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Firth, N. orcid.org/0000-0003-1984-6869, Bone, C. orcid.org/0000-0002-6000-7680 and Holt, R. (2020) Health psychology attendance: A multilevel analysis of patient-level predictors and therapist effects. Health Psychology. ISSN 0278-6133

https://doi.org/10.1037/hea0001021

Health psychology attendance: a multilevel analysis of patient-level predictors and therapist effects

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No funding was available specifically for this project.

We would like to acknowledge David Saxon for his advice and support.

Abstract

Objective: The study investigated adult outpatient Health Psychology appointment attendance, cancellation, and missed appointments (A/C/M). The first objective was to determine which demographic and process factors predicted the probability of A/C/M. The second objective was to determine whether there remained residual significant differences in A/C/M between therapists (i.e. a "therapist effect"), after controlling for explanatory variables. **Methods:** A practice-based retrospective 2-year cohort study. 3-level multilevel models were constructed and tested to analyse the probability of A/C/M at a) assessment appointments (N = 1,175), and b) follow-up appointments (N = 5,441). **Results:** After controlling for predictor variables, significant therapist effects were found for attendance (10.0–13.0%) and cancellation (4.4%) at follow-up appointments (but not assessments), indicating significantly different attendance rates at follow-up between therapists. Predictors of attendance at follow-up included patient age, pre-therapy symptom severity scores (including Risk and Symptom scores), and completion of intake questionnaires. Early morning follow-up appointments were least likely to be cancelled, followed by late afternoon and finally mid-day appointments. Treatment intensity predicted attendance, but among qualified therapists, qualification type and pay level were non-significant. No significant predictors of attendance at assessment were detected. **Conclusions:** Attendance at Health Psychology outpatient appointments varies significantly according to patient, therapist, and appointment factors. Key routinely collected variables are predictive of attendance at follow-up. Clinical implications include the potential to identify patients at risk of non-attendance, and target engagement interventions to these patients. Research directions include closer examination of variability in follow-up attendance between therapists.

Keywords: Multilevel Analysis, Appointments and Schedules, Psychotherapy, Health Workforce

Introduction

The prevalence of chronic non-communicable diseases globally is growing rapidly (Beaglehole & Bonita, 2008) - 145 million Americans live with chronic conditions, with increases of over 30% expected by 2030 (Anderson, 2010). In England, around 8% of the population (over 4 million people) live with co-morbid physical health and mental health conditions, with £10 billion annually spent on poor mental health and wellbeing associated with long-term conditions (Naylor et al., 2012). As a result, closer integration of mental and physical health care has been recommended (Naylor et al., 2012; Royal College of Psychiatrists, Royal College of General Practitioners, British Psychological Society, & Royal College of Physicians, 2015). Health psychology services (clinics) provide psychological interventions and strategies to people struggling to manage physical health conditions and any associated mental health problems. In the United Kingdom, large scale initiatives such as the Improving Access to Psychological Therapies (IAPT) national programme are now beginning to expand their focus to include long-term conditions and medically unexplained symptoms (National Health Service England, 2016).

Non-attendance of appointments has numerous negative consequences for the effective delivery of psychological interventions, whether due either to short notice cancellation, or to missed appointments (“did not attend” or “DNA”). Non-attendance disrupts the continuity and regularity of treatment, with evidence suggesting that this is related to reduced patient improvement (Reardon, Cukrowicz, Reeves, & Joiner, 2002). Some patients do not return to treatment, prematurely terminating the intervention. There is a robust evidence base linking premature termination with poor clinical outcomes, such as reduced symptom change and rates of reliable and clinically significant improvement (e.g. Barrett, Chua, Crits-Christoph, Gibbons, & Thompson, 2008; Cahill et al., 2003; Firth, Barkham, Kellett, & Saxon, 2015). Non-attendance adds to the financial costs of care delivery as a result of factors such as lost payment, wasted resources (e.g. lost clinical and administrative time), damaged community perception, and staff costs/turnover due to low morale (Klein, Stone, Hicks, & Pritchard, 2003; Moore, Wilson-Witherspoon, & Probst, 2001; Pekarik, 1985). Non-attendance can also impact on the provider's capacity to see other patients, increasing waiting times and affecting the timeliness and/or effectiveness of treatment (e.g. Barrett et al., 2008; Pekarik, 1985). In order to improve the delivery of interventions, it is therefore important to understand which factors predict non-attendance of appointments.

Empirical research examining patient demographic factors suggests that younger people may be less likely to attend mental health appointments (Fenger, Mortensen, Poulsen, & Lau, 2011; Pantalon, Murphy, Barry, Lavery, & Swanson, 2014). The impact of gender/sex and education is more contentious and conflicting (Fenger et al., 2011; Murphy, Mansell, Craven, Menary, & McEvoy, 2013; Pantalon et al., 2014). Complicating the evidence is the fact that studies have investigated relatively disparate contexts, such as first appointments versus aftercare appointments, or different clinical contexts such as severe psychiatric and dual diagnoses versus primary care (Binnie & Boden, 2016; Murphy et al., 2013; Pantalon et al., 2014). Different factors may well be implicated at different stages of treatment, and for different populations.

Evidence also links severity of mental health problems with attendance, with extremes of symptom severity (high or low) and chronicity (under one month or above two years) predicting DNAs (Binnie & Boden, 2016; Di Bona, Saxon, Barkham, Dent-Brown, & Parry, 2014; Fenger et al., 2011; Swift, Whipple, & Sandberg, 2012). Di Bona et al. (2014) found these factors had higher predictive value than socio-demographic variables.

People may experience multiple barriers to mental health attendance, including cumulative effects (Paige and Mansell, 2013). By definition, patients attending health psychology interventions typically have to contend with additional challenges to their physical health that may make it difficult for them to attend appointments. Examples include difficulties with cognition, vision, mobility, pain, gastro-intestinal symptoms, and fatigue. Symptoms and other contributory factors may also vary at different times (e.g. throughout the day, or dependent on weather/climate/season). As such, attendance at health psychology clinics may follow different patterns and for different reasons than in more general psychotherapy contexts. Paterson, Charlton, and Richard (2010) reviewed factors predicting attendance at chronic disease clinics. They found a lack of consistency in the evidence, although there were several similarities with the above literature on generic psychological therapy contexts.

