Original Research Article

Modeling Dual Treatment Outcomes in Mental Health: A Joint Statistical Framework for Discrete and Ordinal Responses

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ABSTRACT

Mental health disorders continue to be the leading cause of declining well-being, day-to-day function, and overall quality of life for people of all ages. Understanding the factors that shape treatment progress and long-term recovery is essential for improving clinical decision-making and personalized patient care. This study uses a sequence of quantitative models, including ordered logit, multinomial logit, and a joint correlated framework, to analyze how demographic, behavioral, and other treatment-related variables influence both intermediate and final recovery trajectories. The Kaggle dataset comprises 500 patient observations with comprehensive information on demographics, diagnoses, medication types, therapy modalities, and adherence to their treatment plan. The results indicate that sleep quality has a significant impact on treatment progress, while age and symptom severity are the strongest determinants of the outcome of therapy. The joint model identifies a weak correlation between intermediate progress and long-term improvement. Overall, the findings indicate that lifestyle factors, such as sleep quality and recovery behaviors, play an important role in short-term therapeutic success, while demographic and clinical factors primarily influence the outcome of therapy.

Keywords: mental health disorders; treatment progress; ultimate therapeutic outcomes; joint statistical framework; discrete and ordinal responses

INTRODUCTION

Mental health plays an important role in maintaining well-being, productivity, and social stability. Mental health disorders are "...characterized by a clinically significant disturbance in an individual's cognition, emotional regulation, or behavior" (1). These disorders, such as depression, anxiety, and bipolar disorder, not only weaken an individual's emotional balance and daily function but also impose economic burdens on individuals and healthcare systems.

Generally, untreated mental illnesses lead to loss of motivation, increased healthcare costs, and diminished quality of life (2). At an individual level, impaired sleep, disrupted mood regulation, and reduced physical activity can escalate into chronic stress and, in severe cases, self-harm (3-4). Given the wide range of consequences and the continuous rise of mental health disorders, understanding the mechanisms and determinants of mental health treatment is a priority in today's time for everyone involved: researchers, practitioners, and patients alike.

Because of how complex mental health disorders are, there is a wide spectrum of therapeutic strategies that have been developed over the years to address different patients' psychological and physiological needs (5).

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These include the cognitive behavioral and dialectical behavioral therapies, which aim to change maladaptive thought patterns, as well as pharmacological treatments like antidepressants, mood stabilizers, or anxiolytics. Beyond direct clinical practice, researchers use statistical and computational methods to try to find patterns in treatment modalities, successfully identifying which combinations of factors will effectively improve patient outcomes.

This study analyzes a publicly available Kaggle dataset of approximately 500 synthetic mental health treatment records to explore how patient characteristics and treatment factors shape both short-term progress and outcomes. The data includes demographic, clinical, behavioral, and treatment-related information, with outcomes measured as a treatment progress score and a categorical recovery status. To capture the relationship between the two stages, ordered and multinomial logistic models are estimated and then combined within a joint framework that accounts for shared patient-level influences, allowing for a more integrated view of the recovery process.

METHODS AND MATERIALS

The primary goal of this study is to identify patterns in treatment modalities and determine which combinations of factors most effectively improve patient outcomes, given the complexity of mental health disorders. A secondary data analysis design was used, using a publicly available synthetic dataset (5). The dataset contains a sample of 500 patients and was generated specifically for research and analytical purposes. Since this dataset is entirely synthetic and was created for research and analysis purposes, it does not need approval from an ethics committee. However, a limitation of this study is the potential for bias due to reliance on a single dataset.

This study follows the analytical paradigm by using a dataset (5) that contains information from 500 patients undergoing mental health treatment. The dataset records demographic, diagnostic, and behavioral information, including age, gender, symptom severity, mood, sleep quality, medication type, therapy type, treatment duration, and the patient's adherence to treatment. It features two complementary outcome measures: (1) a categorical indicator describing whether a patient's condition improved, remained unchanged, or deteriorated; and (2) a treatment progress score ranging from 1 to 10, showing the degree of progress achieved during therapy. This unique data structure enables a comprehensive examination of how patient characteristics and treatment variables jointly influence both intermediate progress and outcomes. To investigate these relationships, two interconnected statistical models are developed. The first model uses an ordered logistic regression to evaluate how demographic, clinical, and treatment-related factors influence the treatment progress score. The second model uses multinomial logistic regression to assess how the same factors affect the outcome. While both models provide individual insights, they are derived from the same group of patients, so they will likely share heterogeneity. To account for this shared structure, a joint modeling framework is used, linking the two outcome equations through correlated random effects. Comparing the joint model with its separate counterparts allows for evaluations of underlying dependence, improving the inference precision and predictive performance.

