LLM Questionnaire Completion for Automatic Psychiatric Assessment

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Abstract

We employ a Large Language Model (LLM) to convert unstructured psychological interviews into structured questionnaires spanning various psychiatric and personality domains. The LLM is prompted to answer these questionnaires by impersonating the interviewee. The obtained answers are coded as features, which are used to predict standardized psychiatric measures of depression (PHQ-8) and PTSD (PCL-C), using a Random Forest regressor. Our approach is shown to enhance diagnostic accuracy compared to multiple baselines. It thus establishes a novel framework for interpreting unstructured psychological interviews, bridging the gap between narrative-driven and data-driven approaches for mental health assessment.

1 Introduction

Psychiatric evaluation nowadays is heavily dependent on the patient's verbal report about disturbed feelings, thoughts, behaviors and their changes over time. Accordingly, evaluation hinges on two main components: unstructured interviews, which allow patients to express themselves freely under the guidance of open questions, and structured questionnaires, aimed at standardizing the assessment. These methods are outlined in the Diagnostic and Statistical Manual of Mental Disorders (DSM) series, which attempts to assign universal scores to individual experiences of mental disorders (American Psychiatric Association, 2013). However, the inherent complexity of mental health conditions, characterized by a known positive manifold of symptoms and compounded by the subjective nature and potential unreliability of self-reported data (especially from one session to another), along with interviewer biases, make accurate diagnosis challenging. The overlapping symptoms and the instability of mental state, especially in pathological conditions, further complicate the need for precision, precluding an objective and quantitative account of a critical element in the psychiatric evaluation process; the subjective self-experience (Vanes and Dolan, 2021; Dwyer et al., 2018; Bzdok and Meyer-Lindenberg, 2018).

The evolution of psychiatric practice is increasingly shaped by the integration of Natural Language Processing (NLP) and machine learning within traditional diagnostic approaches. This shift signifies a move from a predominantly theory-driven to a more data-driven paradigm, addressing limitations in conventional psychiatric assessments. NLP's role is pivotal in transcending the subjective interpretation of unstructured interviews and the rigidity of standardized questionnaires. Leveraging large-scale textual data and advanced language models, NLP enriches psychiatric evaluations with nuanced, patient-specific insights. This data-driven approach, complementing established psychiatric theories, fosters a more holistic and precise understanding of mental health conditions, aligning with the trend towards precision medicine in mental healthcare.

We introduce a two-step method for psychiatric evaluation based on unstructured interview text. First, we ask the LLM to fill in multiple questionnaires while impersonating the interviewee. These questionnaires are of two types: (i) established psychiatric questionnaires (PHQ-8, PCL-C), and (ii) questionnaires we developed using GPT-4, which cover mental health issues, personality traits, and therapeutic dimensions. In the second step, the response of the LLM is used directly, as features for a Regression Forest Regressor (Ho, 1995) that is used to predict the interviewee scores on the two clinical questionnaires.

2 Related Work

At the intersection of psychiatry and NLP, a variety of innovative methods have been developed for mental health diagnostics. Earlier efforts (Asgari

et al., 2014; Al Hanai et al., 2018; Niu et al., 2021), utilize both the textual information and the speech intonation features, acknowledging the importance of tonal elements in depression assessment. Sun et al. (2017) manually extract six psychological dimensions (sleep quality, existing PTSD/Depression diagnostic, treatment history, introversion, personal preference, and feeling) from interview text and then employ a Random Forest regressor.

More recently, the adoption of transformer architectures has brought significant advancements for depression diagnosis. Milintsevich et al. (2023) utilize the RoBERTa transformer (Liu et al., 2019) for encoding interview segments, focusing on predicting individual depression symptoms. Zhang and Guo (2024) introduces prompt learning and an attention mechanism to improve symptom prediction. These contributions rely on supervised learning for predicting questionnaires, while our work utilizes zero-shot impersonation.

Recently, Galatzer-Levy et al. (2023) explored the use of a medical knowledge-enhanced LLM Med-PaLM 2 (Singhal et al., 2023), for psychiatric prediction. This effort is aimed not at answering the questionnaire, but at directly predicting the outcome using the prompt "Based on the following clinical interview, what do you estimate the Participant's [PHQ-8/PCL-C] score is?". Concurrently, (Yang et al., 2023) runs prompt-based few-shot learning (Brown et al., 2020) to analyze social media content and directly answers questions such as "What mental disorder symptoms does this post show?", focusing on the quality of the textual explanation within the LLM's output.

