Outcome prediction and profiling in a police force occupational psychological therapies service: An interpretable machine learning approach

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Abstract

Psychological distress of current and former employees is an important factor in occupational mental health, particularly in high pressure work environments such as policing. However, the factors that predict successful treatment outcomes are not well understood, with outcome prediction remaining a substantial challenge. The aim of this study is to examine dominance and non-linearity in the predictors of treatment outcomes for clients attending a specialist occupational psychological therapies service provided to police officers and their families. Four machine learning algorithms are applied to model outcomes in clients' psychological distress, with the results showing that the more complex gradient boosted machine is most accurate. Interpretable machine learning approaches are used to open the black box of more complex machine learning algorithms. The results show improvements in client outcome scores through attending the service, as well as differences in the extent of improvement across different client characteristics. The findings reveal more complex non-linearity in the dominant predictors of outcomes than past research. Dominant predictors include the clients' baseline level of psychological distress, length of the episode, the clients' diagnosis, and factors relating to the client's motivation and completion of the full episode. Floor and ceiling effects are observed in baseline characteristics and episode length, with heterogeneity in the impact of discharge status, condition, and motivation.

1.0 Introduction

Psychological distress can have important negative consequences for individuals' mental health, as well as negative economic impacts due to work lost (Ling et al. 2016) and decreased productivity (Burns et al. 2023). Past studies have found differences in the level of psychological distress across occupations, with individuals in some occupations affected by higher levels of psychological distress than others (Hilton et al. 2008; Burns et al. 2023). This has been linked to factors such as working conditions (Marchand, Demers, and Durand 2005), as well as exposure to stressful situations such as violent and traumatic incidents (Velazquez and Hernandez 2019). Past studies have also found that only a minority of individuals with occupational psychological distress receive treatment (Hilton et al. 2008). This has resulted in some organisations offering occupational psychological therapies services to current and former employees and their families (Ramchand et al. 2019). This reflects the wider impact of occupations on the mental health of employees which extends into retirement, and to the employees family (Fleischmann, Xue, and Head 2020; Dockery, Li, and Kendall 2009; Strazdins et al. 2010). These impacts are particularly prominent in certain occupations which have a higher prevalence of mental health problems, with several studies highlighting differences in the prevalence of mental health conditions across occupations (Stansfeld et al. 2011; Bultmann et al. 2001; Roberts and Lee 1993).

Although psychological therapies are an important mental health intervention, clients do not always benefit from the treatment, and there is limited evidence on the factors that accurately and consistently predict outcomes (Hepgul et al. 2016; Eilertsen and Eilertsen 2023). Past work has shown that it is challenging to predict which clients will respond to treatment (van Bronswijk et al. 2021; Gillan and Whelan 2017), and which factors are predictive of positive outcomes (Tolmeijer et al. 2018). One reason for this is the complexity of the relationships between predictors and outcomes, with non-linear, moderating and mediating relationships (Eilertsen and Eilertsen 2023). Studies have also found that treatment for psychological distress can also benefit organisations, such as by improving employee productivity (Hilton et al. 2009).

Although much of the past work has focused on the use of traditional statistical techniques to identify the determinants of client outcomes following psychological therapy (e.g. Blackshaw et al. 2023), recent studies have begun to apply machine learning (ML) approaches in an attempt to improve the accuracy of models and to identify important predictors (Kourou et al. 2021). These studies offer the potential for important applications in areas such as service evaluation and precision medicine. The aim of these machine learning models can be to improve precision mental health care, which aims to use 'data-driven methods to monitor clients' treatment response, to model their prognosis, and to personalise their treatment accordingly.' (Bone et al. 2021, 231). Central to this aim is predicting the expected treatment outcome (Bone et al. 2021). From a practical perspective, models predicting expected treatment response can be used to identify clients who have not achieved the expected outcome and require further or adjusted intervention (Bone et al. 2021).

Despite this work and the potential applications, it remains challenging to predict outcomes from psychological therapies interventions, with some studies showing low levels of predictive ability (e.g. Aderka et al. 2021). Moreover, machine learning algorithms often generate ‘black box’ models, which are difficult to interpret, which can be problematic in studies aiming to examine specific relationships between variables. This is an important limitation, as it is often of interest to interpret these relationships in psychological research. Interpretable machine learning (IML) approaches have been proposed as one way of achieving overcoming these limitations, enabling researchers to examine relationships in the data (Henninger et al. 2023; Molnar 2022). However, to date, few studies have implemented IML approaches to interpret models generated by black box machine learning algorithms in predicting treatment outcomes in psychological therapies. Therefore, to gain further insight, techniques from IML are also used to examine relationships between the dominant predictors and change in psychological distress, enabling the identification of more complex non-linear patterns and floor and ceiling effects.

Although past studies highlight important factors, they have not focused on identifying the dominant predictors. Moreover, most past work has drawn on traditional regression-based approaches to identify the most important predictors, and these approaches have documented limitations when assessing dominance (Azen and Budescu 2003). Moreover, traditional regression based approaches tend to be less accurate than machine learning approaches (Chou et al. 2023). This study therefore adopts an exploratory machine learning methodology to identify the dominant predictors of change in psychological distress following treatment.

This study aims to contribute to these gaps in the literature by applying ML and IML approaches to examine the factors that determine changes in psychological distress following psychological therapies treatment by an occupational mental health service. The psychological therapy treatment is offered to current and former employees of a national police service, as well as spouses, partners and children who may have been impacted by the vocation. The service itself was established under government legislation to address personal concerns by serving and retired officers relating to their time and experiences in the force. The context of the service is particularly important as past work has identified high prevalence of mental health problems in police officers and their families, resulting from work related trauma and stress (Gershon et al. 2009; Syed et al. 2020; Velazquez and Hernandez 2019; Lennie 2023; Davidson, Berah, and Moss 2006). Police officers can also be reluctant to seek treatment for mental health problems due to stigma, and concerns around confidentiality and career impact (Velazquez and Hernandez 2019; Haugen et al. 2017). It is therefore important to provide mental health support to police officers and their families (Lennie 2023).

Data relating to clients who were treated by the occupational mental health service is used in the present study. Four ML algorithms are applied to model the relationships, including logistic regression, single decision trees, random forests, and gradient boosting. IML techniques are then used to interpret the most accurate model. Permutation variable importance is used to identify the dominant predictors of treatment outcomes. Partial dependence plots (PDPs) are used to examine the shape of the relationships between the dominant predictors and change in psychological distress. The results show that gradient boosting and random forests are most accurate in predicting change in psychological distress. Dominant predictors include the length of treatment, baseline levels of psychological distress, condition, and motivation. The results also reveal more complex non-linearity in the relationships between predictor variables and psychological distress than shown in past studies.

This paper proceeds as follows. Section 2 presents the background to the study, providing an overview of the relevant literature relating to mental health problems in police officers, as well as past work that has applied ML to predict client outcomes from psychological therapies. Section 3 presents the methodology for the study. This is followed by the results and discussion in sections 4 and 5 respectively, before the paper concludes in section 6.

