Using conversational AI to facilitate mental health assessment and improve clinical efficiencies in psychotherapy services in large real-world dataset

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Abstract

Background: Most mental health service providers face the challenge of increasing demand in the absence of increases in funding or staffing. To overcome this supply-demand imbalance, providers need to increase efficiencies to cope with the demand.

Objective: Here, we test whether artificial intelligence (AI) enabled solutions can enable mental health practitioners to use their time more efficiently, and thus reduce strain on the service and improve patient outcomes.

Methods: In this study, we focus on the usage of an AI solution (Limbic Access) in the referral and assessment process in UK’s national health service (NHS) first-line psychotherapy service. Data was collected from 9 Improving Access to Psychological Therapies (IAPT) services across England from 64,862 patients.

Results: We show that the use of this AI solution improves clinical efficiency by reducing the time clinicians spend on mental health assessments. Furthermore, we find improved outcomes for patients using the AI solution in a number of key metrics, such as reduced wait times, reduced dropout rates, improved allocation to accurate treatment pathways and, most importantly, improved recovery rates. When investigating the mechanism by which the AI solution achieved these improvements, we find that the provision of clinically relevant information ahead of a clinical assessment was critical for these observed effects.

Conclusions: Our results emphasise the utility of using AI solutions to support the mental health workforce and highlight that AI solutions can increase efficiencies and in parallel improve mental healthcare for patients.

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Using conversational AI to facilitate mental health assessments and improve clinical efficiencies within psychotherapy services in a large real-world dataset

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Abstract

Background: Most mental health care providers face the challenge of increased demand for psychotherapy in the absence of increased funding or staffing. To overcome this supply-demand imbalance, care providers must increase efficiency of service delivery.
Objectives: In this paper, we examine whether artificial intelligence (AI) enabled digital solutions can help mental healthcare practitioners to use their time more efficiently, and thus reduce strain on the service and improve patient outcomes.
Methods: In this study, we focus on the usage of an AI solution (Limbic Access) to support initial patient referral and clinical assessment within the UK's National Health Service (NHS). Data was collected from 9 Improving Access to Psychological Therapies (IAPT) services across England, comprising 64,862 patients.
Results: We show that the use of this AI solution improves clinical efficiency by reducing the time clinicians spend on mental health assessments. Furthermore, we find improved outcomes for patients using the AI solution in a number of key metrics, such as reduced wait times, reduced dropout rates, improved allocation to appropriate treatment pathways, and most importantly, improved recovery rates. When investigating the mechanism by which the AI solution achieved these improvements, we find that the provision of clinically relevant information ahead of a clinical assessment was critical for these observed effects.
Conclusions: Our results emphasize the utility of using AI solutions to support the mental health workforce, highlighting further the potential for AI solutions to increase efficiency of care delivery and improve clinical outcomes for patients.

1 Introduction

Common mental illness has become the largest cause of disability worldwide [Nochaiwong et al., 2021]. Access to high quality mental healthcare is therefore crucial, with up to 25% of the population suffering from depression or anxiety disorders [Horackova et al., 2019, De La Torre et al., 2022]. The COVID 19 pandemic has further spotlighted the need for accessible mental health treatment, precipitating increased cases of anxiety, depression and other mental health symptoms [Busetta et al., 2021, Murch et al., 2021, Ornell et al., 2021, Marques et al., 2020, Loosen et al., 2021, Thome et al., 2021]. Addressing this high demand is challenging for many mental health services that already struggle to provide adequate treatments with limited resources, resulting in impaired patient experience and ultimately worse treatment outcomes [Scott, 2018b].

One particular challenge that mental health services face is the long wait time between the point from when a patient seeks support and when they begin treatment. For instance, in the English National Health Service (NHS), between 2021 and 2022, 31% of referrals to Improving Access to Psychological Therapies (IAPT) services dropped off the wait list before starting treatment, and 9% of patients waited more than 6 weeks for their clinical assessment [NHS Digital, 2022]. Additionally, a further 47% of patients experienced “hidden waits” of over 28 days between clinical assessment and their first treatment session, contrary to guidance from the National Institute of Health and Care Excellence (NICE), which highlights the importance of timely access to treatment [Larsson et al., 2022].

Unfortunately, against the backdrop of rising referrals, the needs of patients are unlikely to be addressed through an increase in clinical workforce, and in fact there exists a national shortage of qualified staff [Adams et al., 2021]. To remedy this precarious situation, it has been repeatedly suggested that digital tools might represent a viable opportunity to improve efficiency and quality of service delivery, as well as enhancing patient outcomes and experience [Jayaraajan et al., 2022, Rudd and Beidas, 2020, Koutsouleris et al., 2022, Hauser et al., 2022].

Previous studies have explored the use of digital solutions in healthcare settings, such as artificial intelligence (AI)-based interventions and conversational agents. However, these studies have mainly focused on treatment support or remote monitoring [Car et al., 2020]. Moreover, there exists little evidence for the efficacy of such tools in real-world clinical settings [Car et al., 2020, Laranjo et al., 2018]. Within the field of mental healthcare, the use of AI and conversational agents has mainly focused on self-care tools [Pham et al., 2022], whereas, the efficacy of AI for supporting clinicians in their delivery of high quality care has not been explored. The use of AI is well suited to address the supply-side issues faced by mental healthcare providers by improving the allocation of staff time to boost service capacity through the support and augmentation of clinicians [D'Alfonso, 2020, Ćosić et al., 2020]. For example, AI can enable healthcare professionals to prioritise tasks and streamline processes by automating low-level clinical functions such as adaptive information gathering to inform assessment or treatment sessions conducted by a trained clinician.

