- WHITEPAPER -

# ARTIFICIAL DATA GENERATION IN PSYCHOTHERAPY

## MODELLING AND PREDICTING PATIENT PROGRESS

GONÇALO HORA DE CAVALHO
SOFIA BASÍLIO VALENTE DA SILVA
BRYNJAR ÚLFARSSON
ÞORBJÖRG HELGA VIGFÚSDÓTTIR
KRISTINN R. THÓRISSON

JULY 2023

ICELANDIC INSTITUTE FOR INTELLIGENT MACHINES
VITVÉLASTOFNUN ÍSLANDS

karaconnect

# EXECUTIVE SUMMARY

Leveraging advanced automation, we offer a robust solution poised to revolutionize patient care and research in Psychotherapy. Our approach combines a comprehensive patient questionnaire, two pioneering data generators, and predictive models. This comprehensive patient questionnaire aids in generating thorough patient profiles. The data generators enable the production of an unprecedented volume of psychotherapy data, driving novel insights. Augmented by our predictive models, we facilitate actionable predictions on real patient data.

## Therapeutic alliance

Therapeutic alliance is described as the relationship between a patient and a professional during therapy. A new set of questions was realized and explored as a survey on Therapeutic Alliance. This novel survey amalgamates improved adaptations of pre-existing questions with innovative inquiries, traversing previously uncharted territory in Psychotherapy. The conceptualization of a new questionnaire was derived from the need to address aspects of the patient-therapist relationship, namely: listening, trust, acceptance, mood, confidence of outcome, and problem perspective.

## The artificial data generators (ADG)

The first Automated Data Generator (ADG) we developed leverages the Clinical Outcomes in Routine Evaluation-Outcome Measure (CORE-OM), a prevalent self-report measure in psychotherapy. We have designed technology capable of generating data that mirrors anticipated patient scores, offering valuable insight into potential therapeutic outcomes. The second ADG focuses on synthesizing data related to the aforementioned therapeutic alliance, as well as realistic demographic data for both patients and therapists. The deployment of such an automated generator grants access to virtually limitless data, marking a pioneering application of automation in the sphere of Psychotherapy.

## Modelling and Machine Learning

The integration of AI solutions via Machine Learning (ML) proves invaluable when software must navigate unpredictable scenarios. In the realm of psychotherapy, this technology's capacity to leverage legacy statistical tools utilized in Psychology provides significant advantages. Simply put, ML involves a computer processing data, constructing a model from it, and utilizing this model for predictive purposes. We've fitted a model to our generated data, achieving a gold-standard predictive accuracy of around 97%. Such precision can effectively guide patient treatment and facilitate hypothesis testing on patient data.

Kara Connect was established in 2015 to enable access to help using digital tools to cross administrative barriers and silos. It built slowly around the needs of the professionals offering their services to clients of all ages. Today Kara offers a white labelled access point for employees, offering various professional services with just a click.

One of Kara's goals is to digitise and expedite paper and pencil questionnaires, namely the therapeutic alliance variables questionnaire which correlates strongly with the outcome of therapeutic work. Using a digital platform to collect this data, Kara has been fulfilling a need in professional's workflow in many different fields by enabling analysis over client relations.

The Kara+ project added questions that measure the alliance and one generic questionnaire that measures anxiety and depression and the connection between the quality of a professional's therapy program and their client's development. Kara, supported by Tækniþróunarsjóður (The Technology Development fund) and in co-operation with IIIM, has worked on launching this digital questionnaire through their platform.

The Icelandic Institute for Intelligent Machines (IIIM) is a nonprofit entity devoted to propelling Iceland's innovation trajectory through the application of automation and Artificial Intelligence (AI) technologies. With an extensive technological palette, ranging from machine learning and robotics to data science, IIIM cultivates strategic synergy between academic researchers and industrial engineers. Leveraging the team's expertise in data processing, AI, and software development, IIIM generates software tools and systems exhibiting novel capabilities across a spectrum of industries.

IIIM's mission is to enrich businesses via custom-made Machine Learning pipelines, meticulously designed to align with each company's objectives. Despite being a nascent and intricate field, AI is currently at the zenith of popularity. Understanding AI necessitates a mathematical mindset, as its processes are intricate and prone to misdirection or incorrect deployment. At IIIM, businesses can rely on a team fortified by over three decades of combined field experience and an exceptional accumulation of academic and industry knowledge. Applying AI requires rigorous testing standards, dictated by an unwavering academic dedication to accuracy. For the past 14 years, this rigorous approach to AI application is precisely what IIIM has been offering to businesses across an expansive array of markets.

# MOTIVATION

Automation provides a compelling solution for maximizing resource efficiency and minimizing financial outlay in knowledge-intensive sectors. It achieves this by facilitating swift data collection or generation and tracking through concise summaries and models. Automated techniques accomplish these tasks in mere minutes, if not seconds - a revolutionary leap from the days or months previously required. This advancement mitigates the reliance on costly, scarce expert human labor.