2.0 Background

2.1 Occupational Mental health in Policing

Police officers work in high pressure environments and can face high levels of stress, with the potential to encounter violence and traumatic events and materials (Brewin et al. 2022). Police officers have previously been found to suffer high levels of occupational stress and mental health conditions such as Post Traumatic Stress Disorder (PTSD) and depression (Violanti 2010; Stanley, Hom, and Joiner 2016; Syed et al. 2020). Although the evidence is mixed due to methodological differences, several studies have found police officers to also have higher rates of suicide than the population average (Stanley, Hom, and Joiner 2016; Violanti and Steege 2021). For example, drawing on US data, (Violanti and Steege 2021) find that law enforcement workers are 54% more likely to die by suicide compared with other occupations. However, the prevalence of mental health problems in police officers vary and depend on job related and personal factors (Liberman et al. 2002; Shane 2010; Syed et al. 2020).

Work related stress and trauma faced by police officers can increase psychological distress (Liberman et al. 2002), and has been found to be associated with conditions such as depression, PTSD, substance abuse, suicide and suicidal ideation (Gershon et al. 2009; Syed et al. 2020; Komarovskaya et al. 2011; Velazquez and Hernandez 2019). In addition to the negative impacts on mental health, factors such as organisational stressors can also have a negative impact on the police officers job performance (Shane 2010). However, the extent of additional stress and workplace trauma, and the associated mental health problems faced by police officers depend on factors such as the job context, with relatively lower levels of stress in rural and suburban contexts and in administrative functions (Shane 2010). Relatedly, whether the officer works in criminal, emergency, or community divisions has also been identified as important due to differences in the occupational environment (Habersaat et al. 2015). Other organisational factors such as bureaucratic structures, reward and punishment mechanisms, and management factors can also influence police officers' level of stress (Shane 2010). In addition, factors related to the content of the job also influence the level of stress, such as shift work, long hours, and violence (Lennie 2023; Shane 2010).

Past research has also identified risk factors for mental health problems in police officers including gender (Syed et al. 2020; Violanti and Steege 2021; Violanti 2010), ethnicity (Violanti 2010), trauma incidents (Syed et al. 2020; Leino et al. 2011; Brough 2004), traumatic materials (Brewin et al. 2022), the work environment and organisational stressors (Habersaat et al. 2015; Morash and Haarr 2006; Violanti et al. 2017; Brough 2004; Liberman et al. 2002), a lack of social support and coping strategies (Syed et al. 2020), and the specific role of the officer (Violanti and Steege 2021). Although some studies have found age to be an important predictor of mental health problems in police officers (Violanti and Steege 2021), in a meta-analysis (Syed et al. 2020) find that age is generally unrelated to mental health problems in police officers. Focusing specifically on risk factors for suicide in police officers Chae and Boyle (2013, 91) highlight the importance of 'organisational stress, critical incident trauma, shift work, relationship problems, and alcohol use and abuse'.

More generally, past work has also focused on the factors related to psychological distress in high pressure occupations such as firefighters, medical professionals and policing. For example, Brown, Mulhern, and Joseph (2002) highlight the importance of work-related incidents in psychological stress amongst firefighters in Northern Ireland. Also drawing on a sample of firefighters, Baker and Williams (2001) highlight the importance of work stress and problem solving on psychological distress. In a study of nurses in China, Zhou et al. (2017) find that coping strategies partially mediate the relationship between psychological capital and psychological distress.

In addition to the factors associated with mental health problems in police officers, literature has also focused on prevention and treatment interventions. Treatments for mental health problems can include psychosocial interventions such as Cognitive Behavioural Therapy (CBT), behaviour therapy, exposure and response prevention (ERP), supportive therapies such as counselling, alternative therapies such as acupuncture, and exercise-based therapy (Vieira et al. 2022; Peñalba, McGuire, and Leite 2008), as well as pharmacotherapy interventions (Mithoefer et al. 2018). A substantial body of evidence exists providing various levels of empirical support for different mental health treatments (Chambless and Ollendick 2001). For example, CBT has been found to be effective in treating anxiety, but there is less evidence for the effectiveness of psychodynamic and supportive therapy relative to CBT (Hunot et al. 2007). For example, in a review of the literature on the use of psychosocial interventions to prevent psychological disorders, Peñalba, McGuire, and Leite (2008) find that police officers may benefit from these interventions, but that the current body of evidence is limited in terms of the quality of the studies. In another review of studies focusing on stress management interventions in police officers, Patterson, Chung, and Swan (2012) fail to find evidence for a beneficial impact. However, they also highlight that the studies reviewed were of low quality, calling for a need for further research. Several studies have focused on the use of psychosocial interventions to prevent psychological problems in police officers (Peñalba, McGuire, and Leite 2008). However, the evidence for their effectiveness is limited, with more research required in this area (Peñalba, McGuire, and Leite 2008). A large body of literature also focuses on pharmacological interventions in treating mental health problems (e.g. Williams et al. 2022; Omori et al. 2010), with some studies focusing on police officers and first responders. For example, Mithoefer et al. (2018) find that MDMA in combination with psychotherapy was effective in treating PTSD in first responders.

In addition to the occupational impacts on police offer mental health, the families of police officers can also face a psychological impact, for example, through intergenerational and secondary trauma (Lennie 2023; Davidson, Berah, and Moss 2006). This is coupled with issues arising around childcare and running the household due to police officers shift work (Agocs, Langan, and Sanders 2015). The psychological impact of police work on officers' families has resulted in the recognition of the need to provide specialised mental health services to the families of police officers, as well as to officers themselves (Lennie 2023).

The high prevalence of mental health problems in police officers points to the importance of monitoring and effective interventions (Syed et al. 2020). Occupational mental health services have been put in place to support police officers. Based on interviews with 110 law enforcement agencies in the US, Ramchand et al. (2019) describe the provision of mental health and suicide prevention services available to law enforcement officers. These range from minimal service provision through health insurance or municipal Employee Assistance Programmes, which is not specific to law enforcement, through to in-house provision of services, and more integrated and comprehensive services. More proactive service provision included services such as in-house mental health services, critical incident review, peer support, chaplains, and health and well-being programmes. However, they also recognise that more research is required to evaluate the effectiveness of these interventions.

A large body of past work has identified a range of factors associated with the effectiveness of treatment for mental health problems in a variety of occupational and non-occupational healthcare settings. Baseline characteristics have been found to be important in predicting the level of improvement during treatment. For example, C. J. Bryan et al. (2012) find that patients presenting at an integrated primary care behavioural health service with more severe mental health problems improved more quickly than those presenting with less severe problems. Other studies have focused on 'dose effects', which consider the length of psychotherapy treatment (Howard et al. 1986). Some of these studies have shown improvements in mental health over a small number of appointments. For example, C. Bryan, Morrow, and Appolonio (2010) report clinically meaningful improvements in the first two to three appointments, whilst also noting that clients presenting with more severe conditions required more appointments. Other studies also note ‘sudden gains’ in patients with mental health problems, where patients make substantial improvements between single appointments (Tony Z. Tang et al. 2007; T Z Tang and DeRubeis 2005; Hardy et al. 2005).

Motivation and engagement have also been identified as important in outcomes from treatment. For example, drawing on self-determination theory and a sample of outpatients with severe mental illness, Jochems et al. (2017) highlight the importance of motivational factors in clinical outcomes. Psychiatric comorbidities have also been found to influence treatment outcomes for a range of mental health conditions (Krishnan 2003; Campbell et al. 2007; Green et al. 2006). However, other studies have found that certain combinations of mental health comorbidities are associated with increased levels of improvement through treatment (Olatunji, Cisler, and Tolin 2010).

