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Research paper

Predicting treatment outcome in psychological treatment services by identifying latent profiles of patients

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ABSTRACT

Background: The outcomes of psychological therapies for anxiety and depression vary across individuals and symptom domains. Being able to predict treatment response from readily available patient data at presentation has potentially important benefits in aiding decisions about the most suitable interventions for a patient. This paper presents a method of identifying subgroups of patients using latent profile analysis, and comparing response to psychological treatments between these profiles.

Methods: All outpatients taken into treatment at two psychological treatment services in London, UK and who provided basic demographic information and standardized symptom measures were included in the analysis (n = 16636).

Results: Latent Profile Analysis was performed on intake data to identify statistically different groups of patients, which were then examined in longitudinal analyses to determine their capacity to predict treatment outcomes. Comparison between profiles showed considerable variation in recovery (74–15%), deterioration rates (5–20%), and levels of attrition (17–40%). Further variation in outcomes was found within the profiles when different intensities of psychological intervention were delivered.

Limitations: Latent profiles were identified using data from two services, so generalisability to other services should be considered. Routinely collected patient data was included, additional patient information may further enhance utility of the profiles.

Conclusions: These results suggest that intake data can be used to reliably classify patients into profiles that are predictive of outcome to different intensities of psychological treatment in routine care. Algorithms based on these kinds of data could be used to optimize decision-making and aid the appropriate matching of patients to treatment.

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1. Introduction

Depression and anxiety disorders are the most prevalent mental health disorders, with lifetime prevalence rates approaching 17% and 29% for major depression and anxiety disorders respectively (Kessler et al., 2005). Psychological interventions are a recommended treatment option, but as outcomes vary across patients, there is a need to consider a more personalised approach to treatment selection. An aim of such an approach is to tailor treatments based on key patient variables, thereby identifying which treatment will provide the best outcome for a particular patient (Goldberger and Buxton, 2013). The successful implementation of such a tailored treatment strategy could also lead to better outcomes and increased cost-effective use of resources.

Research aiming to predict response to treatment for depression and anxiety has been growing. Researchers have adopted a wide array of methods for making predictions, including neuroimaging data (Siegle et al., 2006) and genetic markers (Papakostas and Fava, 2008). However, despite some progress, these have thus far not demonstrated clinical utility and some approaches (e.g. neuroimaging) may not be feasible for routine use (Evans et al., 2006). Using patient information collected as part of routine assessment procedures may have significant potential to aid treatment selection decisions for the clinician and the patient in a way that is realisable at scale across a range of healthcare settings.

Systematic reviews have identified a range of individual patient factors that may predict response to both psychological and pharmacological interventions in depression and anxiety disorders, including variables such as initial symptom severity, relationship status, age, and gender (Mululo et al., 2012; Cuijpers et al., 2008).

Decision support algorithms are increasingly used throughout health care (Sheehan and Sherman, 2012), and although their

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uptake in mental health has been slower, decision support systems are being piloted (Botella et al., 2011; Bowles et al., 2014). Wallace et al. (2013) created a single combined moderator value from weightings of key patient variables, and used this moderator to predict whether pharmacological or psychological treatment would be more effective for a given patient. A significant difference was found between treatment outcomes for patients scoring higher and lower on the combined moderator. DeRubeis et al. (2014) developed the 'Personalised Advantage Index' to predict the final symptom score for a given patient under both psychological and pharmacological treatments. This algorithm showed a significant advantage of one treatment type over the other for 60% of patients in the development sample. However, both methods were developed using samples from small clinical trial populations, and require further evaluation of potential benefits in routine patient samples.

The methods used by Wallace et al. (2013) and DeRubeis et al. (2014) modelled patient variables to create two groups of patients, one responding to antidepressants and the other to psychotherapy. However, it would be of clinical value if algorithms were developed that could predict treatment response to different psychological interventions (Roth and Fonagy, 2006). Previous research has typically used simple regression based analyses to explore the relationship between patient variables and outcomes (Blom et al., 2007), but methods that identify groups of patients with different clusters of intake characteristics may prove more powerful.

Statistical methods for identifying sub-groups of individuals within a diagnostic group such as latent class analysis (Goodman, 1974) and latent profile analysis (Lazarsfeld and Henry, 1968), have been previously used to develop a more refined sub-grouping of patients but these studies did not investigate the implications of this for treatment response, for example, in eating disorders (Duncan et al., 2005; Wade et al., 2006) and personality disorders (Bucholz et al., 2000; Fossati et al., 2001). Further development of these methods has the potential to provide information on groups of patients seeking psychological treatment for depression and anxiety disorders, and the differential response of these groups to psychological interventions. Identifying subgroups of patients at initial presentation could provide valuable information to clinicians and patients which could inform decisions on appropriate treatment choices in routine care.

