Trajectories of depression and anxiety symptoms during psychological therapy for common mental health problems

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Abstract

Background: There is substantial variation in patient symptoms following psychological therapy for depression and anxiety. However, reliance on endpoint outcomes ignores additional interindividual variation during therapy. Knowing a patient's likely symptom trajectories could guide clinical decisions.

Aim: Identify latent classes of patients with similar symptom trajectories over the course of psychological therapy and explore associations between baseline variables and trajectory class.

Method: Patients received high-intensity psychological treatment for depression or anxiety at NHS Improving Access to Psychological Therapies (IAPT) services in South London (N = 16,258). To identify trajectories, we performed growth mixture modelling of depression and anxiety symptoms over 11 sessions. We then ran multinomial regressions to identify baseline variables associated with trajectory class membership.

Results: Trajectories of depression and anxiety symptoms were highly similar and best modelled by four classes. Three classes started with moderate-severe symptoms and showed (1) minimal change, (2) gradual improvement, and (3) fast improvement. A final class (4) started with mild symptoms and demonstrated small improvement. Within the trajectory classes with moderate-severe baseline symptoms, patients in the two classes showing improvement as opposed to minimal change tended not to be prescribed psychotropic medication or report a disability and were in employment. Those showing fast improvement additionally reported lower baseline functional impairment on average.

Conclusion: Multiple trajectory classes of depression and anxiety symptoms were associated with baseline characteristics. Identifying the most likely trajectory for a patient at the start of treatment could inform decisions about the suitability and continuation of therapy, ultimately improving patient outcomes.

Background

Routinely collected patient information can be used to explain some of the variability in outcomes following psychological therapies for depression and anxiety ^{1–4}. Most studies to date have focussed on outcomes measured at the end of treatment, such as remission or recovery. Although clinically informative, reliance on endpoint outcomes may obscure interindividual differences in trajectories of symptoms occurring *during* treatment. Subgroups of patients may follow distinct trajectories, such as initially slow responders who nevertheless achieve good response by the end of treatment. Without a good understanding of these trajectories, treatments might be ended or altered early because patients, or their clinicians, consider the treatment unsuitable.

Person-centred structural equation modelling techniques can be used to reveal unobserved classes (groups or clusters) of individuals who exhibit similar longitudinal trajectories, which differ to those of the other classes. It is then possible to explore how baseline variables are associated with trajectory class membership. Relevant variables could be inspected at the start of treatment to identify a patient's most likely pattern of symptoms throughout therapy, and therefore inform patient and clinician expectations and decisions. Such information could also help monitor whether patients are doing less well than expected and thereby increase positive outcomes ^{5–7}. A previous study investigated symptom trajectories among 4,394 patients who received psychological therapy between 2008 and 2013 at two North London NHS Improving Access to Psychological Therapies (IAPT) sites ⁸. They identified four classes of depression symptom trajectories and five classes of anxiety symptom trajectories. Compared with trajectory classes showing improvement, classes with initially moderate-to-severe symptoms and limited change over time were associated with higher baseline levels of functional impairment, depression, anxiety, or phobia symptoms. No associations were found with age, gender, ethnicity, or prescribed psychotropic medication, despite prior evidence of associations between medication and treatment outcome ⁹. In the present study, we extended these findings in a larger and more ethnically diverse IAPT sample and considered additional baseline variables to test for association. We also used more recent data which is likely of higher quality due to improvements in recording patient information in IAPT ^{10,11}.

Method

Sample

The sample came from anonymised patient records of routinely collected data from the four IAPT services of the South London and Maudsley (SLaM) NHS Foundation Trust. Using the Clinical Record Interactive Search ¹², we extracted patients who had received psychological therapy for symptoms of depression or anxiety from July 2014 onwards and whose treatment had ended by September 2020, irrespective of the reason for ending. IAPT high-intensity therapies are formal psychological treatments with more therapist involvement and a higher number of sessions than low-intensity therapies. From the 115,304 patients covering 587,120 sessions extracted, we identified a high-intensity treatment sample of 16,258 patients and 110,773 sessions

for analysis (see Figure 1 and Supplementary Information 1). We included up to 11 sessions, including a baseline assessment. Patients primarily received cognitive-behavioural therapy (CBT) or counselling. To be representative of patients receiving treatment, we did not exclude patients scoring below clinical thresholds on depression and anxiety symptom scales.

We assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008. All procedures involving human patients were approved by SLaM IAPT (Institute of Psychiatry Research Ethics Committee: 15/SC/0586, CRIS approval: 16010).