2.2 Dominance and heterogeneity of outcome predictors

Past work has highlighted complex and heterogeneous relationships in the factors that influence mental health problems in police officers (Habersaat et al. 2015). Despite this recognition, traditional statistical techniques such as linear regression dominate the literature, limiting the ability to identify more complex non-linear relationships. Alongside this, traditional regression-based approaches face limitations in ascertaining the relative importance, or dominance, of variables (Azen and Budescu 2003), which has resulted in the use of dominance analysis techniques in the wider literature (Halonen et al. 2018; Sun et al. 2017). Machine learning techniques are ideally placed to study this complexity, providing the opportunity to identify more complex non-linearity than traditional regression-based approaches, as well as providing measures of variable importance enabling the identification of dominant predictors (Graham and Bonner 2022).

The use of machine learning to improve understanding and delivery of mental health services has attracted substantial attention in the academic literature as well as in practical service delivery settings. Past studies have applied machine learning methods to a range of problems in mental health contexts such as patient screening (Souza Filho et al. 2021), predicting non-attendance at appointments (Regan et al. 2023; Di Bona et al. 2014), dropout (Giesemann et al. 2023), treatment optimisation (Kelly et al. 2012; Schwartz et al. 2021; van Bronswijk et al. 2021), precision treatment (Bzdok and Meyer-Lindenberg 2018), treatment response and outcomes (Vieira et al. 2022; Kannampallil et al. 2022), treatment resistance (Pigoni et al. 2019; Perlis 2013), and remission (Kannampallil et al. 2022).

Some past work has applied machine learning approaches to predict mental health outcomes. For example, Hilbert et al. (2020) use a range of ML algorithms to predict patient outcomes following CBT treatment. Also focusing on CBT, Ewbank et al. (2020) use deep learning to examine the relationship between the quantity of different features of CBT and patient outcomes, also assessed based on improvement in generalised anxiety disorder 7 (GAD-7) and patient health questionnaire 9 (PHQ-9 scores). They identified relationships between specific features of CBT and patient outcomes.

Aderka et al. (2021) draw on random forests, adaboost and support vector machine algorithms to predict sudden improvements in patients being treated for severe depressive disorder. However, the predictive accuracy of their models was low, with Area under the ROC Curve (AUC) around 0.5. Bone et al. (2021) developed a model to predict improvement in patients affected with depression and anxiety. They applied logistic regression and other machine learning algorithms to predict improvement PHQ-9 and GAD-7 scores. They found that their models generalised well to psychological therapy services in other contexts. Leighton et al. (2019) use regularized regression to predict symptom remission, social recovery, vocational recovery and quality of life for patients diagnosed with psychosis. Montorsi et al. (2024) draw on life course data to predict depression using machine learning algorithms, finding gradient boosting to be the most accurate algorithm.

Studies have also focused on predicting patient outcomes in specific contexts such as following medication. For example, drawing on a range of data from patients diagnosed with depression, Iniesta et al. (2016) use elastic nets to predict the percentage improvement in Montgomery-Asberg Depression Rating Scale (MADRS), and patient remission based on the Hamilton Rating Scale for Depression (HRSD). Their dataset includes a range of variables relating to factors such as demographics, severity, symptoms, and medication used. They find some evidence for the predictive value of the medication data. Overall, their models explained up to around 10% of the variation in the improvement, and around 18% of the variation in remission. Kim et al. (2019) use ML to examine patient outcomes in response to lithium and quetiapine in patients with bipolar disorder. Using elastic net regularization, their most accurate model for patients prescribed lithium explained 17.4% of the variation in the clinical global impressions scale-bipolar and for patients prescribed quetiapine, their model explained 32.1% of the variation. Kannampallil et al. (2022) apply machine learning techniques to clinical trial data to predict treatment outcomes in patients with depression, finding that ML models can be useful in helping to identify which antidepressants are likely to benefit a patient. Recent studies have also begun to use more novel and 'big data' sources to predict treatment outcomes. For example, Kuo et al. (2023) draw on natural language processing to predict patient outcomes from therapy transcripts. Tolmeijer et al. (2018) use data from functional MRI to predict symptom improvements in clients diagnosed with schizophrenia.

3.0 Methodology

3.1 Data

Data for the study are obtained from the patient administration system of a police service occupational psychological therapies service, which offers a range of interventions to current and former employees and their immediate family. Ethical approval (CMFC-22-003) to access the anonymised secondary data was provided by Ulster University Ethics Committee. Individual level data are obtained relating to client characteristics, episode details, and test scores for clients who attended the service between 2008 and 2023. Observations are only included for clients who are discharged from the service, and who have at least two recorded CORE-OM (Clinical Outcomes in Routine Evaluation-Outcome Measure) scores (Evans, John Mellor-Clark, Frank Mar 2000), which are used to construct the dependent variable.

Dependent variable: Psychological Distress

Psychological distress is measured as the change in the clients CORE-OM score between their first and last recorded CORE-OM score within an episode of care. This means that clients must have at least two CORE-OM scores to be included in the analysis. The CORE-OM score is a routinely applied questionnaire used to assess psychological distress. It includes 34 questions relating to four areas including 'well being, problems/symptoms, life functioning and risk to self and others' (Evans, John Mellor-Clark, Frank Mar 2000, 247). All questions are measured on 5-point scales from 0-4, meaning that total scores can range from 0 to 136, with higher scores indicating higher levels of psychological distress.

Independent variables

The independent variables focus on client demographics, mental health conditions, risk assessments, treatment, and episode details. Demographic variables include age, gender, and marital status. Data on the clients' diagnoses and mental health conditions is also included, as well as more general information relating to working alliance, client motivation, and psychological mindedness. The clients' severity is also included. Three variables relating to risk are included: the client's risk to self, risk to others, and their Red-Amber-Green (RAG) status. The type of treatment is also included. Episode details include the time difference between the first and last CORE-OM score, reason for discharge, as well as whether the client did not attend or could not attend any appointments. The clients' baseline CORE-OM score is also included.

3.2 Data Analysis

The first stage in the data analysis was to carry out an exploration of the data, including descriptive statistics and visualisations. This revealed some data quality issues which were addressed prior to the final analysis, the output of which is presented in the results section. Data quality issues are common in data obtained from real-world healthcare administrative systems and can have a detrimental impact on results if not addressed (Miao et al. 2023; Zolbanin, Delen, and Hassan Zadeh 2015). Categories in some variables had small cell counts and were therefore combined both to improve models and to ensure client privacy. This strategy avoids discarding observations listwise due to small cell counts. Diagnosis categories with small cell counts were combined into an 'Other' category. The 'Fleeting Thoughts', ‘Plan’, and ‘Plan and Intent’ categories were collapsed into a ‘risk’ category in the ‘risk_others’ variable. Similarly, ‘Plan’ and ‘Plan and intent’ was collapsed into ‘plan_or_intent’ in the ‘risk_self’ variable. The ‘Moderate’ and ‘Poor’ categories in the ‘working_alliance’ variable were collapsed into ‘Moderate_poor’. For categorical variables with missing data, ‘Unknown’ or ‘not recorded’ categories were used rather than discarding missing data listwise. The data quality measures were designed to retain as much data as possible, hence minimising the potential of introducing bias into the sample, as well as minimising any negative impacts on interpretation of the final models.

After cleaning and exploring the data, a series of machine learning algorithms are applied to model the relationships between the independent variables and the change in psychological distress, measured using the change in CORE-OM score. In total, four machine learning algorithms are used to analyse the data: linear regression, single decision trees, random forests and gradient boosted machines.