Digital innovation to support referral and clinical assessment is earmarked as a key area to increase service capacity within mental healthcare. One of the main aims of the referral process is to collect information that can be used at clinical assessment to identify symptoms and triage patients into appropriate treatment pathways. Therefore, the referral process and clinical assessment represent promising targets for automation. These early parts of the care pathway are typically conducted by trained mental health professionals and demand considerable time from overburdened clinical staff. Indeed, studies have found that NHS IAPT services spend up to 25% of their annual budget on clinical assessments [Scott, 2018a]. Automation in this area represents a viable opportunity to release clinical time and resources that could be reallocated to other stages of the care pathway.

In addition to service efficiencies, other patient benefits can be generated through implementation of AI-enabled digital solution. Direct benefits include reduced barriers to entry, such as social stigma and time-constraints [Lattie et al., 2022], resulting in a more accessible and patient-focused referral process. Additionally, previous research suggests that patients are more likely to report severe symptoms on digital solutions [Torous et al., 2015], which can lead to more accurate referral information. As a result, clinicians stand to receive a more comprehensive overview of the problems faced by their patients. This presents an opportunity to accelerate the clinical assessment, improve pathway allocation, and spend more time during clinical contacts to focus on building a strong relationship with the patient. Indirectly, increased overall efficiencies of the service will free up resources that can be re-allocated to increase the number of available treatment sessions, which is known to improve clinical outcomes [Gyani et al., 2013].

In this study, we evaluate the impact of an AI self-referral tool - a conversational AI chatbot (Limbic Access) - in a real-world scenario. This AI self-referral tool is already implemented as part of routine care across multiple NHS IAPT services in England. We analyse data from one service provider with IAPT services across England. Data was collected from 64,862 patients that referred into care either via the AI self-referral tool, or via alternative methods of referral. We show that the AI solution improves clinical efficiencies, reduces wait times and dropout rates, provides more accurate treatment allocation, and increases recovery rates. We further show that front-loading the collection of clinically relevant information ahead of the clinical assessment is a major driver for these observed improvements. Our findings thus provide novel empirical evidence that mental healthcare can be significantly improved through AI solutions that support trained clinicians in their daily work.

2 Methods

2.1 AI self-referral tool

Here we evaluate the effects of a novel AI self-referral tool (Limbic Access), which was implemented as part of routine mental healthcare in several NHS IAPT services. This self-referral tool is a con versational chatbot integrated into the service's website, and assists patients in making a referral by collecting the necessary intake information as required by the IAPT programme (e.g. eligibility criteria, contact details, and demographic information). Furthermore, the chatbot collects additional clinical information about the patient's presenting symptoms, such as the Patient Health Questionnaire-9 (PHQ-9) [Kroenke et al., 2001], Generalised Anxiety Disorder Assessment (GAD-7) [Spitzer et al., 2006], the Work and Social Adjustment Scale [Mundt et al., 2002], and a selection of additional screen ing questions. These routine outcome measures and screening questions are typically not collected at the point of referral in IAPT. All the inforation collected by the AI self-referral tool is then attached to the referral record within the IAPT service's electronic health record in order to support the clinician in preparing a high-quality and high-efficiency clinical assessment.

It is important to note that when guiding a patient through the referral into IAPT, the AI tool utilises a "check-point", where there exists a point at which the patient has provided the minimal information required to submit a referral. At this check-point, all required information to submit the patient to the service as a new referral has been collected. However, patients are then asked whether they would like to provide additional *clinical* information regarding their mental health issues, which is specifically designed to facilitate a human-led clinical assessment (see Figure 1). This additional information includes free text input regarding the patient's presenting symptoms as well as standard ized, clinically validated routine outcome measures and screening questions. Empirically, most patients choose to provide the additional information ($\sim$ 97% of referrals), however a subset of patients only provided the minimally required information at referral ($\sim$ 3% of referrals). This allows us to imple ment a quasi-experimental design to test the effects of collecting this clinical information on patient treatment outcomes.

2.2 Clinical implementation of the AI self-referral tool

In order to derive maximal clinical value from an AI self-referral tool, the appropriate implementation of this tool within the wider service environment is of critical importance. Indeed, the realised benefits of any digital tool rely on how it is used in practice.

Within the evaluated psychotherapy service (Insight IAPT), the clinical information collected by the AI self-referral tool was used to triage the severity of patient case presentations (for example, mild, moderate and severe cases of depression can be differentiated based on magnitude of the PHQ-9 score). The case presentation, symptom severity, and additionally any associated risk factors are then used by the service to schedule the appropriate duration for a human-led clinical assessment (i.e. complex or severe cases require longer assessment slots, and simpler or mild cases may only require shorter assessment slots). In this way, the IAPT service can used this information to allocate clinical resources in a tailored and efficient manner.

The psychotherapy service additionally enabled a "direct booking" feature within the AI self-referral tool, which provided a means for patients to directly book a preferred time for their human-led clinical assessment directly in the service calendar, thus reducing the administrative burden on the service and enabling faster access to a clinical assessment.