Measures

Outcomes were self-report questionnaires administered each session. Current symptoms of depression and anxiety were measured respectively by the Patient Health Questionnaire 9-item version (PHQ9) ¹³ (range 0-27; case threshold in IAPT ≥ 10) and the Generalized Anxiety Disorder 7-item scale (GAD7) ¹⁴ (range 0-21; IAPT case threshold ≥ 8). We selected baseline self-reported patient characteristics to investigate for associations with class membership based on the available data and previously reported associations with treatment outcomes ^{2,8,9,15}; Supplementary Information 2).

Figure 1. Flowchart detailing the exclusions applied to retain IAPT patient data suitable for analysis.

¹ Record of administrative activities; not treatment or assessment sessions with recorded outcomes

² The first session in IAPT is often an assessment or triage session with treatment beginning formally at the second session. If the first to second session interval exceeded 30 days, the second session was used as the baseline. This was not repeated, as therapy with additional long intervals between the 'new' baseline and second session was considered too disrupted for stable conclusions.

³ Growth mixture modelling assumes time intervals are invariant across patients. Although high-intensity treatment is usually weekly, the naturalistic nature introduced substantial variance. In an attempt to limit this, sessions after a 30-day interval were excluded. See Supplementary Table 1 for session interval descriptives with and without this filtering.

⁴ We limited the analysis to high-intensity interventions due to the difference in the average number of sessions and level of structure between intensities. However, most IAPT patients receive at least one low-intensity session because of the stepped-care format. Furthermore, the assessment/triage session may be labelled as low intensity.

⁵ For sufficient covariance coverage for both outcomes (using the Mplus default minimum 0.10), and as modelling a higher number of sessions than most patients had received could make optimal solutions invalid and unstable ¹⁶. Descriptives of the number of sessions before and after this limitation are reported with Supplementary Table 2.

Statistical Analyses

Trajectory Class Models

We estimated separate growth mixture models (GMMs) for symptoms of depression and anxiety. For greater detail of the procedure, including all model selection criteria, see Supplementary Information 3. To first determine the single trajectory form which best fit the observed data overall we compared linear¹⁷, quadratic^{8,18,19} and negative log-linear (base 10)^{20,21} trajectories ('latent growth curves'). We then modelled up to six latent trajectory classes using GMM, each with the best-fitting form we had identified, to determine the optimal number of classes. This revealed whether the data was better explained by multiple latent growth curves than the single average one, indicating clusters of patients with similar trajectories rather than one group with homogeneous symptom change. The upper number of six classes was informed by past studies of trajectories during psychological therapy, which suggest between three and five classes^{8,20-22}. We compared each model to a model with one fewer class based on fit indices including Bayesian Information Criterion (BIC; see Supplementary Information 3). We favoured models that were interpretable in terms of clinical utility as well as past literature and theory. For statistical stability, we excluded models with classes containing less than 5% of the sample^{8,23}. We described patients in each class and the overlap between depression and anxiety classes.

We followed recommendations²⁴⁻²⁶ to first perform a version of GMM with zero variance (latent class growth analysis; LCGA). This is a simpler, less computationally demanding model that makes the often unrealistic assumption that all individuals in a class follow exactly the same trajectory. In LCGA, the variance of our outcome can only be explained by classes, which can result in trajectory classes that differ only in terms of starting score. We compared this simpler model to a GMM where the variance in each intercept was freed such that it could have a non-zero value but was constrained to be equal between classes, whilst the slope variance was fixed at zero. This allowed differences to be revealed in the patterns of change over time (the slope of each class) rather than initial symptom levels (the intercept of each class). This specification has successfully been used in previous symptom based GMMs^{18,20,22}. Our latent growth curve and LCGA results were similar between IAPT service-specific models (Supplementary Figure 1) therefore analyses were performed across all four IAPT services. We used Mplus version 8.3²⁷, alongside R version 3.6.3²⁸ and the MplusAutomation package²⁹.

Missing Data

Missing outcome data was handled using full information maximum likelihood under the missing at random assumption. To support this assumption, patients included in the analytical sample were compared to excluded patients using suitable group difference tests. The large sample size could result in statistical significance of negligible differences, therefore we primarily considered effect sizes. If a participant had no observed data for the PHQ9 or GAD7 they were omitted from the model of that outcome. Due to non-normal distributions of the outcomes (see Supplementary Figure 2), we specified maximum likelihood estimation with robust standard errors (Mplus option 'MLR').

