Adherence Forecasting for Guided Internet-Delivered Cognitive Behavioral Therapy: A Minimally Data-Sensitive Approach

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Abstract—Internet-delivered psychological treatments (IDPT) are seen as an effective and scalable pathway to improving the accessibility of mental healthcare. Within this context, treatment adherence is an especially pertinent challenge to address due to the reduced interaction between healthcare professionals and patients. In parallel, the increase in regulations surrounding the use of personal data, such as the General Data Protection Regulation (GDPR), makes data minimization a core consideration for real-world implementation of IDPTs. Consequently, this work proposes a Self-Attention-based deep learning approach to perform automatic adherence forecasting, while only relying on minimally sensitive login/logout-timestamp data. This approach was tested on a dataset containing 342 patients undergoing Guided Internet-delivered Cognitive Behavioral Therapy (G-ICBT) treatment. Of these 342 patients, 101 (~30%) were considered non-adherent (dropout) based on the adherence definition used in this work (i.e. at least eight connections to the platform lasting more than a minute over 56 days). The proposed model achieved over 70% average balanced accuracy, after only 20 out of the 56 days (~1/3) of the treatment had elapsed. This study demonstrates that automatic adherence forecasting for G-ICBT is achievable using only minimally sensitive data, thus facilitating the implementation of such tools within real-world IDPT platforms.

Index Terms—Interaction data, machine learning, mental healthcare, e-health, adherence forecasting, sensitive data.

I. INTRODUCTION

MENTAL illness is associated with major individual, societal and economical challenges, which currently accounts for 20% of the burden of disease worldwide [1]. Fortunately, effective evidence-based somatic and psychotherapeutic treatments have been developed for a wide variety of mental disorders [2], [3], [4], [5]. Cognitive Behavioral Therapy (CBT) is a popular and effective form of psychological treatment for an array of mental disorders and is considered by some to be “the gold standard in the psychotherapy field” [6]. However, despite clear evidence of the effectiveness of CBT [3], [7], an important gap still exists between the needs of patients and the presence of affordable and timely services [8], [9]. This gap - which mainly stems from social stigma, lack of healthcare workers and under-prioritization of mental health services [8] - combined with the high economical cost associated with mental health [1], [10], [11] has created a strong demand for more affordable and accessible treatments [9].

Internet-delivered psychological treatments (IDPT) [12] offer an attractive and scalable pathway to improve the accessibility of mental healthcare. In particular, Guided Internet-delivered Cognitive Behavioral Therapy (G-ICBT) has been shown to be effective for a wide range of mental illnesses and in some cases provides comparable outcomes to in-person CBT [13], [14]. Consequently, several platforms have been developed worldwide to provide patients access to G-ICBT. eMeistring [15], [16] is one such platform that offers G-ICBTs for social anxiety disorder, panic disorder and depression. The three interventions available on the platform are comprised of text-based modules focusing on psychoeducation, behavioral activation, and cognitive reappraisal in the case of depression and psychoeducation, working with automatic thoughts, behavioral experiments, shifting focus, and relapse prevention for the social anxiety and panic disorders interventions. These text-based modules also feature various intervention-specific homework assignments (e.g. identifying thoughts, sleep diary registration, activity planning) to be filled within the platform itself as well as exercises (e.g. exposure to agoraphobic situations). Therapist guidance is provided at least once a week via a secure email system and when judged necessary phone calls can also be arranged. Detailed descriptions of the intervention for panic disorder [15], social anxiety disorder [16] and depression [17] are provided in their associated reference, while Fig. 1 showcases the platform’s user interface. eMeistring is currently available to the public in parts of Norway, with plans to be deployed nationwide within the next two years.

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The law of attrition [18] is a landmark paper which states that for many eHealth trials it should be expected that substantial participant dropout will occur, particularly in the case of internet-delivered treatments. Thus, despite the effectiveness and availability of G-ICBT, patient adherence to this form of treatment remains an important challenge [19], as participant dropout impacts treatment outcome and results in wasted time for both the patient and clinician. Unfortunately, assessing patient adherence in the context of G-ICBT is especially challenging due to the sparsity (or lack of) direct interactions between the clinician and the patient. Further, any strategy used to assess adherence would need to require minimal resources from the clinician, as one advantage of G-ICBT is that the psychotherapist can oversee more patients. Consequently, having a tool that can automatically identify individuals likely to dropout early in the intervention based on the participant’s behavior, would allow the clinician to perform meaningful, targeted intervention (e.g. providing reminders, scheduling direct interactions, modifying the treatment) more effectively.

Simultaneously, there are increasing regulations regarding the acquisition and use of personal data being implemented globally. The General Data Protection Regulation (GDPR) [20], which came into effect on May 25th 2018, is a prime example of this. Similar regulations are being adopted worldwide such as the California Consumer Privacy Act (CCPA) in the United States, the General Data Protection Law (LGPD) in Brazil and the Personal Information Protection and Electronic Documents Act (PIPEDA) in Canada. Many of these follow the blueprint of the GDPR, and this in combination with the wide territorial scope, makes the GDPR unmatched in terms of global influence [21]. In these regulations, there are commonly certain categories of data that evoke particular concern. For instance, article 9 of the GDPR and 11 of the LGPD place stricter requirements on the processing of data belonging to categories such as health, sexual orientation, and political opinion of the data subject. Thus, the use of such data can be cumbersome and sometimes even impossible. Generally, data generated in the context of a healthcare intervention would fall within such categorization, as it represents highly sensitive information. On top of strict requirements, one of the core tenants of the GDPR and similar regulations is the data-minimization principle (see article 5 (1)(c)). This obligates data collectors to use the minimum amount and least sensitive data necessary to achieve the purpose of the data collection. As such, being able to use the smallest amount of data which also contains the minimal amount of personal information to achieve useful adherence prediction is an auspicious target. Consequently, the main aim of this paper is to demonstrate the feasibility of minimally data-sensitive automatic adherence forecasting, solely relying on a pseudonymized user id [22] and their login/logout timestamps.