As well as the issues above, to our knowledge patients' attendance of psychological provision in physical health care contexts has been relatively under-researched (compared for example with traditional mental health and medical contexts). Furthermore, this study addresses three additional key gaps in the evidence base. Firstly, the literature to date has made little distinction between cancelled appointments and DNAs. Each has different consequences both for care providers and for patients, and so it is important to determine similarities and differences in their causation. Secondly, despite evidence linking disease clinic attendance with healthcare practitioner factors (Paterson et al., 2010), until recently (Xiao, Hayes, Castonguay, McAleavey, & Locke, 2017) no research has investigated the extent to which psychology attendance rates vary between therapists. This is known as a therapist effect (Baldwin & Imel, 2013; Barkham, Lutz, Lambert, & Saxon, 2017). Thirdly, although evidence suggests that severity of psychological symptoms is related to attendance, it is important to determine more specifically what types of psychological symptom disrupt attendance, in order to implement effective strategies to predict and prevent non-attendance. The current study addressed this by examining different domains of psychological symptom severity, as measured by four sub-domains of the Clinical Outcomes in Routine Evaluation – Outcome Measure (CORE-OM; Evans et al., 2002).

The current study took a pragmatic, practice-based approached to investigation, focusing on variables that are likely to be routinely collected by (and therefore available to) clinics offering psychological care. Although pragmatic in design, the study can be conceptualised in line with Andersen's healthcare utilization model as focusing on contextual (e.g. clinic) factors as well as individual factors (Andersen, 1995; Andersen, Davidson, & Baumeister, 2014). Similarly, the study focused on aspects of all three major components posited by Andersen's model (predisposing, enabling, and need factors), although the study did not attempt complete coverage of these concepts, and the authors acknowledge that these factors are not exhaustive.

Aims & Objectives

The study aimed to undertake a pragmatic practice-based investigation of the variability in patient attendance at outpatient appointments in an adult Health Psychology clinic. The first objective was to determine readily available predictors of attendance, cancellation and DNA at a) assessment appointments, and b) follow-up appointments. The second objective was to determine whether there remain significant differences in patient attendance between different therapists (a therapist effect), after controlling for predictors.

Method

Study Context

Data for the current study were from a specialist outpatient adult health psychology clinic in the United Kingdom that provides outpatient appointments in a community hospital setting. Health Research Authority approval for the study was granted (19/HRA/0918), and research governance approval was provided by the host NHS (National Health Service) Trust. As the patient data were solely retrospective, routinely collected, and anonymised, the Health Research Authority stated that ethical approval was not required for this study.

Clinical Setting

Clinic. The clinic offers provision into multiple care contexts (primary care/frontline, secondary care/specialist, and hospice/palliative), with the majority of clinical work falling within a secondary care delivery context. Referrals typically come from general practitioners (a.k.a. family physicians), community mental health teams, and specialist consultants. The clinic encourages collaborative referrals and provides information to referrers and for prospective patients about the service, as well as providing feedback to referrers in cases of inappropriate referral. Following referral, patients are required to opt-in to an assessment appointment. The clinic typically offers one assessment appointment within 4 weeks of referral. Intake monitoring questionnaires (including clinical and demographic data) are requested at assessment but not required. Where appropriate, assessment is followed by an offer of around 6 follow-up intervention appointments once the patient has reached the top of the waiting list (typically 3-6 months). Follow-up typically involves psychological therapy, psychoeducation, and/or psychological skills training. Appointments are arranged in advance, by agreement between the patient and therapist. Although traditional 50 minute appointments on a weekly or two-weekly basis are standard, therapists are able to offer flexible appointment durations and frequencies in accordance with patient preference and clinical judgement. Treatment is free at the point of delivery, and the clinic imposes no financial penalty for missed appointments.

Patients. Patients are adults across the lifespan with long-term or life-limiting physical health conditions. Up to half of patients suffer from pain-related conditions. Reasons for referral typically involve either a) adjustment to and coping with physical health problems, b) improving functioning and quality of life, c) symptom management skills and strategies, d) phobias, compliance and motivational issues affecting engagement with physical interventions, and e) mood or psychological issues that are causing or exacerbating physical health problems.

Therapists. Assessment appointments at the clinic are provided by qualified therapists. These included clinical psychologists, counselling psychologists, and psychotherapists. After assessment, follow-up psychotherapy appointments are also primarily provided by qualified therapists. However at times, psychoeducational relaxation skills appointments are also offered by assistant psychologists. Assistant psychologists have completed undergraduate and/or master's degrees but are not yet qualified as psychologists or psychotherapists. The intensity of treatment offered (relaxation skills and/or psychotherapy) is decided jointly by the patient and therapist at the assessment appointment.

This study took a practice-based approach, aiming to represent typical health care provision in the clinic. As such, relaxation skills appointments with assistant psychologists were included in the main analysis alongside psychotherapy appointments offered by qualified therapists (with models controlling for treatment intensity). This approach is supported by evidence in mental health contexts that has found therapist effects in alternative psychological workforces (Firth et al., 2015). However, sensitivity analyses were also conducted, that included only appointments with qualified therapists (see Sample section).

Sample

The study used routine attendance data collected over 2014 and 2015 from all patient contacts offered by the clinic. Stage one inclusion criteria required that the time, date, and attendance data were recorded for each appointment, producing a sample of 8,816 appointments for 1,387 patients seen by 31 therapists. From this sample, a sub-sample was derived for each respective analysis (see Figure 1). In each sub-sample, stage two inclusion criteria required that if the patient had been offered appointments by more than one therapist during their episode of care, only appointments with the first therapist (chronologically) were included.

This was done in order to reduce the chances of data dependence/bias in the sample. The first analysis investigated the probability of attendance at assessment appointments. The second analysis investigated the probability of attendance at follow-up appointments. In order to assess patient predictors of attendance at follow-up appointments, the stage 3 inclusion criterion applied to this sub-sample required that patients' symptom severity data and demographic data had been recorded at their prior assessment appointment.

Two sensitivity analyses of follow-up appointments were conducted. The first excluded all relaxation skills appointments offered by assistant psychologists, to only include appointments offered by qualified therapists. The second included only appointments offered by the final therapist (chronologically; rather than the first therapist), where applicable.