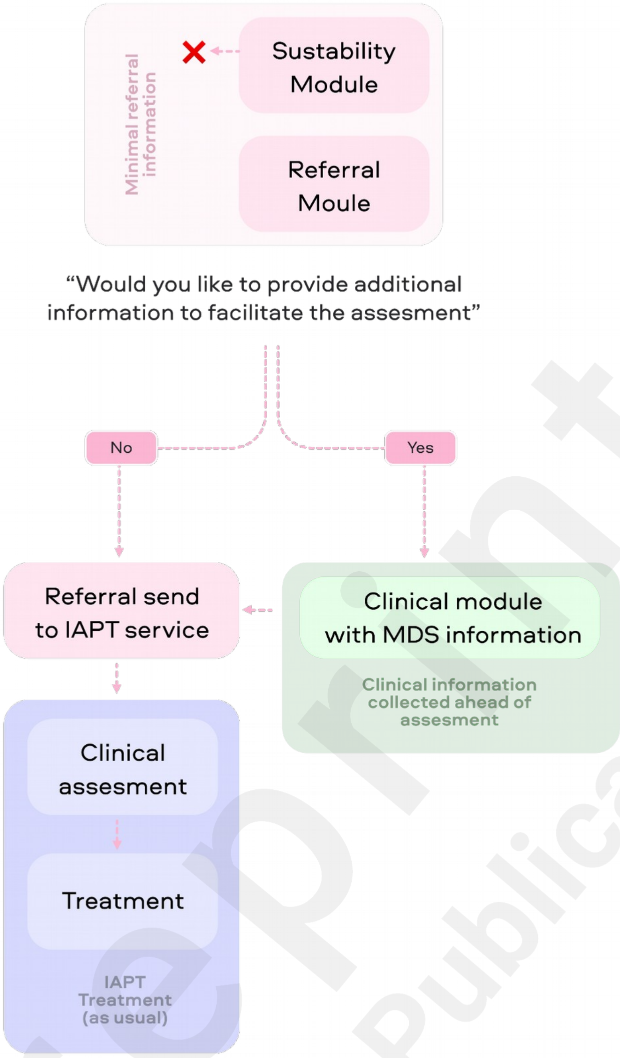

Figure 1: Pathway of the AI e-referral tool. The tool is embedded on an IAPT service's webpage(s) and "pops up" when a potential patient navigates to that page. Upon initiating an interaction with the chatbot, the eligibility of the patient is determined in the eligibility module. If ineligible, the patient is signposted out of the service (red cross). The eligible patient then continues through the referral module which produces the minimal data set needed in order to refer the patient to the IAPT service. After the referral module, the patient is asked whether they would like to provide additional information. If they consent, they fill in additional information regarding their mental health issues, which is added to the referral record sent to the IAPT service. If they disagree, their referral is sent directly to the IAPT service. MDS=Minimum data set.

Finally, all clinical information collected in the AI self-referral tool is programmatically transferred into the service's chosen patient management system where it can be accessed by the clinician leading the clinical assessment. This supports the reviewing clinician with richer contextual information.

These authors believe these implementation decisions for an AI self-referral tool are crucial to consider with respect to the expected effects on service efficiencies and quality of care.

2.3 Design

The real world data was collected from patients entering and receiving mental health care treatment through one specific provider of NHS IAPT services (Insight IAPT) between November 2021 and August 2022. Participating mental health services comprised 9 individual IAPT services in different regions throughout England. This allowed us to work with representative data from patients experiencing mental health issues across the UK.

In this study, we examined the between-group and within-group effects of this AI self-referral solution. In the between-group context, we compared patients who referred themselves to IAPT services through the AI tool with patients who were referred through other methods (telephone referrals, re ferrals via a webform, GP referral, referrals via other primary healthcare). Comparison of these two groups was made possible due to the constant availability to patients of alternative self-referral methods alongside the AI self-referral tool. Overall, this data comprised 64,862 patients, where 21,568 patients were referred through the AI self-referral tool and 43,294 patients were referred through alternative routes.

In the within-group context, we compared users referring through the AI self-referral tool who also completed the full clinical information (clinical information group: 20,860 patients) with those users that only completed the minimally required information for a referral (no clinical information group: 686 patients). This allowed a comparison of the effects of providing clinical information ahead of the assessment in order to evaluate some of the mechanisms by which the AI self-referral tool achieved its effects. Minimal referral information was defined as patients not completing all relevant clinical information asked for in the self-referral process. It was expected that only a small proportion of patients would not provide the full clinical information as the AI self-referral tool was designed to increase engagement and ensure that a maximal number of patients complete all relevant information ahead of the clinical assessment.

As determined by the NHS and in accordance with NICE principles [Ross, 2002], clinical audit studies within the IAPT framework do not require additional patient consent or ethical approval [Ross, 2002]. Moreover, the study team received written confirmation from the Health Research Authority (HRA) England that this study constitutes a service evaluation and thus did not require additional ethical approval. When registering to use the AI self-referral tool, patients provided written informed consent as part of a privacy policy agreement, allowing the service to use anonymised patient data for audit purposes and to support research.