Many research groups have illustrated the positive association of patient adherence to treatment outcome and have investigated how different population and treatment characteristics (e.g. demographic, psychometric, treatment credibility) relates to adherence [23], [24], [25], [26], [27], [28]. For example, Karyotaki et al. [29] identified through a meta-analysis of self-guided web-based interventions for depression that gender, age, education level and co-morbid anxiety symptoms could be used as predictors of adherence. However, few works have considered the use of machine learning (ML) for adherence forecasting on an individual basis. Wallert et al. [30] trained a random forest based on information available during the first treatment (demographic, clinical, psychometric and linguistics), which achieved an accuracy of 64% for adherence prediction of IDPT. More recently, Forsell et al. [31] showed the feasibility of predicting treatment failure of a 12-week G-ICBT treatment for depression, social anxiety disorder and panic disorder based on screening, pre-treatments and weekly symptom self-rating, reaching an average balanced accuracy of 63% after 2 weeks and 71% after 6 weeks. Importantly, this met the accuracy threshold of 65-70% at which clinicians become willing to act on predictions [32]. Both cases however rely heavily on sensitive personal medical and/or biometric data for forecasting. Further, due to the forecasting methods employed in these works, a different model has to be trained at each step of the treatment (i.e. the same model cannot be used to forecast at day 7 and day 8).

Consequently, this work’s main contribution is to demonstrate the feasibility of adherence forecasting for G-ICBT using a minimally data-sensitive approach by leveraging a self-attention deep neural network [33]. Importantly, only a single instance of the proposed model needs to be trained to be able to forecast at any step of the treatment. The proposed method is evaluated on real-life patients using the eMeistring platform, with a collected dataset composed of 342 individuals undergoing G-ICBT treatment for depression, social anxiety disorder or...
panic disorder. For reproducibility purposes, the full code employed in this research is available at the following link: https://github.com/UlysseCoteAllard/AdherenceForecastingGICBT

This paper is organized as follows. The three treatment programs (depression, social anxiety disorder and panic disorder) available on the eMeistring platform alongside the data collected from these programs are described in Section II. Section III then presents the data processing and adherence prediction methods considered in this work. Finally, the results and the associated discussion are covered in Section IV and V respectively.

II. EMEISTRING AND DATA COLLECTION

Since 2015, the eCoping clinic (eMeistring.no) at Haukeland University Hospital, Bergen, Norway has offered a G-ICBT for social anxiety disorder, panic disorder and depression. All patients admitted for specialized mental health treatment within the health region associated with eCoping are referred by their general practitioner. Subsequently, referred patients admitted for treatment were invited for an in-person assessment interview at the clinic. Patients were informed in the meeting about G-ICBT being one of the treatment options available.

Patients willing to consider G-ICBT as a treatment alternative were invited to a diagnostic assessment using the Mini International Neuropsychiatric Interview (MINI) [34]. Patients interested in starting G-ICBT and who fulfilled the inclusion criteria were offered G-ICBT and invited to participate in this data collection. The inclusion criteria were:

- Panic disorder (with and without agoraphobia)/Social anxiety disorder/Major depressive disorder (mild and moderate) as the primary diagnosis according to the MINI
- 18 years old or more
- Not using benzodiazepines or other sedatives on a daily basis
- If using antidepressant, the dosage must have been stable for the preceding four weeks
- Able to read and write in Norwegian
- No current suicidal ideation
- No current psychosis
- No current substance abuse
- Not currently in need of other immediate treatment (i.e. due to a more severe primary diagnosis/crisis or exhibiting suicidal ideations)
- Has Internet access

The suicidal ideation and psychosis symptoms were assessed in a face to face clinical interview before treatment. Self-report questionnaires were further employed to evaluate suicidal ideation during treatment. “In immediate need for other treatment” meant that if the patient were in need of other treatment due to a more severe diagnosis, they were excluded. The data recording protocol was approved by The Western Regional Committee for Medical and Health Research Ethics in Norway (2015/878) and (2012/2211/REK). Written informed consent was obtained from all participants, and no financial compensation was provided. The initial dataset was comprised of 398 patients. The distribution of the participants for the considered diagnostics was as follows: panic disorder (124), social anxiety disorder (169) and depression (105). The patient characteristics are presented in Table I. Note that, to remove trivially non-adherent participants, only those who connected more than once to the eMeistring platform were considered in this work, resulting in a dataset containing 342 participants.

All three treatments were module-based and lasted a maximum of 14 weeks. The panic disorder and social anxiety disorder G-ICBT were both comprised of 9 modules, while the depression G-ICBT was comprised of 8 modules. In all cases, the therapist provided guidance through a secure email system using an average of 10-15 minutes per week per patient. For a detailed description of each treatment, see [15] for Panic Disorder, [16] for Social Anxiety Disorder and [17] for Depression.

A. Login/logout Data as a Minimally Sensitive Source of Information From a Regulatory Perspective

The GDPR regulates the use of personal data, such as its acquisition, processing and storage, for any entity conducting activity within the EU. Following the framework of the GDPR, the more risk the acquired data represents, the more stringent the requirements are for its processing. This risk is determined by multiple factors, including the context in which the information is collected, the sensitivity it represents and how easy it is to identify a person from it. Determining the level of risk and the resulting measures that must be taken to protect the data requires a complex legal analysis which would be outside the scope of this work. Instead, this subsection presents an initial legal argument as to why although login/logout timestamps are considered sensitive data when collected within a healthcare context, they represent the least sensitive type of information that can be extracted from an IDPT setting for user-adherence forecasting.