This study used latent profile analysis on a large dataset of patients with depression and anxiety disorders receiving psychological treatment to attempt to identify statistically distinct groups of patients varying on demographic characteristics and initial symptom severity, and to explore if treatment outcomes differed between these groups.

2. Method

2.1. Setting

The dataset used for this analysis was taken from two psychological treatment services in London, UK and includes all patients accepted for treatment. Both services treat individuals with depression and anxiety disorders, offering a range of evidence-based psychological interventions (IAPT, 2008; NCCMH, 2011). The services adopted a 'stepped care' approach to treatment (IAPT, 2008) with brief interventions provided as the first step of treatment (for example Guided Self-Help, e.g. Williams, 2006), and formal psychological therapies at the second step (such as Cognitive Behavioural Therapy). Patients may be 'stepped-up' to formal interventions if initial treatment with a brief intervention is not successful. A number of patients accepted into treatment will have had a single treatment session for advice and consultation from a clinician, and therefore provided data for only one time point.

2.2. Participants

All patients taken into treatment between September 2008 and March 2012 who had baseline self-rated severity of symptoms information on either the Patient Health Questionnaire - 9 (PHQ-9; Kroenke et al., 2001) or the Generalised Anxiety Disorder assessment (GAD-7; Spitzer et al., 2006), served as the discovery dataset (n=16636) for the latent profile analysis. Of the included sample, 99.78% of patients had an initial PHQ-9 score and 99.62% an initial GAD-7 score.

For the analysis of treatment outcomes, only patients from this dataset who scored above clinical caseness were included, and the cut offs used by the services are scores of 10 and 8 for patients on the PHQ-9 and GAD-7 respectively (IAPT, 2011). Patients who received only one single treatment for advice or consultation were not included in the analysis of treatment outcomes, as these required two time-point scores on the symptom scales to calculate.

A second dataset of patients referred between April 2012 and August 2013 was used as a validation sample (n=4683).

2.3. Measures

The patient characteristic variables included in the analysis are displayed in Table 1, and are all collected routinely as part of the services' standardised dataset of patient information. 90% of patients entering treatment have complete data in routine care (IAPT, 2012).

2.4. Plan of analysis

2.4.1. Latent profile analysis

Latent profile analysis (LPA) is an extension of latent class

Table 1
Patient variables included in the latent profile analysis.

Variable	Type of variable	Description
Age at referral	Continuous	Age of patient
Gender	Dichotomous	'Male' or 'female'
Self-rating of depressive symptoms	Continuous	Score on Patient Health Questionnaire (PHQ-9; Kroenke et al., 2001)
Self-rating of anxiety symptoms	Continuous	Score on Generalised Anxiety Disorder Scale (GAD-7; Spitzer et al., 2006)
Level of personal and social functioning	Continuous	Score on Work and Social adjustment Scale (W&SAS; Mundt et al., 2002)
Medication prescription status	Dichotomous	'Prescribed' or 'not prescribed' psychotropic medication at referral.
Welfare status	Dichotomous	'Receiving benefits' or 'not receiving benefits' from UK welfare support.
Ethnic group	Dichotomous	'White' or 'non-white' ethnic group
Phobia self-rating	Dichotomous	'Phobia' or 'non-phobia', classified by a score of 4 or more any one of the three phobia items (IAPT, 2011).

analysis to incorporate categorical, continuous and ordinal variables (Hagenaars and McCutcheon, 2002). Analysis was conducted in Mplus version 7 (Muthén and Muthén, 2012), on the initial Sept 2008 to March 2012 dataset (the discovery dataset). This discovery dataset was split into two independent samples and LPA was performed separately on these samples to allow comparison and confirmation of the profile structure in two samples.

To identify the best fitting model for the datasets, the Vuong-Lo-Medell-Rubin Likelihood Ratio test (VLMR-LRT; Lo et al., 2001) and the Bootstrap Likelihood Ratio Difference test (B-LRT) were compared alongside the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and entropy values. Both the B-LRT and the VLMR-LRT compare the K model (current model with K number of profiles) to K-1 model (model with one less profile), with a significant p-value indicating the K model fits the data better than the model with one less profile. A non-significant finding (p-value $> =0.05$) suggests that the model with one less profile provides a better fit for the data, and the more parsimonious model would be preferred. Lower AIC and BIC value indicate better model fit, whereas higher entropy values indicate higher accuracy in classification for the model.

As there was no prior hypothesis on the exact number of patient profile groups from the data, the analysis was conducted starting with a two profile model, and increasing the number of profiles until the VLMR-LRT became non-significant. The B-LRT was then used to confirm against the K-1 model using a parametric bootstrap procedure (Asparouhov and Muthén, 2012; Geiser, 2013). Information from the AIC, BIC and entropy values were also used to inform model fit.

This method was applied to both split samples of the discovery dataset to confirm whether the same profile structures were identified across samples.