2.4 Outcome measures

The outcome measures reported here are assessed routinely during mental healthcare delivered by IAPT services. Anonymous data is publicly reported on the NHS digital website (NHS Digital, 2020) for evaluation of IAPT service performance. Therefore, no additional data, beyond routine care data, was collected for this study.

2.4.1 Assessment duration

We were interested to evaluate whether the usage of the AI self-referral tool improved clinical efficiencies by reducing the time required to complete a high-quality clinical assessment. The required length of the clinical assessment is measured in minutes.

2.4.2 Wait time for clinical assessment

We were interested to evaluate whether the usage of the AI self-referral tool reduced the wait time for clinical assessment. The required wait time for clinical assessment is measured in days, from the day of referral to the day of the clinical assessment.

2.4.3 Wait time for treatment

We were interested to evaluate whether the usage of the AI self-referral tool reduced the wait time to the start of treatment. The wait time for the treatment is measured in days, from the day of the referral to the day of the first treatment session. Only data of patients who entered treatment were used for this analysis as for some patients in the clinical assessment it might be decided that no treatment is required.

2.4.4 Dropout rate

We were interested to see whether the usage of the AI self-referral tool would reduce the likelihood of patients dropping out of the service at any point during the care pathway. Dropouts were defined as those patients that cancelled an appointment and did not re-book a new appointment. This is measured as a percentage of patients dropping out from treatment.

2.4.5 Change in allocated treatment level

We were interested to evaluate whether the usage of the AI self-referral tool would enable a more accurate clinical assessment. A more accurate clinical assessment would manifest in patients being assigned to the appropriate treatment pathway and therefore the treatment pathway would be less likely to change during treatment. Changes in treatment are known as step-ups and step-downs in NHS IAPT. We measured the accuracy of treatment allocation as the percentage of patients for whom their treatment was stepped-up or down. Only data from patients who received and finished treatment were used for this analysis as the accuracy of treatment allocation can only be assessed after treatment ends.

2.4.6 Recovery rates

We were interested to evaluate whether the use of the AI self-referral tool would enable a higher rate of recovery in the IAPT service. Recovery of patients is assessed at the end of treatment, and the definition of reliable recovery is systematically used in IAPT services [Jacobson and Truax, 1992]. This is measured by administering an appropriate disorder specific outcome questionnaire and is defined as a significant reduction in symptom scores (PHQ-9: improved by at least 6 points; GAD-7: improved by at least 4 points) from the beginning to the end of treatment, as well as a score below the clinical cut-off at the end of treatment. We measure the recovery rate as the percentage of patients who achieved reliable recovery. Only data from patients who received and finished treatment were used for this analysis as only after completed treatment could reliable recovery can be assessed.

2.5 Analysis

For the analysis of wait time to treatment, we only analysed data from patients who had entered treatment. For changes in treatment allocation and recovery rates analyses, we included patients who had finished their treatment.

Since this was not a randomized controlled trial, there may have been differences in the characteristics of the patients referring through the AI tool versus the standard pathway, as well as *within* the AI self-referral tool cohort between patients with clinical information and patients without clinical information. Therefore, we statistically controlled for these potential differences to ensure that our observed results could not be explained by these confounding factors.

The confounding factor of main concern was the severity of the patients' mental health symptoms. This data was included for every patient, allowing us to control for this when comparing the AI and standard referral pathways. We measure severity as the step of treatment level that patients were assigned to and controlled for severity in any analysis we conducted.

There was only limited information about the group of other referral pathway patients available to ensure the anonymity of this group. No demographic information or any personally identifiable information was provided for these patients to ensure fully anonymous data. Therefore, we were unable to control for demographic differences or any other personal information in this data group.

For patients who referred through the AI tool, demographic information was available. Therefore, for comparison of patients who did, and did not, provide the full clinical information (all who referred via the AI self-referral tool), all analyses controlled for a list of demographic variables (age, gender, ethnicity, disability status, receiving previous mental health support).

In order to adequately control for the above-mentioned covariates, we constructed multiple linear regression models for continuous outcome measures and multiple logistic regression models for binary outcome measures. Group was used as a predictor variable (AI versus standard referral comparison: 0=standard referral, 1=AI self-referral; clinical information versus no clinical information comparison: 0 = no clinical information 1 = clinical information) and severity was included as a covariate. For the clinical assessment time, wait time to clinical assessment and wait time for treatment, severity (and demographics) were the only potentially confounding effects we controlled for.

For dropout rates, it is possible that increased assessment and wait times could have led indirectly to increased dropouts. Therefore, we controlled for severity (and demographics), assessment and wait time as covariates in the logistic regression model to predict dropout rates. This analysis will reveal whether the effects on dropout rates are completely explained by the changes in assessment and wait time or whether the usage of the AI self-referral tool has an additional and independent effect on dropout rates.

Changes in treatment allocation could potentially be influenced by all these factors mentioned above, including dropout rates. Therefore, we controlled for severity (and demographics), dropout rates, assessment and treatment times in the logistic regression for predicting changes in treatment allocation.

Finally, the recovery rate is the last measure of interest which in principle could be influenced by all the factors mentioned above, especially changes in treatment allocation (i.e. accuracy with which treatment allocation was assigned) could potentially explain why differences in recovery rates were observed. In order to evaluate whether the effects on recovery rate could be explained by effects on these other variables or whether it represented independent and additional effects of the AI solution, we included severity (and demographics), assessment time, wait time, dropout rates and changes in treatment allocation as covariates in the logistic regression predicting recovery rates.

