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RESEARCH ARTICLE

First impressions matter: The influence of initial assessments on psychological treatment initiation and subsequent dropout

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Abstract

Objective This study investigated if patients' experience of an initial assessment may be associated with outcome expectations, and with subsequent treatment attendance.

Method The sample comprised $n = 6051$ patients with depression/anxiety disorders, nested within $k = 148$ assessing therapists. Multilevel modelling (MLM) was used to examine therapist effects on treatment initiation and subsequent dropout, adjusting for patient-level characteristics. We tested associations between early outcome expectancy measured at an initial assessment with attendance at a first therapy session, and with dropout after initiation. Variability in mean expectancy ratings in the caseloads of assessing therapists was examined using the intracluster correlation coefficient (ICC).

Results Therapist effects partly explained the variance in treatment initiation and dropout. Pre-treatment outcome expectations significantly predicted treatment initiation but not dropout for the subgroup of patients who started treatment. Approximately 16% of variability in mean expectancy ratings was explained by therapist effects (ICC = 0.159) after controlling for patient-level covariates.

Conclusions Patients assessed by some therapists are more likely to have higher outcome expectations, which influences their decision to initiate treatment thereafter. Once patients start therapy, early expectancy measured at assessment no longer influences their attendance, but the "first impression" from an initial assessment does influence their subsequent likelihood of dropout.

Key words: psychotherapy; dropout; attrition; attendance; expectations

Clinical or Methodological Significance of this Article Patients assessed by some therapists reported systematically higher outcome expectations and were significantly more likely to attend subsequent therapy appointments. This evidence suggests that initial assessments leave a lasting impression that influences patients' motivation to start and continue attending therapy thereafter. Using a single-item measure of expectancy (range 0–10) at the end of an initial assessment can help therapists to identify patients who have a lower probability of initiating therapy (scores ≤5) and who may require additional motivational and expectancy-enhancing interventions.

Treatment dropout is defined as the patient's unilateral discontinuation of treatment before an agreed endpoint with their provider (Westmacott et al., 2010). Dropout is common in psychological services, and it has been estimated to occur in approximately 19.7% of cases (Swift & Greenberg, 2012). The probability of dropout is known to vary across therapists, therapy type, treatment modality (i.e., computerized vs. in person) and presenting problems. For example, in a meta-analysis of dropout in psychotherapy studies, Swift and Greenberg (2014) found that integrative treatments resulted in lower dropout rates for patients with depression and post-traumatic stress disorder, while

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dialectical-behaviour therapy resulted in the lower dropout for patients with eating disorders. Another meta-analysis focussing on moderators of dropout from cognitive behavioural therapy found that dropout was significantly higher in patients with depression, in e-therapy, and in outpatient vs. inpatient care (Fernandez et al., 2015).

Furthermore, it is well known that dropout tends to mostly occur early in patients' treatment pathway (Fernandez et al., 2015). In fact, many patients drop out of psychological services even before they start treatment and after having been assessed as eligible, which is referred to as *nonattendance* (e.g., Delgadillo et al., 2015) or *non-engagement* (e.g., Self et al., 2005) by different authors. While sometimes patients state that feeling better was a reason for dropping out (Ghaemian et al., 2020; Simon et al., 2012), dropout is most often associated with low satisfaction (Björk et al., 2009; Ghaemian et al., 2020; Khazaie et al., 2016) and with poor symptomatic treatment response (Barrett et al., 2008; Cahill et al., 2003; Delgadillo et al., 2014). One plausible explanation for the dropout-outcome association is that patients who drop out early receive an inadequately small dose of treatment, which is insufficient to effect change in accordance with the dose–response literature (Robinson et al., 2020). According to qualitative studies, patients may not persist with accessing an adequate and therefore therapeutic dose of therapy because they find some aspects of the treatment setting or process dissatisfying or burdensome (e.g., see Ghaemian et al., 2020; Khazaie et al., 2016). An alternative explanation is that these explicit reasons for dissatisfaction (i.e., unhappy with the therapist, the group setting, or the online format) may be influenced by implicit cognitive processes (e.g., expectations) that modulate patients' motivation to seek and to persist with psychological treatment.