According to the GDPR article 4 (15) and recital 35, personal data relating to health, referred to as “health data”, may be defined as any type of information collected within the provision of healthcare services, which may reveal information relating to the current or future physical or mental health status of the person. Thus, information contained within medical records (e.g. psychometrics, medications, diagnosis, clinical self-report) are unsurprisingly understood to be defined as health data regardless of the context in which they are collected, as they in themselves would be able to reveal information relating to the health status of the person. Contrastingly, other sources of data such as demographic characteristics, login/logout timestamps, mouse and keystrokes dynamics would not in themselves reveal any information about the health status of the person but are nevertheless considered health data when collected during the provision of healthcare services such as an IDPT. However, there exists an important distinction between these sources of information. Both mouse and keystrokes dynamics may also be categorized as biometric data (see article 4 (14)), as they through certain processing can be used to identify a person [35], [36].
The participant had to engage with the platform (i.e., the period of time over which the participant is exposed to the intervention), characterized through the following parameters [37]:

| Parameter       | Definition                                                                 |
|-----------------|-----------------------------------------------------------------------------|
| Frequency       | The number of times the participant partakes in the intervention.             |
| Duration        | The length of each interaction.                                             |
| Amount          | The total number of words written (from a sensitive text).                  |

Engagement, from a user-behavior perspective, is typically characterized through the following parameters [37]:

| Parameter       | Definition                                                                 |
|-----------------|-----------------------------------------------------------------------------|
| Amount          | The total number of words written.                                           |
| Duration        | The length of each interaction.                                             |
| Frequency       | The number of times the participant partakes in the intervention.             |

Pursuant to article 9 of the GDPR, using any source of information belonging to a special category of data, of which both health and biometric data fall under, is prohibited, unless strict requirements are met. Further, following article 32 the conditions associated with using this data (e.g., transmission, storage) must reflect the level of risk associated with processing the information. Thus, while all data collected during an IDPT would presumably be classified as belonging to a special category of data under the GDPR, ultimately, it is the level of risk they represent that will be the main bottleneck in terms of implementation. Notably, login/logout timestamps do not carry any inherent information that places it in a special category of data, rather it is categorized as such solely due to the context in which it is collected. Therefore, login/logout timestamps may be considered on the peripheral of what article 9 of the GDPR intends to prohibit and as such will be in the lower bound of the risk associated with its processing. Note that, other metrics such as number of words written, or certain demographic information might also share this characteristic. However, what makes login/logout timestamps an attractive metric is that they can be derived entirely from outside the intervention, meaning that it circumvents the need for high-risk processing (e.g., counting the number of words written from a sensitive text) to produce low-risk metrics (e.g., number of words). Finally, combining multiple low-risk sources of information may heighten the risk to the data-subject and would require increased justification due to the data minimisation principle. Thus, relying solely on login/logout timestamps for adherence forecasting within a healthcare context may substantially lower the burden of implementation and offers a promising source of information to be used in real-life applications.

### B. Adherence Definition

In this work, a patient is considered adherent when achieving a sufficient level of interactive engagement with the G-ICBT. Engagement, from a user-behavior perspective, is typically characterized through the following parameters [37]:

- **Amount**: the total number of words written.
- **Duration**: the length of each interaction.
- **Frequency**: the number of times the participant partakes in the intervention over a given period of time.
- **Depth**: the number of times the participant partakes in the intervention over a given period of time.

Within this work, adherence forecasting was performed using between 7 to 42 days of user-interaction data (login/logout). In other words, the model had to predict at least two weeks in advance whether a patient would end up being adherent or not. The lower-bound cutoff was selected to provide a full week-cycle of login/logout data as the participant’s weekly schedule might strongly influence their pattern of interaction with the treatment. An upper-bound cutoff at day 42 was selected as some symptom trajectories were shown to experience more changes around week 5-6 [38], [39].

To avoid indirect overfitting of the dataset when designing the model, the participants were divided into two non-overlapping subsets. The first subset referred to as the Exploration Dataset.
The Self Attention Network’s architecture employed for adherence forecasting contains 1186 learnable parameters. GAP refers to the Global Average Pooling operation. The plus sign refers to element-wise summation. A dropout of 0.1 is also applied in the Multi-Head Attention (MHA) module, immediately after the MHA and in the Feed Forward module. Note that the input fed to the network is of shape Tx2 (shown transposed in the figure), where T represents the length (in days) of the example, which is variable (between 7 and 42 days in this work).

A. Data Pre-Processing

Considering the first login data entry as the start of the first session of the G-ICBT, the following features were computed each day from the login/logout data:

- Whether or not the participant logged in during this particular day (0 or 1).
- The total time the participant was logged during this particular day.

Then, feature-wise scaling was performed such that the values were centred around the mean with a unit standard deviation:

$$X' = \frac{X - \mu}{\sigma}$$ (1)

Where $\mu$ and $\sigma$ represent the mean and standard deviation of the current training set fold.

Then, for each participant, these feature vectors were aggregated sequentially to form a first $2 \times 7$ matrix that represented the first 7 days of a given user’s interaction data. A copy of this initial matrix was then created and concatenated with the feature vector of day 8 to form a new matrix. This process was then repeated for day 9, 10 and so on. Thus, a total of 35 matrices (examples) with a number of columns ranging from 7 to 42 were created for each patient contained within the dataset. This sequential data representation had two objectives: 1) Reducing the potential loss of information from aggregating the login/logout data to form a single feature vector. 2) Enabling the same trained model to forecast the adherence of a user at any point during the considered time span (7 to 42 days).