2.4.2. LPA sample treatment outcomes

Following the identification of the latent profiles of patients, the next step was to determine whether there were differences in treatment outcomes between the patient profiles. Patients were allocated to the latent profile with the highest probability of profile membership. The primary outcome was the percentage of patients in each group meeting the 'recovery' criteria, which is the key performance indicator for the services and is defined as moving from clinical caseness on the PHQ-9 or GAD-7 symptom measures (or both) to below clinical caseness on both measures. In addition to this performance indicator, analysis of recovery or reliable change (Jacobsen and Traux, 1991) following intervention, clinical deterioration and dropping out of treatment were also calculated. These were defined as:

- Recovery: Scoring above clinical caseness cut-off at initial assessment on either symptom measure and scoring below the cut-off on both measures at final assessment following treatment.
- Recovery or Reliable change: Either in recovery as defined above or showing reliable improvement between initial and final assessment on both the PHQ-9 and GAD-7. Calculated using the reliable change index (Jacobsen and Traux, 1991; Evans et al., 1998).
- Clinical Deterioration: Deterioration was defined as reliable clinical change in a negative direction (increase in score) between initial and final assessment on either measure. Calculated using the reliable change index (Jacobsen and Traux, 1991; Evans et al., 1998).
- Dropout from treatment: Defined as either dropping out of treatment, or as declining treatment after two or more treatment sessions by the service.

These outcomes were then compared across patient profile groups. A series of logistic regression analyses were performed, entering only two profiles on each occasion as the independent variable (for example, profile 1 vs. profile 2) to allow a direct comparison of the odds ratio of each outcome between the profiles. Analysis was conducted using STATA 12 (StataCorp, 2011).

2.4.3. Validation sample treatment outcomes

After calculating the treatment outcomes across the groups in the discovery sample, the validation sample (patients from April 2012 to August 2013) was used to test whether the predictive relationships between intake LPA patient profiles and outcome were maintained in a second independent sample of patients attending the same services.

2.4.4. Treatment outcomes by intensity of intervention.

Following the comparison of outcomes between the discovery and validation datasets by latent profiles, a comparison of outcomes between individuals receiving brief interventions or formal psychological therapies was performed. For this analysis, the discovery and validation included samples were combined. As the focus of this analysis was difference between intervention intensities, only patients who were treated with just one intensity of intervention were included; patients who were stepped up during the course of treatment were excluded as they would have received both interventions.

The likelihood of achieving positive outcomes following treatment was compared between the two intensities of intervention for each latent profile, and logistic regression analysis was performed with the level of intervention as the independent variable for each latent profile.

3. Results

3.1. Latent profile analysis

A random 50% split of the development sample resulted in two samples of n=8321 (Discovery sample 1a) and n=8315 patients (Discovery sample 1b). Model comparison statistics are presented in Appendix 1. The LPA for discovery sample 1a yielded significant p-values on the VLMR-LRT comparing successive models, from a two-profile solution to an eight-profile solution ($p=0.0057$ at the eight-profile model), as well as decreasing AIC and BIC values. Although the BIC and AIC values were slightly lower for the nine-profile solution, the VLMR-LRT produced a non-significant p-value ($p=0.3551$) suggesting that increasing the number of profiles was not a better fit for the data (Asparouhov and Muthén, 2012; Geiser, 2013). The entropy value was also higher for the eight-profile solution suggesting higher classification accuracy, and therefore the VLMR-LRT indicated eight-profile solution was preferred, in line with previous latent profile analyses (Rajendran et al., 2015; Merz and Roesch, 2011). B-LRT was performed on the eight-profile solution, with a significant finding between the eight and seven profile models ($p<0.0001$).

The LPA for discovery sample 1b also yielded significant increases in model fit according to the VLMR-LRT up to the eight-profile model ($p<0.0001$ for the eight-profile model compared to the seven-profile model) with decreasing AIC and BIC values, and again the nine-profile model produced a non-significant VLMR-LRT p-value ($p=0.940$). The B-LRT confirmed a significant p-value for the eight-profile model compared to the seven-profile model ($p<0.0001$).

Following confirmation of an eight-profile model structure from the two independent split samples, the dataset was recombined, and the same method of LPA applied on the full sample

Table 2
Latent profiles and associated patient characteristics.