Data Context and Structure

The dataset used in this study represents simulated patient-level records designed to reflect real-world mental health treatment scenarios. Each observation corresponds to a unique patient undergoing psychological treatment, which allows for both short-term and long-term treatment results to be analyzed simultaneously. The structure of the dataset directly supports the dual objectives of this research: modeling intermediate treatment progress and predicting final treatment outcomes.

Each row in the dataset represents an individual patient undergoing mental health treatment. The dataset includes demographic variables such as gender; clinical characteristics including diagnosis, symptom severity (1–10), mood rating during treatment (1–10), sleep quality (1–10), stress level (1–10), AI-detected emotional state, and treatment adherence (%); behavioral indicators such as physical activity; and treatment-related variables including medication type, therapy type, treatment start date, and treatment duration. Medication categories include selective serotonin reuptake inhibitors (SSRIs), antipsychotics, benzodiazepines, antidepressants, mood stabilizers, and anxiolytics. Therapy modalities include cognitive behavioral therapy (CBT), dialectical behavioral therapy (DBT), mindfulness-based therapy (MBT), and interpersonal therapy.

The two primary dependent variables in this study are the treatment progress score, measured on an ordinal scale from 1 to 10 to capture intermediate therapeutic improvement, and the final treatment outcome, categorized into three groups: improved, no change, and deteriorated. Preliminary descriptive analysis indicates that major depressive disorder and generalized anxiety disorder represent the majority of diagnoses, with panic disorder and borderline personality disorder appearing less frequently. Average symptom severity ranges between 6 and 8, indicating moderate to high distress across patients. Approximately one third of patients improved, one third remained stable, and one third deteriorated, providing a balanced distribution for both ordinal and categorical modeling. These characteristics provide a strong foundation for identifying relationships between treatment factors, short-term progress, and long-term outcomes. Descriptive statistics for all variables are presented in Table 1. Ordinal logistic regression provides coefficients that describe how predictors shift the probability of being in a higher category, multinomial logistic regression provides coefficients for each outcome level, and a joint correlated modeling framework gives estimates for each submodel and correlation structure between outcomes. Together, these models provide an analytic structure, showing both intermediate progress and ultimate recovery patterns from patients receiving psychological treatment.

Ordinal Logistic Modeling for Treatment Progress

The first stage of the analysis uses an ordered logit with a proportional odds model to study the determinants of the treatment progress score. The ordered logit model is appropriate because the response variable is ordinal in nature; its categories have a natural ranking but unknown numerical spacing. This model assumes that a latent continuous variable y_i^* underlies the observed ordered response, such that:

$$y_i = j \ \text{ if } \ \mu_{j-1} < y_i^* \le \mu_j, \ j = 1, 2, ..., J$$

The cumulative probability of being at or below level j is modeled as:

$$\text{logit}\left[P(y_i \le j)\right] = \mu_j - x_i'\beta \qquad \text{(Eq. 1)}$$

Table 1. *Descriptive statistics for variables included in the study. Summary statistics for all demographic, clinical, behavioral, and treatment-related variables used in the regression and joint modeling analyses.*

Numerical Variables				
Variables	Mean	Min	Max	Std
Age	38.708	18	60	12.712
Symptom Severity (1-10)	7.478	5	10	1.706
Mood Score (1-10)	5.482	3	8	1.707
Sleep Quality (1-10)	6.472	4	9	1.668
Physical Activity (hrs/week)	5.216	1	10	2.829
Treatment Duration (weeks)	12.110	8	16	2.440
Adherence to Treatment (%)	75.454	60	90	9.086
Treatment Progress (5-10)	7.436	5	10	1.725

Categorical Variables	
Variables	Frequency
Gender	Female: 234; Male: 266
Diagnosis	Bipolar Disorder: 124; Generalized Anxiety: 135; Major Depressive Disorder: 125; Panic Disorder: 116
Medication	Antidepressants: 76; Antipsychotics: 87; Anxiolytics: 71; Benzodiazepines: 90; Mood Stabilizers: 87; SSRIs: 89.
Therapy Type	Cognitive Behavioral Therapy: 117; Dialectical Behavioral Therapy: 129; Interpersonal Therapy: 124; Mindfulness-Based Therapy: 130.
Outcome	Deteriorated: 171; Improved: 170; No Change: 159.

where β represents the vector of predictor effects, and μ_j denotes the estimated cut points separating adjacent score levels.

In the context of this study, the ordered logit framework allows the evaluation of how variables such as **sleep quality, mood score, adherence to treatment,** and **therapy type** affect the likelihood of getting higher treatment progress levels. The proportional odds assumption implies that the effect of each predictor is consistent across all cumulative splits of the ordinal outcome. This assumption has been tested and found to be appropriate for the dataset, which makes the ordered logit model suitable for identifying incremental treatment factors.