Associations of Baseline Variables with Trajectory Class

Associations between variables measured at the start of treatment and trajectory class membership were tested using multinomial regression. To handle missing data in the baseline variables, we ran multiple imputation using the ‘mice’ package in R, including all variables besides class and specifying 20 imputed datasets and 20 iterations³⁰. Patients were allocated to the trajectory class for which they had the highest probability of membership and this ‘most likely’ class was the regression outcome. IAPT service was included as a covariate. We assessed statistical significance using a Bonferroni adjusted p -value threshold of $p < 0.025$ to account for the two independent models.

Results

Sample Descriptives

The descriptives for the sample of 16,258 patients are in Supplementary Table 3. Patients had an average age of 38 years (SD = 13, range 16-94), 68% were female and 60% identified their ethnicity as ‘White’. At baseline, the mean scores were PHQ9: 13.98 (SD = 6.39) and GAD7: 12.53 (SD = 5.39), and 34% of patients reported being prescribed psychotropic medication. In IAPT, patients receive ‘problem descriptors’ to indicate the disorder for which they will be treated. Whilst patients do not necessarily meet all diagnostic criteria for that disorder, or would not meet criteria for other disorders, we will refer to this as ‘diagnosis’. The most frequent diagnosis was depression (41%). The average number of sessions received, after limiting to a maximum of 11 including the initial assessment, was 6.81 (SD = 2.67), with 12% receiving only the minimum 3 sessions and 18% receiving 11 (Supplementary Table 2). At each session, over 99% of the patients remaining in treatment had complete PHQ9 and GAD7 scores (Supplementary Table 4). Participants in the analytical sample were similar to excluded participants (Supplementary Table 5), besides differences that reflected inclusion criteria (e.g. number of sessions).

Growth Mixture Models

For both depression and anxiety symptoms, the best-fitting latent growth curve form was quadratic (Supplementary Information 4). On average, patients’ symptoms were initially moderate and improved steadily over approximately the first five treatment sessions, then minimally to the final session. For latent class growth analysis, a four-class model was selected as the optimum solution for each outcome (Supplementary Information 5). The trajectories were largely uninformative as they primarily differed in terms of baseline severity (intercept). We therefore estimated growth mixture models (GMMs) with free but equal variance in the intercepts; these are the focus of our results.

Depression Symptoms Growth Mixture Model

For depression symptoms, a four-class GMM was selected based on fit indices alongside clinical and theoretical considerations (Supplementary Information 6). Figure 2a provides the mean trajectories of the four classes. Three classes showed moderate-severe symptoms at baseline. One of these showed no notable

change (*moderate-severe plateau*; grey squares), the second had steady improvement (*moderate-severe, gradual improvement*; pink diamonds) and the third demonstrated fast improvement initially which plateaued after the sixth treatment session (*moderate-severe, fast improvement*; blue triangles). A fourth class showed mild symptoms and little improvement over the first four sessions which then plateaued (*mild, small improvement*; green circles). Approximately half of patients were assigned to this *mild* class, with 14-18% in each of the other classes. At the final treatment session modelled, almost none of *moderate-severe plateau* patients had 'recovered' to below PHQ9 and GAD7 case thresholds (< 1%). Recovery was also low in the *gradual improvement* class (19%), but higher in the *fast improvement* and *mild* classes (68% and 59% respectively). Dropout was higher in the *gradual improvement* and *plateau* classes (20% and 19%) than *fast improvement* and *mild* classes (15% and 11%). The mean number of sessions was, however, similar across classes. The *plateau* class had the highest proportion referred to other services (11%). The full descriptives from the model are in Supplementary Information 7.

Anxiety Symptoms Growth Mixture Model

For anxiety symptoms, the GMM also suggested a four-class model (Figure 2b; model selection and descriptives in Supplementary Information 8 and 9). The trajectory classes for anxiety were very similar to that of depression and as such we used the same labels. However, more patients in the anxiety GMM were assigned to the *moderate-severe plateau* and *moderate-severe, fast improvement* classes, and fewer to the *moderate-severe, gradual improvement* and *mild, small improvement* classes. Most patients who followed a *plateau* or *gradual improvement* trajectory had not recovered by the tenth treatment session (1% and 35% recovered, respectively), whilst most patients in the *fast improvement* and *mild* classes had (69% and 64%). The *plateau* class had the highest proportion of dropout (23%) and referral to other services (9%).