	Full sample	LP1 (18.05%)	LP2 (22.67%)	LP3 (3.08%)	LP4 (4.05%)	LP5 (8.50%)	LP6 (9.10%)	LP7 (12.44%)	LP8 (22.11%)
Age – Mean (SD)	37.9 (13.36)	33.47 (8.46)	30.74 (7.48)	66.83 (9.71)	65.16 (8.88)	54.25 (7.85)	40.72 (9.10)	42.74 (9.44)	29.68 (6.90)
PHQ-9 – Mean (SD)	13.85 (6.67)	5.37 (3.03)	11.28 (3.16)	4.59 (3.09)	10.76 (3.59)	17.88 (3.43)	13.36 (3.38)	22.86 (2.78)	18.85 (3.14)
GAD-7 – Mean (SD)	12.35 (5.51)	5.26 (2.71)	12.56 (2.98)	3.74 (2.58)	10.85 (3.26)	15.94 (2.88)	7.99 (2.78)	18.38 (2.50)	16.43 (2.79)
W&SAS – Mean (SD)	17.85 (9.69)	8.69 (5.79)	14.53 (6.23)	6.99 (6.32)	11.79 (7.14)	18.15 (7.38)	20.87 (6.69)	31.72 (5.74)	22.28 (7.11)
Gender - n(%) female	10793 (66%)	1906 (65%)	2570 (69%)	335 (68%)	451 (68%)	905 (65%)	850 (57%)	1166 (57%)	2610 (72%)
Ethnic Group - n (%) Non-White	3151 (22%)	452 (17%)	547 (17%)	46 (11%)	70 (12%)	219 (18%)	346 (27%)	498 (28%)	973 (31%)
Medication prescribed – n (%) Prescribed	5802 (39%)	721 (27%)	691 (20%)	114 (28%)	195 (33%)	659 (53%)	789 (59%)	1357 (73%)	1276 (38%)
Welfare status - n (%) on benefits	3834 (28%)	297 (12%)	262 (8%)	32 (9%)	48 (9%)	472 (40%)	679 (54%)	1258 (74%)	786 (26%)
Phobia Self-rating - n (%) phobia	7592 (51%)	585 (21%)	1261 (37%)	99 (23%)	205 (35%)	755 (60%)	750 (55%)	1738 (93%)	2199 (66%)

of n=16636 to generate probabilities of profile membership for each patient in the sample. As before, VLMR-LRT showed a significant p-value up to the nine-profile model ($p=0.699$) with the eight profile model selected and probability of profile membership assigned to each case in the analysis.

Descriptive statistics for the full sample and the distribution of patient characteristics for each LP are displayed in Table 2 (a graphical representation of the profiles and description of each profile is available in Appendix 2). Comparing each patient profile to the full sample means and distribution, as well as to the other profiles provides an understanding of the characteristics of each group of patients. For example, latent profile 1 (LP1) is a younger, lower symptom severity group (on both PHQ-9 and GAD-7) and tends to score low on the phobia scale, as well as being less likely to receive public welfare benefits and prescribed psychotropic medication compared to the overall sample. LP2 has a similar age, gender, and ethnic group distribution to LP1, but with higher symptom severity and lower functioning, as well as having a higher probability of phobia. LP7 has the highest intake symptom severity (means of 23 and 19 on the PHQ and GAD), with a high probability of receiving public welfare benefits, prescribed medication, and phobia symptoms. There was a large variation in the size of the patient profiles, with LP3 and LP4 having a smaller share of the population (3.1% and 4.1%) compared to LP2 and LP8 (22.7% and 22.1%).

3.2. Treatment outcomes

The next step was to test whether the LPA groups were predictive of response to treatment. Of the n=16636 patients included in the LPA, n=2691 (16.18%) scored below clinical caseness on both symptom measures, and n=3252 patients (19.55%) only received a single treatment session. This resulted in n=10,693 patients included in the analysis of treatment outcomes for the discovery sample.

Full tabulation of all outcomes by LP are presented in the first section of Table 3, and odds ratios (OR) from logistic regression analyses between profiles for each outcome are presented in Appendix 3. Inspection of the recovery outcomes shows a large variation between the patient profiles. For example LP1 has the highest recovery rate across the profiles, with 74% of patients in recovery at endpoint after treatment. The worst outcomes were for LP7, with just 15% in recovery, indicating that recovery is 4.9 times more likely in LP1 compared to LP7. Logistic regression comparing these two profiles showed the odds of recovery are 16.75 higher for patients in LP1 compared to those in LP7 (OR=16.75, 95% CI=13.4–20.9, $p<0.001$). As expected, when outcome is defined by the rates of reliable change or recovery the picture improves somewhat, with positive outcomes for LP7 increasing to 22% reliable change or recovery following treatment. Fig. 1 compares the recovery alone against the reliable change or recovery outcomes across profiles. LP5 and LP8 display the biggest differences between these two outcomes, and it might be that different outcomes are to be expected for certain profiles.

Less variation was found between patient profiles for treatment dropout compared to recovery. Nevertheless, the LPA groupings still robustly distinguish cases that subsequently dropped out,

Table 3
Outcome by latent profile for the discovery and validation samples.