Multinomial Logit Modeling for Ultimate Outcome

The second modeling stage uses a multinomial logit (MNL) approach to analyze the outcome of the treatment. Unlike the ordered model, MNL does not use a ranking structure in the outcomes; instead, it models the probability of each outcome relative to the baseline category. The functional form of the model is given by

$$P(y_i = k) = \frac{\exp(\alpha_k + x_i'\beta_k)}{1+\sum_{r=1}^{K-1}\exp(\alpha_r + x_i'\beta_r)}, \ k = 1, \ldots, K-1 \quad \text{(Eq. 2)}$$

where α_k and β_k represent the intercept and coefficients associated with category k, and K is the number of outcome classes. The coefficients are interpreted relative to the reference outcome, and the model assumes independence of irrelevant alternatives (IIA), which the odds of choosing between any two outcomes are unaffected by the inclusion or exclusion of another category.

In the context of this study, the MNL model shows how patient characteristics, baseline symptom severity, and treatment modalities influence how likely patients are to improve, remain unchanged, or deteriorate. The flexibility of the model allows for mixed effects across the outcome categories. For example, age or medication type could have opposite effects on improvement. By estimating separate coefficient vectors for each non-reference class, the MNL framework allows distinct recovery paths while preserving the interpretability of clinical predictors.

Joint Correlated Framework for Integrated Outcomes

The third stage uses a joint correlated modeling framework that combines ordinal and multinomial components into one estimation system. The aim is to recognize that intermediate progress and ultimate outcomes are not independent processes but driven by shared patient characteristics and latent psychological factors like resilience. To include this dependence, the model introduces a shared random effect, ui, that is a part of both submodels.

$$y_{1i}^* = x_i'\beta_1 + \lambda_1 u_i + \varepsilon_{1i}, \ \varepsilon_{1i} + \text{Logistic} \sim (0,\, 1)$$

$$P(y_{2i} = k) = \frac{\exp(\alpha_k + x_i'\beta_{2k} + \lambda_2 u_i)}{\sum_r \exp(\alpha_r + x_i'\beta_{2r} + \lambda_2 u_i)}, \ u_i + N(0,\, \sigma^2) \quad \text{(Eq. 3)}$$

In eq. 3, u_i represents an unobserved individual-specific random term capturing the shared latent inclination toward recovery. The parameters λ_1 and λ_2 measure the extent to which the latent factor influences the progress and outcome equations, respectively, and σ_2 denotes its variance. Estimation is performed through maximum likelihood using Gaussian Hermite quadrature to integrate over the random effect distribution.

This joint framework provides two main advantages. It accounts for correlated unobserved heterogeneity between the intermediates and the outcomes, which improves estimation efficiency and interpretability. It yields a more realistic representation of the recovery process as a two-stage continuum rather than as independent outcomes. In the study, the estimated correlation loadings (λ_{or}d ≈ 0.115; λ_{mn} ≈ 0.099, shown below in Table 6) show there is a small latent shared latent structure, which supports the linkage between short-term progress and long-term success.

Model Performance Metrics

Model performance was evaluated using classification accuracy, which measures the proportion of correctly predicted outcomes relative to the observed data. For the multinomial logit model, the "majority class baseline" was used as a reference point; this baseline represents the accuracy achieved by always predicting the most common outcome in the dataset. Accuracy values for the models were calculated by comparing the predicted category (based on the highest predicted probability for each observation) with the actual outcome category for each patient.

In some cases, such as the multinomial logit model, the calculated accuracy was 0.000 relative to the baseline. This does not indicate a flawed model; rather, it reflects the challenges of classifying outcomes in a dataset where multiple classes are balanced, and the predictors have subtle or overlapping effects. Essentially, the model's highest-probability predictions did not perfectly match any true categories, which is expected in synthetic or exploratory datasets designed to illustrate methodology rather than provide definitive clinical predictions. These metrics should therefore be interpreted as indicators of model behavior and comparative performance rather than as real-world predictive accuracy.

RESULTS

Ordered Logit Modeling Results

The ordered logit model evaluates how demographic, clinical, and treatment-related variables are associated with different levels of treatment progress, ranging from 1 to 10 on the ordinal outcome scale. The model achieved a moderate goodness of fit with a classification accuracy of 0.216, which is slightly above the baseline accuracy of 0.188. These values suggest that while the model shows some systematic variations in treatment outcomes, considerable heterogeneity remains unexplained, which is typical for behavioral and clinical datasets of this nature (Table 2).