There is evidence to suggest that treatment dropout is associated with patients' expectations related to treatment (see review by Greenberg et al., 2006). Several types of expectations may be relevant, relating to the *duration* of therapy (Swift & Callahan, 2011), the *outcome* of therapy (Zimmermann et al., 2017), and the *role* of the patient and therapist (Aubuchon-Endsley & Callahan, 2009). From this perspective, patients who drop out may become dissatisfied due to a mismatch between their *duration* or *role* expectations and their actual treatment experience, or they might have poor *outcome* expectations so they do not start therapy or they do not persist with therapy even if their experience is satisfactory. *Outcome expectancy* refers to a patient's prognostic beliefs about the consequences of engaging in treatment, which can be rated on a continuum from low to high expectations of improvement (Constantino et al., 2011). Meta-analyses of psychotherapy studies have found replicated evidence that positive outcome expectations are associated with better clinical outcomes (Constantino et al., 2011, 2018). Although there is evidence that outcome expectancy is associated with changes in mental health symptoms, fewer studies have investigated direct associations with nonattendance or dropout. One study by Swift et al. (2012a) found no significant relationship between pre-treatment outcome expectancy and attendance at an initial therapy appointment (i.e., initiation). A second study by Norberg et al. (2011) also found patients that did not attend therapy had equally high outcome expectations as those who attended, suggesting that early outcome expectations may not be important in determining treatment initiation. However, in both of these studies, the role of the therapist in potentially influencing patient outcome expectations was not assessed. Furthermore, some studies have found significant expectancy-dropout associations (Schindler et al., 2013; Snippe et al., 2015). In view of this mixed evidence, it remains unclear if outcome expectations influence treatment initiation and dropout.

The present study aimed to investigate if early (e.g., pre-treatment) outcome expectancy may be associated with treatment initiation and dropout in a psychological therapy service. The study was guided by three hypotheses: (1) Patients with more optimistic outcome expectations will have a higher probability of starting therapy. (2) Of those who start therapy, patients with more optimistic outcome expectations will have a higher probability of completing therapy rather than dropping out. (3) There will be systematic variability in outcome expectancy ratings across different therapists' assessment caseloads, which will be greater than that expected by chance, after controlling for patients' characteristics.

Method

Design and Ethical Approval

This was a retrospective cohort study, analysing fully anonymous archival clinical data from a psychological therapy service in the north of England. The assembly and analysis of this dataset was approved by the North East-Newcastle & North Tyneside NHS research ethics committee and the Health Research Authority (REC Reference: 15/NE/0062).

Setting, Interventions and Eligibility Criteria

The participating service was part of the national *Improving Access to Psychological Therapies* (IAPT) programme in England, now known as *NHS talking* *therapies services for anxiety and depression*. These services offer evidence-based psychological interventions for common mental health problems, organized in a stepped care pathway in accordance with clinical guidelines (National Institute for Health and Care Excellence, 2011). Most patients are initially offered brief (≤ 8 sessions) low intensity guided self-help interventions based on principles of cognitive behavioural therapy (CBT). Patients who are unresponsive to guided self-help and those with conditions where only psychotherapy is indicated (e.g., post-traumatic stress disorder) are offered high intensity psychological interventions over a longer time frame (up to 20 sessions). High-intensity treatment options include CBT, interpersonal psychotherapy, person-centred experiential counselling, brief dynamic interpersonal therapy, and other interventions recommended by clinical guidelines (NICE, 2011). Psychological interventions provided by these services follow treatment protocols endorsed by clinical competency frameworks (e.g., Lemma et al., 2008; Roth et al., 2009; Roth & Pilling, 2008) and are delivered under regular clinical supervision.