	% of sample	Recovery				Reliable change or recovery				Deterioration				Treatment drop out			
		Yes	No	Total	%	Yes	No	Total	%	Yes	No	Total	%	Yes	No	Total	%
Discovery sample																	
LP1	**6**	493	170	663	74	495	168	663	75	73	590	663	11	175	488	663	26
LP2	**28**	1593	1357	2950	54	1807	1143	2950	61	256	2694	2950	9	904	2046	2950	31
LP3	**1**	48	18	66	73	48	18	66	73	11	55	66	17	11	55	66	17
LP4	**5**	287	221	508	56	309	199	508	61	53	455	508	10	103	405	508	20
LP5	**10**	330	776	1106	30	470	636	1106	42	74	1032	1106	7	317	789	1106	29
LP6	**10**	498	581	1079	46	542	537	1079	50	211	868	1079	20	351	728	1079	33
LP7	**15**	232	1340	1572	15	340	1232	1572	22	79	1493	1572	5	624	948	1572	40
LP8	**26**	802	1947	2749	29	1100	1649	2749	40	174	2575	2749	6	1094	1655	2749	40
Total	**100**	4283	6410	10,693	40	5111	5582	10,693	48	931	9762	10,693	9	3579	7114	10,693	33
Validation sample																	
LP1	**6**	218	70	288	76	220	68	288	76	27	261	288	9	77	211	288	27
LP2	**27**	613	635	1248	49	715	533	1248	57	105	1143	1248	8	441	807	1248	35
LP3	**1**	26	9	35	74	26	9	35	74	3	32	35	9	9	26	35	26
LP4	**6**	152	109	261	58	160	101	261	61	23	238	261	9	54	207	261	21
LP5	**11**	140	355	495	28	174	321	495	35	35	460	495	7	185	310	495	37
LP6	**10**	221	267	488	45	240	248	488	49	96	392	488	20	172	316	488	35
LP7	**15**	95	614	709	13	150	559	709	21	52	657	709	7	302	407	709	43
LP8	**25**	303	856	1159	26	438	721	1159	38	87	1072	1159	8	534	625	1159	46
Total	**100**	1768	2915	4683	38	2123	2560	4683	45	428	4255	4683	9	1774	2909	4683	38

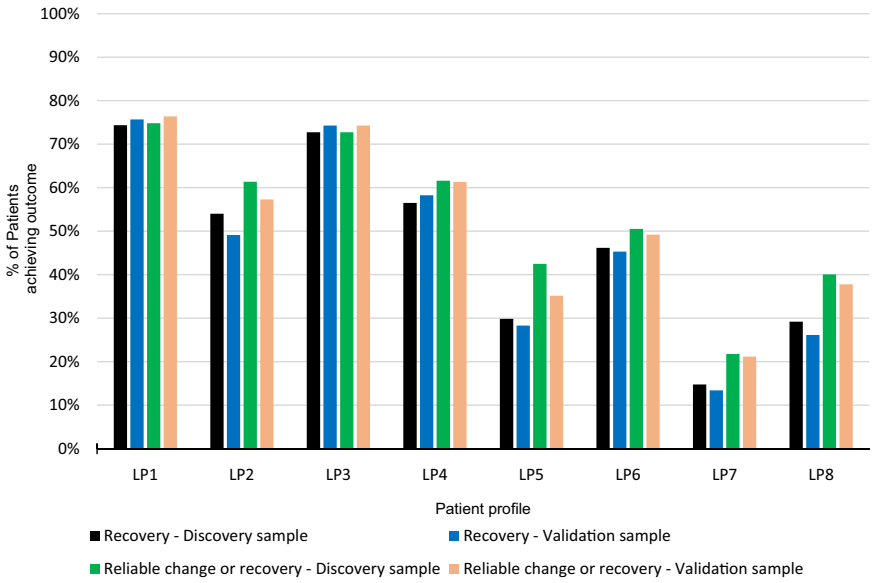

Fig. 1. Percentage of patients by latent profile who recovered and recovered or showed reliable change (discovery and validation samples).

with, for example, 2.35 times more drop outs in LP8 versus LP3 (17% versus 40%; OR=3.31, 95% CI=1.7–6.3, $p<0.001$). Although the rates of clinical deterioration were low in the sample overall (9% for the full sample), there was significant variation between profiles, for example 4 times greater probability of deterioration was found in LP6 compared to LP7 (5% versus 20%; OR=4.59, 95% CI=3.5–6.0, $p<0.001$).

3.3. Validation sample treatment outcomes

The second dataset of patients, referred to the service between April 2012 and April 2013 included n=4683 patients. Membership to each latent profile was calculated using the posterior probabilities of group membership from the original LPA. This calculation provides each patient in the new sample a probability of membership to each latent profile using their patient variables at intake. Outcomes for the validation sample are displayed in the second section of Table 3. By comparing the outcomes for each patient profile from the discovery sample to this validation sample shows remarkably similar probabilities of each outcome. For example, LP1 have the highest probability of recovery at 76% and LP7 the lowest with 13% recovery follow treatment. LP6 have the highest probability of deterioration (20%) and LP8 are the most likely to drop out (46%). The only major difference between recovery and reliable change rates between the discovery and validation samples, displayed in Fig. 1, appears to be a slightly reduced percentage of patients in LP5 who achieved recovery or reliable change (42% discovery sample vs. 35% in the validation sample). The major differences in prediction of treatment dropout and clinical deterioration between the two samples were for LP3, but the number of patients in the second dataset meeting the inclusion criteria for this patient profile was very low (just n=29 patients included in the analysis) making the results difficult to interpret.