B. Self-Attention Network

A compact Self-Attention-based network inspired by [33] was designed to leverage the sequential information that naturally arises within the data generated from this work’s context. The network’s architecture is presented in Fig. 2. AdamW [40] was employed for the network’s optimization with a batch size of 64. The variable sequences’ lengths were padded when creating each batch and a mask of the padding was used when feeding the batches to the network. The learning rate ($lr = 0.001306$) was selected from the Exploration Dataset by random search [41] using a uniform random distribution on a logarithmic scale between $10^{-5}$ and $10^{0}$ with 100 candidates. During the random search, the following hyperparameters were also considered:

- Input embedding size [1, 2, 4, 8, 16, 32, 64, 128]. Value selected: 4
- Number of heads: [1, 2, 4, 8]. Value selected: 4
- Number of neurons in the feed forward network’s hidden layer: [1, 2, 4, 8, 16, 32, 64, 128]. Value selected: 32
- Dropout: [0., 0.1, 0.2, 0.3, 0.4, 0.5]. Value selected: 0.1
- Number of Encoder Layer: [1, 2, 3]. Value selected: 3

10% of the training data was held out as a validation set to perform early stopping (20 epochs threshold). Additionally, learning rate annealing with a factor of five and a patience of ten was also employed. Finally, to alleviate the effect of using an imbalanced dataset (~30% of participants were non-adherent
to the treatment), a per-class weighted cross-entropy loss was employed as the criterion to optimize during training where the per-class weight was obtained as follows:

$$\frac{1}{\text{# of examples from the given class}}$$ \hspace{1cm} (2)

In other words, the network was punished further when making mistakes on the underrepresented class (dropout) than on the overrepresented class (adherent) proportionally to each class’ size.

In this work, the previously described trained network will be referred to as the **Self-Attention Network**. The Self-Attention Network’s implementation written with PyTorch [42] and training procedure are made readily available here: https://github.com/UlysseCoteAllard/AdherenceForecastingG-ICBTgithub.com/UlysseCoteAllard/AdherenceForecastingG-ICBT.

### C. Threshold for Success

Following the practice established in [31], this work considers three empirical thresholds to contextualize the classifier’s performance. Importantly, when considering these thresholds one should look not only at if they are exceeded, but also how early in the treatment the model’s forecast can surpass them. Note that all thresholds are defined using the **balanced accuracy** which is defined as follows:

$$\text{Balanced Accuracy} = \frac{1}{2} \left( \frac{TP}{TP + FN} + \frac{TN}{TN + FP} \right)$$ \hspace{1cm} (3)

where TP, TN, FP and FN stands for true positive, true negative, false positive and false negative respectively. Balanced accuracy was employed over the simple accuracy in this work to avoid inflating the performance estimates due to the class-imbalance present in the dataset.

1) **Threshold 1: Better Than Random**: The first threshold assesses whether or not the model’s forecasting of user-adherence can perform better than chance. This was evaluated by considering if the lower bound of 95% confidence interval for the balanced accuracy was above 50%.

2) **Threshold 2: Minimal Threshold Where Clinicians Will Take Action**: Eisenberg and Hershey [32] reported that clinicians were willing to take action based on predictions once their accuracies reached 65–70%. As the main purpose of an adherence forecasting system for G-ICBT is to empower the clinician to perform more precise targeted interventions, whether they would be willing to act on the system’s prediction is critical. Thus, the second threshold was considered to be reached when the lower bound of the 95% confidence interval for the balanced accuracy surpassed 65%.

3) **Threshold 3: Threshold Where Clinicians Will Take Action**: The third threshold was considered to be reached when the lower bound of the 95% confidence interval for the balanced accuracy surpassed 70%.

Note that while threshold 2&3 were defined based on preliminary work [32] that is nowadays relatively outdated, said work was to the best of our and previous work’s knowledge [31] the only empirical data currently available.

### D. Ablation Studies

Three ablation studies were conducted to quantify the impact of some of the decisions made when designing the model.

1) **Weighting of the Loss Function**: A first ablation study was performed to evaluate the importance of the per-class weighting. The comparison was made by training the network with and without weighting each example based on their associated class prevalence. In both cases, the average balanced accuracy was computed over 20 independent runs.

2) **Training With a Fixed Sequence Length vs All Sequence Lengths Simultaneously**: To better understand the effect of training the network with multiple sequence lengths simultaneously, a second ablation study was conducted. The performance of the Self-Attention Network when training over multiple sequence lengths was compared to training the network using only information from a single, fixed sequence length. This comparison was made using the average balanced accuracy computed over 20 independent runs for both methods. The sequence lengths selected were based on the days that the model surpassed threshold 1, 2 and 3 as well as the longest sequence length considered in this work (42 days). Note that for comparison fairness, hyperparameter optimization using random search, as described in Section III-B was performed for each fixed sequence length considered.

Mann-Whitney-U [43], a non-parametric null-hypothesis significance test for unpaired data, was applied to compare if training the classifier with examples aggregated from different sequence lengths led to a different performance than training the same model with fixed-sequence length.

3) **Alternative Definition of Adherence**: As previously stated, what is considered **sufficient engagement** from the participants varies based on both the context and structure of the G-ICBT. Therefore, to evaluate the ability of the proposed approach to cope with different and more stringent definitions of adherence, two alternatives adherence definition were proposed. Table II summarizes the two alternative definitions and compares them with the one used throughout this work. Note that these alternative definitions were defined solely to evaluate the adaptability of the proposed approach and as such they do not have an explicit clinical basis. For comparison fairness, hyperparameter

| TABLE II | THE TWO ALTERNATIVE DEFINITIONS OF ADHERENCE COMPARED TO THE ORIGINAL DEFINITION |
|----------|---------------------------------------------------------------------------------|
|          | Original                          | Alternative A                      | Alternative B                      |
| Duration | Min. 56 days                      | Min. 56 days                       | Min. 56 days                       |
| Frequency| 8 connections                     | 12 connections                     | 16 connections                     |
| Amount   | 60 seconds                        | 150 seconds                        | 300 seconds                        |
| % Participants | ~30%               | ~49%                      | ~74%                           |
| Non-Adherent |                             |                                       |                                |

The number of connections stated in Frequency have to occur over at least 56 days. Additionally, each connection has to last longer than the number of seconds stated in the Amount row, to be considered.
optimization using random search, as described in Section III-B was performed for each new adherence definition.

IV. RESULTS

In this section, all evaluation metrics were computed using the scikit-learn python library version 1.0.2 [44].

A. Results of Adherence Forecasting

Fig. 3 shows the average balanced accuracy over time computed over 20 independent runs. The first threshold is exceeded on day 7 (corresponding to the smallest sequence length considered by the model). The second and third thresholds are surpassed on day 11 and 20 respectively.