Patients seeking psychological treatment for common mental disorders either self-referred to the participating service or were referred by a medical or health professional. All patients accessed an initial assessment appointment conducted by a qualified psychological wellbeing practitioner or psychotherapist in the service. These assessments were either telephone-based or in person and lasted approximately 40 min. Assignment to the assessing practitioner in routine care was quasi-random, based on the availability of each available practitioner and the waiting list order for each referred patient. Following clinical practice guidelines, these assessments covered the patient's presenting problems, their impact, history, current life circumstances and treatment goals (National Collaborating Centre for Metal Health, 2018). The function of assessment appointments was (1) to determine suitability for psychological treatment in this setting, and (2) to discuss and agree a treatment recommendation. Patients presenting with common mental disorders (e.g., major depressive disorder, anxiety disorders and phobias, post-traumatic stress disorder, obsessive-compulsive disorder, etc.) and without acute suicidal risk were offered access to stepped care psychological interventions after the assessment appointment. Most often, the assigned therapy is delivered by a different therapist to the person conducting the initial assessment appointment. Those with acute suicidal risk or severe mental disorders (e.g., bipolar disorder, psychotic symptoms) were signposted to other specialist services.

The study included anonymised clinical and demographic data for a consecutive of sample of adult (≥18) patients who attended an initial assessment during a 2-year period and who were deemed eligible to access stepped care interventions in this service following the process and criteria outlined above.

Measures

In order to test each of the three hypotheses outlined above, three dependent variables of interest were investigated. (1) *Initiation* was a binary variable, denoting whether or not patients assessed as eligible for psychological treatment started therapy. Those who did not attend any therapy appointments after an initial assessment were coded "0" and those who attended at least one appointment were coded "1."

(2) *Dropout* was a binary variable that applied only to the subgroup of patients who initiated therapy. The operational definition of dropout in this study is consistent with the notion of *unilateral discontinuation of treatment* (Westmacott et al., 2010), and refers to cases where the patient no longer continued to attend subsequent therapy sessions that were offered by the therapist. In this treatment setting, the therapists recorded the eventual reason for discharge (i.e., case no longer accessing the service) in clinical case records. This reason for discharge was either marked as "completed treatment" or "dropped out" based on the service's policy regarding treatment attendance. Typically, therapists would offer the expected number of low intensity (6–8 sessions) or high intensity appointments (12–16 sessions, and up to 20 for those with severe symptoms) following clinical guidelines (The National Collaborating Centre for Mental Health, 2018). If a patient failed to attend a scheduled appointment, they received a letter asking them to contact the service within two weeks if they wished to schedule further appointments. Those who did not contact the service to re-schedule after two weeks were considered to have dropped out and were sent a letter confirming this. Based on clinical case records, those who completed their agreed course of treatment were coded "0" and those who unilaterally discontinued treatment were coded "1."

(3) Outcome expectancy was systematically measured using a continuous single-item measure that all participants self-rated at the end of their initial assessment appointment, and immediately after discussing a specific treatment recommendation (e.g., guided self-help, cognitive behavioural therapy, etc.) with the assessing therapist. The question is worded as follows: "At this point in time how confident are you that this kind of treatment will work for you on a scale of 0 to 10, where 0 means not all and

10 means definitely?." This specific expectancy question was previously validated as a reliable predictor of treatment outcomes in both low and high intensity psychological interventions (Delgadillo et al., 2016; Delgadillo & Gonzalez Salas Duhne, 2020).

