0.536*** | -0.482*** | 0.942*** | -0.502*** | - | -0.095*** | -0.170*** | -0.157*** | -0.065*** | -0.469*** |
| 9. Anticipated coping | 0.905 (0.951) | 0.567 | 0.514*** | -0.237*** | 0.460*** | 0.525*** | 0.376*** | -0.343*** | 0.412*** | -0.363*** | - | 0.547*** | 0.216*** | 0.063*** | 0.476*** |
| 10. Physical symptoms | 19.709 (16.593) | 0.436 | 0.596*** | -0.248*** | 0.564*** | 0.613*** | 0.452*** | -0.389*** | 0.521*** | -0.392*** | 0.724*** | - | 0.272*** | 0.071*** | 0.811*** |

| Variable | M (SD) | ICC | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 11. Physical discomfort | 1.695 (0.750) | 0.406 | 0.583*** | -0.241*** | 0.868*** | 0.901*** | 0.550*** | -0.552*** | 0.605*** | -0.560*** | 0.510*** | 0.592*** | - | 0.134*** | - |
| 12. Depressive state (t) | 3.590 (1.253) | 0.668 | 0.209*** | 0.233*** | -0.315*** | 0.327*** | -0.243*** | 0.252*** | 0.319*** | 0.308*** | 0.084*** | - | - | - | - |
| 13. Depressive state (t + 1) | 0.540 (0.356) | - | - | - | - | - | - | - | - | - | - | - | - | - | - |

*Note: Depressive state (t) is the continuous score for current depressive state; depressive state (t + 1) is the binary value for depressive state at the next time point (0 = no depressive state; 1 = depressive state). M = grand mean; SD = between-person standard deviation of person-specific means; ICC = intraclass correlation. Below diagonal = between-person correlations; above diagonal = within-person correlations.* **p < 0.001.*

### 3.2 Prediction Model Results and Evaluation

Figure 2 [Figure 2: see original paper] presents the optimal depressive state prediction model I. Across five five-fold cross-validations, this model achieved an average sensitivity of 0.801 (SD = 0.028), average specificity of 0.640 (SD = 0.046), and average AUC of 0.799 (SD = 0.020). This indicates the model had high probability of correctly identifying depressive states, acceptable probability of correctly identifying non-depressive states, and could discriminate between depressive and non-depressive states with good accuracy. Specifically, the model showed three pathways indicating individuals would likely experience depressive states in the subsequent period: (1) individuals with high cumulative mean levels of negative affect (distress) ($> 1.85$); (2) individuals with moderate cumulative mean levels of negative affect (distress) (1-1.85), low cumulative mean of stressors ($\leq 0.75$), and current negative affect (distress) slightly above their cumulative average (deviation $> 0.24$); and (3) individuals with moderate cumulative mean levels of negative affect (distress) (1-1.85), high cumulative mean of stressors ($> 0.75$; indicating an average of nearly one stressor every three hours), and high current rumination levels ($> 2.08$). This prediction model demonstrates that using three stress process factors (distress negative affect, stressors, and rumination) and their dynamic characteristics can effectively predict subsequent depressive states, with various dynamic features of stress processes playing important roles in dynamic prediction of depressive states.

The prediction model I also shows that distress negative affect plays a key role in predicting subsequent depressive states. However, previous research has found that individuals with depressive symptoms or risk show less disclosure of their emotional states (Kahn & Garrison, 2009; Macdonald & Morley, 2001) and perceive high burden and intrusiveness when frequently reporting emotional states (De Girolamo et al., 2020; Van Genugten et al., 2020). Moreover, frequent measurement of positive and negative affect may be operationally difficult in actual depression monitoring and prediction research. Therefore, this study attempted to remove positive and negative affect from predictor variables to further explore a depression prediction model without emotional states.

**Figure 2**. Dynamic prediction model I of stress processes (t) on depressive state (t + 1)
*Note: All partitioning variables have parameter instability test p-values < 0.001.*

### 3.3 Supplementary Analysis

Figure 3 [Figure 3: see original paper] presents the depressive state prediction model without emotional predictor variables. Across five five-fold cross-validations, this model achieved an average sensitivity of 0.716 (SD = 0.029), average specificity of 0.672 (SD = 0.033), and average AUC of 0.756 (SD = 0.030). This indicates that model II, without positive and negative affect, showed slightly decreased prediction performance but could still discriminate between depressive and non-depressive states with good accuracy. According to model II, three pathways indicated individuals would likely experience depressive states in the subsequent period: (1) individuals with high cumulative mean of present stress coping (> 3.12) but also high subjective stress perception (> 3.02); (2) individuals with high cumulative mean of present stress coping (> 3.12), low subjective stress perception (≤ 3.02), but high current rumination levels (> 2.97); and (3) individuals with low cumulative means of both present stress coping (≤ 3.12) and anticipated stress coping (≤ 5.77), and strong physical discomfort (> 21.20).