Supplementary Table 6 shows the overlap of trajectory classes between the depression and anxiety models. For example, 39.5% of patients in the depression *gradual improvement* class were in the anxiety *moderate-severe plateau* class, compared with 6.6% of the depression *fast improvement* class. In the anxiety model, 4.5% of the *gradual* and 0.8% of the *fast improvement* class were in the *plateau* depression class. Of the depression *plateau* class, 88.8% were in the anxiety *plateau* class, whilst fewer (48.4%) of the anxiety *plateau* class were in the depression *plateau* class.

Figure 2. Four-class growth mixture model of a) depression symptoms (PHQ9) and b) anxiety symptoms (GAD7), during high-intensity psychological therapy (N = 16,258).

Note: This shows the model estimated mean and observed mean trajectories of each class. Patients had a likelihood of belonging to each trajectory class; counts and proportions (%) are based on their ‘most likely’ class membership.

Associations of Baseline Variables with Trajectory Class

Conditional Growth Mixture Model of Depression Symptoms

Higher baseline anxiety was associated with reduced odds of belonging to the *mild, small improvement* class, compared to the reference class *moderate-severe plateau* (Figure 3, Supplementary Table 7). Patients who had higher functional impairment, were prescribed psychotropic medication, or were not working (e.g. retired) compared with employed were less likely to be in the *mild* or the *moderate-severe, fast improvement* classes. Unemployed individuals or those reporting a disability had lower odds of being in the *fast* or *gradual improvement* or *mild* classes (i.e. improvement classes). Compared with White ethnicity patients, patients who identified as Black, Asian, multi-ethnic (‘mixed’), or ‘other’ ethnicity were less likely to follow the *mild*

trajectory compared to the *moderate-severe plateau*. Patients identifying as Asian also had lower odds of belonging to the *fast improvement* class. Compared with patients with a depression diagnosis, patients with GAD, panic/phobia, adjustment, OCD or 'other' disorder were more likely to be in the *mild* class. However, PTSD and OCD were associated, respectively, with decreased odds of the *fast* or *gradual improvement*, and *fast improvement* trajectories. Age and gender had no notable associations.

Conditional Growth Mixture Model of Anxiety Symptoms

Higher depression or impairment scores at baseline and non-worker status were associated with decreased odds of being in the *moderate-severe*, *fast improvement* or *mild*, *small improvement* trajectory classes than to the reference, *moderate-severe plateau* (Figure 3, Supplementary Table 8). Unemployed patients or those prescribed psychotropic medication were less likely to belong to any improvement trajectory class. Patients reporting a disability were also less likely to be in the *fast* or *gradual improvement* classes. Patients identifying as Black, compared with White, were less likely to be in the *gradual improvement* class. Asian ethnicity was associated with lower odds of the *fast improvement* or *mild* class. Compared with a depression diagnosis, all diagnoses besides 'other' were associated with lower odds of the *mild* class. Additionally, patients with PTSD and OCD were less likely to be in the *fast improvement* class. Males were more likely than females to be in the *mild* class.

Figure 3. Multinomial regressions of trajectory class membership using baseline variables for a four-class growth mixture model of depression symptoms (PHQ9) and a four-class growth mixture model of anxiety symptoms (GAD7), during high-intensity psychological therapy (N = 16,258).

Note: The reference class in each model was *moderate-severe plateau*. Service, indicating where the patient received treatment, was included as a covariate and had four categories. Error bars represent 95% confidence intervals. PHQ9 = Patient Health Questionnaire 9-item version, GAD7 = Generalised Anxiety Disorder 7-item scale. Comorbid symptoms refers to baseline GAD7 score in the depression model, and baseline PHQ9 score in the anxiety model. Functional impairment was measured by the Work and Social Adjustment Scale. Employment status ‘Non-worker’ included homemaker, carer, retired and student. Diagnosis is IAPT ‘problem descriptor’: GAD = generalised anxiety disorder; Panic/phobia = panic disorder, agoraphobia, social phobia, specific phobia; MADD = mixed anxiety and depressive disorder; PTSD = post-traumatic stress disorder; OCD = obsessive-compulsive disorder; ‘Other’ included somatoform disorder and severe mental illness.

Discussion

Overview

We identified patterns of change in depression and anxiety symptoms during high-intensity psychological therapy among 16,258 patients. A quadratic slope was optimal, consistent with previous studies^{8,18,19}. For both outcomes the data were best explained by four classes of trajectories. Patients within a class exhibited similar trajectories, which differed to other classes.