[Figure 1 here please]

Measures

There were three binary outcome variables: 1) whether or not a patient attended the appointment, 2) whether or not a patient cancelled the appointment, and 3) whether or not a patient DNA the appointment.

Patient predictor variables were as follows: 1) the appointment time, 2) the appointment weekday, 3) the season of the appointment (Spring, Summer, Autumn, Winter), 4) patient age, 5) patient sex, 6) therapist-patient sex match (i.e. whether the dyad was male-male/female-female or not), 7) days since last offered appointment, 8) time on waiting list between assessment and follow-up, 9) whether or not the patient had intake severity questionnaire scores recorded after their assessment appointment, 10) severity of patient scores at assessment on the CORE-OM (Clinical Outcomes in Routine Evaluation – Outcome Measure; Evans et al., 2002). The CORE-OM is a 34-item multi-domain measure of psychological distress. The measure produces an overall symptom severity score, as well as four sub-scale scores; Risk, Functioning, Symptoms/Problems (depression, anxiety, physical problems, and trauma), and Wellbeing. The CORE-OM has shown internal consistency of $\alpha = 0.93\text{-}0.95$ (Barkham, Gilbert, Connell, Marshall, & Twigg, 2005) and outpatient test-retest reliability of .88 (Barkham, Mullin, Leach, Stiles, & Lucock, 2007). Strong convergent validity with measures such as the Beck Depression Inventory (BDI-II) and Clinical Interview Scale – Revised (CIS-R) has also been shown (Cahill et al., 2006; Connell et al., 2007).

This study tested the significance of patients' overall CORE-OM scores, as well as individual sub-scale scores. Overall CORE-OM scores range between 0-40, with higher scores indicating greater distress. For comparability purposes, sub-scale mean scores (0-4) can be multiplied by 10 to produce standardised scores also ranging from 0-40.

Variables 7 and 8 (days since last offered appointment and time on waiting list) were only able to be calculated for a subset of the sample, given these variables required data on previous sessions that for some patients fell outside the sample period and hence was unavailable. Sub-sample sizes for these variables were 5,046 (days since last appointment) and 3,539 (time on waitlist), out of 5,441 follow-up appointments meeting stage one and stage two inclusion criteria.

There were also three therapist-level predictor variables. The first was treatment intensity: low intensity treatment involved relaxation skills delivered by assistant psychologists ($k = 7$), whilst high intensity treatment involved psychotherapy interventions delivered by qualified therapists ($k = 24$). Qualified therapists were further differentiated using two more variables; qualification type (clinical psychologist, $k = 18$; counsellor/psychotherapist, $k = 5$), and therapist pay level using UK Agenda for Change pay bands (band 7, $k = 13$; band ≥ 8, $k = 10$).

Pay level was included as a measure of seniority/experience. Category specifications were designed to avoid difficulties due to low numbers of therapists in some sub-categories.

Data Extraction and Abstraction

Patient data were extracted by the first author in the same format that they were originally input by the clinic's data administrators. Therapist data was recorded by the clinic and combined with patient data by the lead author. The first author pseudonymised the data and used an automated process to remove records according to exclusion criteria. Seasons were operationalised as Spring (Mar-May), Summer (June-Aug), Autumn, (Sep-Nov), Winter (Dec-Feb). No other variables were re-operationalised from their original coding.

Analysis

Healthcare provision can be thought of as a hierarchical relationship, with appointments clustered by patient, and patients clustered by therapist. Multilevel modelling (MLM) is an analytical technique that explicitly models variance at each level of the hierarchy. MLM was therefore used to analyse the data for this study.

Multilevel models used Iterative Generalised Least Squares (IGLS) estimation using 1st order MQL and then 2nd order PQL approximation procedures (Rasbash, Steele, Browne, & Goldstein, 2012). Models were created separately for attendance, cancellation, and DNA at a) initial appointments, and b) follow-up appointments. Variables and random effects were tested incrementally. First, single level models were tested. Random intercepts were next tested at each additional level, before testing explanatory variables. Model significance at each stage was tested using model coefficients' *Z*-ratios, which were required to exceed the 95% confidence level (1.96).

Therapist effects were indicated by significant random intercepts at the therapist level. The size of each therapist effect was calculated by simulation method (Goldstein, Rasbash, &

Browne, 2002), with significance assessed using Z-ratios. The therapist effect is the proportion of total unexplained variance that is attributable to differences between therapists, and so is expressed from 0-100%.

As variables were tested on three models measuring related constructs (assessment, cancellation, and DNA), significance of variables in the final models was re-tested, adjusting alpha across the three models using the Holm-Bonferroni method for multiple comparisons (Holm, 1979).

Results

The study sample included 1,072 patients in total with valid intake data completed. The average age was 48 years (SD = 13.7), and 67% of patients were female. The mean CORE-OM intake score was 18.8 (SD = 7.5). Mean sub-scale scores were as follows: Risk (4.9, SD = 6.4), Functioning (18.4, SD = 8.5), Symptoms (24.0, SD = 8.9), and Wellbeing (25.1, SD = 9.6).

Assessment Appointments

There were 1,175 assessment appointments (1,047 patients; 22 therapists) meeting stage one and two inclusion criteria. Of these, 960 were attended, 131 were cancelled, and 84 were DNAd. On average, there was an 82.5% predicted probability that a patient would attend an assessment appointment. There was a 10.6% predicted probability that a patient would cancel, and a 6.9% predicted probability that a patient would DNA.

Attendance, DNA, and cancellation probability was found to vary significantly between patients (p = .001, .015, .018 respectively). There were no significant differences found between different therapists. Appointment time, weekday, and season, and therapist qualification type and pay level were all tested for significance. However, none of these variables significantly predicted attendance, DNA, or cancellation at assessment appointment. Patient demographics and intake severity CORE-OM scores were not tested, as these were only linked with attendance data after assessment attendance. All assessments were completed by qualified therapists, so treatment intensity was not applicable.

Follow-up Appointments

There were 5,441 follow up appointments offered (1,148 patients; 31 therapists) meeting stage one and two inclusion criteria (4,122 attended, 893 cancelled, and 426 DNAd). Of these, 4,631 were linked with patient intake data completed at assessment. A mean of 4.7 follow-up appointments were planned per patient (SD = 4.69), and patients attended a mean of 3.6 appointments (SD = 3.9).