Depression symptoms were assessed using the Patient Health Questionnaire (PHQ-9; Kroenke et al., 2001), where each of nine items is rated on a 0–3 Likert scale denoting symptom frequency in the last two weeks, yielding an overall severity score between 0 and 27. Anxiety symptoms were assessed using the Generalized Anxiety Disorder questionnaire (GAD-7; Spitzer et al., 2006), where each of seven items is rated on a 0–3 Likert scale yielding an overall severity score between 0 and 21. Functional impairment was assessed using the Work and Social Adjustment Scale (WSAS) (Mundt et al., 2002) which rates functioning across five domains: work, home management, social life, private leisure activities, and family relationships. Additional data sources included a pseudonymised identifier for the therapists who conducted initial assessments and patients' characteristics (age, gender, ethnicity, employment status, use of pharmacotherapy, baseline symptom severity and functional impairment). These patient-level clinical and demographic covariates were included in order to adjust for case-mix in the estimation of therapist effects, informed by prior studies in this treatment setting that have found significant associations between patient-features with both treatment initiation and subsequent dropout (e.g., see Sweetman et al., 2023).

Sample Characteristics

The study sample was filtered from all available clinical records ($n = 13961$), after excluding records for patients who were ineligible for psychological therapies in the participating service ($n = 3132$), those where case records could not be matched to a unique assessing therapist ($n = 4680$), those under 18 years of age ($n = 88$), and records for therapists who only assessed one patient ($n = 10$).

Pseudonymised identifiers were available for all therapists who conducted initial assessments in this service; however, identifiers for therapists who provided the interventions that followed the initial assessment were not available in the study dataset. The dataset of eligible cases comprised records for $n = 6051$ patients initially assessed by $k = 148$ therapists. Therapists' initial assessment caseload size ranged from 2 to 211; mean = 79.98 (SD = 51.31). In this sample, the mean age (SD) was 37.23 (13.65) and 64.2% were females. Approximately 39.7% were unemployed and 44.7% were using pharmacotherapy. The majority (91.1%) of patients were from a white British background and 8.9% were from an ethnic minority. Mean (SD) baseline scores were PHQ-9 = 14.96 (6.19), GAD-7 = 13.52 (4.98), WSAS = 19.11 (9.04). Analysis of baseline PHQ-9 scores showed that 79.7% ($n = 4820$) patients had depression scores within the moderate to severe range and 72.3% ($n = 4375$) patients had anxiety scores within the moderate to severe range on the baseline GAD-7. The mean outcome expectancy rating for the full sample was 7.29, SD = 1.86.

Statistical Analysis

Multilevel modelling (MLM). MLM was used to test each of the three study hypotheses. The model structure included patient-level data (level 1) nested within therapists who conducted initial assessments (level 2); including random intercepts for the therapist-level. Initial predictors entered into the models were all available demographic and clinical characteristics for patients. The dependent variable used in each of the three models was: (1) initiation, (2) dropout, (3) expectancy ratings. Following conventional model-building guidelines (Raudenbush & Bryk, 2002), continuous predictors were grand mean-centred and MLM was performed in iterative steps, starting with single-level models and eventually fitting multi-level and covariate-adjusted models that optimized goodness-of-fit. Given our focus on outcome expectancy, this variable was entered at the last step of MLM, after attaining the best-fitting and parsimonious model including only significant patient-level predictors, in order to control for case-mix (e.g., relevant clinical and demographic differences between patients, which are associated with dropout). Thus, following conventional guidelines for MLM, we applied backward elimination of non-significant predictors in order to calculate the model ICC with precision and to avoid including noise variables in the model that tested the primary hypothesis (an optimal and best-fitting case-mix adjusted model was attained before entering expectancy into the last step of the model-building procedure). Model fit was examined after each modelling step by inspecting the standard error of regression coefficients and the loglikelihood ratio test. All analyses were performed using MLwiN software v3.05 (Charlton et al., 2020).