3 Results

3.1 Between group results: patient referrals made via the AI tool versus alternative routes

We first tested whether the groups of patients were comparable in terms of their severity of mental health conditions. The groups differed in their severity (Mann-Whitney-U test, $p < .00000001$). Patients referring through the AI self-referral tool showed slightly lower severity (mean step of care = 1.5) than patients referred through other means (mean step of care = 1.69). While this was expected based on anecdotal evidence that patients referring through standard pathways show higher severity than patients referring through the AI tool, this indicates that it is critical to control for severity in the subsequent analyses.

3.1.1 Assessment time

A major aspect of an AI self-referral tool is the clinical efficiencies generated through this product by reducing the time needed for a clinical assessment. Indeed, in the AI group (mean assessment time = 41.6min) the clinical assessment required on average 12.7 min less time (see Figure 2A) compared to the standard referral pathway group (mean assessment time = 54.4min). This effect was statistically significant ($t(64861)=-116.57$, $p < 10^{-500}$) and this effect could not be explained by differences in severity as the effect remained significant after controlling for this factor ($p < 10^{-500}$). This indicates that usage of AI in the self-referral process creates clinical efficiencies by reducing clinical assessment times.

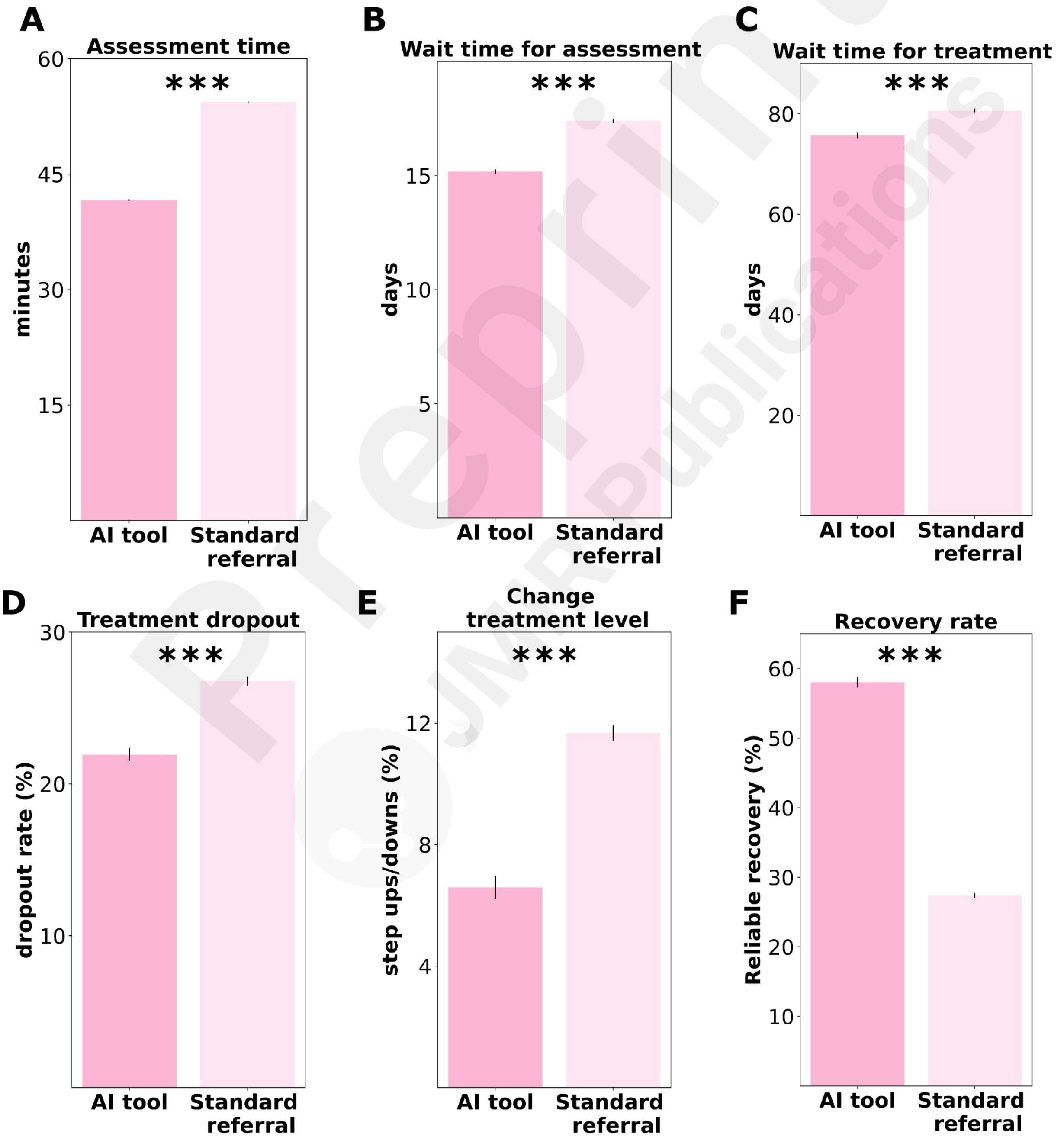

Figure 2: Comparison of treatment outcomes between referrals through the AI e-referral tool vs standard referrals.