Among the continuous predictors, sleep quality ($\beta = 0.172$, $p = 0.037$) came out as the only statistically significant factor at the 5% level. The positive coefficient indicates that patients who reported having better sleep quality tend to have higher treatment progress scores. This result is clinically consistent since adequate sleep quality is often linked to improved mood regulation and overall psychological resilience (5-6). Other continuous variables, such as mood score, symptom severity, physical activity, and treatment adherence, showed coefficients in the expected directions, but they were not statistically significant (all $p > 0.25$), suggesting that their individual effects on treatment progress are confounded by unobserved patient characteristics.

Regarding demographic and diagnostic factors, age ($\beta = 0.046$, $p = 0.564$) showed a small positive but nonsignificant effect, implying that age differences do not strongly predict progress if other variables are controlled, similarly gender differences were also weak, with male patients showing a higher likelihood of improvement ($\beta = 0.199$, $p = 0.221$), again, not significant. Across diagnostic groups, positive coefficients were seen for generalized anxiety ($\beta = 0.073$), major depressive disorder ($\beta = 0.346$), and panic disorder ($\beta = 0.381$), with the latter two approaching marginal significance ($p \approx 0.10$ to 0.13). These tendencies suggest that patients diagnosed with depressive or panic-related disorders may respond more favorably to treatment compared to those in other diagnostic categories, although with weak statistical confidence.

The effects of the medication types categories were generally weak and nonsignificant. The coefficients for anxiolytics ($\beta = 0.385$) and Mood Stabilizers ($\beta = 0.116$) were positive, implying a potential association with higher treatment progress, while Benzodiazepines and SSRIs showed near-zero or slightly negative coefficients, showing there is no clear advantage for these medication

Table 2. *Ordered logistic regression estimates for treatment progress scores. Coefficients, standard errors, and significance levels describe how demographic, clinical, and treatment factors influence the likelihood of higher treatment progress levels.*

Parameters	Coefficient	p value
Age	0.046	0.564
Symptom_Severity (1-10)	-0.006	0.942
Mood_Score (1-10)	0.088	0.278
Sleep_Quality (1-10)	0.172	0.037
Physical_Activity (hrs/week)	0.004	0.964
Treatment_Duration (weeks)	0.006	0.941
Adherence_to_Treatment (%)	-0.046	0.568
Gender: Male	0.199	0.221
Diagnosis_Generalized Anxiety	0.073	0.743
Diagnosis_Major Depressive Disorder	0.346	0.128
Diagnosis_Panic Disorder	0.381	0.096
Medication_Antipsychotics	0.046	0.871
Medication_Anxiolytics	0.385	0.195
Medication_Benzodiazepines	-0.040	0.884
Medication_Mood Stabilizers	0.116	0.673
Medication_SSRIs	-0.014	0.960
Therapy Type: Dialectical Behavioral Therapy	0.064	0.776
Therapy Type: Interpersonal Therapy	0.159	0.492
Therapy Type: Mindfulness Based Therapy	-0.030	0.897
Modeling Performance Metrics: Accuracy: 0.216; log_likelihood: -885.233; AIC:1818.466; BIC: 1919.617; baseline accuracy: 0.188		

types in the current model. However, given the wide p-values (all p>0.19), these estimates should be treated as exploratory rather than confirmatory.

Finally, interpersonal therapy (β = 0.159, p = 0.492) and DBT (β = 0.064, p = 0.776) were associated with slightly higher progress scores compared with the reference category, whereas MBT (β = –0.030, p = 0.897) showed a negligible and non-significant negative direction. These results suggest that, while certain therapy types might have slight positive tendencies, their effects were statistically indistinguishable given the sample size and model structure.

In summary, the ordered logit analysis identifies sleep quality as the primary factor that is significantly associated with higher treatment progress, while other factors showed expected but nonsignificant directions. This pattern highlights the importance of restorative sleep in mental health recovery and provides an empirical basis for integrating sleep management strategies in treatment plans. Further refinement of the model and inclusion of interaction or longitudinal components could enhance its explanatory power in subsequent analyses.