Growth Mixture Models

Both the depression and anxiety models had three classes with moderate-severe symptom scores at baseline. Using only intake symptom severity would therefore not allow a clinician to distinguish between three very different trajectories. One of these trajectories showed little or no change, labelled *moderate-severe plateau*. The other two classes improved: *moderate-severe, gradual improvement* changing more steadily than *moderate-severe, fast improvement*. The fourth class, *mild, small improvement*, had average baseline symptoms below clinical thresholds, and thus less capacity for large improvements. These trajectory classes were broadly consistent in number and shape with a previous IAPT study by Saunders et al. (2018), despite several sample and methodological differences.

The *gradual improvement* class may be of particular clinical relevance as the apparent lack of early response could lead to premature alteration or termination of treatment. Until around session four, the symptom change is indistinguishable from the *moderate-severe plateau* trajectory. ‘Recovery’ in IAPT reflects both depression and anxiety symptom scores falling below clinical thresholds by the final session. Recovery was lower in the *gradual* than the *fast improvement* class, especially for the depression model. Reflecting this, patients in the *gradual* class were more likely to experience minimal improvement in the *other* outcome. This can be seen in the higher proportion of the depression *gradual* class in the anxiety *plateau* class compared with that of the depression *fast improvement* class, and the lower proportion of the anxiety *gradual* class in the depression *plateau* class. The *gradual improvement* class might represent patients who require a high number of treatment sessions to show recovery. Supporting this, a study of high-intensity CBT found that most patients who significantly improved did so within 14 sessions⁹ and a systematic review of therapy dose recommended up to 26 sessions for patients who have improved but not recovered before this point³¹.

The *moderate-severe plateau* class may also represent patients who would benefit from more treatment, although some ‘non-responders’ would probably not recover even after a very high number of sessions³². Notably, the frequency of onward referrals in this class suggested the presence of co-occurring problems that required specialist services. That said, despite limited symptom change, some patients may have experienced other, unmeasured, benefits such as prevention of events like deterioration or hospitalisation. More patients belonged to the *plateau* class for anxiety than depression. This may be driven by disorders such as OCD and PTSD, which on average require a greater dose of therapy to observe improvement than most depression

and anxiety disorders ⁹, and are better detected by the GAD7 than the PHQ9 ³³. However, slightly over half of the anxiety *plateau* class showed improvement in depression symptoms, whilst most patients in the depression *plateau* class did not as were also in the anxiety *plateau* class.

Patients in the *fast improvement* class generally appeared to require fewer than ten treatment sessions. They were below case thresholds after an average of four treatment sessions and had the highest recovery rate, in-line with meta-analytic evidence that reliable symptom improvement by the fourth session predicts recovery ³⁴. It is important to continue treatment for several sessions after remission to help prevent false positives or relapse ⁹, however, this finding warrants further investigation as it could have implications for service efficiency.

The model estimated mean initial symptom score for the *mild, small improvement* trajectory class, for both depression and anxiety models, was below case threshold, yet all patients had received high-intensity therapy. This was consistent with the observed baseline means. However, scores varied around these means and patients could meet the threshold on the other symptom measure; the majority of patients in these classes were an observed case on one or both measures. These patients may also have had additional symptoms not assessed by the PHQ9 or GAD7. Therefore, it would be inappropriate to conclude that high-intensity treatment was unwarranted.

Associations of Baseline Variables with Trajectory Class

The most consistent associations with trajectory class membership were prescribed medication, reporting a disability, and employment status, which were associated with lower odds of being in any of the improvement classes compared with *moderate-severe plateau*. These associations are especially informative as they discriminated between higher baseline score individuals who improved or not. Employment status was specifically associated with the *moderate-severe plateau* class, consistent with findings from endpoint treatment outcome studies ^{2,35}. Despite associations with treatment outcomes in endpoint studies ⁹, the prior IAPT trajectory study found no association with medication ⁸. Neither employment or disability were included in the trajectory study, and the present findings highlight the importance of routinely recording such information. These additional factors may negatively impact therapy response and acknowledging and supporting patients to navigate them might reduce the likelihood of a *moderate-severe plateau* trajectory. This supports the argument for psychological services working closely with employment advisors, as per the IAPT manual ³⁶.

Higher functional impairment was associated with decreased odds of the *fast improvement* and *mild* classes, but not the *gradual improvement* class. This variable may therefore be useful for discriminating between *fast* and *gradual improvement*. The effect sizes for functional impairment were smaller than those for symptom scores, but still notable given they reflected the association for a one-unit difference on the WSAS, which has a wide scoring range.