**Figure 3**. Dynamic prediction model II of stress processes (t) on depressive state (t + 1)
*Note: Predictor variables exclude positive and negative affect and their dynamic characteristics. All partitioning variables have parameter instability test p-values < 0.001.*

This study is the first to use multilevel decision trees (i.e., GLMM trees) to construct a dynamic prediction model of college students' daily stress processes on their depressive states. The findings show that the optimal prediction model I including emotional states (AUC = 0.799) identified key predictive stress process factors: distress negative affect (stress emotional reactivity), stressors, and rumination (stress cognitive reactivity). The prediction model II without emotional states also demonstrated good prediction performance (AUC = 0.756), indicating that integrating present and anticipated stress coping (stress behavioral reactivity), rumination (stress cognitive reactivity), physical discomfort (stress physiological reactivity), and subjective stress perception can achieve relatively accurate prediction of depressive states. Moreover, results show that beyond current levels of stress processes, dynamic characteristics such as cumulative means and deviations play important roles in real-time prediction of depressive states. Grounded in theoretical foundations of the stress-depression relationship and employing data-driven machine learning algorithms, this study systematically investigated the complex predictive mechanisms of stress processes on depressive states, providing an effective decision-making tool for dynamic prediction of depressive states in daily life and making important contributions to both theoretical and practical research on depression prediction.

## 4. Discussion

### 4.1 Key Findings on Dynamic Prediction of Depressive States

This study first found that various components of daily stress processes contribute to predicting individuals' depressive states to varying degrees. Among these, distress negative affect was the strongest risk factor for subsequent depressive states. Extensive previous research has also found strong positive associations between negative affect and depressive symptoms (Cooke et al., 2022; Merz & Roesch, 2011; Starr et al., 2023), consistent with our findings. More importantly, based on the fear-distress two-dimensional structure of state negative affect (Cooke et al., 2022), this study further revealed that distress negative affect plays an important role in dynamic prediction of depressive states, while fear affect has relatively weaker predictive effects. This suggests that emotion-related depression intervention practices should focus on individuals' distress emotions in design and implementation, and future research should explore dynamic associations with individuals' states based on more refined structures of negative affect. Additionally, in dynamic prediction of depression, the cumulative mean of experienced stressors and individuals' current rumination levels also play unique roles. When individuals have moderate cumulative mean levels of distress, have been continuously experiencing daily stressors (in this study, an average of nearly one stressor every three hours), and have high rumination in recent periods, they are likely to show depressive states in the subsequent period. This is consistent with the perseverative cognition hypothesis, which posits that individuals' rumination exacerbates and prolongs the negative health effects of stressors (Brosschot et al., 2006) and is closely related to the onset and maintenance of various clinical symptoms including depression (Watkins & Roberts, 2020).

Although the model dominated by distress negative affect achieved optimal prediction of depressive states, the study found that a model without emotional factors could also achieve good prediction performance. Specifically, depressive states could be predicted relatively accurately by integrating stress reactivity across behavioral, cognitive, and physiological domains plus subjective stress perception. In the depressive state prediction model without emotions, the cumulative means of present and anticipated stress coping were the core nodes with initial classification function, representing key factors for predicting depressive states. When individuals had relatively poor present and anticipated stress coping over the past period (i.e., low cumulative means), high physical discomfort (slightly above the overall average across all individuals and occasions) predicted subsequent high depression risk. Previous research has found bidirectional interactions and dynamic associations between depressive symptoms and physical symptoms across different time scales (Goldring & Bolger, 2021; Long et al., 2018; Luo et al., in press). This study further found that when individuals' recent average stress coping was poor, physiological discomfort could effectively predict subsequent depressive states. Moreover, even when individuals had good present stress coping over the past period, if they subjectively perceived high stress levels, or if stress perception was low but rumination was high, they still had high subsequent risk for depressive states. This indicates that different components of the stress process may influence subsequent depressive states through complex combinational relationships.