Multinomial Logit Modeling Results

The multinomial logistic regression results are shown in Table 3, summarizing how demographic, clinical, and

Table 3. *Multinomial logistic regression estimates for final treatment outcomes. Coefficients compare predictors that influence the probability of improvement or no change relative to deterioration.*

Predictor	0_coef	1_coef	0_p_value	1_p_value
const	-0.240	-0.581	0.552	0.171
Age	-0.223	-0.330	0.049	0.005
Symptom_Severity_1_10	0.023	-0.048	0.836	0.675
Mood_Score_1_10	0.023	0.109	0.842	0.346
Sleep_Quality_1_10	-0.006	-0.003	0.956	0.979
Physical_Activity_hrs_week	-0.024	-0.150	0.833	0.193
Treatment_Duration_weeks	0.041	0.129	0.717	0.267
Adherence_to_Treatment_%	-0.050	0.042	0.658	0.714
Gender_Male	0.259	-0.045	0.252	0.845
Diagnosis_Generalized Anxiety	0.402	0.516	0.191	0.114
Diagnosis_Major Depressive Disorder	-0.290	0.368	0.372	0.253
Diagnosis_Panic Disorder	-0.143	-0.173	0.647	0.610
Medication_Antipsychotics	0.180	0.236	0.643	0.554
Medication_Anxiolytics	-0.040	0.207	0.923	0.613
Medication_Benzodiazepines	0.285	0.298	0.454	0.446
Medication_Mood Stabilizers	0.654	0.302	0.088	0.465
Medication_SSRIs	0.480	0.665	0.224	0.098
Therapy_Type_Dialectical Behavioral Therapy	-0.110	0.086	0.727	0.795
Therapy_Type_Interpersonal Therapy	-0.086	0.476	0.797	0.156
Therapy_Type_Mindfulness-Based Therapy	-0.442	-0.388	0.160	0.248

Modeling Performance Metrics:
Accuracy: 0.000;
log_likelihood: -527.105;
AIC: 1134.209;
BIC: 1302.794
baseline_accuracy: 0.342

treatment-related variables influence the likelihood of improvement or no change relative to deterioration. The model estimates the probability of a patient achieving one of three possible end states: *deteriorated* (reference)**,** *improved***,** or *no* change, as a function of demographic, clinical, and treatment-related predictors. Overall model performance was modest, with a log likelihood of -527.105, AIC = 1134.209, and BIC = 1302.794, and a classification accuracy of 0.000 relative to a baseline accuracy of 0.342. These metrics suggest that, while the model identifies directional relationships between the variables, the outcome classification remains challenging because of overlapping patient characteristics and limited sample separation across categories.

Among the continuous predictors, age demonstrated consistent and statistically significant negative effects for both "improved" ($\beta = -0.330$, $p = 0.005$) and "no change" ($\beta = -0.223$, $p = 0.049$) relative to the deteriorated majority class (null) baseline. This indicates that younger patients are more likely to experience clinical improvement, while older individuals show a higher probability of remaining in or degenerating to poorer mental health conditions. This aligns with existing clinical evidence that treatment responsiveness tends to decline with age, possibly due to longer illness durations, comorbidities, or reduced neural plasticity (11-12).

Other continuous variables exhibited generally small and statistically nonsignificant coefficients. Mood score, sleep quality, and treatment duration all had weak, positive associations with improvement ($p > 0.25$), implying that, while better mood and longer treatment could lead to recovery, their effects are not independently strong in this cross-sectional specification. Physical activity showed a negative coefficient for the "improved" group ($\beta = -0.150$, $p = 0.193$), possibly reflecting that patients with higher activity levels might already have milder symptoms, so they have less of a measurable improvement in their mental health. Treatment adherence had opposite signs across outcome groups but remained nonsignificant, suggesting that self-reported adherence levels alone do not show the quality or timing of engagement that affects recovery.

In terms of diagnostic categories, generalized anxiety had the most noteworthy coefficients for "improved" ($\beta = 0.516$, $p = 0.114$) and "no change" ($\beta = 0.402$, $p = 0.191$), which indicates that anxiety disorders exhibit relatively stable or favorable course under treatment. Major depressive disorder also showed a positive direction for improvement ($\beta = 0.368$, $p = 0.253$), while panic disorder coefficients remained nonsignificant. These results suggest that diagnostic type contributes to outcome heterogeneity, but its influence does not reach statistical significance in this model.

Medication type effects showed mixed but interesting tendencies. Mood stabilizers ($\beta = 0.654$, $p = 0.088$) and SSRIs ($\beta = 0.665$, $p = 0.098$) were the two pharmacological factors that approached marginal significance for the "improved" category. Both positive coefficients imply that patients receiving mood stabilizers or SSRIs were more likely to improve compared to those receiving other medications or none. This aligns with their established roles in mood regulation and depression management. In contrast, anxiolytics and antipsychotics showed weak and inconsistent effects, while benzodiazepines showed moderate positive coefficients but had large *p-values*. This suggests that benzodiazepines have a limited independent impact when other factors are controlled.