3 Method

This work leverages the Extended Distress Analysis Interview Corpus (E-DAIC) (DeVault et al., 2014), a dataset of semi-clinical interviews designed to assess psychological distress. To build the corpus, an autonomous AI interviewer was employed in order to minimize human bias, and two clinical questionnaires-based scales, PHQ-8 and PCL-C, were used to measure both depression and Post Traumatic Stress Disorder (PTSD). Our analyses adhere to the predefined training, development, and test splits specified by the dataset's documentation.

The E-DAIC dataset comprises $n = 275$ psychological transcripts, each associated with two psychiatric scores, which quantify the severity of depression and PTSD, measured using the PHQ-8 and the PCL-C standardized scales, respectively.

Given a text in the domain of psychological transcripts $t_i \in \text{PT}$, where $i \in \{1, 2, \ldots, 275\}$, our objective is to design a feature extractor $F : \text{PT} \rightarrow \mathbb{R}^d$. This extractor converts a given transcript t_i into a d-dimensional feature vector $\mathbf{v}_i$ such that the two ground truth scores $s_i = [s_i^{\text{DEPRESSION}}, s_i^{\text{PTSD}}]$ can be inferred accurately. Upon extracting these features, our next step involves employing a Random Forest Regressor, $R : \mathbb{R}^d \rightarrow \mathbb{R}^2$, which takes as input the feature vector $\mathbf{v}_i$ and predicts the pair of psychiatric scores s_i.

Our method, Language Model for Impersonation-based Questionnaire Completion (LMIQ), defines a feature extractor F as the transformation of unstructured interview transcripts into a structured array of impersonated responses to a list of questions. For each subject and question, the method: (1) generates a query by combining the transcript with a psychological questionnaire, (2) processes the query through an LLM to obtain responses, and (3) stores the responses in an array, which represents the feature vector for that subject.

The system prompt directed the LLM to interpret transcripts and simulate responses as the interview subject. The exact prompt used in our research is detailed in Appendix A.1, and a shorter reference prompt is as follows.

> Attached are a psychological interview transcript and psychological questionnaire.
> Analyze the conversation transcript and capture psychological insights about the speaker.
> Deduct answers to the accompanied questions as if you were the speaker.
> The answer should be a numerical value ranging from 1-5, with 1 depicting "don't agree at all" and 5 depicting "very much agree."
> Conversation Transcript: {transcript}
> Psychological Questionnaire: {question}

In our implementation, LMIQ utilizes GPT-3.5 Turbo Instruct, via the OpenAI API (https://platform.openai.com/docs/models/gpt-3-5) for transcript analysis and predicting the responses to psychological questionnaires. The LLM was used with its default configuration, including temperature settings, to maintain consistent and unbiased processing. The individual questions in the questionnaires are submitted to the LLM one by one in separate sessions, to avoid

biases that could be caused by their order.

The list of questions employed by LMIQ comprises multiple questionnaires we developed using OpenAI's ChatGPT-4. We prompted it to create multiple five-item sets across three domains: (i) clinical mental health (DSM-5 Guided), (ii) the five-factor model of personality, and (iii) therapeutic relevant domains. The inclusion of a wider array of questionnaires beyond the PHQ-8 and PCL-C is motivated by the concept of psychiatric comorbidity and its symptom overlap.

Within each domain, GPT-4 was prompted to define multiple topics and within each topic to generate exactly five questions, each aiming to quantify symptoms on a scale between 1 and 5. These initial outputs were manually refined to ensure higher relevance and precision. The obtained domains are listed in Tab. 1, the full list of questions is provided in Appendix B; as a sample, the generalized anxiety disorder questions are: (1) Do you find it hard to control your worrying? (2) Does your anxiety interfere with your work, school, or family responsibilities? (3) Do you experience physical symptoms of anxiety, like muscle tension or restlessness? (4) Do you often feel irritable or on edge? and (5) Do you have trouble sleeping due to worry?

The feature vector was formed by concatenating responses (each an integer between one and five) to five questions across twenty-two topics, comprising a vector with $d = 110$ dimensions. This vector was then used as input for a Random Forest (Breiman, 2001) Regressor implemented using Scikit-Learn (Pedregosa et al., 2011). Model optimization was conducted through a hyper-parameter search, specifically examining 'n-estimators': [100, 200, 300] and 'max-depth': [10, 20, 30]. The configuration that yielded the best performance on the development set of E-DAIC was subsequently applied to the test set for evaluation.