3.4. Intensity of intervention

The analyses above present the variations in outcomes between latent profiles following any treatment from the services. However, it is also of interest to explore whether there are differences in outcome between the different intensities of treatment within latent profiles. To explore if there were any differences in symptom severity of patients receiving different treatments, the mean initial PHQ-9 and GAD-7 score for patients receiving brief or formal interventions was compared within each LP (Appendix 4). Independent samples *t*-tests show that the only differences in mean symptom severity scores were for LPs 1 and 2. Mean PHQ-9 scores were significantly higher in the formal intervention group for LP1, although the GAD-7 score was significantly higher for patients receiving brief interventions. For LP2, the mean PHQ-9 score was significantly lower for patients receiving formal psychological therapies, whereas the initial GAD-7 score was higher in this group compared to patients receiving brief interventions. Of course a range of variables other than scores of a symptom severity scale influence the presentation and course of a mental disorder.

The first section of Table 4 displays the percentage of patients who recovered after receiving either brief interventions or formal psychological therapy only, as well as the odds ratio and p-value for recovery between the two interventions. Significant ORs ($p<0.05$) were found for LP2 (OR=1.32, 95% CI=1.13–1.54, $p=0.001$), LP6 (OR=1.39, 95% CI=1.11–1.75, $p=0.004$) and LP7 (OR=1.66, 95% CI=1.24–2.22, $p=0.001$), with increased odds of recovery for individuals in these profiles receiving formal interventions instead of more brief interventions.

The second section of Table 4 presents the percentage of patients achieving the recovery or reliable change outcome and odds ratios from logistic regression analysis. The results are similar to those for the recovery alone outcome, with significant odds ratios in favour of formal interventions found for LP2 (OR=1.28, 95% CI=1.09–1.51, $p=0.002$), LP6 (OR=1.29, 95% CI=1.03–1.63, $p=0.027$) and LP7 (OR=1.33, 95% CI=1.04–1.69, $p=0.022$). Additionally, the odds of achieving this outcome are significantly higher following formal interventions for patients in LP8 as well (OR=1.19, 95% CI=1.01–1.4, $p=0.036$).

The percentage of patients showing clinical deterioration following either brief or formal interventions is displayed in the first section of Table 5. Although a significant difference was found between brief and formal interventions for the total sample (OR=1.19, 95% CI=1.04–1.36, $p=0.014$), the only profile where a significant difference was found between the intensities of interventions was for LP7 (OR=1.73, 95% CI=1.08–2.76, $p=0.023$). The LP showing the largest difference between interventions was LP3, although this was not significant (OR=3.78, 95% CI=0.93–15.41, $p=0.063$).

Table 4
Percentage of patients achieving recovery and achieving recovery or reliable change with odds ratios, for brief and formal interventions.

Recovery						
Profile	**Brief interventions**		**Formal Interventions**		**OR**	**95% CIs**
	Total cases in LP	% recovery	Total cases in LP	% recovery		
LP1	511	75	231	79	1.26	0.87, 1.84
LP2	2192	52	917	59	1.32*	1.13, 1.54
LP3	47	72	39	72	0.97	0.38, 2.51
LP4	372	58	236	56	0.89	0.64, 1.24
LP5	739	30	442	31	1.05	0.81, 1.35
LP6	675	45	525	53	1.39*	1.11, 1.75
LP7	675	11	959	17	1.66*	1.24, 2.22
LP8	1715	29	965	32	1.11	0.94, 1.32
Total	6926	42	4314	41	0.98	0.9, 1.06
Recovery or reliable change						
Profile	**Brief interventions**		**Formal Interventions**		**OR**	**95% CIs**
	Total cases in LP	% recovery or improvement	Total cases in LP	% recovery or improvement		
LP1	511	75	231	79	1.25	0.86, 1.82
LP2	2192	60	917	66	1.28*	1.09, 1.51
LP3	47	72	39	72	0.97	0.38, 2.51
LP4	372	64	236	59	0.82	0.58, 1.14
LP5	739	41	442	44	1.11	0.87, 1.4
LP6	675	49	525	56	1.29*	1.03, 1.63
LP7	675	19	959	24	1.33*	1.04, 1.69
LP8	1715	39	965	44	1.19*	1.01, 1.4
Total	6926	49	4314	49	0.97	0.9, 1.04

* OR significant at $p < 0.05$.