A) Assessment time (in minutes) B) Wait time from referral to assessment (in days) C) Wait time from referral to first treatment session (in days) D) Dropout rates from treatment E) Accuracy of treatment allocation (measured as step ups/downs in treatment level) F) Recovery rate (reliable recovery). Error bars indicate standard errors (note that due to the large sample size some standard errors are very small and thus hard to see). $^{***}p < .000000001$

3.1.2 Wait time for clinical assessment

Next, we investigated whether the AI self-referral tool affected the time patients had to wait for their clinical assessment. Indeed, in the AI group, the wait time for a clinical assessment was shorter (mean=15.2 days, see Figure 2B) compared to the standard referral pathway group (mean=17.4 days). This effect represented an average reduction of wait time of 2.2 days and was statistically significant (t(64861)=-14.66, $p < 10^{-47}$). This effect could not be explained by differences in severity as the effect remained significant after controlling for this factor ($p < .0000001$). This indicates that the AI tool reduced wait times for clinical assessments.

3.1.3 Wait time to treatment

Next, we investigated whether the AI self-referral tool affected the time patients had to wait until the first treatment session. In the AI group, the wait time for the first treatment session was shorter (mean=75.6 days, see Figure 2C) compared to the standard referral pathway group (mean=80.6 days). This effect represented an average reduction of wait time of 5 days and was statistically significant (t(33269)=-7.1, $p < 10^{-11}$). This effect could not be explained by differences in severity as the effect remained significant after controlling for this factor ($p < .0000001$). This indicates that the AI tool reduced wait times for accessing mental health treatment.

3.1.4 Dropout rate

Next, we investigated whether the AI self-referral tool affected the probability of patients dropping out of treatment. The probability of dropping out from treatment was significantly reduced (t(33269)=- 9.03, $p < 10^{-18}$) from a 26.7% probability in the standard referral pathway group to 21.9% probability in the AI tool group (see Figure 2D). This effect could not be explained by differences in severity or assessment and wait times, as the effect remained significant after controlling for this effect ($p < .0000001$). This indicates that usage of the AI tool in the self-referral process reduced the likelihood of patients dropping out during the treatment pathway.

3.1.5 Change in allocated treatment level

Next, we investigated whether the AI self-referral tool affected the accuracy of clinical assessment by investigating effects on changes in treatment allocation (i.e. the lower rate of changes equals improved accuracy of clinical assessment). Changes in treatment allocation were significantly reduced (t(20317)=-8.290, $p < 10^{-21}$) from 10.5% of patients receiving a change in treatment in the standard referral pathway group to 5.8% in the AI tool group (see Figure 2E). This effect could not be explained by differences in severity, dropout rates, assessment or wait times, as the effect remained significant after controlling for these factors ($p < .0000001$). This indicates that the AI self-referral tool improves clinical assessment accuracy, thus requiring fewer changes in treatment allocation during treatment.

3.1.6 Recovery rates

Finally, we investigated whether the AI self-referral tool affected the recovery rates of patients. Indeed, in the AI group (recovery rate=58.0%) the recovery rates were significantly higher (t(20317)=38.7, $p < 10^{-300}$, see Figure 2F) than in the standard referral pathway group (recovery rate=27.4%). The effect size is noteworthy as the recovery rate was twice as high in the AI group than in the standard referral pathway group. This effect could not be explained by differences in severity, dropout rates, assessment and wait times, or by changes in treatment allocation as the effect remained significant after controlling for these factors ($p < .0000001$). This indicates that the usage of AI tool in the referral process improves the recovery rates of patients referred through this tool, in addition to the other effects presented in this report.

3.2 Within group results: the effect of additional clinical information collected ahead of human-led clinical assessment

Having established the effects of referring through an AI self-referral tool compared to other methods of referral, we investigated more closely the mechanism through which these improvements were achieved.