Indeed, the depressive state prediction models in this study demonstrate that multiple components of daily stress processes cumulatively impact individuals, jointly predicting their subsequent depression risk. Previous research on stress process components has noted that stress pile-up over time is an important predictor of individuals' health status. Stress pile-up refers to the accumulation of stress events and/or stress reactivity over time (Smyth et al., 2018, 2023). Almeida et al. (2020) found that pile-up of both stress events and negative emotional reactivity to stress effectively predicted subsequent lower physical activity levels, whereas negative emotional reactivity alone had no significant predictive effect. This study similarly found pile-up effects, where individuals' distress (negative emotional reactivity to stress) and experienced stressors jointly predicted higher subsequent depression risk. Furthermore, this study revealed multiple complex combinations and pathways through which other stress processes predict subsequent depressive states (e.g., joint prediction of depressive states by poor stress coping and physical discomfort), promoting more systematic and in-depth understanding of the complex relationships and mechanisms between stress processes and depressive states, and advancing the development of cumulative risk theories related to stress processes.

Additionally, the roles of dynamic characteristics such as cumulative means and deviations of stress processes in predicting depressive states warrant attention. In the dynamic prediction models, cumulative means of distress, stressors, and present and anticipated stress coping played key roles in initial prediction stages, while deviations of distress at the current moment from individuals' cumulative averages could further assist in predicting depressive states in the subsequent period. This suggests that in tree-structured depressive state prediction models, initial prediction stages primarily rely on overall average levels of certain stress process factors over the past period, while terminal prediction pathways mostly use instantaneous levels or deviations from average levels of various stress process factors in recent moments for more refined auxiliary judgment. Thus, instantaneous levels, cumulative means, and deviations of stress processes can complement each other in predicting individuals' depression risk. This also suggests that future research could combine multiple dynamic characteristics of predictive factors to achieve more accurate and effective dynamic prediction (Czyz et al., 2023).

### 4.2 Contributions, Limitations, and Future Directions

This study makes important contributions in both theoretical and practical aspects. Theoretically, it enriches and expands previous research on the stress-depression relationship from a dynamic perspective, deepening understanding of the complex predictive mechanisms through which stress processes influence depressive states. Previous research has systematically organized multiple factors in daily stress processes (Almeida, 2024) and examined dynamic associations between various factors and depressive states (Connolly & Alloy, 2017; Kang et al., 2023; Starr et al., 2023; Zawadzki et al., 2022). By integrating and analyzing multiple daily stress process factors and their dynamic characteristics, this study identified key stress process factors for predicting depressive states and revealed the synergistic predictive effects of various factor combinations, promoting understanding of cumulative risk and advancing related theoretical development. Moreover, the study demonstrates the importance of simultaneously considering instantaneous levels, cumulative means, and deviations as dynamic indicators for depression risk prediction, expanding dynamic prediction pathways and indicator construction approaches for stress processes' effects on depression.

Practically, this study combines multilevel decision trees with ecological momentary assessment to construct a near-term warning model for depressive states with both interpretability and predictive accuracy, providing an effective decision-making tool for real-time monitoring and identification of potential depression risk in daily life. Previous studies have also used ecological momentary assessment to record depression-related states in daily life (Asare et al., 2022; De la Barrera et al., 2024), but these studies' prediction indicators based on intensive longitudinal data were only used to predict single-occasion depressive symptoms, ultimately remaining at the inter-individual level to examine individual characteristics predicting depression risk. This study advances further by examining the intra-individual level, investigating real-time prediction of individuals' subsequent depressive states by multiple stress processes and their dynamic indicators, which can effectively answer the key clinical questions of "when intervention is needed" and "who needs intervention," thereby guiding the implementation of just-in-time adaptive interventions (JITAI; Nahum-Shani et al., 2018).

This study has several limitations. First, both stress processes and depressive states were measured using self-report methods, which may be subject to common method bias. Future research could consider using wearable devices for more objective measurement of physiological indicators related to stress and depressive states (Asare et al., 2022). Second, participants were all college students. Although recent meta-analyses have found over 30% of college students suffer from depression (Li et al., 2022), indicating the value of investigating and constructing dynamic prediction models for depressive states in this population, dynamic prediction and real-time intervention for depressive states in broader populations remain to be studied. Third, this study considered limited daily stress processes and dynamic indicators. For example, Wu and Wang (2024) systematically organized various dynamic indicators related to emotion (e.g., emotional variability and emotional inertia) and summarized group differences between clinical and healthy populations on these indicators. At the within-person level, real-time scores on these indicators over time could also be applied to dynamic prediction of individuals' subsequent depressive states. Future research could more comprehensively examine daily stress processes (e.g., specific stress coping strategies) and their dynamic indicators to more holistically investigate prediction and decision-making models of dynamic stress processes on individuals' depressive states.

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*Note: Figure translations are in progress. See original paper for figures.*