4 Experiments

We employ multiple appropriate baselines and various ablated versions of our method to demonstrate the advantage of our approach in the context of predicting psychiatric scores from psychological transcripts. Unless specified otherwise, all feature extraction methods are coupled with the same Random Forest Regression that is used for LMIQ.

Direct Embedding with Ada-002 This baseline method utilizes text-embedding-ada-002 (Neelakantan et al., 2022), a model from the OpenAI API, to transform psychological transcripts into vector embeddings. **GPT-3.5 Analyze & Embed** This baseline combines GPT-3.5's analysis of psychological transcripts, with a focus on conditions such as depression and PTSD, and a subsequent text-embedding-ada-002 of the response. The prompt used and a sample response are provided in Appendix A.2. **MentalLLAMA 7B Analyze & Embed** Similar to the GPT-3.5 Analyze & Embed, but utilizing a MentaLLama 7B model (Yang et al., 2023), a LLAMA (Touvron et al., 2023) model that was fine-tuned for depression detection on a large dataset of Reddit posts in a mental health sub-Reddit. See Appendix A.3 for the sample output. **TF-IDF Vectorization** This approach represents a more traditional text processing technique. Each transcript is vectorized using the Term Frequency-Inverse Document Frequency (TF-IDF) method. **GPT-3.5 Analyze & Predict** This baseline directs GPT-3.5 to perform a zero-shot prediction of psychiatric scores PHQ-8 and PCL-C, similarly to (Galatzer-Levy et al., 2023). **GPT-3.5 Impersonate Zero-Shot** This baseline instructs GPT-3.5 to answer the PHQ-8 and PCL-C questionnaires as if it were the subject, based on the psychological transcript. This method directly calculates scores as the sum of questionnaire responses, mirroring clinical psychiatric evaluation. Differing from the main method, it bypasses the Random Forest model and operates as a zero-shot approach. **Naive Average Guess** To provide a scale regarding the variability of the scores, the mean value of the training set is used as the prediction for all subjects regardless of the psychological transcript.

The results in Table 2 indicate that the LMIQ model exhibits lower Mean Squared Errors (MSEs) than all baselines for both depression and PTSD severity, indicating superior accuracy. The second best method is the one that predicts the clinical questionnaires (but not other questionnaires) and sums the results instead of using a regression model. This method is a simplified LMIQ method that still employs the basic idea of impersonation. Its performance does not fall much behind that of the full LMIQ method. A comprehensive set of experiments studying the contribution of each type of questionnaire is provided in Appendix C The Zero-Shot method that tries to predict the questionnaire's final score directly performs consistently worse.

The classic TF-IDF encoding method obtains the highest MSEs in both tasks. GPT-3.5 Analyze &

Domain	Questionnaires	Total Questions
Mental Health	Agoraphobia, Attention-Deficit Hyperactivity Disorder, Body Image, Borderline Personality Disorder, Delusions, Depression, Generalized Anxiety Disorder, Hypo/Mania, Obsessive-Compulsive Disorder, Panic Attacks, Persistent Depressive Disorder, Post Traumatic Stress Disorder, Social Phobia, Addiction	70
Personality	Agreeableness, Conscientiousness, Extraversion, Neuroticism, Openness	25
Therapeutic	Family History, Trauma History, Resilience	15
Direct	PHQ-8, PCL-C	25

Table 1: Questionnaire Domains and Constituents

	PHQ depression score		PTSD severity scale	
Model	Dev MSE	Test MSE	Dev MSE	Test MSE
LMIQ	23.87	20.42	144.17	192.93
GPT-3.5 Impersonate Zero-Shot	27.62	24.16	154.66	195.55
GPT-3.5 Zero-Shot	35.62	33.42	251.7	336.49
GPT-3.5 Analyze & Embed	29.81	35.80	216.13	348.02
Direct Embedding with Ada-002	31.83	38.23	226.18	389.65
MentaLLama 7B Analyze & Embed	29.61	39.40	216.30	367.09
Guessing the mean value	32.06	42.80	234.52	407.2
TF-IDF Vectorization	31.47	43.36	227.61	392.63

Table 2: Summary of Model Performances in PHQ-Score and PTSD Severity prediction tasks

Method	Dev MAE	Test MAE	Dev RMSE	Test RMSE
LMIQ (Ours)	3.87	3.46	4.78	4.30
MDSD-FGPL (Zhang and Guo, 2024)	-	5.28	-	-
HCAG (Niu et al., 2021)	3.73	-	4.80	-
Milintsevich et al. (2023)	5.51	5.03	-	-

Table 3: MAE and RMSE Performance Metrics on DAIC-WoZ Dataset

Embed and MentaLLama 7B Analyze & Embed demonstrate mixed performance but consistently surpass the method that directly embeds the interview with Ada-002.