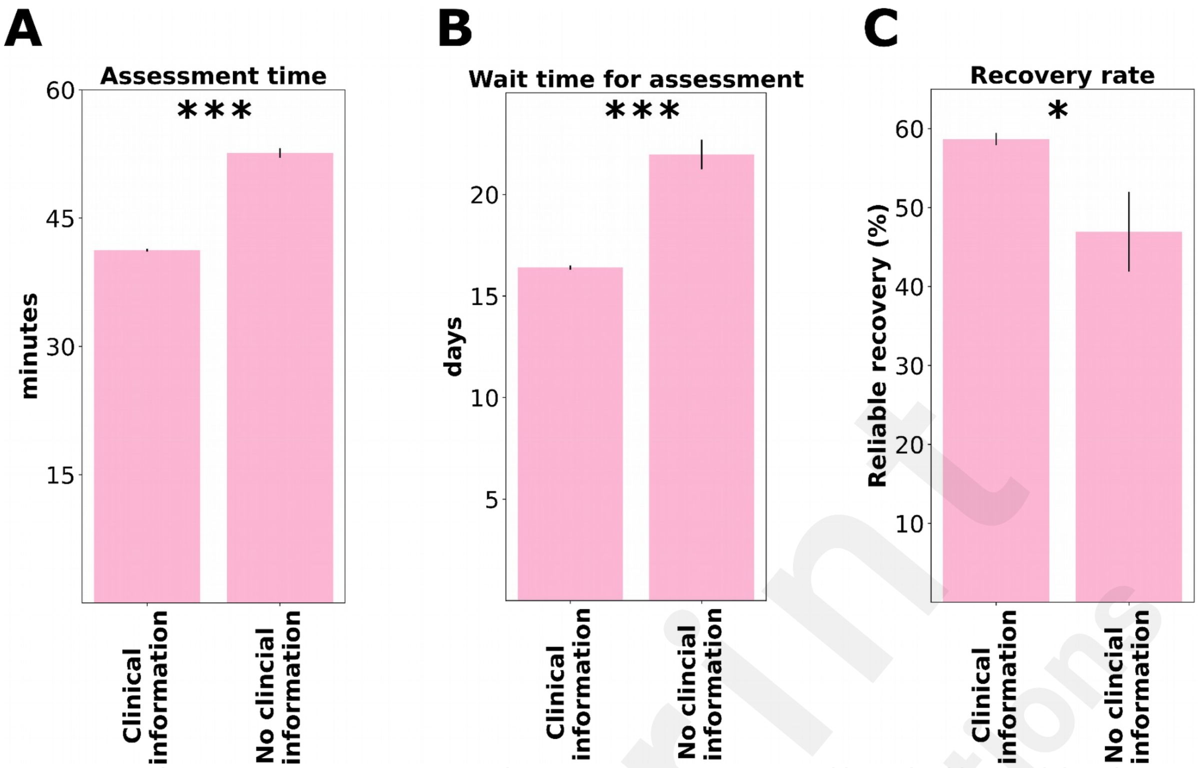

Figure 3: Comparison of treatment outcomes between AI-tool referrals with and without clinical information A) Assessment time (in minutes) B) Wait time from referral to assessment (in days) C) Recovery rate (reliable recovery). Error bars indicate standard errors (note that due to the large sample size some standard errors are very small and thus hard to see). ***$p < .001$, **$p < .01$

Our initial hypothesis was that provision of clinically relevant data ahead of the assessment would enable the clinicians to better prepare their assessment and create efficiencies in their management of the clinical assessment, further enabling them to arrive at accurate clinical conclusions. To test this hypothesis we investigated only subjects referring through the AI self-referral tool, comparing patients who had provided clinical information in their referral to patients who provided no clinical information.

First, we ensured that the groups of patients did not differ with respect to the most relevant characteristics. Indeed, the groups did not differ with respect to severity (Mann-Whitney-U test, p=.17), age (Mann-Whitney-U test, p=.42), gender (Mann-Whitney-U test, p=.44), ethnicity (Mann Whitney-U test, p=.39), disability status (Mann-Whitney-U test, p=.62) or previous mental health treatment (Mann-Whitney-U test, p=.76). This indicates that the groups were largely comparable. Nevertheless, we included these variables as covariates in the following analyses to also ensure that even subtle differences were controlled for.

For the group where additional clinical information was provided (mean assessment time = 40.6 min) the clinical assessment required on average 12.3 min less time compared to the group without clinical information (mean assessment time = 52.8 min). This effect was statistically significant (t(21545)=-16.16, $p < 10^{-57}$, see 3A) and this could not be explained by differences in severity or demographics as the effect remained significant after controlling for these factors ($p < .0000001$)

Furthermore, in the group of patients with clinical information, the wait time for a clinical assessment was shorter (mean=15 days) compared to the group without clinical information (mean=20.2 days). This effect represented an average reduction of wait time of 5.2 days and was statistically significant (t(21545)=-9.7, $p < 10^{-22}$, see 3B) and could not be explained by differences in severity or demographics as the effect remained significant after controlling for these factors ($p < .0000001$).

Finally, in the group with clinical information (recovery rate=58.7%) the recovery rates were signif icantly higher (t(5990)=2.3, $p = .019$, see 3C) than in the group without clinical information (recovery rate=46.9%). This effect could not be explained by differences in severity, demographics, dropout rates, assessment and wait times, or by changes in treatment allocation as the effect remained significant after controlling for these factors (p=.03).

Interestingly, there were also some effects which seemed not to be driven by the clinical information provided ahead of time. There were no significant differences between patients with and without clinical information regarding dropout rates (p=.26), wait time for treatment (p=.51) and the allocation to the accurate treatment level (p=.86). This suggests that the use of an AI self-referral solution improves access and treatment, with some of its effects being specific to the provision to a clinician of high-quality symptom data.

4 Discussion

In this study, we investigated the effects of implementing an AI self-referral tool in the referral and assessment process for mental healthcare. To this end, we compared patients referred through this AI tool against patients referred through other means of referral within the same IAPT services and in a comparable time frame. In doing so, we demonstrated the improved service efficiency and clinical efficacy associated with this novel tool. Moreover, we investigated the mechanism through which these improvements were achieved, finding that the provision of clinical information ahead of the mental health assessment was critical for many of the observed effects.

We found that the patients accessing care through the AI tool showed reduced time required to complete their human-led clinical assessment, reduced wait times for the assessment and treatment sessions, reduced dropout rates, improved accuracy of treatment allocation and improved recovery rates. Moreover, we showed that the reduced assessment times, reduced wait times for assessment and increased recovery rates were largely driven by the additional clinically-relevant information collected from patients during their referral via the AI tool.