Attendance.

Follow-up attendance was significantly predicted by whether or not the patient had completed intake data questionnaires ($p<.001$; Figure 2a). For an average follow-up appointment, a patient with completed intake data recorded was predicted to have a 73.0% probability of attending, compared with 59.2% for a patient without intake data.

The time at which the appointment was offered was significant, indicating a U-shaped curve in attendance throughout the day ($p = .026$; Figure 2a). For a patient with completed intake data recorded (81% of appointments), there was an 80.3% probability of attending an 8am appointment, a 72.5% probability of attending a 1pm appointment, and a 75.0% probability of attending a 4pm appointment. The weekday and season in which the appointment took place were not significant. Days since last appointment ($n = 5,046$) was not significant. Time on waitlist ($n = 3,539$) was also not significant, even after testing interactions with a) whether or not the current appointment was the first after the waiting list, or b) the current appointment number as a continuous variable (e.g. 1st ,2nd, 3rd appointment since waiting list).

For patients with recorded intake data linked to appointments, in addition to the above predictors, patient age ($p < .001$) and total CORE-OM score ($p = .017$) were also significant in predicting attendance. On average, an increase in patient age of 10 years was associated with a 4.1% greater chance of attending a follow-up appointment (Figure 2b). On average, a CORE-OM score 10 points higher was associated with a 2.7% lower predicted chance of attendance. CORE-OM Risk subscale score was not significant in predicting attendance. Although CORE-OM Functioning, Symptoms, and Wellbeing subscale scores were significant when tested in isolation, when more than one score was included in the model (or in combination with the total CORE-OM score) they all became non-significant.. The total CORE-OM score was the most highly significant (highest Z-score) and so was retained in the final model. Patient sex, as well as therapist-patient sex match were not significant.

Treatment intensity was a significant predictor of attendance ($p = .003$), while qualification type and therapist pay level were not. A patient invited to a follow-up appointment with a qualified therapist had a predicted 75.1% chance of attending, whilst a patient invited to a relaxation skills appointment with an assistant psychologist had a predicted 62.0% chance of attending. After controlling for predictor variables, significant unexplained variance remained between therapists (i.e. a significant therapist effect was detected, $p = .022$). The therapist effect was 10.0% for patients seeing qualified therapists ($n = 4{,}242$, $k = 23$), and 13.0% for patients seeing assistant psychologists ($n = 389$, $k = 7$). Excluding assistant psychologists from the model produced a therapist effect of 9.9% for qualified therapists ($p = .023$, $n = 4{,}242$).

[Figure 2 here]

Did not attend (DNA).

The probability of DNA at follow-up was again significantly predicted by whether or not patients had recorded intake data ($p < .001$), with a predicted 8.0% chance that a patient with recorded intake data would DNA a follow-up appointment, compared with 18.3% for a patient without recorded intake data. However, the time, weekday, and season of the appointment were not significant. Days since last appointment (n,= 5,046) was not significant. Time on waitlist (n = 3,539) was also not significant, even after testing interactions with a) whether or not the current appointment was the first after the waiting list, or b) the current appointment number as a continuous variable (e.g. 1^{st} ,2^{nd}, 3^{rd} appointment since waiting list).

For patients with recorded intake data linked to appointments, age ($p < .001$) and CORE-OM Risk subscale score ($p = .003$) were significant predictors of DNA. On average, being 10 years older was associated with a 2.9% lower DNA chance (see Figure 2b). For a 20 year old patient, there was a predicted 20.0% probability of DNA, compared with a 2.3% predicted probability for an 80 year old patient. On average, an increase of 10 points in risk score was associated with an approximate 3.4% increased DNA chance (Figure 3a). Thus, a patient with a risk score of 0 had a predicted 6.8% chance of DNA, compared with 17.3% for a patient scoring 20. The total CORE-OM score and each other CORE-OM subscale score (Functioning, Symptoms, and Wellbeing) were all non-significant. Patient sex, as well as therapist-patient sex match were also not significant.

Treatment intensity was a significant predictor of DNA ($p < .001$), while qualification type and therapist pay level were not. A patient invited to a follow-up appointment with a qualified therapist had a 6.5% chance of DNA, whilst a patient invited to a relaxation skills appointment with an assistant psychologist had a 17.9% chance of DNA. After controlling for treatment intensity, there was no longer significant unexplained variance detected between therapists. In other words, there was no detectable therapist effect for DNA in this study.

Cancellation.

Whether or not the patient had recorded intake data was not a significant predictor of cancellation, although the time of the appointment was ($p < .001$). A patient attending at 8am had a 14.5% probability of cancellation, compared with a patient attending at 4pm with a 22% probability of cancellation. The weekday and season of the appointment were not significant. Days since last appointment ($n = 5{,}046$) was not significant. Time on waitlist ($n = 3{,}539$) was also not significant, even after testing interactions with a) whether or not the current appointment was the first after the waiting list, or b) the current appointment number as a continuous variable (e.g. 1^{st}, 2^{nd}, 3^{rd} appointment since waiting list).

For patients with recorded intake data linked to appointments, patient age was again significant in predicting cancellation ($p < .001$). An average 20 year old patient had a predicted 23.9% chance of cancelling, compared with an average 80 year old patient with a 13.3% chance of cancelling (Figure 2b). CORE-OM Symptoms subscale score was significant ($p = .041$). An increase of 10 points in pre-therapy symptoms score was associated with a 1.3% increased chance of cancellation (Figure 3b). Therefore, an average patient with a symptom score of 10 had a predicted 15.9% chance of cancellation, compared with a 19.8% chance for an average patient with a symptom score of 40. The total CORE-OM score, Risk score, and Functioning score were all non-significant. Although the CORE-OM Wellbeing score was significant in isolation, entering both Wellbeing and Symptoms scores into the model made both non-significant. The total Symptoms score was the most highly significant (highest Z-score) and so was retained in the final model. Patient sex, as well as therapist-patient sex match were also not significant.

There were no significant effects on cancellation found for treatment intensity, qualification type, or therapist pay level. However, there was significant unexplained variance detected between therapists ($p = .013$; therapist effect 4.4%). Excluding assistant psychologists from the model produced a therapist effect for qualified therapists of 4.3% ($p = .018$, $n = 4{,}242$).