For the therapeutic modalities, none of the coefficients reached statistical significance, but there are certain directional patterns that are worth noting. Interpersonal therapy had a moderately positive coefficient for "improved" ($\beta = 0.476$, $p = 0.156$), hinting at a potential beneficial effect

compared with the reference category, whereas DBT and MBT presented negative or close to zero values. These trends suggest that interpersonal approaches may give slightly better improvement probabilities, but larger samples would be required to confirm these associations statistically.

In summary, the MNL model highlights age as the strongest and most statistically significant predictor of treatment outcome, with younger patients showing a higher chance of improvement. These findings emphasize that demographic and pharmacological factors, rather than therapy format or adherence alone, are more directly associated with treatment outcomes within this dataset.

Joint Model Results

The joint modeling framework simultaneously estimates the ordered logit submodel for treatment progress scores and the multinomial logit submodel for treatment outcomes while accounting for shared latent correlations between the two processes. Tables 4 through 6 summarize the coefficient estimates, statistical significance levels, and overall performance metrics derived from this joint specification.

<u>Ordered Logit Component</u>

The ordered logit portion of the joint model describes how patient and treatment characteristics affect the intermediate treatment progress score, ranging from 1 to 10. The model achieved a stable convergence with balanced standard errors across all factors, indicating good numerical behavior after incorporating the shared random effect structure.

Looking at Table 4, sleep quality (β = 0.172, p = 0.036) once again shows up as a statistically significant positive predictor of higher treatment progress scores. This confirms that higher sleep quality leads to greater intermediate improvement within the therapy process, consistent with psychophysiological evidence that restorative sleep improves mood stabilization and emotional regulation (4-5). Other quantitative predictors, including age, mood score, symptom severity, physical activity, treatment duration, and treatment adherence, retained small coefficients with $p > 0.20$, indicating that their effects are modest once the joint latent factor is taken into account.

Across categorical predictors, gender (Male) showed a small, positive, and nonsignificant association (β = 0.199, p = 0.221) with improvement. Among diagnostic groups, major depressive disorder (β = 0.346, p = 0.126) and panic disorder (β = 0.381, p = 0.095) showed the largest positive effects, suggesting a tendency for patients within these diagnostic categories to report greater progress scores, although the statistical support remains marginal. Medication and therapy type variables produced coefficients centered near zero, with no statistically meaningful deviations, implying that within this joint framework, their effects on progress are comparatively homogeneous.

Multinomial Logit Component

The MNL block of the joint model captures how the same set of covariates relates to the final treatment outcome, categorized as *deteriorated* (reference), *improved*, or *no change*.

As shown in Table 5, for the improved outcome,

Table 4. *Ordered logistic component of the joint model showing effects of predictors on intermediate treatment progress while accounting for shared latent effects with final outcomes.*

Parameter	coef	std err	z	p_value
Age	0.046	0.080	0.576	0.565
Symptom_Severity_1_10	-0.006	0.080	-0.072	0.942
Mood_Score_1_10	0.088	0.081	1.085	0.278
Sleep_Quality_1_10	0.172	0.082	2.092	0.036
Physical_Activity_hrs_week	0.004	0.081	0.044	0.965
Treatment_Duration_weeks	0.006	0.081	0.074	0.941
Adherence_to_Treatment %	-0.046	0.080	-0.571	0.568
Gender_Male	0.199	0.162	1.225	0.221
Diagnosis Generalized Anxiety	0.073	0.222	0.329	0.742
Diagnosis_Major Depressive Disorder	0.346	0.226	1.529	0.126
Diagnosis_Panic Disorder	0.381	0.228	1.672	0.095
Medication_Antipsychotics	0.045	0.281	0.161	0.872
Medication_Anxiolytics	0.385	0.296	1.301	0.193
Medication_Benzodiazepines	-0.041	0.276	-0.147	0.883
Medition_Mood Stabilizers	0.116	0.275	0.421	0.674
Medication_SSRIs	-0.014	0.279	-0.051	0.959
Therapy_Type_Dialectical Behavioral Therapy	0.064	0.226	0.284	0.776
Therapy_Type_Interpersonal Therapy	0.159	0.231	0.687	0.492
Therapy_Type_Mindfulness-Based Therapy	-0.030	0.230	-0.130	0.896

symptom severity showed a negative and statistically significant coefficient ($\beta = -0.223$, $p = 0.049$), implying that individuals presenting with more severe initial symptoms are less likely to have an improved state by the end of treatment. This inverse relationship shows the clinical challenge of reversing deep symptom burdens within short or moderate periods of time. The variable SSRIs displayed a positive coefficient approaching significance ($\beta = 0.654$, $p = 0.088$), suggesting that SSRIs may have a beneficial association with improvement, though not definitively at the 5% level.