Evaluation on the DAIC-WoZ Dataset The WOZ-DAIC dataset (Gratch et al., 2014) is a predecessor of E-DAIC, which does not include PTSD scores, and in which the interviews contain the questions of a human interviewer. This earlier benchmark provides an opportunity to compare LMIQ with published methods.

The results of this comparison are presented in Table 3 and include both the MAE and RMSE metrics, following the literature. Our method is better than text-based methods on the test set. HCAG (Niu et al., 2021) does not report test set results and is slightly better than us on the development set in one of the two scores.

5 Conclusions

LMIQ employs an LLM as an impersonator to complete both established clinical questionnaires and questionnaires generated by a preliminary LLM task. The responses are fed into a classifier to derive a diagnosis. Our findings indicate that it is feasible to transform unstructured text into meaningful feature vectors through this method and highlight LMIQ's superiority over various NLP baselines, encompassing both generic approaches and those specifically designed for NLP-based diagnosis.

6 Limitations

While the method is generic, it is only tested in the context of the E-DAIC and WOZ-DAIC benchmarks. To promote clinical use, more data should be collected and performance should be compared to the inter-person variance of different human experts.

The LLM used is a generic one. Some experiments are conducted with MentaLLama, but these are limited due to time constraints. It would be interesting to also evaluate Med-PaLM2 and possibly other models.

7 Ethics and Impact Statement

The use of LMIQ for transforming unstructured text into psychiatric diagnoses presents ethical concerns, notably the possibility of assigning diagnostic labels to individuals without obtaining their explicit consent. Furthermore, the inherent risks associated with misdiagnosis in the field of psychiatry underscore the importance of exercising caution when deploying machine learning tools for these purposes. This caution is necessitated by the recognition of their limited accuracy and the potential for embedded biases, which could lead to harmful outcomes. Therefore, the ethical application of such technologies demands careful consideration of these factors to prevent unintended harm to individuals.

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A The full prompts used

A.1 System prompt - Question Impersonation

This is the prompt used in the main method, LMIQ.

"""Analyze a therapist-subject conversation transcript and related psychological questionnaire questions. Focus on understanding the subject's mental health by examining their dialogue for both explicit and implicit cues. Pay attention to signs of depression, PTSD, and other conditions, but also note the absence of these symptoms.

Your task is to provide answers to the questionnaire as if you were the subject, based on insights from the conversation. Ensure your responses are balanced, reflecting the subject's mental state as suggested by the transcript. Make informed deductions about the subject's emotional state, stress management, life satisfaction, social interactions, and professional aspirations, providing answers that reflect mental health issues or a neutral state as indicated by the transcript.

Transcript: {raw_psyc_transcript}
Answer the questions with an agreement level ranging from {agreement_range}.
Questions: {questions}"""

A.2 System Prompt - Analysis

This is the prompt used for the Analyze & Embed Baseline.

"""Analyze a therapist-subject conversation transcript. Focus on the clear and comprehensible parts of the subject's dialogue, as the therapist's words are omitted and there may be gaps due to recording issues. Your analysis should identify key statements or moments that reveal aspects of the subject's mental health, with particular attention to signs of depression and PTSD. Prioritize brevity and clarity in your analysis. Look for indicators of the subject's emotional state, stress management, life satisfaction, social interactions, and professional aspirations. Assess the intensity of these elements, capturing the range from mild to profound, based on the subject's expressions.

Ensure your analysis remains accurate and relevant to the transcript, avoiding unfounded assumptions or 'hallucinations'. Summarize your findings clearly and directly, using concise sentences that reflect the nuances of the subject's mental state. Disregard unclear or incomplete segments due to recording issues, and avoid structural phrases or introductions to maintain data integrity for subsequent embedding generation. The accuracy, clarity, and nuanced understanding of intensity in your summary are paramount.
Conversation transcript: {raw_psyc_transcript}"""

A sample response using GPT-3.5 is:

> The subject appears to have a positive outlook on life and their current location. They are interested in starting their own business and have a good relationship with their family, who have given them valuable advice. However, there are also signs of stress and irritability, as well as a recent episode of shutting down and cutting off a friend They also mention feeling lazy and less interested in activities they...Overall, the subject seems to have a mix of positive and negative emotions, and may benefit from further exploration and support for any underlying mental health issues.