One discipline ripe for such automation is Psychotherapy. In this field, therapists juggle multiple patients daily, requiring meticulous attention to detail and progress tracking to ensure patient improvement. Therapists' primary objective is to discern the most effective treatment for the patient's problems or disorders. These conditions are often gauged through paper-based questionnaires, administered throughout the therapy to monitor the patient's status. However, this manual approach breeds uncertainty during treatment. Therapists must invest substantial time in recollecting and reevaluating each client's state, making patient progress tracking arduous and often contributing to therapist burnout.

Amid these automation gaps, numerous variables, including demographics and patient cognitive state data (such as additional questionnaires, EEG, fMRI), can be gathered during therapy. This wealth of information harbors tremendous potential for Machine Learning (ML) and data analysis applications, opening doors for substantial improvements in the field.

# Challenges

Psychotherapy faces significant challenges tied to data collection procedures that may impede progress and inhibit the application of innovative research and ideas. These challenges encompass:

- **Paper Dependency:** Traditional reliance on paper-based questionnaires often leads to improper or inconsistent data storage, making it unusable. Additionally, these documents frequently get lost post-therapy, and the methodology incurs extra costs due to necessary data digitization efforts.

- **Gradual data collection:** Current mechanisms yield data-points heavily reliant on therapy length (number of sessions per client) and the frequency of questionnaire administration. This practice, usually determined by professional preference and experience, results in non-reproducible data, complicating the construction of a consistent data set.

- **Limited Software Solutions**: Implementing data storage solutions for public facilities poses a challenge due to the scarcity of such solutions. Execution further compounds issues, requiring expert hiring, grappling with complex deployment, costs, and GDPR constraints.

- **Legal and Privacy Concerns**: Data collection and utilization are frequently constrained by legal considerations pertaining to client privacy and data security.

Despite the aforementioned challenges, there exist viable pathways to enhance data collection processes in psychotherapy. One such innovation is the Artificial Data Generator (ADG), a software capable of producing data following specific probability distributions. Sophisticated ADGs can generate data that realistically mirrors expected patterns or true data distributions.
Understanding extant variables and patient behaviors is paramount to the successful implementation of a robust ADG for psychotherapy data. This, in turn, empowers the development of an effective Machine Learning model capable of providing insightful predictions. By employing artificial yet realistic data, we circumnavigate associated legal hurdles, while also enabling the generation of virtually unlimited volumes of data, a critical requirement for high-accuracy predictive models.

# ARTIFICIAL DATA GENERATORS

As noted earlier, an Artificial Data Generator (ADG) can produce vast quantities of data in a specified format, often used as a surrogate for real-world data. Numerous approaches and techniques underpin this process, contingent on the intricacy of modeling real data and the understanding of existing trends and patterns. When designing an ADG, initial considerations should include the data's use-cases, format, and inherent patterns.

In this project, the identified use-case involved leveraging artificial data to train machine learning models aimed at predicting a patient's future status in psychotherapy. The data format adhered to a widely-used therapy questionnaire and a survey assessing the patient-therapist relationship. As a result, two generators were required to accommodate the two distinct data formats.

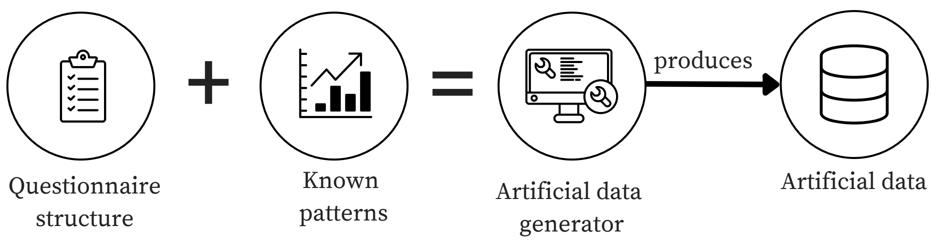



Figure 1: The general flow in implementing the Artificial Data Generators.

Figure 1 depicts the implementation flow of the ADGs in this project, where the structure of the questionnaire and the known patterns are built into the generator which produces the artificial data corresponding to patients filling out the questionnaire and the survey. Patterns known about the questionnaire included boundaries on future values given prior information, correlation between the different domains, and normally distributed patient progression.

The following sections concern details on each of the generators, the structure of the data, and some of the patterns identified.

# Clinical Outcomes in Routine Evaluation-Outcome Measure (CORE-OM)

The first ADG is based on the Clinical Outcomes in Routine Evaluation-Outcome Measure (CORE-OM), a widely used self-report measure in psychotherapy that assesses the patient on four different domains: risk, well-being, functioning, and problems. Each of the domains contain a different amount of questions, 6, 4, 12, and 12 respectively. CORE-OM domains are further divided into ranges (Table 1) that explain to a degree the assessment of the patient, the higher the score, the more severe the current status of the patient is for that domain.

| Core-OM Scoring | Well-being | Risk | Functioning | Problems |
|---|---|---|---|---|
| Normal | 0-2 | 0-2 | 0-14 | 0-14 |
| Mild | 3-4 | 3-5 | 15-18 | 15-18 |
| Moderate | 5-7 | 6-10 | 19-25 | 19-25 |
| Severe | 8-11 | 11-16 | 26-33 | 26-33 |
| Extremely Severe | 12-16 | 17-24 | 34-48 | 34-48 |

**Table 1**: CORE-OM scoring for each of the categories and ranges associated with patient status.

Each question in the questionnaire is answered on a 5-point Likert scale of 0 (Not at all) to 4 (Most or all the time), an example can be found in Figure 2.