To provide a more holistic view of the Self-Attention Network’s performance, Fig. 4 presents the confusion matrices for day 7, 11, 20 (the threshold-surpassing day) and 42 (the upper bound sequence length). The values reported in these confusion matrices correspond to the average number of true positive, true negative, false positive and false negative as predicted by the Self-Attention Network over 20 independent runs. Additionally, Fig. 5 shows the Precision-Recall Curve and Precision-Recall Area Under the Curve (PR-AUC) of the network’s performance for these same four sequence lengths. Note that the PR-AUC is calculated using the Average Precision as suggested in [45]. These metrics were computed using the Scikit-Learn V1.0.2 [44].

B. Ablation Studies

1) Weighting of the Loss Function: Fig. 6 presents the average balanced accuracy using the Self-Attention Network trained with and without per-class weighting.

2) Training With a Fixed Sequence Length vs All Sequence Lengths Simultaneously: Fig. 7 presents the performance of the Self-Attention Network when trained over multiple sequence lengths. Note that for comparison fairness, hyperparameter optimization using the random search described in Section III-B is performed for each fixed sequence length considered.

For all sequence lengths (7, 11, 20 and 42 days), the null hypothesis cannot be rejected (p > 0.05) according to the Mann-Whitney-U test (see Table III for details). Thus, there is no statistical significant difference between the two methods.
**TABLE III**  
RESULTS OF THE **MANN-WHITNEY-U** TESTS ON THE MODELS TRAINED WITH A FIXED SEQUENCE LENGTH VERSUS MODELS TRAINED WITH ALL SEQUENCE LENGTHS

| Sequence Length | U-Value | p-Value |
|-----------------|---------|---------|
| 7               | 198.0   | 0.9681  |
| 11              | 152.0   | 0.2005  |
| 20              | 156.5   | 0.2460  |
| 42              | 139.0   | 0.1010  |

*The null hypothesis that the two populations are equal is rejected at p<0.05.*

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**Fig. 5.** Precision-Recall Curves and their associated Average Precision (higher is better) over 20 runs for sequence lengths of 7, 11, 20 and 42 computed over 20 independent runs. The blue line (Baseline) shows the expected performance of a random classifier corresponding to the proportion of non-adherent labels. The shaded areas represents the standard deviations. AP stands for Average Precision which is the estimator for the Precision-Recall Area Under the Curve (PR-AUC). STD for Standard Deviation.

**Fig. 6.** Point plot comparison of the average balanced accuracy between training the Self Attention Network with and without per-class weighting over 20 runs. The blue dotted line corresponds to the network trained with per-class weighting, while the full orange line corresponds to the network trained without. The error bars correspond to the 95% confidence interval of the balanced accuracy. The three thresholds for success considered in this work are shown as horizontal lines to help contextualize the performance of both training approaches.

**Fig. 7.** Comparisons of the average balanced accuracy over 20 runs when training the Self-Attention Network over multiple sequence lengths simultaneously versus training the model using only data from a single sequence length. The Self Attention Network trained over multiple days is represented by the blue bar plots. The networks trained over a single day are represented by the hashed orange bar plots. The error bars represent the 95% confidence interval of the balanced accuracy. In the case of single day training, random search for hyperparameter selection is performed independently for each sequence length. The horizontal lines represent the three thresholds for success considered.

**Fig. 8.** Point plot comparison of the average balanced accuracy over 20 runs when predicting different levels of user engagement. Original (the blue line) corresponds to the definition of adherence used in this work. Alternatives A and B correspond to more stringent definitions of user engagement as defined in Table II. The error bars correspond to the 95% confidence interval of the balanced accuracy.

3) **Alternative Definition of Adherence:** Fig. 8 shows a point plot of the model’s performance based on the different adherence definitions considered.

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**V. DISCUSSION**

Achieving robust adherence forecasting within the context of G-ICBT would enable better management of the limited resources available within mental healthcare. In practice, such capabilities would help clinicians identify which patients are more likely to dropout, fostering more targeted intervention to increase retention rates or allowing earlier redirection of individuals towards more suitable treatment. A substantial hindrance for such a goal to be achieved however, is the validation and deployment of adherence forecasting models, as they generally require highly sensitive data from individual patients for accurate forecasting to occur [30]. This highly sensitive data problem might be one of the main reasons why adherence prediction for G-ICBT using ML is still understudied. As such, this paper proposes performing adherence forecasting on an individual basis using ML by solely leveraging non-sensitive information. However, with a decrease in data-sensitivity comes a decrease in the quantity and quality of information that may be derived from patients during their G-ICBT treatment.

The signal that can be derived from login/logout data is inherently noisy as one cannot distinguish a user’s meaningful interaction with the program from an idle connection to the service. Thus, the major finding in this study is that treatment adherence to G-ICBT can be predicted with a balanced accuracy above 70% after 20 days (when only 36% of the treatment is completed) despite relying solely on login/logout data. This well exceeds the performance of a random classifier and is in line with...
clinicians’ subjective preference of “good enough” predictive ability [32]. This finding is reinforced by Fig. 4 and 5 as it can be seen that the proposed model is relatively robust to the class imbalance and overall tends to be more pessimistic regarding the likelihood of a patient to be adherent to the treatment.