The model building process follows a standard machine learning workflow (Kuhn and Johnson 2013). The data is first split into a training and test set, with 80% of the observations used to train models and 20% used to assess the accuracy of the model. This helps to provide an objective assessment of the model's accuracy by using data not involved in the training process. Model parameters are tuned using ten-fold cross validation repeated five times for robustness. Following this process, two sets of models were built. The first included all variables, with the aim of focusing on understanding the relationships between variables in the dataset. The second group of models excluded variables that would not be known at the initial appointment stage, such as the episode length and the reason for discharge. These latter models provide a more realistic estimate of how well the model might perform if implemented in practice to make predictions at the early stages of a clients’ treatment.

IML is used to interpret the most accurate machine learning model. Permutation variable importance is used to identify the dominant predictors. Permutation variable importance is a model agnostic approach to identify the most important predictors in a machine learning model. It works by permuting each variable in turn and measuring the decrease in model accuracy when predictions are made using the data with the permuted variable. PDPs are then used to study the shape of the relationship between the most important predictors and the treatment outcome. PDPs work by making predictions when the variable of interest is set to every possible value in turn. The predictions for each value of the variable of interest are then visualised to show the effect of different values on the outcome.

4.0 Results

Results of the descriptive statistics

Descriptive statistics for the dataset are presented in Table 1. The mean change in psychological distress measured using the CORE-OM score is an overall reduction of 32, and this takes place over an average of 319 days. Figure 1 and Table 2 show the change in CORE-OM score by band during the episode of care. Overall, this illustrates a general trend towards clients core scores decreasing, with a majority of clients moving into the healthy, low, and mild bands. However, it should also be noted that some clients are also in the moderate to severe and severe categories in their last recorded CORE-OM score. Figure 2 presents histograms showing the distribution of the first and last CORE-OM scores recorded in the episode, whilst Figure 3 presents a histogram of the change in CORE-OM score between the first recorded score and the last recorded score in the episode. Overall, both figures illustrate the general improvement in psychological distress during the episode of care. A paired sample t-test found that there was a statistically significant ($p<0.001$) difference between the mean first and mean last recorded CORE-OM score within the episode of care.

Focusing on the independent variables, the results show that almost two thirds of clients (71%) are male. Over half (56%) are married, with 20% single and 13% divorced/separated. The overall mean age is 50. In terms of the clients' mental health conditions, most are recorded as 'Combination' (62%), followed by 'Other' (20%) and 'Psychological Trauma' (18%), with the most frequent subcategories including PTSD (43%), depression (16%), and anxiety disorder (14%). The most frequently recorded second subcategories are Depression (26%), anxiety disorder (8.6%), and PTSD. Data are also included on a range of existing conditions, which provides some additional detail. However, the primary conditions are more frequently populated on the system. Most clients have no risk to themselves disclosed (62%), followed by 'fleeting thoughts' (34%), with a smaller proportion reporting a plan or intent (4.3%). 94% of clients do not have a risk to others disclosed, with 6.4% having a reported risk to others. 47% of clients have no recorded RAG status, whilst 34% are reported as green, 14% as red, and 5.9% as amber. A majority of clients are classified as having moderate severity (52%), with 34% severe, and 14% mild. Just under 7% of clients are recorded as having not attended or cancelled an appointment. This should be interpreted in the context of the sample, which includes clients with at least two CORE-OM scores, so the overall actual rate of missed appointments is likely to be higher as some may not have attended at all or may not have attended enough to have two CORE-OM scores recorded before discharge. Similarly, most episodes have a planned ending, which is either agreed during therapy (48%), planned from the outset (22%), or agreed at the end of therapy (21%). A majority of clients are discharged with a status of 'Treatment Completed' (79%). The most frequent treatments are CBT (66%) and CBT + EMDR (31%). 91% of clients have a good working alliance, with 82% having good motivation, and 81% having good psychological mindedness.

Characteristic	**N = 798**[1]
core_change	-32 (26)
core_first	65 (23)
date_diff	319 (247)

Gender	
F	228 (29%)
M	570 (71%)
Marital	
Civil Partnership	64 (8.0%)
Divorced/Separated	103 (13%)
Married	444 (56%)
Not specified	15 (1.9%)
Single	156 (20%)
Widowed	16 (2.0%)
age	50 (12)
category_condensed	
Combination	492 (62%)
Psychological Trauma	145 (18%)
Other	161 (20%)
sub_category_condensed	
Anxiety Disorder	111 (14%)
Bereavement	37 (4.6%)
Depression	126 (16%)
PTSD	342 (43%)
Trauma	43 (5.4%)
Work related stress	55 (6.9%)
Other	84 (11%)
second_sub_category_condensed	
Anxiety Disorder	69 (8.6%)
Depression	211 (26%)
not_recorded	303 (38%)

PTSD	51 (6.4%)
Trauma	36 (4.5%)
Other	128 (16%)
risk_self	
Fleeting Thoughts	270 (34%)
plan_or_intent	34 (4.3%)
No Risk Disclosed	494 (62%)
risk_others	
risk	51 (6.4%)
No Risk Disclosed	747 (94%)
rag	
Amber	47 (5.9%)
Green	268 (34%)
Red	109 (14%)
not_recorded	374 (47%)
severity	
Mild	112 (14%)
Moderate	417 (52%)
Severe	269 (34%)
dna_cna	55 (6.9%)
discharge_status	
Declined Tmt	29 (3.6%)
Didnt complete tmt	58 (7.3%)
Didnt Engage	7 (0.9%)
DNA/CNA	13 (1.6%)
No tmt required	14 (1.8%)
Return to referrer	34 (4.3%)

Tmt inapprop	14 (1.8%)
Treatment Completed	629 (79%)
treatment	
CBT	529 (66%)
CBT + EMDR	249 (31%)
EMDR	20 (2.5%)
ending	
Planned: Agreed at end of therapy	168 (21%)
Planned: Agreed during therapy	384 (48%)
Planned: from outset	174 (22%)
Unplanned: Client did not wish to continue	45 (5.6%)
Unplanned: Due to loss of contact	27 (3.4%)
working_alliance	
Good	725 (91%)
Moderate_poor	73 (9.1%)
motivation	
Good	656 (82%)
Moderate	125 (16%)
Poor	17 (2.1%)
psychological_mindedness	
Good	643 (81%)
Moderate	141 (18%)
Poor	14 (1.8%)
adjustment_disorder_problem_exists	25 (3.1%)
anger_management_problem_exists	14 (1.8%)
anxiety_disorder_problem_exists	124 (16%)
bereavement_problem_exists	46 (5.8%)

depression_problem_exists	221 (28%)
other_problem_exists	52 (6.5%)
ptsd_problem_exists	305 (38%)
work_related_stress_problem_exists	64 (8.0%)
[1] Mean (SD); n (%)	

Table 1: Descriptive Statistics

Category	**Score Band**	**First**	**Last**
Healthy	0 to 5	28	305
Low	6 to 9	44	149
Mild	10 to 14	132	131
Moderate	15 to 19	205	101
Moderate to severe	20 to 24	207	68
Severe	25 +	182	44
Total		798	798

Table 2: Summary of first and last CORE-OM scores recorded in the episode of care. CORE-OM scores are presented as simple scores showing category and score bands (Barkham et al. 2006)

Figure 1: histogram showing the change in CORE-OM score between the first measured score and the last measured score in the episode of care.