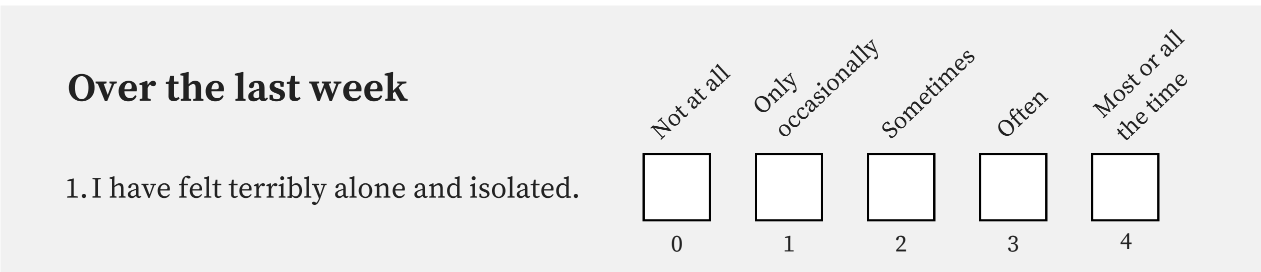



**Figure 2**: Example question from CORE-OM.

The CORE-OM was designed to evaluate/measure change in on-going therapy, to aid practitioners instrument a tailored treatment that best benefits the patients and the issues at hand. In the ADG, the data generated always contains CORE-OM scores for each of the categories mentioned in Table 1, and it can optionally generate demographics data following real probability distributions of current Icelandic demographic data.

The scores generated are based on likelihoods which can be seen in Table 2, where a patient filling out CORE-OM can start in any of the status ranging from Normal to Extremely Severe, and end in any of those status once the last questionnaire has been answered. Once the start and end likelihoods are chosen, the values for the other sessions are selected between those ranges (start and end). Take a patient that begins therapy in the status of **Extremely Severe** in the category **Risk** of CORE-OM, and ends with a **Mild** status in the same category. This patient would consequently have a starting score in the range of [17-24] for Risk, and a final score in the range of [3-5], where the scores for the sessions between the first and last would be in the range of [24, 3], as the client is very likely to improve.

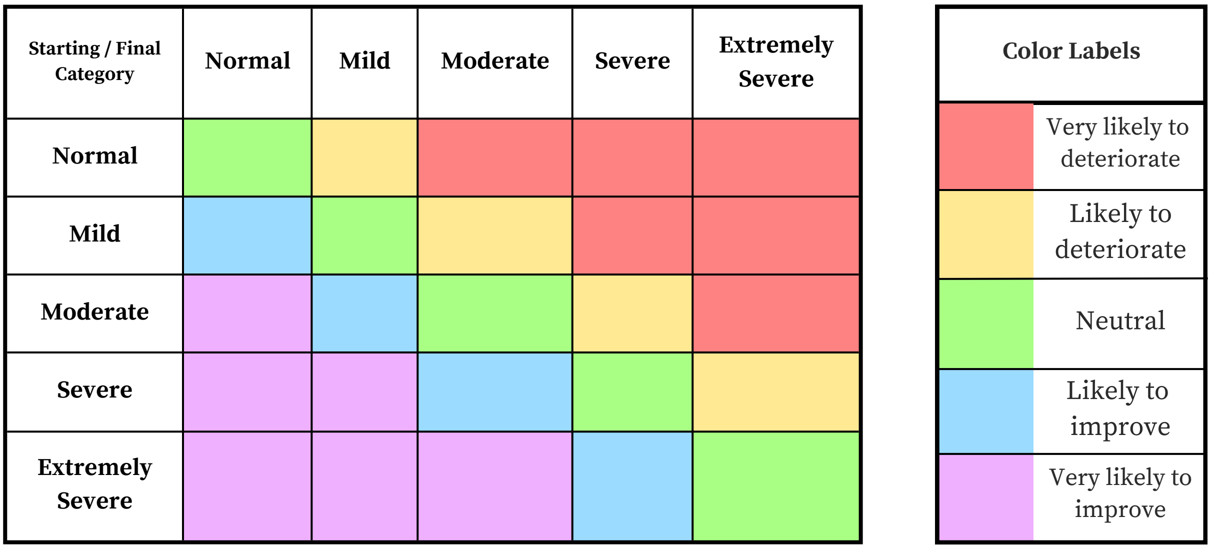



**Table 2:** Patterns for generation of CORE-OM data based on the likelihood of patient improvement from start of therapy until the end of therapy.