For multilevel models with binary outcomes, the variance partition coefficient (VPC) measure was obtained using a linear threshold model (Snijders & Bosker, 2012). First order marginal quasi-likelihood (MQL) estimation was used initially. However, this procedure can sometimes lead to inflated estimates of cluster (i.e., therapist) effects, so 2nd order predictive quasi-likelihood (PQL) estimation was also used as a sensitivity analysis (Rasbash et al., 2020). Random slopes were fit to determine whether the relationship between expectancy and initiation varied significantly between therapists. The intracluster correlation coefficient (ICC) was calculated to estimate the proportion of variance attributable to the therapist-level (i.e., therapist effect). Furthermore, a caterpillar plot was used to visualize the extent to which mean expectancy ratings varied between therapists' assessment caseloads. Overall, three fully adjusted models were developed, two binary outcome models (initiation; dropout) using a logit link function and one linear model using a continuous outcome (expectancy). The second model (dropout) was only conducted in the subsample of $n = 4633$ cases that started therapy.

Sensitivity analyses. In order to maximize the overall sample size, the main analyses described above included therapists who assessed a minimum of two patients. However, the statistical power to reliably model cluster effects is influenced by the overall number of clusters and the ratio of level-one (i.e., patients) to level-two (i.e., therapist) subjects (Maas & Hox, 2005; Schiefele et al., 2017). Therefore, to evaluate the robustness of the results, we repeated all analyses using a subset of data from therapists who assessed a minimum of 30 patients.

Results

Treatment Initiation Analysis

Of those who were eligible to access therapy, $n = 985$ (16.3%) did not attend any treatment appointments after their initial assessment. Hence, 83.7% ($n =$ 5066) of eligible patients started therapy. The mean expectancy rating for the subsample that disengaged with the service after assessment was 7.20 (SD = 2.03), and for the subsample that started treatment it was 7.31 (SD = 1.83).

The main effects for the fully adjusted and best-fitting MLM examining predictors of initiation are displayed in Table 1. Expectancy ratings were significantly associated with initiation, such that a 1-point increase in the expectancy scale was associated with a 5% increased probability of initiation; OR = 1.05 (95% CI: 1.01, 1.10), $p = .012$. Older patients were more likely to attend; unemployed patients and those receiving pharmacotherapy were less likely to attend. A significant interaction between employment status and pharmacotherapy revealed that unemployed patients taking medications were the least likely to start therapy. A random slope for expectancy was not statistically significant, indicating that the expectancy-initiation relationship was consistent across therapist caseloads. There was a significant therapist effect explaining approximately 11% of variability in initiation; 11.15% (1st order MQL), 10.65% (2nd order PQL). The same results were obtained in the sensitivity analysis with a restricted subsample.

Dropout Analysis

Within the sample of patients that started therapy, 29.5% dropped out and 70.5% completed their agreed course of treatment. The mean (SD) expectancy rating for the subsample that dropped out was 7.28 (1.86) and it was 7.38 (1.78) for the subsample that completed treatment.[1]

The main effects for the MLM examining predictors of dropout are displayed in Table 2. Expectancy ratings were not significantly associated with dropout after controlling for covariates; OR = 0.98 (95% CI: 0.95, 1.02), $p = .376$. Older patients were less likely to drop out; unemployed patients and those with more severe baseline depression (PHQ-9) and functional impairment (WSAS) were more likely to drop out. There was a significant therapist effect explaining approximately 2% of variability in dropout; ICC = 2.08% (1st order MQL), 2.14% (2nd order PQL). The same results were obtained in the sensitivity analysis with a restricted subsample.

Analysis of Variability in Mean Expectancy Across Therapist Caseloads

The main effects for the fully adjusted and best-fitting MLM examining predictors of expectancy

Table 1. Main effects of fully-adjusted multilevel model predicting therapy attendance following an initial assessment.

	B	Standard Error	Odds ratio	95% Confidence intervals		p
Age	0.015	0.003	1.016	1.010	1.021	<.001
Unemployed	−0.173	0.074	0.841	0.727	0.972	0.019
Pharmacotherapy	−0.747	0.354	0.474	0.236	0.949	0.035
Expectancy	0.051	0.020	1.052	1.011	1.109	0.012

Table 2. Main effects of fully-adjusted multilevel model predicting dropout after starting therapy.