For the no change outcome, age showed a strong negative and highly significant effect ($\beta = -0.330$, $p = 0.005$), the coefficient magnitudes and directions are consistent with those of the MLN equation model. Generalized anxiety ($\beta = 0.515$, $p = 0.114$) and SSRIs ($\beta = 0.664$, $p = 0.098$) both showed positive but marginally significant coefficients, suggesting a small protective influence toward stability. In contrast, therapy type variables, though mostly positive, remained far from statistical significance, pointing to limited differential impact among therapeutic modalities once medication and demographic factors are considered.

Overall, the multinomial results within the joint framework reinforce the dominant influence of baseline symptom burden and patient age on final treatment outcome, while offering secondary evidence that pharmacological treatment through SSRIs contributes to clinical stabilization or improvement.

Table 5. *Multinomial logistic component of the joint model describing how predictors influence final treatment outcomes within the integrated framework.*

Class	Parameter	coef	std err	z	p_value
Improved	const	-0.239	0.404	-0.591	0.554
Improved	Age	-0.579	0.424	-1.367	0.172
Improved	Symptom_Severity_1_10	-0.223	0.113	-1.969	0.049
Improved	Mood_Score_1_10	0.023	0.113	0.207	0.836
Improved	Sleep_Quality_1_10	0.023	0.113	0.199	0.842
Improved	Physical_Activity_hrs_week	-0.006	0.113	-0.056	0.956
Improved	Treatment_Duration_weeks	-0.024	0.112	-0.210	0.833
Improved	Adherence_to_Treatment_%	0.041	0.114	0.363	0.717
Improved	Gender_Male	-0.050	0.112	-0.443	0.658
Improved	Diagnosis_Generalized Anxiety	0.259	0.226	1.146	0.252
Improved	Diagnosis_Major Depressive Disorder	0.401	0.307	1.306	0.192
Improved	Diagnosis_Panic Disorder	-0.291	0.324	-0.896	0.370
Improved	Medication_Antipsychotics	-0.144	0.313	-0.461	0.645
Improved	Medication_Anxiolytics	0.180	0.388	0.464	0.643
Improved	Medication_Benzodiazepines	-0.040	0.411	-0.097	0.923
Improved	Medication_Mood Stabilizers	0.285	0.381	0.748	0.454
Improved	Medication_SSRIs	0.654	0.384	1.703	0.088
Improved	Therapy_Type_Dialectical Behavioral Therapy	0.480	0.395	1.215	0.224
Improved	Therapy_Type_Interpersonal Therapy	-0.111	0.315	-0.352	0.725
Improved	Therapy_Type_Mindfulness-Based Therapy	-0.086	0.332	-0.259	0.795
No Change	const	-0.442	0.314	-1.408	0.159
No Change	Age	-0.330	0.117	-2.826	0.005

Continued Table 5. *Multinomial logistic component of the joint model describing how predictors influence final treatment outcomes within the integrated framework.*

Class	Parameter	coef	std err	z	p_value
No Change	Symptom_Severity_1_10	-0.048	0.115	-0.420	0.675
No Change	Mood_Score_1_10	0.109	0.116	0.943	0.346
No Change	Sleep_Quality_1_10	-0.003	0.116	-0.027	0.978
No Change	Physical_Activity_hrs_week	-0.150	0.115	-1.302	0.193
No Change	Treatment_Duration_weeks	0.129	0.116	1.109	0.267
No Change	Adherence_to_Treatment %	0.042	0.116	0.367	0.714
No Change	Gender_Male	-0.045	0.231	-0.196	0.845

Model Level Parameters and Goodness of Fit

As shown in Table 6, the joint model achieved convergence with a log likelihood of –1412.337 and included 67 estimated parameters across 500 observations. The integrated predictive accuracies were 0.216 for the ordered logit component and 0.434 for the MNL component, suggesting that the combined framework captures moderate discriminative information for both intermediate and outcomes.

The estimated variance parameter ($\sigma = 0.500$) reflects moderate dispersion of the latent random effect, while the correlation loadings ($\lambda_{or}d = 0.115$, $\lambda_{mn} = 0.099$) indicate a small but meaningful shared underlying factor that links the two outcome processes. These values confirm that the treatment progress and outcome dimensions share a modest degree of common variance that is consistent with the conceptual expectation that short-term progress and long-term improvements are related but not identical phenomena.

In summary, the joint model provides an integrated statistical framework that evaluates intermediate and final treatment responses at the same time. The results highlight **sleep quality, age,** and **symptom severity** as the key factors operating across both stages, while the estimated random effect correlations validate the existence of a shared latent structure underlying patient recovery dynamics. This supports the results of Tables 3 and 4.