The output format of this generator is a time-series where each row is a different session in therapy with the most recent CORE-OM scores for a patient. Patients have a varying number of sessions, and are tracked with a patient ID, as seen in Table 3.

| cid | date | session | risk | wellbeing | functioning | problems |
|---|---|---|---|---|---|---|
| 1 | 2021-03-12 | 1 | 23 | 15 | 19 | 18 |
| 1 | 2021-03-14 | 2 | 23 | 15 | 19 | 16 |
| 1 | 2021-03-28 | 3 | 22 | 15 | 19 | 15 |
| 1 | 2021-04-11 | 4 | 21 | 13 | 17 | 11 |
| 1 | 2021-05-09 | 5 | 21 | 13 | 17 | 10 |
| 1 | 2021-06-06 | 6 | 21 | 12 | 17 | 8 |
| 1 | 2021-07-31 | 7 | 19 | 12 | 17 | 7 |
| 1 | 2021-08-25 | 8 | 14 | 12 | 16 | 7 |

**Table 3:** Example output from the CORE-OM ADG.

# Survey on Therapeutic Alliance

Therapeutic alliance is described as the relationship between a patient and a professional during therapy. This is a widely researched topic within psychotherapy and other fields in which group-work is relevant for a positive outcome or accomplishment of goals.
Currently, surveys exist to assess patient-therapist relationships through a set of questions, namely Psychosis Specific Bond Scale (PSB), Scale To Assess Therapeutic Relationships in Community Mental Health Care (STAR), Agnew Relationship Measure (ARM-5), Therapist Empathy Scale (TES), and others. The second generator is however, based on a new set of questions realised as a Survey on Therapeutic Alliance. The survey is composed of modified versions of existing questions, and brand-new ones which breach concepts previously considered. The conceptualisation of a new questionnaire was derived from the need to address certain aspects of the patient-therapist relationship that were otherwise not covered in the aforementioned surveys. In relation to patient experience, these concepts include:

- **Listening**: perceived capability of a therapist to demonstrate understanding towards patient concerns or points of view.
- **Trust**: existing assurance or positive reliance on the practitioner.
- **Acceptance**: status of openness to talk about the problems at hand.
- **Mood**: current state of mind, sometimes affecting receptiveness to advice, listening, and behaviour.
- **Confidence of outcome**: belief in the current treatment.
- **Problem perspective**: increasingly positive perspective of existing problems in ongoing therapy.

| Nr. | Concept | Patient Version | Therapist Version |
|---|---|---|---|
| 1 | **Listening** | My therapist/counsellor understood and heard my point of view. | I heard and understood my client's point of view. |
| 2 | **Trust** | My therapist/counsellor and I share a trusting relationship. | My client and I share a trusting relationship. |
| 3 | **Acceptance** | I am ready to share my problems with my therapist/counsellor. | I feel my client is ready to share his/her problems with me. |
| 4 | **Variance between sessions** | How much has your problem bothered you in the last week? | I feel my client is progressing well. |
| 5 | **Mood today** | How did you feel in today's session? | How productive did you feel your session was today? |
| 6 | **Confidence of outcome** | I believe our work together will help me. | I believe our work together will help my client. |
| 7 | **Problem perspective** | What I do in the treatment gives me a new perspective of my problems. | |

**Table 4**: Patient and therapist versions of therapeutic alliance and progress assessment questions.

The questions in Table 4 are scored on a 5-point Likert Scale, (i.e. from 1 to a maximum of 5 points) where the higher the score, the more positive the answer is. Although the survey contains seven questions, the survey is not administered as a whole. Each question in the survey has a session in which it should be administered for the first time, and an update rate (when it should be asked again). the logic in place is due to the topical nature of the questions. Particular questions will not yield any meaningful values in the earlier stages of psychotherapy, and yield change in short intervals. For example, question 7 pertains to the treatment which will not be designated in the first couple of sessions. Table 5 depicts the previously mentioned logic, where administration start is the session number when the question is first asked, and administration rate is how many sessions must pass before the question is asked again.

| Survey Question Nr. | Administration Start | Administration Rate |
|---|---|---|
| 1 | 1 | always |
| 2 | 4 | 4 |
| 3 | 4 | 4 |
| 4 | 5 | 4 |
| 5 | 1 | always |
| 6 | 5 | 4 |
| 7 | 3 | 3 |

**Table 5**: Administration logic of survey questions. always = the question is asked every session.

The benefits of administering such a survey is many-fold. The questions are meant to help professionals better understand the current situation from the patient's perspective, and compare perceptions of progress. If administered along with CORE-OM or other outcome measures, the results may further the research on the effects of patient-therapist alliance on the progress and improvement of patients in psychotherapy.

The survey ADG was built following previous research, and under the assumption that there is a connection between psychotherapy outcomes and therapeutic alliance. Each question in the survey was assigned a weight for each of the domains in the CORE-OM, such that the sum of all the weights was equal to 1. These weights indicate the significance of a domain for each of the questions in the survey. For example, question 7 in the survey, "What I do in the treatment gives me a new perspective of my problems", will have a stronger connection to the domain of Problems in CORE-OM. For that reason, the domain of Problems yields a higher weight than the other domains for question 7. The preliminary values given to the weights are shown in Table 6. These weights can be changed and used to test hypothesis on the correlation between CORE-OM categories and the survey on Therapeutic Alliance.

| Survey Question Nr. | Weight for Risk | Weight for Wellbeing | Weight for Functioning | Weight for Problems |
|---|---|---|---|---|
| 1 | 0,3 | 0,3 | 0,25 | 0,15 |
| 2 | 0,3 | 0,3 | 0,25 | 0,15 |
| 3 | 0,3 | 0,3 | 0,1 | 0,3 |
| 4 | 0,2 | 0,1 | 0,35 | 0,35 |
| 5 | 0,2 | 0,35 | 0,45 | 0 |
| 6 | 0 | 0,3 | 0,3 | 0,4 |
| 7 | 0,2 | 0,2 | 0,2 | 0,4 |