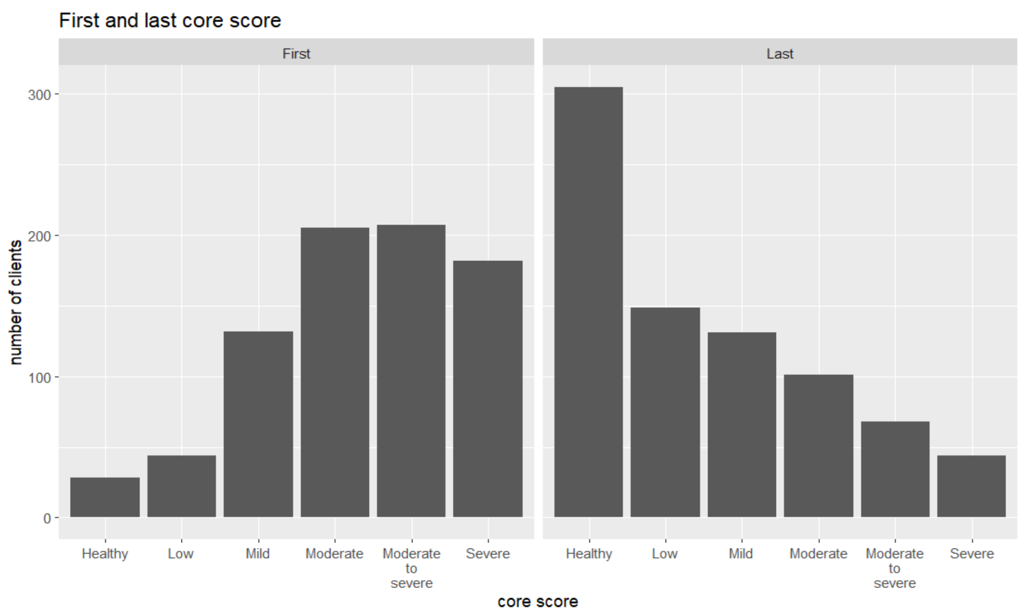


Figure 2: Histogram of the clients' first recorded CORE-OM score, and the clients' last recorded CORE-OM score in the episode of care. The red line indicates the clinical cut-off point (a CORE-OM score of 34).

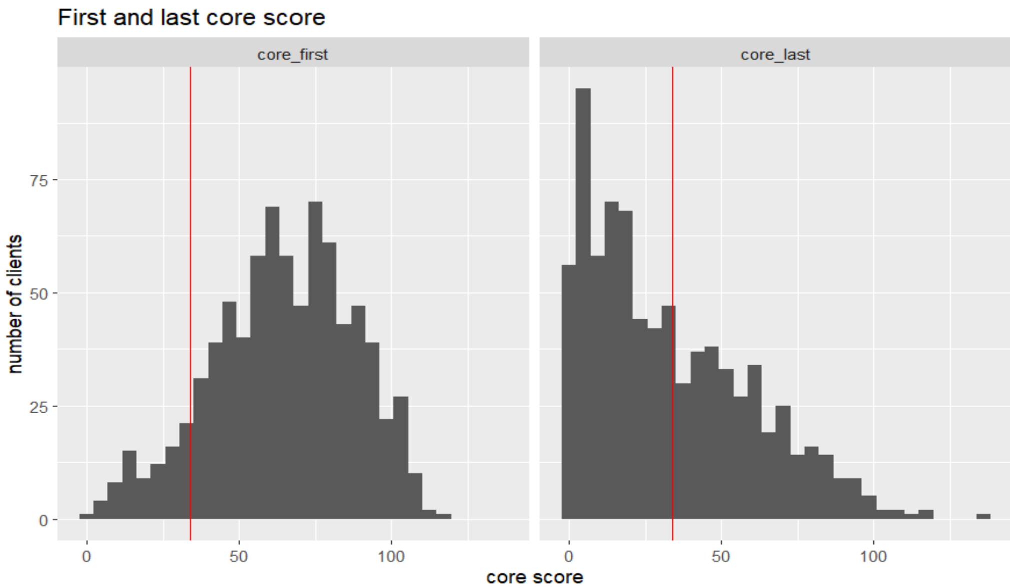
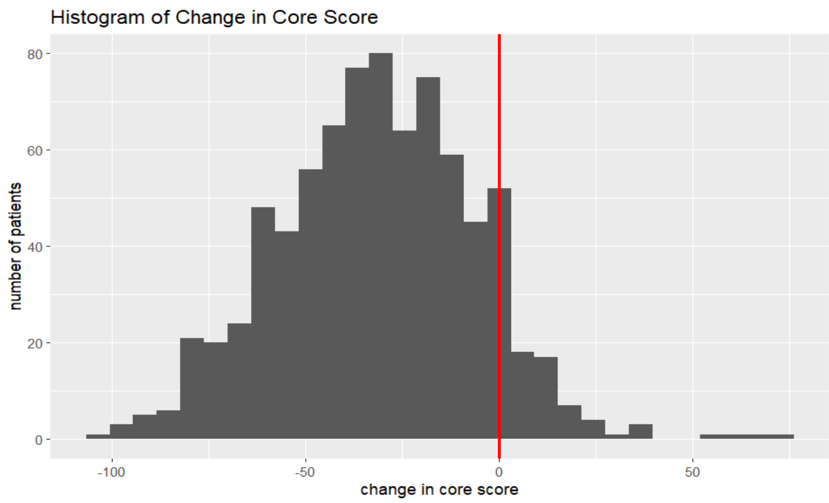


Figure 3: Mean change in CORE-OM score between the first and last recorded score in the episode of care. The red line indicates the clinical cut-off point (a CORE-OM score of 34).



Results of the machine learning analysis

The accuracy of the machine learning models is presented in tables 3 and 4, with table 3 presenting the model accuracy for models including all predictors, and table 4 presenting the model accuracy for models excluding predictors not known at the initial appointment stage. Model accuracy is assessed using the hold out test data and shows that the GBM is the most accurate model overall in the models including all variables, with a RMSE of 20.66, and an R-squared of 0.352. The RF has the second highest RMSE and R-squared, and the highest MAE overall. The LM is third most accurate, followed by the CART. The accuracy of the models excluding variables that are known later in the episode is lower for each model, and the RF performs best on RMSE and R-squared, whereas the GBM performs best on the MAE. For consistency, the variable importance measures are presented for both GBM models.

Algorithm	**RMSE**	**R-squared**	**MAE**
GBM	20.6612394	0.3518859	16.4528748
RF	20.7578708	0.3453331	16.3941762
CART	22.7008893	0.2365836	17.9829075
LM	21.5487619	0.3194561	16.6800101

Table 3: Model accuracy on test data for models including all variables

Algorithm	**RMSE**	**R-squared**	**MAE**
GBM	22.1850011	0.2577002	17.3025250
RF	22.1110304	0.2597466	17.5192792
CART	23.4202476	0.1945751	18.2126851
LM	22.8730826	0.2440213	18.1588249

Table 4: Model predictive accuracy excluding factors that are unknown at the point of initial assessment

Figures 3 and 4 present the results of the permutation variable importance, for the GBMs including all variables and the subset that are known at the initial appointment. The permutation scores and confidence intervals are presented in Appendix 1 tables A1 and A2. Overall for the model including all variables, the baseline level of psychological distress, assessed using the clients' first CORE-OM score, is the most important predictor of overall change in psychological distress. This is followed by the discharge status and whether the client has PTSD. The length of time between the first and last CORE-OM score in the episode is the fourth most important predictor, followed by the clients' level of motivation in fifth place. Whether the client has depression is sixth most important. This is followed by the reason for the ending of the episode in seventh place, the client's severity, in eighth place, the clients second diagnosis condition subcategory in ninth place, and the clients RAG status in tenth pace. A similar pattern can be observed in Figure 4 amongst the dominant predictors, except that age and working alliance become relatively more important.