[Figure 3 here]

Statistical adjustment across models

As variables were tested on three models measuring related constructs (assessment, cancellation, and DNA), the final models were used to retest significance of all variables, adjusting alpha across the three models using the Holm-Bonferroni method for multiple comparisons (Holm, 1979). All significant effects remained significant at the adjusted alpha values.

Non-significant Variables

None of the following variables were significant in any model: patient sex, therapist-patient sex match, the weekday or season of the appointment, the number of days since the last offered appointment, or the number of days the patient spent on the waiting list. Although the CORE-OM Functioning and Wellbeing scales were significant in some models in isolation, they became non-significant when entered alongside other CORE-OM scores that had more significant coefficients (greater Z-values). As such they were ultimately not significant in any final model.

Sensitivity Analysis

Sensitivity analyses excluding assistant psychologists from the sample (i.e. only including qualified therapists) produced identical models to the main analyses, and therapist effects estimates within 0.1% of those in the main analysis (as reported earlier). In addition, sensitivity analyses including only appointments offered by the final therapist (compared with the main analyses, which included only appointments offered by the first therapist), also produced identical models, whether or not assistant psychologists were included.

Differences between Therapists

After controlling for therapist type and patient variables, there was significant variation detected between therapists in the probability of patient attendance (10.0% for qualified therapists, 13.0% for assistant psychologists) and cancellation (4.4% for all therapists) at any one follow-up appointment. There was no significant difference between therapists detected regarding DNA, after controlling for treatment intensity. The therapist effects detected were not explained by either qualification type (clinical psychologist vs. psychotherapist/counsellor) or pay level (band 7 vs band ≥ 8). Inspection of therapist residuals (Figure 4) indicated that only one therapist (ID #4) had a significantly higher than average probability of patient attendance, and only two (#3 and #12) were significantly lower than average. Regarding cancellation, one therapist (#12) had a significantly higher than average probability of cancellation, whilst two therapists (#4 and #1) had significantly lower than average probabilities of cancellation. All were qualified therapists.

[Figure 4 here please]

Therapist #4 was happy to be identified to the authors, and some possible hypotheses to explain these findings follow. Therapist #4 was the clinical lead for the clinic over the recorded time period, and was the only therapist to work full-time. This may have meant that they were able to have been more flexible with appointments, reducing the need for short-notice cancellation. Patients may have had more trust or respect for the therapist given their status, increasing attendance. Reasons for the attendance rates of therapists #1, #3, and #12 are less clear. There were no significant differences between therapists in the probability of patient DNA.

Discussion

The study aimed to undertake a pragmatic practice-based investigation of factors associated with patient attendance, cancellation, and DNA at Health Psychology appointments, including variation between therapists. Rates of attendance and non-attendance were comparable with existing research in mental health contexts (e.g. Binnie & Boden, 2016; Fenger et al., 2011) and medical-focused chronic disease contexts (e.g. Murdock, Rodgers, Lindsay, & Tham, 2002; Weinger, McMurrich, Yi, Lin, & Rodriguez, 2005). There were a number of significant predictors of attendance at follow-up appointments. Consistent with previous findings in mental health and chronic disease/medical contexts (Binnie & Boden, 2016; Fenger et al., 2011; Paterson et al., 2010), age and intake clinical severity scores both predicted attendance, whilst sex was non-significant. Older patients were less likely both to cancel or DNA appointments. Intake severity appeared to be a more nuanced predictor - patients with higher risk scores were more likely to DNA, whilst patients with higher symptom scores (depression, anxiety, physical problems, and trauma) were more likely to cancel appointments. Risk scores may on average be more closely aligned with a range of internal and/or interpersonal states predicting DNA (compared with cancellation), such as experiencing chaotic and complex/challenging histories and relationships (including with health care systems), under-developed coping strategies and/or interpersonal skills, extreme hopelessness and lack of motivation, etc. In contrast, those with increased symptoms may also find it difficult to attend appointments, but greater psychological stability may enable them to more effectively communicate with clinics and therapists about their situation (leading to cancellation rather than DNA).

Patient wellbeing scores may be useful as an alternative predictor for cancellation. Wellbeing was initially a significant predictor before symptom score was included in the model (symptom score was ultimately a stronger predictor in this study). Similarly, substituting the functioning, wellbeing, or symptoms subscale scores for the total CORE-OM score all significantly predicted attendance (although again, the total CORE-OM score was the strongest predictor). In contrast, functioning scores did not predict DNA or cancellation even in the absence of other CORE-OM scores. Future research may benefit from seeking to clarify these relationships and the mechanisms involved.

Patient attendance was predicted not only by the severity of patients' intake measure data, but also by whether or not they had intake data recorded per se - patients without recorded intake measures were more likely to DNA appointments. If these patients were failing to complete intake measures, one possible explanation for this association may relate to their engagement or attitudes towards therapy (or attitudes towards other concepts that might influence engagement with therapy, such as privacy or stigma). Ajzen's (1991) Theory of Planned Behaviour states that the most important predictor of behaviour is intention as a function of attitudes, subjective norms and perceived behavioural control. The contemporary mental health empirical literature reflects this, with studies finding individuals' attitudes to be predictive of attendance, including positive attitudes towards self-disclosure (Murphy, Mansell, Craven, & McEvoy, 2016). Of course, this explanation is unlikely to be comprehensive; other reasons patients may not complete intake measures include physical or cognitive limitations, among others. This corresponds with the finding that patients with greater symptom severity were more likely to cancel appointments, although this study found that completion of intake measures was associated with DNA specifically, rather than cancellation.

Cancellation was associated with time of day. Appointments at the beginning of the day (and to a lesser extent the end of the day) were less likely to be cancelled and more likely to be attended than mid-day appointments. No significant association was found for the day of the week, or the time of year. However, subtle relationships may exist that this analysis was not able to detect, but that may additionally impact people living with chronic illnesses (e.g. weather conditions). The current study was able to detect associations in appointment timing, but not causation. It is not clear whether earlier appointments are easier for patients to attend, or whether patients who are more likely to attend prefer earlier appointments. Other variables of interest for future research might include the referral reason and source, as well as the waiting time for appointments. Some patients may be more primed to accept and engage with psychological interventions due either to their prior medical experiences or narratives, to the nature of their physical or mental health conditions, or to the timing or frequency of appointments.