Fig. 6 shows that using per-class weighting systematically improves the forecasting performance at the beginning of the training and overall consistently performs equal to or better than not using per-class weighting. Thus, considering that this type of weighting comes at no extra cost during both the training and inference phase, its use should be considered a net benefit to the model. Interestingly, from Fig. 7 and from the Mann-Whitney-U test, it can be seen that having a single model able to predict multiple sequence lengths does not hinder performance compared to having a different model for each specific sequence length. A possible explanation is that the relatively small dataset used could have advantaged the multi-sequences approach, as considering sequence lengths of various sizes from the same patient acted as a form of data augmentation. Nevertheless, given this work’s context, small datasets (when compared to other areas in ML) is a reality that has to be contended with, at least in the near future. Further, for real-life implementation, it is desirable that a single model is able to contend with any sequence length as otherwise, one would have to deploy one model per time-step considered, onto the G-ICBT platform, thus rapidly increasing maintenance costs. Such considerations also naturally hold for ML algorithms unable to contend with temporal data without relying on feature extraction to characterize the signal as a pre-processing step (e.g. support vector machine [46], random forest [47], linear discriminant analysis [48]). Interestingly, the results presented in Fig. 8 support the initial hypothesis that the proposed model will, in general, more easily forecast adherence when its definition is based on stricter requirements for user-engagement. This characteristic in conjunction with the model’s ability to easily adapt to new adherence definitions is important to enable the clinician to nuance the level of user-engagement required, to help underpin their decision making in relation to the patient adherence.

Beyond login/logout timestamps, other types of data that also appear minimally sensitive could be useful in predicting patient adherence in Internet-delivered Cognitive Behavioral Therapy (ICBT). For example, in a trial of ICBT for patients who reported symptoms of anxiety, depression or both following a myocardial infarction event, Wallert et al. [30] showed that the number of words written in the first homework was the third strongest predictor of adherence, after self-assessed cardiac-related fear and the patient’s sex. Thus, the number of words written during the first interaction (or similar statistics) with the online platform could represent an interesting possibility for further investigation in minimally data-sensitive approaches to adherence forecasting. However, two important caveats have to be made. 1) Because these statistics would be derived from highly sensitive information (the patient’s thoughts within the context of a medical intervention), the data controller (e.g. the hospital) would need to process the data and derive the relevant minimally sensitive statistics. Otherwise, the sensitive data would have to be sent to the data processor (e.g. the company providing the adherence prediction) and thus the more stringent regulations would automatically apply, defeating the purpose of a minimally data-sensitive approach. Contrastingly, an advantage of using login/logout timestamps is that they are not derived from sensitive data and as such can be transmitted to the data processor as-is. 2) As previously stated, one of the cornerstones of the GDPR and similar regulations is data-minimization. As such, the amalgamation of data (e.g. using login/logout timestamps in conjunction with the number of words written in the first homework) to perform adherence prediction, needs to improve the performance of the system to a degree that would justify the corresponding increase in collected data. Notably, this is especially pertinent as this work has shown that login/logout timestamps, on their own, provide information that can be leveraged to perform adherence forecasting for patients undergoing G-ICBT treatment. Therefore, login/logout data intrinsically contains information that can be used to predict the behavior of an identifiable natural person (as defined within the GDPR). In other words, from a regulatory perspective login/logout timestamps are no longer subject to the requirements in the GDPR solely due to them being collected in a healthcare context, but instead due to the information the data contains as has been illustrated in this work. Consequently, following the core principle of data minimization and in light of this work, it seems that even stronger justification would be needed to use additional and/or more sensitive data to perform such forecasting.

Automatic adherence forecasting for G-ICBT should be viewed as a tool that can supplement available mechanisms used to follow patients during their treatment. Relying solely on the prediction of these models to identify potentially non-adherent users poses the risk of masking certain categories of patients which, for example, might not have been sufficiently represented in the training dataset. Further, an important challenge that remains to be addressed for the applicability of automatic adherence forecasting in a real-world context is the feedback-loop effect that will result from the clinician considering the model’s adherence prediction when deciding which patients require a more targeted intervention. In other words, it should be expected that the model predicting: “Patient A: Non-Adherent,” might result in the patient factually finishing the program (through the clinician acting on this prediction), even if the counterfactual (i.e. if the model was not used) would have resulted in the patient dropping out. This challenge will be especially critical when considering how to update the adherence forecasting model over time as data collected while the system is active will necessarily be biased with this model-clinician-patient interaction.

Interestingly, if a tool using the proposed approach to automatically forecast patient’s treatment adherence came to be used in practice, it would highlight and possibly valorize login/logout timestamps as a meaningful source of information for the guiding psychologist. As this information can easily be accessed by the clinician, it is possible that they would, in time, learn to predict the patient’s treatment adherence via these data. Thus, beyond the legal motivation of using a minimally-data sensitive approach, relying on a small amount of interpretable information might have the added effect of fostering this type of learned association from the guiding psychologist. Evaluating whether
this potential learned mapping would be useful or detrimental to the interactions with the patients (both due to the feedback loop previously mentioned and the fact that the learned model itself will not be perfect) is however, outside of the scope of this work. Nonetheless, this is another factor that will have to be considered for the eventual deployment of such a tool on a G-ICBT platform.

A. Limitations

This work’s main limitation is also its main motivation. Being able to share and utilize data which originates from ongoing patient treatment to benchmark new ML models is understandably highly restricted and regulated. As such, for the dataset used in this work to be made available as a future benchmark, substantial information removal and pseudonymization had to be performed. Thus all information regarding demographic, clinical (including followed treatment) and interaction data (excluding login/logout) from the patients had to be stripped away from the dataset used in this work.

As a direct consequence of the strict information removal, the proposed algorithm could not be compared against a model having access to more meaningful information (e.g. demographic, psychometric, linguistic) from the patients, to contextualize the impact of using the proposed minimally-invasive approach.

Another limitation was the absence of a gold standard to benchmark the proposed approach against. This limitation was an additional motivation for making the dataset used in this work public, so that new methods can be compared to each other more easily.

It is also important to highlight that to obtain a sufficiently large dataset, the three populations of patients having a primary diagnosis of panic disorder, social anxiety disorder or depression were aggregated together. However, due to the pseudonymization processing which took place prior to this work, the patient’s diagnostic was not available within the dataset used. Unfortunately, as a consequence of the nature, symptomatology and course of disease of these disorders, there may exist differences regarding both patients’ adherence and adherence forecasting accuracy between these three populations. Thus, while this work showed that it is possible to perform automatic adherence forecasting based solely on login/logout timestamps generated from a G-ICBT treatment, future works will investigate how these performances vary across primary diagnosis and G-ICBTs.