In the previous IAPT trajectory study, higher functional impairment and symptom scores similarly showed greater likelihood of the corresponding *moderate-severe plateau* class ⁸. Our results were also consistent with a study reporting that patients who had higher baseline scores on the PHQ9, GAD7, WSAS, reported prescribed antidepressants, a disability or unemployment were less likely to improve with an increasing number of sessions, similar to our *plateau* class ⁹.

The associations between *mild* trajectory class and diagnosis in each model were ecologically valid. For example, patients were more likely to be in the *mild* trajectory class of the depression model if they had an anxiety diagnosis compared with depression. Additionally, PTSD and OCD were associated with lower odds of an improvement trajectory class, although improvement may have been observed after a greater number of sessions than modelled here, consistent with existing literature ⁹.

Patients who identified as one of the minoritised ethnic groups rather than White ethnicity were less likely to follow an improvement trajectory, especially the *mild* depression class, indicating that they had more severe symptoms at intake. These findings are consistent with lower recovery rates in national IAPT data and indicate that patients from minoritised ethnic groups may need additional or adapted treatment ³⁷. The ethnic diversity of the sample allowed us to include ethnicity in more detail than the binary variable used in similar studies and therefore identify that this pattern was most pronounced for Asian patients. That notwithstanding, there was insufficient power to analyse associations with ethnicity at an even greater level of granularity and this requires further research.

Strengths and Limitations

A large sample size enabled us to produce more accurate estimates and include a broader range of ethnicity categories and baseline variables, such as employment and disability, compared with previous studies. These important and easily recorded factors could help identify likely symptom trajectories at the start of treatment. However, the results may be confounded by the presence of additional variables that have shown prognostic value in psychological treatment studies of endpoint outcomes, such as chronicity ³. Whilst routinely collected data may generalise to clinical settings more readily than clinical trial data, the provision of different interventions, dependent on diagnosis, makes IAPT data more complex to analyse. Investigations of treatment and diagnosis-specific trajectories were beyond the scope of this study. Similarly, the inclusion of patients with depression diagnoses in the anxiety symptoms model, and vice versa, may have contributed to the high proportion in the *mild* trajectory classes. However, as comorbidity is common between these conditions, and diagnoses in IAPT only represent the condition being treated, we chose to include all patients in both models. Our findings therefore offer a broad representation of what we expect to see in routine clinical settings. Another issue, non-specific to naturalistic data, is dropout. Despite the use of missing data methods, observations at later sessions were based on remaining individuals. We attempted to support the generalisability of our findings by showing only modest baseline differences between the included and

excluded patients. Finally, the GAD7 does not cover core symptoms for disorders such as OCD and PTSD. However, GAD7 does show reasonably high specificity and sensitivity for several disorders including these³³, and therefore provides some indication of likely trajectories for them. Future studies should aim to model trajectories of disorder specific symptoms, and also functional impairment, which is particularly important to patients and potentially improves later in treatment than symptoms³⁸. This was not possible in the present sample due to the extent of missingness on these variables. Modelling a higher number of sessions would also be beneficial, to reveal more about patients who require a greater dose of therapy.

Implications and Conclusions

Using a person-centred analysis allowed us to identify substantial heterogeneity in depression and anxiety symptom change during psychological therapy which could be explained by four classes of trajectories. The identified trajectory classes were differentially associated with baseline variables such as employment, ethnic group, and disability. This is a first step towards using trajectory classes to inform clinical decisions, and therefore improve patient outcomes and service efficacy. More needs to be learned about how to combine variables and predict an individual's most likely trajectory. Having this information at the start of treatment might be informative about likely symptom trajectories and response, providing an opportunity to make appropriate treatment plans.

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Author Contribution

All authors were involved in conceptualising the study. MS performed the data pre-processing and analysis with technical input from EC, JEJB, KAG, and RS. Clinical expertise was provided by JEJB, CRH, KAR, RS and JW. MS drafted the manuscript and all other authors provided critical feedback, including interpretation of results. All authors approved the final version prior to submission. TCE and GB supervised this work.

Data Availability

This study used anonymised patient data from the South London and Maudsley NHS Foundation Trust that is not publicly available. The data can be accessed within a secure firewall via the Clinical Records Interactive Search (CRIS) tool by persons with the appropriate permissions. For more information please contact: cris.administrator@slam.nhs.uk.

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