It is important to note that we conducted multiple control analyses to rule out confounding factors and to establish the independence of these observed effects. Importantly, the severity of cases could not explain the differences between people referring through the AI tool compared to standard referrals. This is particularly important as any difference in recovery rates could be expected to be driven by symptom severity and we have thus ensured that the improvement seen by the AI self-referral tool cannot be explained by symptom severity. Other potentially confounding factors (e.g. users of a new AI solution may have been more motivated to engage in therapy than patients referred by their GP) are beyond the scope of our analyses, and can not conclusively be ruled out. Nevertheless, other studies evaluating the AI self-referral tool (Limbic Access) have also shown overall positive effects on provider level [Rollwage et al., 2022], i.e. showing that IAPT providers using this tool showed overall increased recovery rates compared to matched IAPT providers not using the tool. A selection bias would suggest no overall improvement in treatment outcomes for providers using the tool. This makes a selection bias in form of differences between patients choosing to refer through the AI tool versus choosing to refer through other means an unlikely explanation for the observed results.

A randomized controlled trial would be the gold standard for further confirming the observed effects of this study. However, randomized controlled trials have their own shortcomings as they are costly to run and thus limit the available sample size. We chose our experimental design to allow us to investigate an unprecedented large sample yielding high statistical power and excellent ecological validity for our findings. Moreover, as our comparison is based on referrals within the same IAPT services, representing multiple geographies, our findings are unlikely to be driven by differences in demographic variables or general factors such as geography and should thus transfer to other IAPT services.

In addition, we carefully tested that all observed effects were independent of each other. All the reported effects remained significant when controlling for mutual influences, indicating that using the AI tool in the referral process has beneficial effects on all the variables reported here.

We investigated the mechanisms through which the AI self-referral tool improves clinical efficiencies. We showed that the provision of clinical information in the referral is a critical component of the observed effects. More specifically, we found that patients who provided clinical information in their referral had reduced assessment times, reduced wait times for assessment and increased recovery rates. This indicates that the provision of clinical information ahead of the clinical assessment is a critical ingredient through which the AI tool achieved its effect on the tested outcomes measures. This was hypothesized and shows that an increased amount of relevant information for the preparation of the clinical assessment has beneficial effects on patients and IAPT services.

On the other hand, it is interesting to note that not all effects observed for the AI solution (compared to other means of referrals) appeared to be driven by the provision of clinical information ahead of the clinical assessment. For some of these effects, this might be expected. For instance, the reduction in dropout rates might be more driven by an overall positive experience that patients have when engaging with a friendly chatbot for submitting a referral, independent of the clinical information provided. Similarly, reductions in wait times for treatment might be driven more by general administrative burden and overall resource availability rather than the specific clinical information provided in the referral.

However, it is surprising that the provision of clinical information seemed to not have a significant effect on the accuracy of the treatment allocation. This is an effect which would have been clearly expected to be profiting from clinical information ahead of the clinical assessment. Nevertheless, there are two points to be considered with respect to this finding. First, there was a small number of patients who did not provide clinical information and finished their treatment (153 patients) in this study, which dramatically reduced the power of the analysis compared to the analysis looking at general effects of the AI solution compared to standard pathway referrals. Therefore, the non-significant results could partly be explained by noise in a small sample. Secondly, it is important to note that while the clinical information provided in this version of the AI tool is useful for many aspects of the clinical assessment process, the information is fairly generic, mainly covering information about depression, generalized anxiety and functional impairment. While this is useful to allocate accurate resources in the assessment and prioritize severe cases, it only gives limited information about the more specific symptoms the patient experiences. This is especially true when the patient is suffering from mental health problems that do not represent depression or generalized anxiety. Therefore, the provision of more tailored and specific information at the point of referral would likely yield better results and support improvement regarding the allocation of treatment pathways.

4.1 Conclusion

The set-up for this study was quasi-experimental so that not all confounding factors could be controlled completely. However, we assessed and controlled for the most relevant factors which could have differed between these groups of comparison. Importantly, none of these factors could explain the observed effects and all effects remained significant after controlling for these factors.

It is critical to note that we provided converging evidence from multiple sources of data and different analyses. We conducted multiple control analyses in order to derive the most reliable and robust conclusions. Nevertheless, as none of the analyses included a randomized control trial possibility of confounding factors remains even though we controlled for most factors. Notwithstanding, the different analyses had different strengths and weaknesses and no confounding factor could explain all of the observed results.

This study represents the (to our knowledge) first evidence for real-world impact of an AI-enabled self-referral tool in mental healthcare. The study was conducted with a large sample of patients in a mental healthcare setting, yielding high ecological validity of the reported findings. Excitingly, the results indicate a strong positive real-world impact of this novel AI tool (Limbic Access) on clinical efficacy and efficiencies.

The results highlight the specific, beneficial role that well-designed AI solutions can play in augmenting the work of human clinicians by supporting elements of the clinical work and through this, freeing up clinicians' time. Thus, AI solutions can enable mental healthcare providers to deal with increased demand even within a challenging funding environment that precludes increases in staffing levels.

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6 Competing interests

MR, KJ, JH, BC & RH are employed by Limbic Limited and hold shares in the company. TH is working as a paid consultant for Limbic Limited.

7 Data and code availability

All analyses are based on sensitive clinical data, which we are not permitted to share with third parties. Summary statistics as displayed in the figures and text are available upon request to the corresponding author.

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