VI. Conclusion

This paper presents a minimally data-sensitive approach, based on a self-attention network, to perform adherence forecasting of patients undergoing G-ICBT. Overall, the proposed approach was shown to reach an average balanced accuracy above 65% with a confidence of 95% on day 11 (~20% of the treatment’s total length) and above 70% with a confidence of 95% after only 20 days (~36% of the treatments total length). Thus, the results show that login/logout information is sufficient to achieve robust adherence forecasting. Within a clinical setting, such an adherence forecasting tool could be used by the clinician to perform more targeted intervention with patients that are at risk of dropping-out. Further, because of the minimally data-sensitive approach, the additional requirements due to the context of the data, are minimized. Lastly, a core tenant of the GDPR and similar regulations is the data minimization principle. This principle refers to that only data that is strictly necessary to achieve the purpose of the data collection, shall be collected and processed. By illustrating that low-risk, minimally sensitive data such as pseudonymized login/logout data can achieve practical and useful results, a new benchmark for the data required for adherence forecasting may have been set.

Future works will focus on deploying the proposed solution within a G-ICBT platform to evaluate its usefulness within real-world applications.

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References

[1] D. Vigo, G. Thornicroft, and R. Atun, “Estimating the true global burden of mental illness,” Lancet Psychiatry, vol. 3, no. 2, pp. 171–178, Feb. 2016.
[2] P. Cuijpers, M. Sijbrandij, S. L. Koole, G. Andersson, A. T. Beekman, and C. F. Reynolds III, “The efficacy of psychotherapy and pharmacotherapy in treating depressive and anxiety disorders: A meta-analysis of direct comparisons,” World Psychiatry, vol. 12, no. 2, pp. 137–148, 2013.
[3] J. K. Carpenter, L. A. Andrews, S. M. Witting, M. B. Powers, J. A. Smits, and S. G. Hofmann, “Cognitive behavioral therapy for anxiety and related disorders: A meta-analysis of randomized placebo-controlled trials,” Depression Anxiety, vol. 35, no. 6, pp. 502–514, 2018.
[4] E. Karyotaki et al., “Combining pharmacotherapy and psychotherapy or monotherapy for major depression? A meta-analysis on the long-term effects,” J. Affect. Disord., vol. 194, pp. 144–152, 2016.
[5] E. Karyotaki et al., “The long-term efficacy of acute-phase psychotherapy for depression: A meta-analysis of randomized trials,” Depression Anxiety, vol. 33, no. 5, pp. 370–383, 2016.
[6] D. David, I. Cristea, and S. G. Hofmann, “Why cognitive behavioral therapy is the current gold standard of psychotherapy,” J. Front. Psychiatry, vol. 9, 2018, Art. no. 4.
[7] S. G. Hofmann, A. Asnaani, I. J. Vonk, A. T. Sawyer, and A. Fang, “The efficacy of cognitive behavioral therapy: A review of meta-analyses,” Cogn. Ther. Res., vol. 36, no. 5, pp. 427–440, 2012.
[8] T. Nordgreen et al., “Challenges and possible solutions in cross-disciplinary and cross-sectorial research teams within the domain of e-mental health,” J. Enabling Technol., vol. 15, no. 4, pp. 241–251, 2021.
[9] T. J. Rebello, A. Marques, O. Gureje, and K. M. Pike, “Innovative strategies for closing the mental health treatment gap globally,” Curr. Opin. Psychiatry, vol. 27, no. 4, pp. 308–314, 2014.
[10] J. Olesen et al., “The economic cost of brain disorders in Europe,” Eur. J. Neurol., vol. 19, no. 1, pp. 155–162, 2012.
[11] H. A. Whiteford et al., “Global burden of disease attributable to mental and substance use disorders: Findings from the global burden of disease study2010,” Lancet, vol. 382, no. 9904, pp. 1575–1586, 2013.
[12] G. Andersson, “Internet-delivered psychological treatments,” Ann. Rev. Clin. Psychol., vol. 12, pp. 157–179, 2016.
[13] J. V. Olthuis, M. C. Watt, K. Bailey, J. A. Hayden, and S. H. Stewart, “Therapist-supported internet cognitive behavioural therapy for anxiety disorders in adults,” Cochrane Database Systematic Rev., vol. 3, pp. 1–38, 2016.
[14] G. Andersson, N. Titov, B. F. Dear, A. Rozental, and P. Carlbring, “Internet-delivered psychological treatments: From innovation to implementation,” World Psychiatry, vol. 18, no. 1, pp. 20–28, 2019.
[15] T. Nordgreen, R. Gjestad, G. Andersson, P. Carlbring, and O. E. Havik, “The implementation of guided internet-based cognitive behaviour therapy for panic disorder in a routine-care setting: Effectiveness and implementation efforts,” Cogn. Behav. Ther., vol. 47, no. 1, pp. 62–75, 2018.
[16] T. Nordgreen, R. Gjestad, G. Andersson, P. Carlbring, and O. E. Havik, “The effectiveness of guided internet-based cognitive behavioral therapy for social anxiety disorder in a routine care setting,” Internet Interv., vol. 13, pp. 24–29, 2018.

[17] T. Nordgreen, K. Blom, G. Andersson, P. Carlbring, and O. E. Havik, “Effectiveness of guided internet-delivered treatment for major depression in routine mental healthcare—an open study,” Internet Interv., vol. 18, 2019, Art. no. 100274.

[18] G. Eysenbach, “The law of attrition,” J. Med. Internet Res., vol. 7, no. 1, 2005, Art. no. e402.

[19] O. Johansson, T. Michel, G. Andersson, and B. Paxling, “Experiences of non-adherence to internet-delivered cognitive behavior therapy: A qualitative study,” Internet Interv., vol. 2, no. 2, pp. 137–142, 2015.

[20] “Regulation eu 2016/679 of the European parliament and of the council of 27 april 2016,” General Data Protection Regulation, 2016.