Table 5
Percentage of patients showing clinical deterioration and dropping out of treatment with odds ratios, for brief and formal interventions.

Deterioration						
	Brief interventions		**Formal interventions**		**OR**	**95% CIs**
Profile	Total cases in LP	% deterioration	Total cases in LP	% deterioration		
LP1	511	10	231	10	1.09	0.65, 1.83
LP2	2192	7	917	8	1.11	0.84, 1.49
LP3	47	6	39	21	3.78	0.93, 15.41
LP4	372	7	236	11	1.51	0.86, 2.68
LP5	739	7	442	5	0.61	0.36, 1.04
LP6	675	17	525	21	1.26	0.94, 1.69
LP7	675	4	959	6	1.73*	1.08, 2.76
LP8	1715	6	965	7	1.2	0.87, 1.67
Total	6926	8	4314	9	1.19*	1.04, 1.36
Drop out						
Profile	**Brief interventions**		**Formal interventions**		**OR**	**95% CIs**
	Total cases in LP	% drop out	Total cases in LP	% drop out		
LP1	511	24	231	21	0.85	0.58, 1.23
LP2	2192	31	917	21	0.59*	0.49, 0.71
LP3	47	15	39	21	1.47	0.48, 4.51
LP4	372	22	236	11	0.44*	0.28, 0.72
LP5	739	28	442	24	0.8	0.61, 1.05
LP6	675	32	525	23	0.66*	0.51, 0.85
LP7	675	39	959	32	0.74*	0.6, 0.91
LP8	1715	39	965	32	0.75*	0.64, 0.89
Total	6926	32	4314	26	0.73*	0.67, 0.8

* OR significant at $p < 0.05$.

The second section of Table 5 presents the percentage of patients dropping out of treatment and odds ratios from logistic regression analysis. Overall there was significantly less drop out from formal interventions compared to brief interventions (OR=0.73, 95% CI=0.67–0.8, $p<0.001$). For individual profiles, significant odds ratios were found in favour of formal interventions for LP2 (OR=0.59, 95% CI=0.49–0.71, $p<0.001$), LP4 (OR=0.44, 95% CI=0.28–0.72, $p=001$), LP6 (OR=0.66, 95% CI=0.51–0.85, $p=0.002$), LP7 (OR=0.74, 95% CI=0.6–0.91, $p=0.004$) and LP8 (OR=0.75, 95% CI=0.64–0.89, $p=0.001$). LP3 was the only profile where there was more drop out in patients receiving formal interventions, although this difference was not significant (OR=1.47, 95% CI=0.48–4.51, $p=0.496$).

Although clinical deterioration was more likely following formal interventions, LP7 was the only profile where this difference was significant. Treatment dropout was significantly more likely during brief interventions for five of the eight patient profiles when compared to formal interventions.

4. Discussion

LPA identified eight statistically reliable groups of patients in receipt of psychological treatment and the profile structure was replicated in two independent samples of over 8000 patients each. Importantly, the eight profiles showed significant variation in outcomes following treatment. This variance in outcomes between latent profiles suggests that identification of these groups at initial assessment can provide reliable information about patients' likely response to treatment, which may be of value when making informed treatment selection decisions. The variation in groups was replicated with an independent validation sample, revealing that the predictive associations between latent profile and treatment outcomes were consistent across different samples attending the same services.

The latent profiles identified groups of patients attending services for psychological treatment, who share a set of common characteristics within each group and which is associated with different treatment outcomes. For example, the typical characteristics of patients in LP1 are relatively low levels of depression and anxiety symptom severity, fewer phobic symptoms and relatively high levels of functioning compared to the full sample averages. These patients have a very high likelihood of a positive outcome following treatment (74%) relative to the full dataset (40%), and therefore may be patients for whom brief interventions are likely to be sufficient to achieve a good outcome. It should be noted that 31% of LP1 patients received a formal intervention and considering the high probability of recovery from brief interventions, this might represent an over use of healthcare resource and an unnecessary burden for patients. LP1 and LP3 share a number of similar characteristics, such as low levels of symptom severity and unlikely to be in receipt of welfare benefits, be prescribed medication or have phobic symptoms. However, the mean age of LP3 is twice that of LP1 (33 compared to 67), as well as being less likely to be from a non-white ethnic group (11% compared to 17%), but these differences appear to have little impact on the likelihood of recovery which is very similar for both profiles. As 45% of LP3 patients were in receipt of formal interventions, this again may reflect an unnecessary use of service resource.

Considering patients with poorer outcomes, LP7 show relatively high levels of both depression and anxiety symptoms, which may account for the high proportion prescribed psychotropic medication (74%) compared the full dataset (39%). These characteristics may also contribute to the low number in work (93% were in receipt of welfare benefits). The outcomes for this group are relatively poor for both brief and formal interventions, which may imply that alternative treatment options should be considered. However, the significant difference in recovery between brief and formal interventions suggests that if they were to be treated in the services included in this study then a formal intervention should be considered. The outcomes for recovery or reliable change also suggest that formal interventions might be considered as the initial treatment for patients in LP8, as the outcomes for brief interventions were significantly lower for this profile of patients.