	B	Standard Error	Odds ratio	95% Confidence intervals		*p*
Age	−0.025	0.003	0.975	0.970	0.981	<.001
Unemployed	0.269	0.069	1.309	1.143	1.498	<.001
Baseline PHQ-9	0.039	0.007	1.040	1.026	1.054	<.001
Baseline WSAS	0.015	0.005	1.015	1.005	1.025	0.001
Expectancy	−0.017	0.019	0.983	0.947	1.020	0.376

Notes. Patient Health Questionnaire-9 (PHQ-9); Work and Social Adjustment Scale (WSAS).

are displayed in Table 3. Female patients and those with higher baseline anxiety (GAD-7) had significantly higher average expectancy ratings. Unemployed patients and those with more severe baseline depression (PHQ-9) had lower average expectancy ratings. There was a significant therapist effect explaining approximately 16% of variability in initiation; ICC = 15.87% (full dataset), 18.74% (sensitivity analysis).

The caterpillar plot in Figure 1 displays the therapist intercept residuals with 95% confidence intervals produced by the multilevel model. Therapists are ranked from left to right, according to the mean expectancy ratings in their assessment caseload. The figure shows that most therapists (70.9%) had mean caseload expectancy ratings that were not significantly different to the sample average (shown by the dashed line with the residual of zero). A total of 23 (15.5%) therapists on the left of the figure had significantly lower than average expectancy ratings and 21 therapists (14.2%) on the right of the figure had significantly higher than average ratings. The mean (SD) expectancy rating for below average therapists was 6.12 (.42) and for above average therapists it was 8.37 (.65).

Discussion

This study investigated if patients' experience of an initial assessment was associated with their likelihood to start and to complete a scheduled course of treatment. As we hypothesized, the findings indicate that patients who initiate treatment had higher outcome expectancy ratings than those who did not attend any therapy appointments after an initial assessment. This relationship (positive expectancy-initiation association) was consistent across therapist caseloads. As hypothesized, there was significant variability in mean expectancy ratings across different therapists' assessment caseloads. Some assessors elicited systematically higher-than-average expectancy ratings at the end of their assessment appointments, whereas others elicited systematically lower-than-average ratings. This finding is consistent with recent evidence that variability in patients' outcome expectation measures is partly attributable to therapist effects (Vîslă et al., 2019, 2021). Furthermore, the magnitude of the effect size for expectancy may possibly explain why other studies have not found a significant expectancy-initiation association (Norberg et al., 2011; Swift et al., 2012a). In order to identify the expectancy effect, large enough samples of therapists are necessary, since the extreme outliers make up around 30% where this effect is detectable. Furthermore, even after accounting for the effect of expectancy, there was a significant therapist effect on treatment initiation, consistent with prior studies (Firth et al., 2020; Saxon et al., 2017; Zimmermann et al., 2017).

Contrary to one of our hypotheses, but consistent with other studies (e.g., Berke et al., 2019), early expectancy was not associated with dropout in the subsample of patients who started treatment. This may be explained by the fact that those who start therapy already have high levels of expectancy close

Table 3. Main effects of fully-adjusted multilevel model predicting pre-treatment expectancy.

	β	Standard Error	95% Confidence intervals	*p*
Constant	7.135	0.076	6.987, 7.283	<.001
Female	0.236	0.046	0.145, 0.327	<.001
Unemployed	−0.213	0.046	−0.302, −0.123	<.001
Baseline PHQ-9	−0.028	0.005	−0.037, −0.018	<.001
Baseline GAD-7	0.020	0.006	0.008, 0.031	.001

Notes. Patient Health Questionnaire-9 (PHQ-9); Generalised Anxiety Disorder questionnaire (GAD-7).