One next step might be to test the predictive accuracy of these variables. If variables are able to predict which patients are less likely to attend appointments, future steps may involve identifying causal mechanisms, followed by designing and testing targeted engagement interventions. Future research may also benefit from exploring differences between patients with different types of physical health condition (for example, using a comorbidity index).

Initial assessment appointments were also analysed in the current study. Appointment characteristics were not significant predictors, although significant differences between patients were detected. Patient demographics and severity scores were not tested as predictors of initial appointments, as these data were not linked with attendance data until assessments were attended. Developments in data availability such as transitions to centralised integrated electronic records should make analysis of this kind easier for future research.

This study found that there were no significant differences between therapists in attendance, DNA, or cancellation at assessment appointments. However, there were significant differences between therapists identified in attendance and cancellation of follow-up appointments, after accounting for patient and therapist factors and treatment intensity. This is intuitive - as patients attend multiple follow-up appointments, it appears that some therapists are better able to engage patients in attending sessions than others (including the number of appointments that are cancelled at short notice). This is consistent with recent research on therapist effects in a mental health context by Xiao et al. (2017), finding that therapist impact on attendance was much greater after the third session of treatment. Xiao et al. (2017) used the percentage of non-attended sessions as their outcome variable, finding therapist effects of 1.1 – 1.4% for early non-attendance (up to the third appointment), but 45.7% for "continued treatment" non-attendance (appointment four onwards). The size of attendance-related therapist effects detected in this study (4.4-13.0%) therefore fall within the range detected in Xiao et al. (2017). In comparison, therapist effects in the context of clinical outcomes are most commonly reported between 5-10%, although these are recognised to vary widely between studies (Baldwin et al., 2011; Crits-Christoph et al., 1991). Our results are therefore broadly comparable with the established literature on clinical outcome therapist effects in mental health contexts. What is not yet clear is how these effects overlap – in other words, do the same therapists who have poorer attendance, also have poorer outcomes, particularly with those who complete treatment? If so, which direction is the causality? Further research is recommended.

Treatment intensity was found to be a significant predictor of attendance. Assistant psychologists delivering relaxation skills interventions had lower attendance rates than qualified therapists delivering psychotherapy interventions. One hypothesis for these findings may relate to working pattern and flexibility. Assistant psychologists in this study tended to work fewer hours than qualified therapists, and the therapist with the highest attendance was the only person to work full time. A second hypothesis relates to patient expectations – the therapist with the highest attendance was the clinic lead, and may have commanded more respect from patients. Patients may also have different attitudes towards relaxation skills intervention components, or to assistant psychologists.

In the current study it was not possible to separate the effect of the intervention type from the qualified status of the person delivering that intervention. Whilst this is a limitation of the study, delivery of low and high intensity treatment by separate intensity-specific workforces is arguably consistent with both the theory (e.g. resource efficiency) and implementation (e.g. CSIP Choice and Access Team, 2008) of stepped care systems, in line with the practice-based design of the study.

The fact that significant variability between therapists remained in the model after accounting for treatment intensity (and after excluding assistant psychologists) suggests that other factors are also involved, although qualification type and pay level were not significant predictors. Future research is needed to identify reasons for these therapist effects, as in the established body of literature regarding therapist effects on clinical outcomes (Baldwin & Imel, 2013; Barkham et al., 2017). Previous (mental health focused) research seeking to understand therapist effects on clinical outcomes has identified potential therapist characteristics such as a therapist's ability to maintain a therapeutic alliance, empathy, deliberate practice, and professional self-doubt (Goldberg et al., 2016; Nissen-Lie, Havik, Hoglend, Ronnestad, & Monsen, 2015; Wampold, Baldwin, grosse Holtforth, & Imel, 2017). As such, these may be a useful starting point for future research into attendance-related therapist effects.

The current study demonstrates that attendance factors at follow-up may differ depending on the type of non-attendance (DNA versus cancellation). These findings appear to suggest that cancellation may be more situational or context-dependent (e.g. time of day, therapist differences, level of symptoms/problems), whilst DNA may be more related to intra-personal/psychological processes (e.g. engagement, risk) and less determined by practicalities. In contrast, increased age seems to be highly protective against both cancellation and DNA.

Understanding more about the factors involved in appointment attendance enables clinics to identify patients at risk of disengagement and poor outcome, and to target engagement interventions towards these groups. It may also highlight the need for more flexible health care provision to meet the needs of populations with complex mental and physical health needs (Paige & Mansell, 2013). For example, there is modest evidence for the effectiveness of computerised CBT for people with physical illnesses, although this is unlikely to be suitable for everyone. Information about predictors of attendance could be extremely beneficial as clinics move closer towards personalised medicine delivery models (Academy of Medical Sciences, 2015).

Limitations of the current study principally relate to its pragmatic design. First, the study used readily-available routinely collected data. As such, there are likely to be important predictors of attendance that have not yet been examined because they were not routinely recorded, such as expectations and intentions regarding therapy, stage of change, and socioeconomic factors (e.g. Paterson et al., 2010). In addition, the clinic's lack of integrated electronic health system at the time of analysis limited the availability of certain data (e.g. if the patient did not complete the intake questionnaires). Second, variables were not randomly or systematically assigned. For example, appointment times may be decided by the therapist, patient, or typically collaboration between both. In part for this reason, findings from the current study indicate correlation, rather than causation. Further research is needed to determine the causal relationships involved in these processes. Finally, psychology clinics in health contexts may vary significantly in population, health care delivery framework, and in other clinical and non-clinical areas (as is also true for many mental health clinics). As such, it is unclear how generalizable the findings from this study are. More research is needed in other clinics and health care provision contexts to assess the stability of these factors. On the other hand, this study contributes to the evidence by being the first to our knowledge to investigate patient predictors and therapist effects on attendance in the context of psychological clinics for people with chronic health conditions.