[21] C. Ryngaert and M. Taylor, “The GDPR as global data protection regulation,” Amer. J. Int. Law, vol. 114, pp. 5–9, 2020.

[22] “Data pseudonymisation: Advanced techniques & use cases,” Euc. Union Agency Cybersecurity (ENISA), p. 31, 2021. [Online]. Available: https://www.enisa.europa.eu/publications/data-pseudonymisation-advanced-techniques-and-use-cases

[23] K. Fuhr et al., “Predictors of symptom change and adherence in internet-based cognitive behaviour therapy for social anxiety disorder in routine psychiatric care,” PLoS One, vol. 10, no. 4, 2015, Art. no. e0124258.

[24] A. Vaswani et al., “Attention is all you need,” in Advances in neural information processing systems, 2017.

[25] S. El Alaoui et al., “Predictors of symptomatic change and adherence in internet-based cognitive behavioral therapy,” J. Affect. Disord., vol. 209, pp. 171–180, 2017.

[26] “Data pseudonymisation: Advanced techniques & use cases,” Euc. Union Agency Cybersecurity (ENISA), p. 31, 2021. [Online]. Available: https://www.enisa.europa.eu/publications/data-pseudonymisation-advanced-techniques-and-use-cases

[27] T. Nordgreen, R. Gjestad, G. Andersson, P. Carlbring, and O. E. Havik, “Predicting adherence to internet-delivered cognitive behavior therapy for social anxiety after myocardial infarction: Machine learning insights from the u-care heart randomized controlled trial,” J. Med. Internet Res., vol. 20, no. 10, 2018, Art. no. e10754.

[28] S. Alfonsson, E. Olsson, and T. Hursti, “Motivation and treatment adherence,” J. Affect. Disord., vol. 249, pp. 327–335, 2019.

[29] E. Karyotaki et al., “Predictors of treatment dropout in self-guided web-based interventions for depression: An ‘individual patient data’ meta-analysis,” Psychol. Med., vol. 45, no. 13, pp. 2717–2726, 2015.

[30] J. Wallert et al., “Predicting adherence to internet-delivered psychotherapy for symptoms of depression and anxiety after myocardial infarction: Machine learning insights from the u-care heart randomized controlled trial,” J. Med. Internet Res., vol. 20, no. 10, 2018, Art. no. e10754.

[31] E. Forsell et al., “Predicting treatment failure in regular care internet-delivered cognitive behavior therapy for depression and anxiety using only weekly symptom measures,” J. Consulting Clin. Psychol., vol. 88, no. 4, 2020, Art. no. 311.

[32] J. M. Eisenberg and J. C. Hershey, “Derived thresholds: Determining the diagnostic probabilities at which clinicians initiate testing and treatment,” Med. Decis. Mak., vol. 3, no. 2, pp. 155–168, 1983.

[33] A. Vaswani et al., “Attention is all you need,” in Proc. Adv. Neural Inf. Process. Syst., 2017, pp. 5998–6008.

[34] D. V. Sheehan et al., “The mini-international neuropsychiatric interview (MINI): The development and validation of a structured diagnostic psychiatric interview for DSM-IV and ICD-10,” J. Clin. Psychiatry, vol. 59, no. 20, pp. 22–33, 1998.

[35] O. Perski, A. Blandford, R. West, and S. Michie, “Conceptualising engagement with digital behaviour change interventions: A systematic review using principles from critical interpretive synthesis,” Transl. Behav. Med., vol. 7, no. 2, pp. 254–267, 2017.

[36] M. Maciejewsky and C. Katsara, “Biometric recognition and behavioral detection,” Policy Dept. Citizen’ Rights Constitutional Affairs, p. 12, 2021.

[37] J. Bergstra and Y. Bengio, “Random search for hyper-parameter optimization,” J. Mach. Learn. Res., vol. 13, no. 2, pp. 281–305, 2012.

[38] R. Saunders, J. E. Buckman, J. Cape, P. Fearon, J. Leibowitz, and S. Pilling, “Trajectories of depression and anxiety symptom change during psychological therapy,” J. Affect. Disord., vol. 249, pp. 327–335, 2019.

[39] G. Biau and E. Scornet, “A random forest guided tour,” Int. J. Appl. Pattern Recognit., vol. 3, no. 2, pp. 145–180, 2016.

[40] H. Wallach, “Deep learning,” in Deep learning, vol. 3, no. 2, pp. 145–180, 2016.

[41] A. Paszke et al., “PyTorch: An imperative style, high-performance deep learning library,” Adv. Neural Inf. Process. Syst. 32, H. Wallach et al., Eds., pp. 8024–8035, Curran Associates, Inc., 2019. [Online]. Available: http://papers.neurips.cc/paper/9015-pytorch-an-imperative-style-high-performance-deep-learning-library.pdf

[42] H. B. Mann and D. R. Whitney, “On a test of whether one of two random variables is stochastically larger than the other,” Ann. Math. Statist., vol. 18, pp. 50–60, 1947.

[43] A. Paszke et al., “Scikit-learn: Machine learning in python,” J. Mach. Learn. Res., vol. 12, pp. 2825–2830, 2011.

[44] K. Boyd, K. H. Eng, and C. D. Page, “Area under the precision-recall curve: Point estimates and confidence intervals,” in Proc. Joint Eur. Conf. Mach. Learn. Knowl. Discov. Databases, 2013, pp. 451–466.

[45] W. S. Noble, “What is a support vector machine,” Nature Biotechnol., vol. 24, no. 12, pp. 1565–1567, 2006.

[46] G. Biau and E. Scornet, “A random forest guided tour,” Test, vol. 25, no. 2, pp. 197–227, 2016.

[47] S. Alfonsson, E. Olsson, and T. Hursti, “Motivation and treatment adherence,” J. Affect. Disord., vol. 209, pp. 171–180, 2017.

[48] A. Tharwat, “Linear vs. quadratic discriminant analysis classifier: A tutorial,” Int. J. Appl. Pattern Recognit., vol. 3, no. 2, pp. 145–180, 2016.