Figure 3: Permutation variable importance

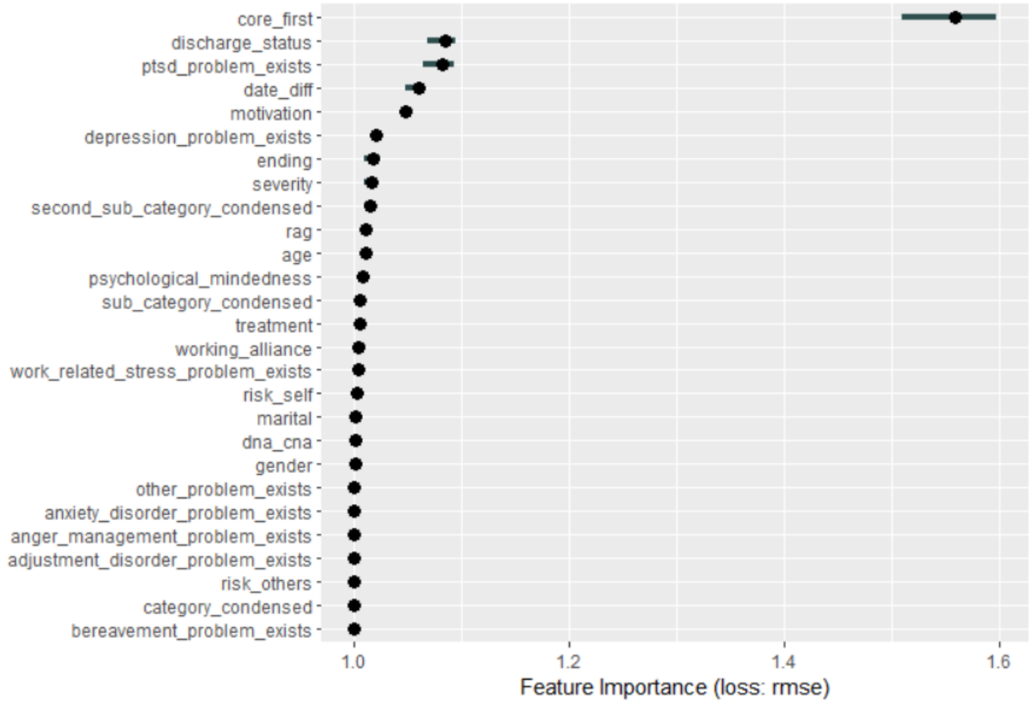


Figure 4: Permutation importance for GBM excluding information not known at the initial appointment

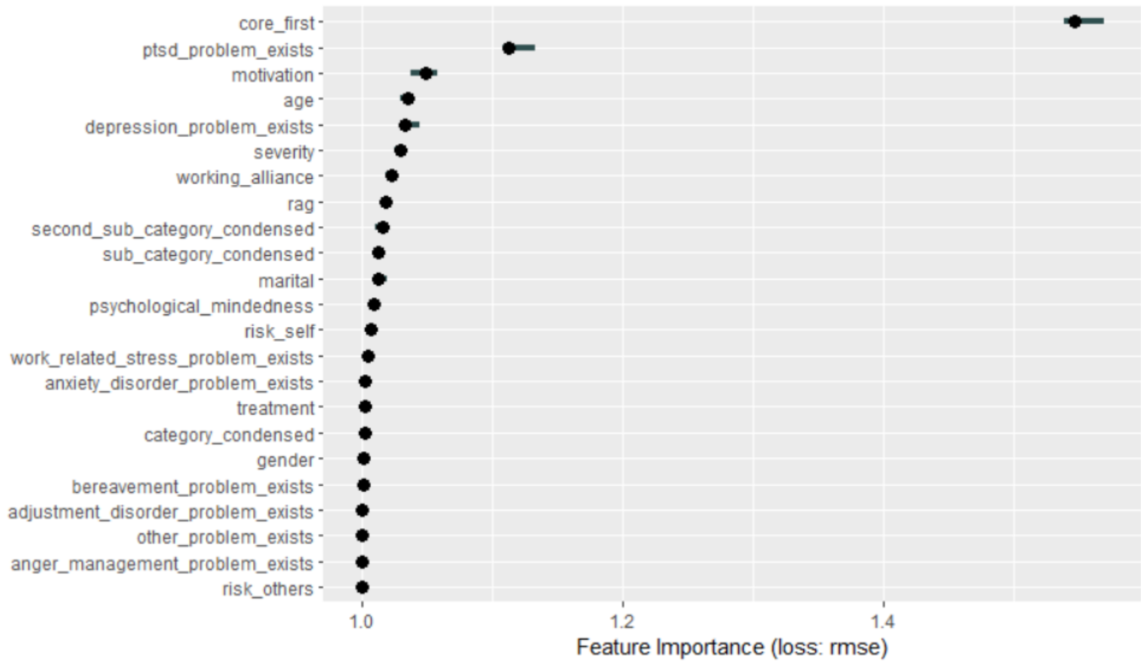
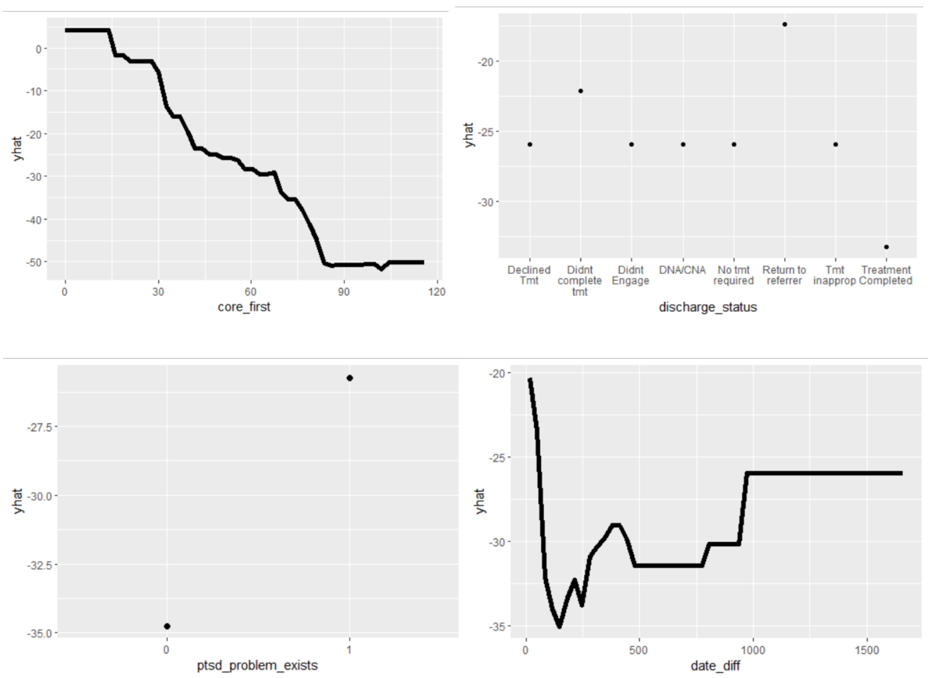
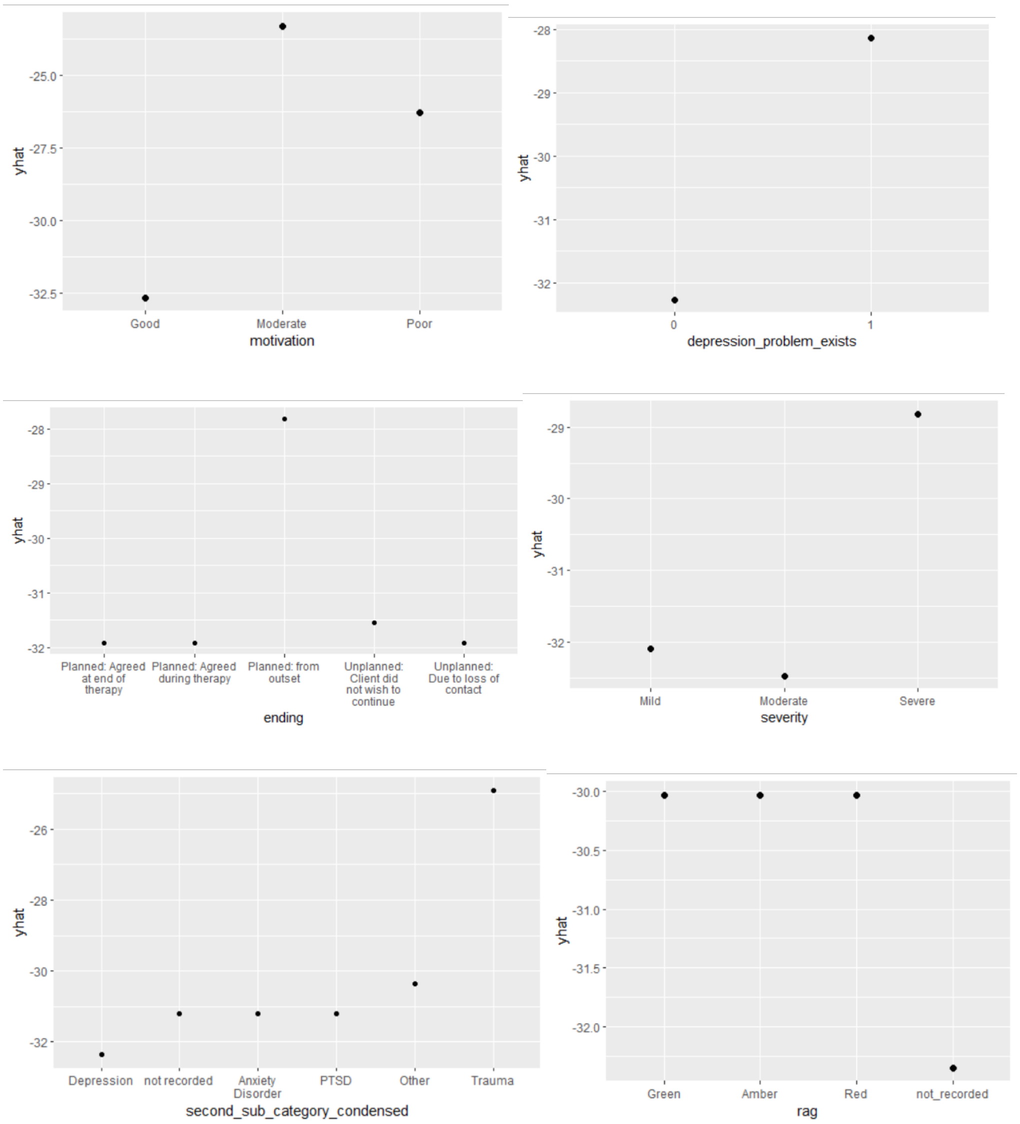