**Table 6**: Preliminary weights assigned to each CORE-OM category in function of each survey question.

The software solution devised in this collaborative project facilitates the extraction of new weights from real data. This empowers experts to generate artificial data closely approximating real-world information. Once the artificial data achieves sufficient accuracy, it serves to validate models and train machine learning models for diverse purposes. It does so without constraining progress due to legal and privacy issues, as the only aspect linked to real patients are the aforementioned weights. Additionally, the acquisition of new weights allows for a quantitative review or confirmation of assertions about the influence of therapeutic alliance on psychotherapy outcomes. This capability enhances the robustness and reliability of insights derived from the psychotherapy process.

The output of the generator (Table 7) is a time-series similar to the output from the CORE-OM ADG (Table 3). With the values for the survey questions as an addition, where a 0 entails the question has not been administered yet according to survey logic.

| cid | date | session | risk | ... | problems | S1 | S2 | S3 | S4 | S5 | S6 | S7 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2021-03-12 | 1 | 23 | ... | 18 | 3 | 0 | 0 | 0 | 3 | 0 | 0 |
| 1 | 2021-03-14 | 2 | 23 | ... | 16 | 3 | 0 | 0 | 0 | 3 | 0 | 0 |
| 1 | 2021-03-28 | 3 | 22 | ... | 15 | 3 | 0 | 0 | 0 | 3 | 0 | 3 |
| 1 | 2021-04-11 | 4 | 21 | ... | 11 | 3 | 3 | 3 | 0 | 2 | 0 | 3 |
| 1 | 2021-05-09 | 5 | 21 | ... | 10 | 3 | 3 | 3 | 2 | 2 | 2 | 3 |
| 1 | 2021-06-06 | 6 | 21 | ... | 8 | 2 | 3 | 3 | 2 | 2 | 2 | 3 |
| 1 | 2021-07-31 | 7 | 19 | ... | 7 | 2 | 3 | 3 | 2 | 2 | 2 | 3 |
| 1 | 2021-08-25 | 8 | 14 | ... | 7 | 2 | 2 | 2 | 2 | 2 | 2 | 3 |

**Table 7**: Example output from the survey ADG, cid is the client (patient) id, date is the date of the session in which both CORE-OM and Survey were administered, risk and problems correspond to the scores for the respective domains in the CORE-OM, S1 to S7 are the scores for questions 1 to 7 in the survey.

# MODELLING AND MACHINE LEARNING

The integration of Artificial Intelligence (AI) solutions through Machine Learning (ML) proves especially advantageous when data is plentiful. However, this is rarely the scenario. In the realm of psychotherapy, the early adoption of machine learning pipelines can catalyze the process of data collection and digitalization. In the field of psychology, this proves doubly beneficial, as it enables the generation of data working backward from available questionnaires. Moreover, such a pipeline accesses all legacy statistical tools used in psychology through ML algorithms.

To put it simply, ML involves a computer processing data, constructing a model from the data, and using it both as a hypothesis about the world and a software tool for tackling problems—usually tasks of classification or regression.

In this project, our focus is regression. This task involves identifying relationships and interactions between variables to predict approximations for new input. Essentially, it solves the problem of finding a functional description of numerical data to predict values for new input. In the context of CORE-OM, aspects like well-being, risk, functioning, and problems, in relation to survey and questionnaire scores (as well as other data, like demographics and other therapy variables) can be learned and predicted with an error rate that can be minimized. This means that given the CORE-OM data, questionnaire scores can be predicted—and vice versa.

In the following sections, we will delve into the ML models tested for predicting a patient's CORE-OM scores.

## Model testing and prototyping

Machine learning projects go through phases of testing and analysis of models to single out the best model for a set use case. This single model selection approach can close opportunities for better models, in performance and explainability, in face of changes in data and the collection of additional unseen data. Our approach considers multiple widely used models that are available for future testing and usage, as well as the model that yielded the best results.

The following table names the models used and their performance on the artificial data generated by the previously defined ADGs:

| Model | MSE | $r^2$ |
|---|---|---|
| GradientBoostingRegressor | 3.83 | 0.969 |
| SGDRegressor | 3.84 | 0.959 |
| RandomForestRegressor | 5.49 | 0.942 |
| AdaBoostRegressor | 6.44 | 0.931 |
| VotingRegressor | 6.97 | 0.925 |
| StackingRegressor | 8.39 | 0.911 |
| decisionTreeRegressor | 22.59 | 0.759 |
| BaggingKnnRegressor | 29.72 | 0.684 |

**Table 9**: Model performance ordered by mean squared error (MSE), and Coefficient of determination ( $r^2$ )

The Mean Squared Error (MSE) denotes the average of the squared differences between the predicted and the actual values - the lower the MSE, the closer the predicted value is to the real one. The Coefficient of Determination ($R^2$) indicates the correlation between the independent and dependent variables, ranging from 0 to 1. The closer $R^2$ is to 1, the stronger the correlation and the higher the probability that the model explains the data accurately. Utilizing weights to generate patterned artificial data will consequently yield high $R^2$ values, as evidenced in Table 9, indicating that the survey questions are correlated to the CORE-OM scores.