In conclusion, this study has found preliminary evidence for differences between therapists (as well as patient demographic, clinical, and health care delivery factors) significantly predicting attendance and different types of non-attendance at health psychology outpatient appointments. Predictors include age, symptom severity, and appointment time. It is important that we learn more about the causal pathways involved in attendance variability at both patient and therapist levels in order to improve clinic effectiveness and efficiency (Klein et al., 2003; Moore et al., 2001; Pekarik, 1985; Reardon et al., 2002). Findings from this study suggest that it may be helpful to develop engagement interventions for younger and higher risk populations.

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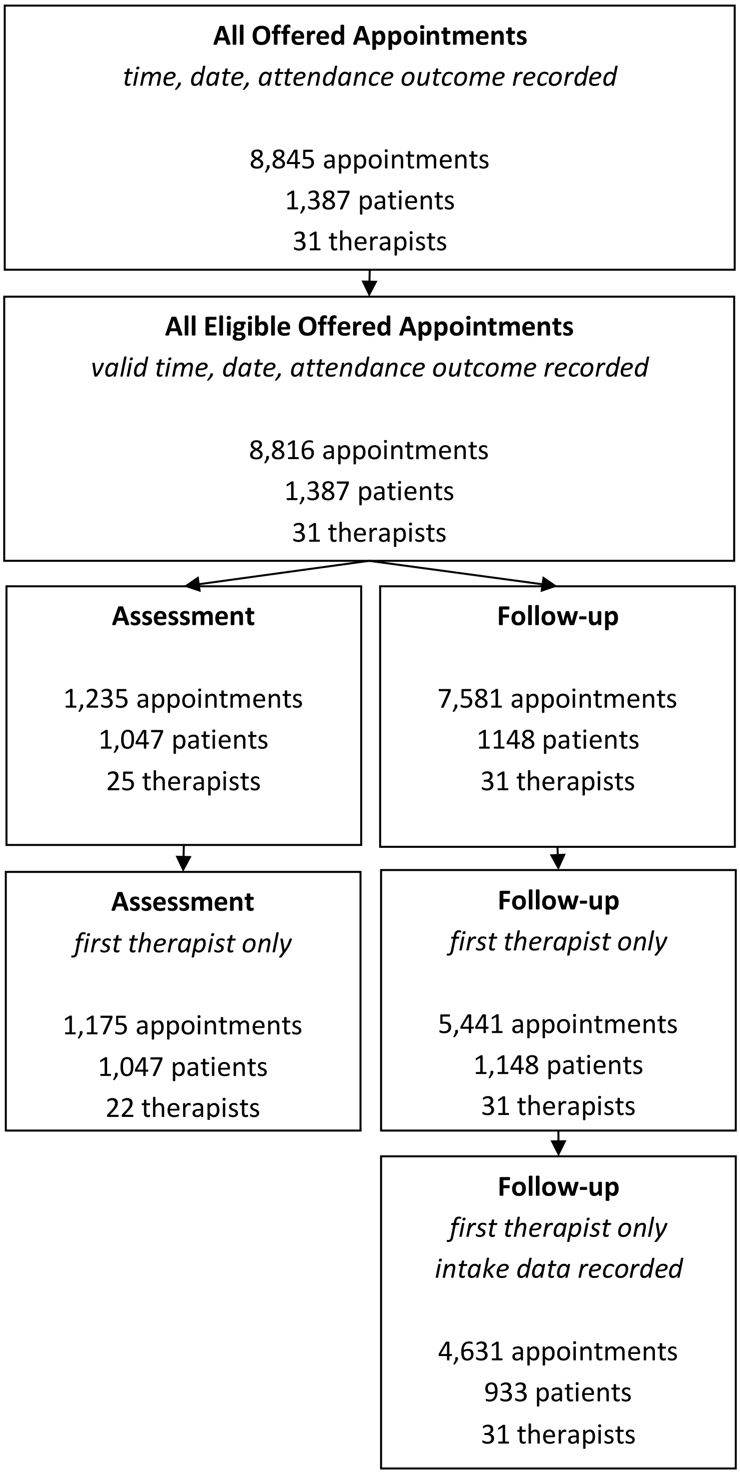
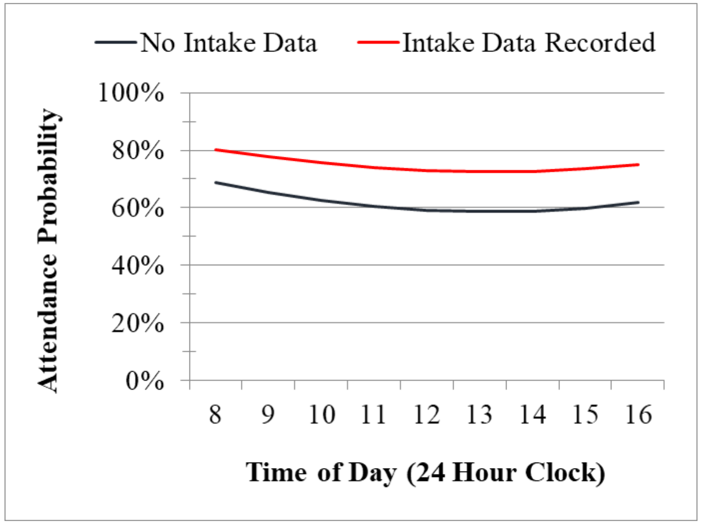
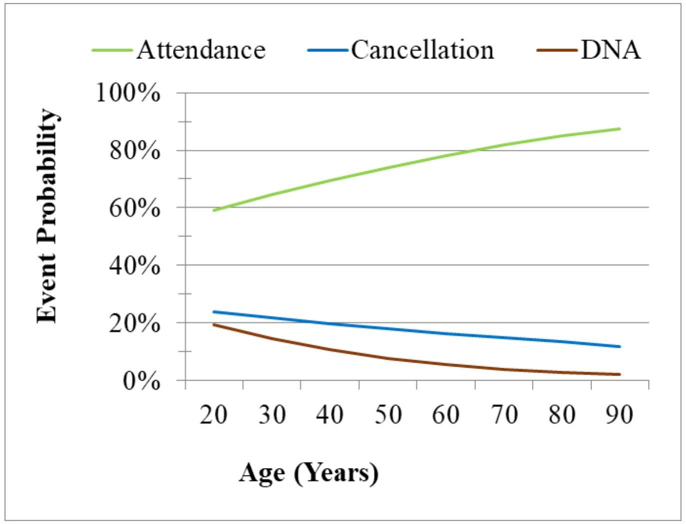


Figure 1. Flow chart to derive sub-samples from main sample.