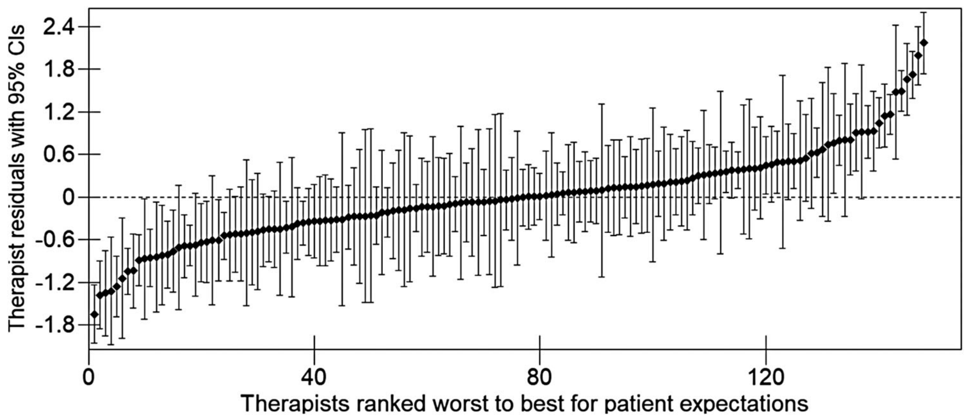

Figure 1. Caterpillar plot of therapist residuals, with 95% confidence intervals (CIs) for mean expectancy ratings within assessment caseloads for different therapists.

to the ceiling of the measure. It is also interesting to note that this measure of expectancy taken at a pre-treatment assessment appointment has previously been found to be a reliable prognostic indicator for post-treatment outcomes in this clinical setting, even after controlling for intake severity and other patient characteristics (Delgadillo et al., 2016). Taken together, these findings indicate that pre-treatment outcome expectancy is associated with initial attendance and post-treatment outcomes, but not dropout. This may be because patients' likelihood to persevere with an agreed course of treatment could be more strongly related to other aspects of the therapist-patient process, such as the working alliance (Sharf et al., 2010) or preference accommodation (Swift et al., 2018). Another likely explanation is that outcome expectancy will have been influenced by the subsequent therapist(s) during the patient's treatment pathway, as shown by Vîslă et al. (2023).

Furthermore, in the present study there was still a significant effect attributable to the therapists conducting initial assessments, explaining approximately 2% of variability in dropout after starting therapy. This is remarkable considering that the assessing therapist was in most cases different to the therapists involved in delivering therapy, particularly since some patients had more than one treatment and therapist in the stepped care pathway. These results fit within a wider body of evidence on therapists effects on dropout (Kivlighan et al., 2019; Xiao et al., 2017).

Currently, relatively little is known about why some therapists seem to have a more positive influence on patients' likelihood of initiating and completing therapy. It may be that these therapists are better able to foster hope, which is one determinant of outcome expectations (Goldfarb, 2002; Swift et al., 2012b). Similarly, the phase model of psychotherapy (Howard et al., 1993) posits that an increased sense of subjective well-being (*remoralization*) occurs early in therapy as patients become more hopeful about the possibility of recovering, after which they attain symptomatic *remediation* and functional *rehabilitation* if they access an adequate dose of therapy. Alternatively, it may be that outcome expectations are influenced by treatment credibility, which are beliefs about how logical and convincing a treatment is perceived to be (Kazdin & Wilcoxon, 1976; Mooney et al., 2014). A related perspective from goal theory proposes that people will devote more resources to achieve a goal if they believe they have a chance of attaining it (Austin & Vancouver, 1996). Future observational studies could investigate recordings from initial assessments to better understand how highly effective therapists may instil a sense of hope, credibility and positive outcome expectancies, in order to generate insights for further experimental studies seeking to enhance attendance and treatment completion.