In terms of performance on the artificial data, the Gradient Boosting Regressor (GBR) model yielded the most effective results, achieving an MSE of 3.83 - a relatively low value given the context of the data - and an $R^2$ of 96%. This implies that the model can explain, on average, 96% of the data, edging close to the 'gold standard' in ML algorithms, typically defined at around 97% (though this value may vary by model, 97% is generally considered excellent).

The Gradient Boosting Regressor (GBR) is traditionally employed to elucidate the relationship between a dependent variable and several independent variables. The GBR operates as an ensemble of weaker models, specifically decision trees, whose collective output surpasses the performance of any single tree. It adopts the standard loss minimization and arbitrary tree initialization found in the random forest algorithm. However, unlike a random forest which initializes every tree simultaneously, the gradient boosting algorithm fits a new tree based on the residuals of the preceding trees, thereby reducing the overall error per tree.
The following illustration demonstrates the regression or prediction of the 'Problems' category on the test set, which was developed using IIIM's data generator for CORE-OM and Survey on Therapeutic Alliance:

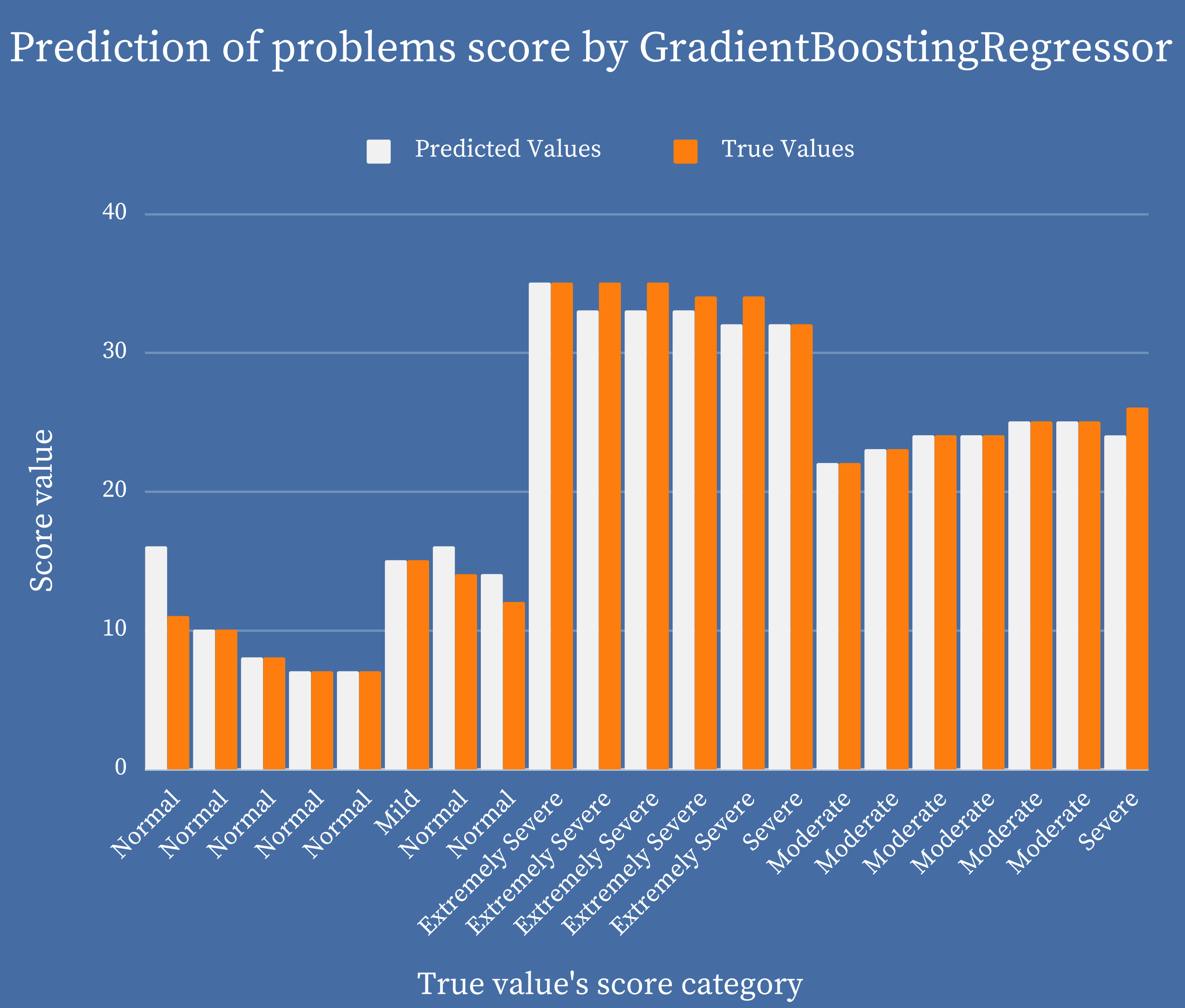



**Figure 3:** Predicting test set of CORE-OM Problems category (Table 1) using the remaining categories previous scores for CORE-OM and previous survey scores.