(a)



(b)

Figure 2. Probability of attendance for patients according to a) time of day, and b) patient age. “Intake Data Recorded” means that the patient completed symptom severity and demographic data at assessment.

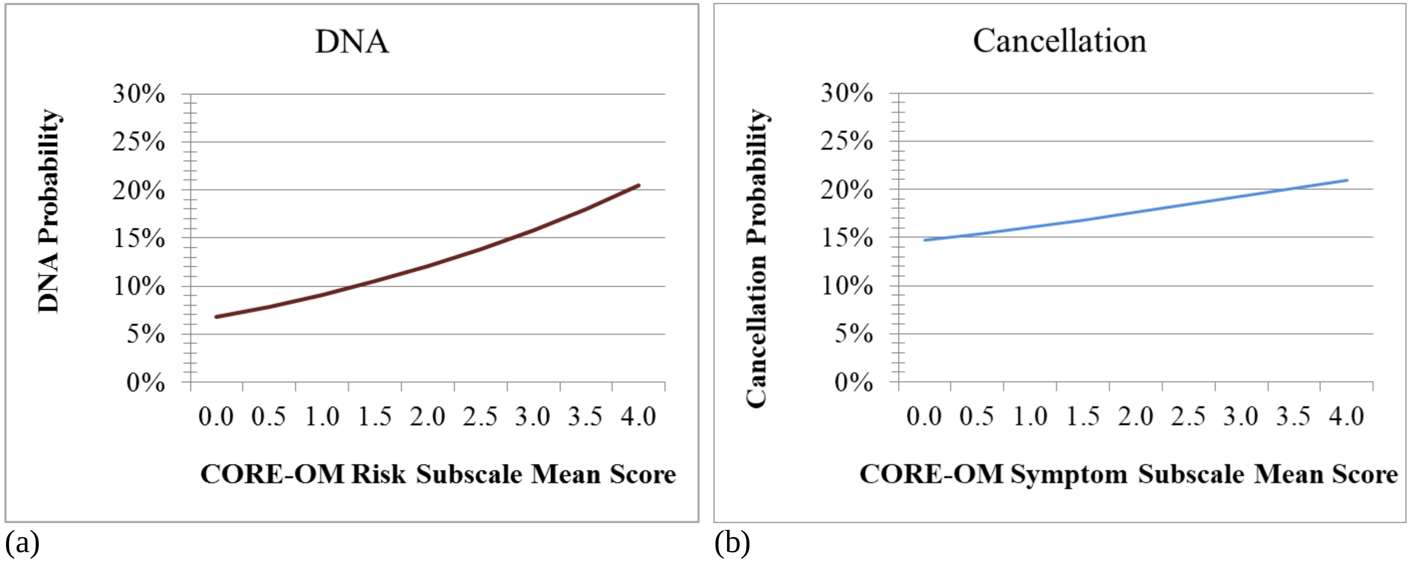


Figure 3. Probability of a) DNA according to risk subscale score, and b) cancellation according to symptom subscale score. DNA = Did Not Attend

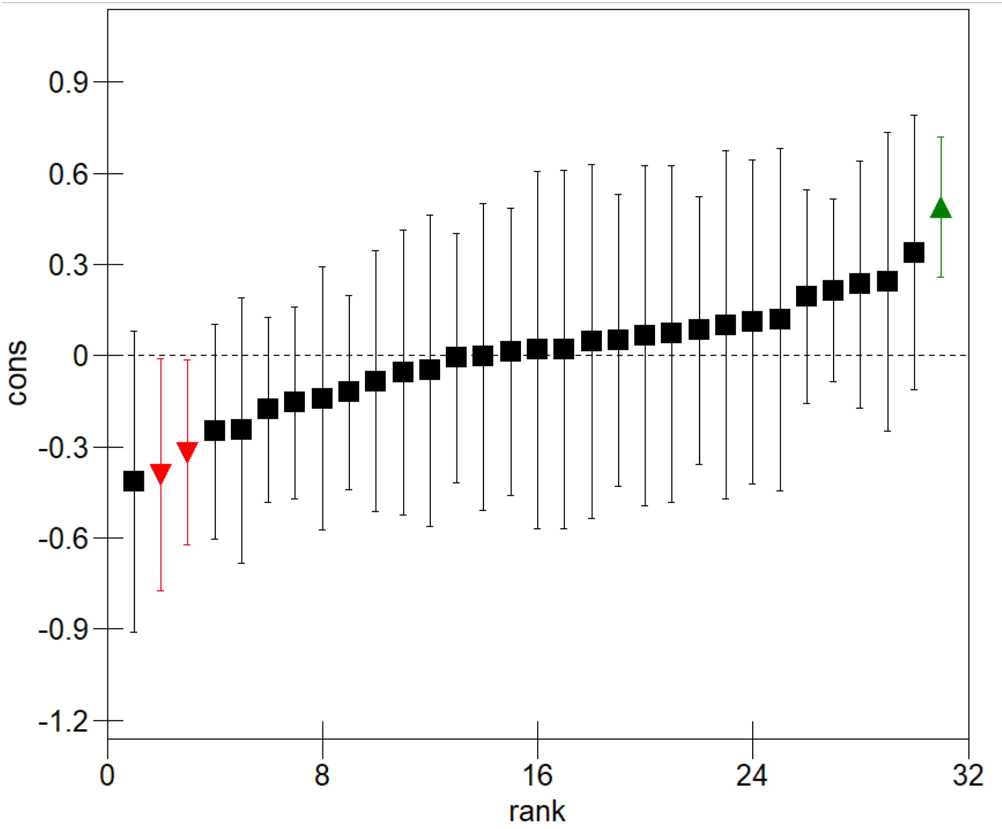


Figure 4. Caterpillar plot showing therapists' attendance residuals. The zero line represents average attendance. Vertical lines indicate 95% confidence intervals. Squares indicate therapists with average attendance probabilities (n = 28). Upward arrows indicate therapists with better than average attendance probabilities (n = 1). Downward arrows indicate therapists with lower than average attendance probabilities (n = 2).