Identifying patients at risk of deterioration is important as it may reduce the likelihood of ineffective or harmful treatments being offered. For example, the deterioration rates for LP6 were four times higher (20%) compared to LP7 (5%), and more than double the mean deterioration for the whole sample (9%). As the probability of recovery for this profile at 46% was similar to the overall recovery rate for the whole sample, this suggests that if treatment were to be offered to this group of patients then a number of additional factors may be worth considering, such as offering formal interventions (as there was a significant difference between brief and formal interventions), the use of additional interventions (for example, medication) and careful sessional monitoring of progress. Similarly, as the probability of drop out is very high in brief interventions for LP7 and LP8 (39%), this information could be used by clinicians either to consider treatment retention as part of the intervention goals, or formal interventions as the initial treatment to reduce the incidence of drop out.

Important clinical information may be derived not only from membership to a single profile, but also which additional profiles the patient shares characteristics with. LPA provides a probability that each case (patient) is a member of each group, with the case allocated to the group to which they have the highest probability of belonging. There will be a range of probabilities of group membership within each profile, and different members of a LP will have a probability of membership from 100% to below 50%. A patient with a probability of less than 100% for a particular group will therefore have a probability of being in other profiles as well as their allocated patient profile. For example, a patient may have a number of characteristics that indicate a 70% probability of being in LP6, and 30% for LP7, which could be viewed as their secondary profile. Identification of these secondary profiles is straightforward using the posterior probability calculation, and may provide additional information, for example, of the risk of deterioration or probability of recovery to inform a clinical decision.

Although previous prediction models have reported significant differences in treatment response (Wallace et al., 2013; DeRubeis et al., 2014), the findings were drawn from small, highly selected trial populations. In contrast, our study has used data from a large sample in routine clinical practice and validated the findings in an additional sample. The ability of the latent profile approach to identify differences in deterioration rates is also important as previous studies (Hannan et al., 2005) have indicated that clinicians may be poor at identifying patients who are likely to deteriorate. Latent profile methods using easily available patient variables offers the possibility of readily identifying sub-groups within a clinical population who are at risk of not improving or may even deteriorate, and for whom formal intervention should be considered as an initial treatment.

5. Limitations

One limitation of this study is that the eight-profile structure was identified in a large sample of patients from two services in the United Kingdom healthcare system, and it is possible that services in other healthcare systems may have different profiles of patients. The profile structure identified in this analysis should be further explored in datasets from additional services. If there is

some variation in profile structure then this could be used to tailor profiles to represent the local population of patients attending the services.

All patient characteristic variables used in this analysis are easily obtainable as part of routine data collection. However, the dataset does not include a number of patient variables, including diagnosis, that might be expected to influence treatment outcomes as well as other variables such as relationship status and response to previous treatment (Mululo et al., 2012). Such factors may be important in further refining the patient profiles and predicting treatment response, but may also contribute to existing treatment selection decisions made by clinicians. Although there were no systematic differences in initial symptom severity scores between patients who received brief interventions or formal psychological therapies within each LP, clinicians will likely have considered additional patient factors when allocating patients to higher intensity treatments.

6. Clinical and research implications

There is potential for the profiles identified in this study to be made available to clinicians, for example by converting the posterior probability calculations used in this analysis into an algorithm that could be hosted either through local clinical data management systems or through an App on a mobile phone or tablet. The information obtained on new patients could be used to inform a discussion between clinician and patient on the appropriate choice of treatment. Aggregation of the data derived from the algorithm could also inform clinic and service audits and evaluations. These approaches should be the subject of future research which explores their feasibility and utility in supporting clinicians and patients to aid decisions on treatment selection (including both psychological and pharmacological treatment). The use of additional information, such as diagnosis or previous treatment response could also lead to refinements to the latent profile analysis and associated algorithms to further increase their utility. This may improve outcomes for both patients and services, and contribute to a more effective and efficient healthcare system.

7. Conclusions

The findings from this study suggest that latent profile analysis may provide a robust method of grouping patients that is predictive of treatment outcome in routine psychological care. The outcomes for each profile following either brief interventions or formal psychological interventions suggest, for some profiles of patients, that higher intensity treatment is more likely to yield positive outcomes, whereas for other groups outcomes between intensities of intervention were very similar. Developing an algorithm using the posterior probabilities of this LPA, and by providing this information to clinicians could aid decision making around treatment selection and increase the likelihood of beneficial experiences from treatment (for example, more intensive treatment offered initially), whilst reducing potentially harmful experiences. Replication of this work in large datasets drawn from other psychological treatment services will be important in establishing the generalisability of this method.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jad.2016.03.011.

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