In Figure 3, we witness a snapshot of the model's precision on the test set, demonstrating an almost exact correlation to the anticipated value.
The finished product encompasses several models that have been benchmarked on artificial data, and are ready to be benchmarked on real data. Notably, the real data doesn't necessarily need to include survey questions or CORE-OM scores; it simply needs to maintain the same time-series format and include two additional questionnaires or features for analysis.

This versatile framework allows for the empirical examination of long-standing assumptions regarding survey questionnaires. The models trained on expected data distributions can be juxtaposed with those fitted on real survey data, allowing us to evaluate if the survey questionnaire assumptions yield predictive value over the real data, and to measure the degree of error involved. This insight is crucial for determining not just the extent of model deviation, but more significantly, the validity of the field's underlying assumptions regarding the explanatory power of questionnaires and surveys.

This bootstrapping technology, which has been instrumental in shaping modern fields like computational cognitive neuroscience, positions psychotherapy within the contemporary age. Here, computational sciences facilitate complex hypothesis testing using large data sets and computationally intensive models, heralding a new era of scientific rigor and precision in the field of psychotherapy.

## Feature Importance and new weights

Feature importance reflects the significance of a feature in ensuring the precision of a regression. It is a value ascribed to each feature—anything else in the data that is not the predicted column—with the sum of all feature importances amounting to one. As previously mentioned, the data generated for the survey is predicated on a matrix that assigns a weight to each CORE-OM category, with the sum of these weights for the categories equaling one. Hence, there are parallels between feature importance and the method for generating survey data. Both methodologies assess how much each feature contributes to the prediction of a value.

Consequently, feature importance can be harnessed to derive new realistic weights once a sufficient amount of data has been collected. This will supply more accurate values for the survey generator, propelling research into the intersection of questionnaires. In other words, it could provide insights into determining the significance of certain questionnaires in predicting the scores of other questionnaires. This could potentially provide a deeper understanding of the relationships and dependencies between different questionnaires used in psychotherapy, which could enhance patient treatment strategies.

To further describe the utility of this method, Table 10 displays the feature importance of GBR models trained to predict each survey question.

| Survey Question Nr. | Weight for Risk | Weight for Wellbeing | Weight for Functioning | Weight for Problems |
|---|---|---|---|---|
| 1 | 0,392 | 0.395 | 0.160 | 0.053 |
| 2 | 0,395 | 0.393 | 0.159 | 0.053 |
| 3 | 0,373 | 0.375 | 0.021 | 0.231 |
| 4 | 0.221 | 0.048 | 0.365 | 0.365 |
| 5 | 0.148 | 0.424 | 0.427 | 0.051 |
| 6 | 6.408 | 0.366 | 0.240 | 0.394 |
| 7 | 0.209 | 0.208 | 0.112 | 0.471 |

**Table 10**: Feature importance outputted by the models in predicting survey questions using CORE-OM scores.

The values are in line with the preliminary weights used in the survey data ADG, displaying the utility of ML models in uncovering percentages assuming no prior knowledge. Furthermore, once a new model is trained on real data, feature importance becomes a greater tool in assessing the crossing of questionnaires (any questionnaire beyond CORE-OM and Survey), and the potential for validating novel questionnaires on account of high accuracy models and meaningful outputs. The following Table 11 demonstrates how one might do such a crossing, in this case we present the reverse of Table 10, where the CORE-OM categories are being used as predictors and survey questions are used as features.

| Core-OM Category | Weight for S1 | Weight for S2 | Weight for S3 | Weight for S4 | Weight for S5 | Weight for S6 | Weight for S7 |
|---|---|---|---|---|---|---|---|
| **Risk** | 0.688 | 0.004 | 0.066 | 0.063 | 0.025 | 0.146 | 0.005 |
| **Well-being** | 0.193 | 0.003 | 0.036 | 0.102 | 0.590 | 0.072 | 0.001 |
| **Functioning** | 0.031 | 0.015 | 0.089 | 0.090 | 0.753 | 0.012 | 0.008 |
| **Problems** | 0.059 | 0.023 | 0.018 | 0.065 | 0.127 | 0.124 | 0.581 |

**Table 11**: Feature importance in predicting CORE-OM scores using survey questions. S1 to S7 correspond to the Survey question 1 to Survey question 7.

# SUMMARY

The integration of Artificial Intelligence (AI) and Machine Learning (ML) into various sectors, including psychotherapy services, comes with a unique set of challenges and opportunities. The blend of these advanced technologies and traditional psychological treatments can significantly transform the efficiency and efficacy of mental health services.

However, while the potential advantages of AI and ML are tremendous, the shift from conventional practices to technologically advanced procedures is not without obstacles. Psychotherapy, as an area dealing with a plethora of sensitive data, faces a distinct set of difficulties in this transformation. Issues such as data privacy, standardization of data collection, and automation pose unique challenges that require careful navigation. The prevalent use of paper-based questionnaires is one such hurdle, as it hampers the digitization and systematic analysis of patient information.