Figure 5 presents the partial dependence plots for the ten most important features that were identified through the permutation variable importance. Alongside the variable importance plots, the PDPs can be used to examine relationships between variables of interest. As the focus here is on examining relationships to gain a rich insight into the data rather than purely predicting outcomes, the PDPs and the discussion which follows draw on the GBM including all variables. The first chart shows that in general as the baseline CORE-OM score increases, the level of improvement increases, as shown by the decreasing predicted CORE-OM score on the y-axis of the chart. The second chart shows that clients who complete treatment are predicted to have the biggest decrease in CORE-OM score. Clients who do not complete treatment or are returned to the referrer are predicted to have a lower decrease in CORE score. The third chart shows that the improvement in CORE-OM score is lower when the client has PTSD. However, both the existence of PTSD and not having PTSD are associated with an improvement in CORE-OM score. The fourth chart shows the relationship between the length of episode and change in core score. There is an initial steep decrease in the core score for episodes lasting up to around 125 days, followed by less of a decrease in the core score. This illustrates that there is less improvement in core scores for clients undertaking very short and very long episodes. Clients with good motivation are predicted to have the largest decrease in CORE-OM score, with moderate and poor motivation associated with a lesser decrease. Clients with depression are predicted to experience less improvement, as are clients whose ending is planned from the outset, and clients who are more severe. Clients with s second sub category of Trauma are predicted to improve less, whereas clients who do not have a RAG status recorded are predicted to improve more.

Figure 5: Partial Dependence Plots for the ten dominant independent variables (based on the GBM including all variables)





Discussion

Theoretical contributions

The findings from the study highlight the dominant factors in predicting changes in psychological distress during an episode of care, as well as non-linearity and floor and ceiling effects. Whilst past studies have identified significant predictors, few studies have considered the relative importance or dominance of these predictors. This could have important practical and theoretical implications in disentangling the relative importance of a range of factors that are predictive of changes in psychological distress. This is particularly relevant when studying the predictors of treatment outcomes, due to the large number of potential predictors and difficulties in identifying consistent predictors (Eilertsen and Eilertsen 2023). Overall, the baseline level of psychological distress and the clients' mental health condition are the most important factors in predicting changes in psychological distress.

The PDP for baseline psychological distress shows that in general, higher baseline levels of psychological distress at the beginning of treatment are generally associated with a greater reduction in psychological distress during the episode of care. This indicates that the most severe cases have the greatest improvement during treatment. This finding supports past work from other contexts. For example C. J. Bryan et al. (2012) find that clients presenting at primary care with more severe mental health problems improved faster than those presenting with less severe mental health problems.

In terms of episode duration, clients undergoing very short and very long episodes had the least improvement in CORE-OM score. The largest improvements were for clients who attend for around 125 days. This finding is supported by past work, which has found the number of sessions attended to be an important predictor of change in CORE-OM score (Blackshaw et al. 2023). Past work has also found that the level of improvement decreases over time, with some studies showing rapid improvements over a short space of time (C. Bryan, Morrow, and Appolonio 2010), or sudden gains in improvement between single appointments (T Z Tang and DeRubeis 2005; Tony Z. Tang et al. 2007; Hardy et al. 2005). Other studies have argued that the optimal treatment duration is more heterogeneous, depending on client symptoms and characteristics (Steenbarger 1994; Kopta et al. 1994). However, the findings from the present study indicate that some clients did not complete their full course of treatment, and indeed the PDP showing the reason for treatment ending highlights the importance of completing treatment. This supports past work which highlights the importance of patient engagement in positive outcomes from treatments in clients with mental health problems (Eilertsen and Eilertsen 2023; Jochems et al. 2012).