Moreover, the need for emphasis on these processes (e.g., enhancement of hope, treatment credibility, outcome expectancy) may plausibly vary depending on patient characteristics, since some may already come into services with high levels of readiness to engage in treatment, whereas others may not. Consistent with prior evidence (Sweetman et al., 2023), the present results indicate that younger age and unemployment are associated with a lower probability of treatment initiation and a high probability of subsequent dropout. Other variables previously found to be associated with lower probability of attendance in this treatment context are referral by a health professional (rather than self-referral), higher socioeconomic deprivation, severe depression and anxiety, severe functional impairment, agoraphobia, and lengthier waiting time in between assessment and initial therapy session (Davis et al., 2020; Giesemann et al., 2023; Sweetman et al., 2023). A promising area for future research is to deploy expectancy/hope/motivation enhancing strategies (see Swift et al., 2012b) in a targeted way, focusing on patients with characteristics that predict a low probability of attendance and treatment completion. Another promising strategy appears to be the targeted prescription of specific treatment modalities (e.g., in-person vs. computerized interventions) based on patients' characteristics, using probabilistic models that help services to identify the treatment option that would minimize chances of dropout and maximize chances of improvement (Gonzalez Salas Duhne et al., 2022).

The adjusted effect size attributable to expectancy indicates that, for each point on the expectancy scale that deviates from the sample mean (mean expectancy score = 7), there is a 5% change in the probability of treatment initiation. For example, a patient who provides an expectancy score of four at the end of an assessment would have a 15% lower probability of treatment initiation relative to the average patient. Patients assessed by the above-average therapists were between 10% and 20% more likely to start treatment by comparison to those assessed by below-average therapists (based on their patients' mean expectancy scores and associated odds of treatment initiation). On this basis, an expectancy score ≤ 5 (associated with a 10% lower probability of treatment initiation) should be taken by clinicians as a signal that the patient may have unsuitably low expectations about therapy and this could prompt an opportunity to discuss their concerns/questions, and to apply the above-mentioned strategies that can enhance expectancy, hope and motivation.

Strengths and Limitations

Strengths of the study design included the systematic collection of expectancy measures across thousands of patients with common mental disorders, who were assessed by over 100 therapists in a naturalistic clinical context. The sample size enabled us to examine therapist effects following contemporary statistical guidelines for multilevel modelling. Furthermore, the partitioning of variance at the therapist and patient levels enabled us to understand the extent to which expectancy influences treatment initiation and dropout with greater precision.

An important limitation of the current study is that expectancy was assessed using a single question, which may limit the extent to which variability in this construct can be detected, by comparison to lengthier questionnaires such as the Credibility/ Expectancy Questionnaire (CEQ; Devilly & Borkovec, 2000) or the Outcome Expectancy Scale (OES; Ogrodniczuk & Sochting, 2010). Nevertheless, the brevity of the expectancy question used in this study made it more feasible to collect data from a large clinical sample, and it has previously been shown to be a reliable predictor of treatment outcomes in this setting (Delgadillo et al., 2016). Further limitations include the lack of available information about the therapists within the sample, other than a therapist identifier that enabled clustering of patients within assessing therapists, but identifiers were not available for the therapists who conducted the treatment. It was, therefore, not possible to examine if the results may differ in cases where the assessing and treating therapist were the same person. Data on the specific treatment that patients were referred to after assessments were not available for analysis, although the majority would have been offered a low intensity guided self-help intervention, in accordance with clinical guidelines (NICE, 2011). Additionally, there were no available recordings from assessment sessions, resulting in a lack of process data to elucidate potential differences between therapists.

Conclusions

Overall, this study demonstrates that the initial assessment process is more than an information gathering exercise, since the initial interaction that patients have with a psychological professional is associated with their treatment outcome expectations and their likelihood to start therapy.

Note

[1] The wide dispersion (0–10) and skewed distribution of these expectancy scores results in similar mean scores across groups. These aggregate means do not provide a reliable indication of effect sizes, and therefore we rely on the results from the fully adjusted MLM to interpret between-group differences and effect sizes.

Disclosure Statement

No potential conflict of interest was reported by the authors.

Data Sharing Policy

In line with the requirements of the ethics review board for this study, requests for access to data are to be made in writing to the corresponding author.

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