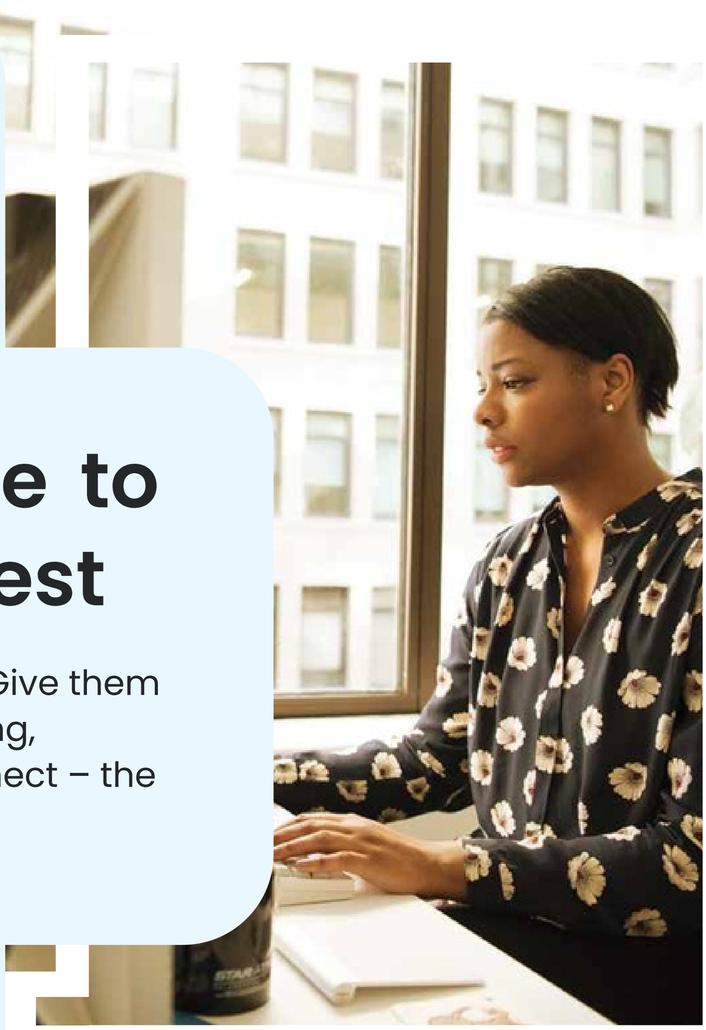
Not only does the manual processing of data from paper-based questionnaires lead to redundant expenditure of funds and resources, but it also reduces the time mental health professionals can dedicate to their patients and other research work. Despite these challenges, the promise of a data-driven approach to psychotherapy is too significant to overlook. Implementing a secure and efficient automated system to handle this data could pave the way for more accurate diagnoses, effective treatments, and overall improved mental health services.

Hence, close collaboration between institutes like the Icelandic Institute for Intelligent Machines (IIIM) and Karaconnect is crucial in this context. By bridging the gap between academic research and industry needs, we can help advance the adoption of automation and AI in psychotherapy and contribute significantly to the evolution of the field. This necessitates a delicate balance between innovation and respect for ethical considerations, particularly with regards to privacy and security, to ensure the successful integration of AI and ML in psychotherapy.

karaconnect

# Power your people to perform at their best

Employees thrive with the right support. Give them proactive access to professional coaching, therapy and other services on Kara Connect – the preventative wellbeing platform.



## Give your employees control

Offer them access to our private and confidential support system.

## Take pressure off your managers

Provide your managers with the tools to help more people effectively.

## A game-changing platform with real ROI

Invest in early prevention, reduce absenteeism and increase productivity.

## Great employers foster great culture

When employees feel better, they do better. And that's good for business.

Kara Connect, the preventative wellbeing platform, complements your EAP by offering tailored early intervention.

Take Action

Tel: +354 692-2629
thorbjorg@karaconnect.com

5x ROI on employee wellbeing from early intervention and prevention

31% expect more wellbeing support from their employers

20x the employee engagement of traditional EAPs

ICELANDIC INSTITUTE FOR INTELLIGENT MACHINES

IIIM

VITVÉLASTOFNUN ÍSLANDS

# ICELANDIC INSTITUTE FOR INTELLIGENT MACHINES

WHERE TOMORROW IS MADE

## OUR MISSION

**Accelerate innovation in Iceland and worldwide**
- through deep expertise in artificial intelligence, data science, simulation, and advanced automation technologies

**Be an innovation catalyst**
- bridging between industry needs and academic basic research, through prototypes and applied research

**Launching "the five P's"**
into the future of automation: People, Projects, Prototypes, intellectual Property and sPinoffs

## OUR SERVICES

### AUTOMATION OPPORTUNITY ANALYSIS

Ensuring return on investment of automation in industrial processes is a challenge. IIIM's unique methodology for identifying real automation opportunities and assessing their benefits and cost has been applied and honed in industry for over a decade.

### TURNKEY BESPOKE PROTOTYPES

IIIM's non-profit status allows for flexible collaboration in creating custom prototypes, producing system components, integrating diverse software solutions. IIIM experts' experience with AI technologies includes everything ranging from well-known solutions to the bleeding edge.

### STRATEGY GUIDANCE

IIIM's experts bring a broad and deep understanding of a wide range of applied AI methods and technologies. This makes them ideal for helping with framework specifications, grant proposal writing, requirements and data analysis, and a wide range of other engineering challenges.

+354 898 0398

info@iiim.is

www.iiim.is