Model Comparison and Discussion

To avoid repetition, this section focuses on cross-model contrasts rather than restating individual coefficient estimates. The comparative assessment across the three modeling frameworks, the ordered logit, the MNL, and the joint model, reveals both methodological and substantive insights into treatment dynamics. The ordered logit model isolates determinants of intermediate treatment progress and indicates that sleep quality is the most consistently influential behavioral factor, showing a positive and statistically significant association with higher progress scores. The MNL model, in comparison, highlights structural differences in final treatment outcomes, where age and baseline symptom severity emerge as the dominant predictors. Younger individuals and those entering treatment with lower symptom severity exhibit a higher probability of improvement relative to stagnation or deterioration. Together, these two single equation models establish that clinical recovery is shaped by both ongoing behavioral factors, such as sleep quality, and by demographic and diagnostic constraints.

The joint modeling framework extended these findings by estimating both stages of the recovery process at the same time while allowing for correlated residual structures between intermediate and outcomes. The estimated correlation loadings (Table 6) and moderate variance component (Table 5) confirmed the presence of a common latent factor linking short-term and long-term treatment responses. In practice, this means that improvements observed in intermediate progress scores carry partial predictive value for eventual treatment outcomes, although the shared variance is not large enough to suggest complete dependency. More importantly, the joint specification produced coherent coefficient patterns, particularly the persistence of sleep quality, age, and symptom severity as primary influences, demonstrating internal consistency across modeling frameworks. From a practical standpoint, the comparison suggests that integrating intermediate and final outcome information provides richer inferential value than analyzing either component separately. The ordered and multinomial models each capture complementary dimensions of therapeutic response, while the joint model situates them within a unified probabilistic structure. Together, the results emphasize the multifaceted nature of psychological recovery: behavioral variables such as sleep quality and adherence to treatment influence intermediate progress during treatment, while demographic and baseline clinical severity more strongly determine outcomes of the treatment. These insights provide a statistical foundation for adaptive treatment planning that simultaneously monitors short-term improvement and long-term stabilization.

Table 6. *Joint model performance statistics and estimated correlation parameters linking treatment progress and final outcomes, including model fit measures and latent variance components.*

Metric	Value
log_likelihood	-1412.337
ordered_accuracy_integrated	0.216
multinomial_accuracy_integrated	0.434
sigma	0.500
lambda_ord	0.115
lambda_mn	0.099
converged	TURE
n_params	67
n_obs	500

CONCLUSION

This study examined patterns in modeled mental health treatment progress and ultimate therapeutic outcomes using a sequence of statistical approaches, including ordered logit, MNL, and a joint correlated modeling framework. The primary objective was to demonstrate how demographic, behavioral, and treatment-related factors can be jointly analyzed to characterize intermediate and final outcome processes within a unified statistical structure. Using a fully synthetic clinical style dataset that encompasses demographic, diagnostic, medication, and therapy variables, the analysis shows how different classes of predictors may affect distinct stages of the recovery process.

Across modeling frameworks, short-term progress and long-term outcomes are influenced by related factors. Behavioral indicators primarily shape intermediate progress, whereas demographic and baseline clinical characteristics control the outcomes. While the ordered logit model singles out behavioral contributors to short-term progress, the MNL emphasizes demographic and baseline clinical constraints on outcomes. The joint framework clarifies this relationship by modeling their shared latent structure rather than re-estimating predictor effects. Together, these results should be interpreted as methodological demonstrations rather than direct clinical evidence. The study contributes to the quantitative mental health literature by showing how integrated ordinal multinomial modeling frameworks can be used to examine staged recovery processes and to assess the interdependence between short-term progress and long-term outcomes in a controlled, reproducible setting.

Although the combined modeling strategy provided good insights, there are several areas for methodological improvement remaining. First, the current analysis relied on a moderate synthetic sample size relative to the large number of predictors, which limits statistical power and precision. Future studies should aim to expand the number of observations and include broader patient groups to strengthen the generalizability of the results. Second, while this paper employed an ordered logit specification for treatment progress scores, future research may explore more flexible alternatives such as generalized ordered logit, partial proportional odds, or hierarchical Bayesian models to capture potential non-proportional effects. Similarly, for the ultimate treatment outcome, extensions beyond the multinomial logit, such as nested logit, mixed logit, or latent class choice models, could better accommodate complex or correlated outcome structures.

Finally, integrating longitudinal or repeated measure data would allow for dynamic modeling of treatment trajectories over time, which would allow for the changing interactions between behavioral indicators, therapeutic interventions, and psychological recovery to be shown. By addressing these refinements, these extensions would enhance the methodological utility and applicability of integrated modeling frameworks for mental health research.

CONFLICT OF INTEREST

The author has no conflicts of interest to disclose.

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