Past work has also highlights the role of client motivation in engagement and positive outcomes from treatment for mental health conditions (Mulder, Koopmans, and Hengeveld 2005; Fuller Torrey and Zdanowicz 2001). The results support these findings, highlighting the importance overall importance of motivation as a predictor of change in psychological distress. The PDP shows that clients with moderate and poor levels of motivation are predicted to have lower levels of improvement in psychological distress during the episode of care. The client's specific mental health condition is also an important determinant of their level of improvement, with PTSD and depression are particularly relevant in predicting changes in psychological distress. The PDP for PTSD shows that clients with PTSD are predicted to have a smaller improvement in their level of psychological distress relative to clients without PTSD.

More generally, it is worth noting the demographics of the clients, who are predominantly male, with an average age of 50. Past work has highlighted that men and older aged people are underrepresented at psychological services (de Lusignan et al. 2012; Di Bona et al. 2014). Although, the gender profile of the service in our study is representative of the gender breakdown of the occupation linked to the service, the demographic breakdown could suggest that males in particular are more inclined to attend occupational based psychological therapy services than more general psychological therapy services offered for example by national healthcare providers, which tend to have a higher proportion of female clients (Di Bona et al. 2014).

Overall, the findings highlight the general trend in improvement in psychological distress through attending the service. This is beneficial for the mental health of police officers and their families, but may also have wider organisational performance implications. Although not examined in the present study, past research has found that improved mental health in workplace settings results in performance benefits such as improved productivity and decreased absenteeism (Goetzel et al. 2002; Hilton et al. 2009; Shane 2010).

Methodological contributions

In addition to the theoretical contributions from the study, the use of the ML method and IML also make a methodological contribution. The findings highlight the relatively higher level of predictive accuracy when using the more complex machine learning algorithms, compared with the more traditional logistic regression model. However, complex ML algorithms have been criticised for their lack of interpretability, which has resulted in a large body of literature and techniques focusing on IML, which aims to facilitate the interpretation of these models (Molnar 2022). These IML techniques create the possibility to derive more theoretical and practical insights from machine learning models. Techniques such as permutation variable importance can overcome some of the limitations with more traditional variable importance measures (Strobl et al. 2007), and provide the opportunity to examine the dominance of predictor variables (Graham and Bonner 2022). PDPs can be further applied to examine the form of relationship between independent and dependent variables and are particularly useful when examining non-linearity. The present study has illustrated both techniques, in identifying the dominant predictors of changes in psychological distress, as well as delving into the more complex non-linear patterns between the independent variables and changes in psychological distress.

Practical contributions

Findings can be used by practitioners to understand the most important predictors of improvement in psychological distress. Practitioners can be cognisant of the differences in outcome across different client characteristics. It is important to help motivate clients and to ensure episodes of treatment are completed. The predictive model can be used in service management through the construction of risk adjusted improvement scores. This can enable actual improvements to be compared with improvements that are predicted by the model. This insight can help to inform discussion when reviewing service performance.

Conclusions and limitations

This study has applied ML and IML techniques to predict and understand changes in psychological distress in clients attending an occupational psychological therapies service. The findings highlight the dominant predictors of changes in psychological distress as well as non-linearity in the relationships. This contributes to both the theoretical and methodological literature, as well as providing important practical insights for psychological therapies services.

However, the study is not without limitations. The dataset is relatively small and from a live system, rather than being designed specifically for the present study. Future work could consider replicating the study in other settings. Future work could also consider including additional data, such as unstructured textual information from client notes, which may enhance the predictive accuracy of models. Larger and unstructured datasets also lend themselves to additional machine learning algorithms such as deep learning, which when combined with these larger unstructured datasets could enhance model accuracy. Incorporation of a higher volume and variety of data in future studies could help to increase the predictive accuracy of the models. Future studies could also consider longer term follow up to examine the extent to which treatment benefits persist over time. These studies could also include randomised control trials of treatment interventions in occupational mental health services.

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Appendix 1: Full permutation variable importance with confidence intervals

	feature	importance.05	importance	importance.95	permutation.error
1	core_first	1.510399	1.559526	1.598096	27.48918
2	discharge_status	1.068021	1.083842	1.094684	19.10448
3	ptsd_problem_exists	1.064433	1.081321	1.093175	19.06004
4	date_diff	1.047196	1.059326	1.061796	18.67234
5	motivation	1.044103	1.046757	1.054326	18.4508
6	depression_problem_exists	1.019641	1.02008	1.021546	17.98057
7	ending	1.008839	1.017555	1.0236	17.93607
8	severity	1.009068	1.015623	1.019461	17.90201
9	second_sub_category_condensed	1.009472	1.013832	1.016719	17.87044
10	rag	1.009024	1.010689	1.014617	17.81504
11	age	1.009764	1.010004	1.012215	17.80296
12	psychological_mindedness	1.006269	1.007423	1.009908	17.75748
13	sub_category_condensed	1.001623	1.005445	1.00622	17.72261
14	treatment	1.000929	1.004701	1.00594	17.70949
15	working_alliance	1.001548	1.004072	1.010322	17.69841

16	work_related_stress_problem_exists	1.002742	1.003532	1.003752	17.68889
17	risk_self	1.000871	1.002299	1.004061	17.66714
18	marital	1.000573	1.001349	1.00238	17.6504
19	dna_cna	1.000215	1.000633	1.001468	17.63778
20	gender	0.999568	1.000177	1.00047	17.62975
21	category_condensed	1	1	1	17.62663
22	risk_others	1	1	1	17.62663
23	adjustment_disorder_problem_exists	1	1	1	17.62663
24	anger_management_problem_exists	1	1	1	17.62663
25	anxiety_disorder_problem_exists	1	1	1	17.62663
26	other_problem_exists	1	1	1	17.62663
27	bereavement_problem_exists	0.999464	0.999653	1.000968	17.6205

Table A1: Permutation variable importance for the predictor variables

	feature	importance.05	importance	importance.95	permutation.error
1	core_first	1.538807	1.546624	1.569256	27.97953
2	ptsd_problem_exists	1.108014	1.112496	1.132789	20.12584
3	motivation	1.03797	1.049024	1.057947	18.97759
4	age	1.029119	1.035719	1.040103	18.7369
5	depression_problem_exists	1.030951	1.032461	1.044431	18.67795
6	severity	1.025504	1.029086	1.033385	18.6169
7	working_alliance	1.017698	1.022617	1.027318	18.49987
8	rag	1.014344	1.0176	1.021717	18.40912
9	second_sub_category_condensed	1.009828	1.015383	1.017677	18.369
10	sub_category_condensed	1.009191	1.012508	1.013225	18.31699
11	marital	1.010461	1.01208	1.018996	18.30924
12	psychological_mindedness	1.0063	1.009093	1.010565	18.25521
13	risk_self	1.00582	1.006868	1.007957	18.21497
14	work_related_stress_problem_exists	1.003331	1.003958	1.005313	18.16231
15	anxiety_disorder_problem_exists	1.001275	1.002746	1.00337	18.14039

16	treatment	1.002087	1.002608	1.004432	18.1379
17	category_condensed	1.001796	1.002409	1.005611	18.13429
18	gender	1.000607	1.001309	1.001559	18.11439
19	bereavement_problem_exists	0.999941	1.000895	1.001106	18.1069
20	adjustment_disorder_problem_exists	0.999868	1.000271	1.000681	18.09562
21	anger_management_problem_exists	1	1	1	18.09071
22	other_problem_exists	1	1	1	18.09071
23	risk_others	0.999201	0.999888	1.00046	18.08869

Table A2: Permutation variable importance (Excluding predictors unknown at the point of initial assessment)