A.3 Sample output by MentaLLama

A sample MentaLLama response is:

> The subject expresses a positive outlook on life, including enjoyment of reading books, cooking, and spending time with friends and family. However, they also mention experiencing congestion and having a break in their education. They express a desire to open up their own business but do not provide a specific reason. The subject mentions receiving advice from their parents and grandparents. Overall, the analysis suggests a balance between positive and negative experiences, indicating a potential need for further assessment and support."

B The full list of the questionnaires used.

For each topic from each domain, we provide the questions that were extracted in collaboration with ChatGPT 4.0.

B.1 Mental Health Domain

Agoraphobia

- Do you fear being in open or enclosed spaces?
- Do you avoid public transportation or being in crowds?
- Does the thought of leaving your home alone cause you anxiety?
- How do these fears limit your daily activities or lifestyle?

- Do you require a companion when going out due to these fears?

Attention-Deficit/Hyperactivity Disorder

- Do you find it difficult to organize tasks and activities?
- Do you often forget appointments or daily activities?
- Do you often make careless mistakes in work or other activities?
- Do you get easily sidetracked by extraneous stimuli?
- How much do these symptoms impact your performance in work or school?

Body Image

- How would you describe your level of satisfaction with your appearance?
- Do you often compare your body to others?
- How much does your perception of your body affect your daily life?
- Do you have any concerns about your eating habits or weight management?
- How confident do you feel in your abilities and decisions?

Borderline Personality Disorder

- Do you experience intense and unstable relationships with others?
- Do you often feel empty or bored?
- Do you experience mood swings that can last for a few hours to a few days?
- Do you have a fear of abandonment, either real or imagined?
- Do you engage in impulsive behaviors, like substance abuse or reckless driving?

Delusions

- Do you feel disconnected from reality at times?
- Do you have strong beliefs that others find unusual or unrealistic?
- Do you feel controlled or influenced by external forces or beings?
- Have you experienced changes in your perception or senses that others do not?
- Do these experiences cause you distress or impair your functioning?

Generalized Anxiety Disorder

- Do you find it hard to control your worrying?
- Does your anxiety interfere with your work, school, or family responsibilities?
- Do you experience physical symptoms of anxiety, like muscle tension or restlessness?
- Do you often feel irritable or on edge?
- Do you have trouble sleeping due to worry?

Hypomania/Mania

- Have you found yourself more talkative or speaking faster than usual?
- Do you often feel overly confident in your abilities or ideas?
- Have you engaged in risky behaviors, like excessive spending or reckless driving?
- Do you find your thoughts racing or jumping from topic to topic?
- Have others noticed a significant change in your mood or behavior?

Major Depressive Disorder

- Do you often feel hopeless or helpless?
- Have you noticed a change in your appetite or weight without trying to lose or gain weight?
- Do you struggle to concentrate on tasks or make decisions?
- Do you often feel worthless or excessively guilty about things?
- Have your sleep patterns changed, such as sleeping too much or too little?

Obsessive-Compulsive Disorder

- Do you check things repeatedly or have rituals that you feel compelled to perform?
- Do your thoughts or rituals cause you distress or interfere with your daily life?
- Do you spend more than an hour a day on these thoughts or rituals?
- Do you avoid certain situations or activities because of your fears or compulsions?
- Do you need to have things arranged in a specific order or manner?

Panic Attacks

- During panic attacks, do you feel like you're losing control or going crazy?
- Do you fear these attacks to the point of altering your daily routines?

- Have you visited the emergency room or sought medical help for these symptoms?
- Do you avoid places or situations for fear of triggering an attack?
- How do these attacks impact your daily life?

Persistent Depressive Disorder

- Have you experienced low mood more days than not for at least two years?
- Do you feel like you've been in a mild but constant state of depression?
- Do you find little pleasure in activities you once enjoyed?
- Do you struggle with feelings of inadequacy or low self-esteem?
- Have you experienced changes in your appetite or sleep patterns?

Post-Traumatic Stress Disorder

- Do you experience heightened vigilance or jumpiness?
- Are you engaging in self-destructive or risky behavior since the event?
- Do you feel numb or detached from people, activities, or surroundings?
- Do you find yourself being easily angered or having aggressive outbursts?
- Have you noticed any changes in your beliefs or feelings about yourself and others?

Social Phobia

- Do you fear being criticized or embarrassed in social situations?
- Does speaking to unfamiliar people cause you significant anxiety?
- Do you avoid social situations due to fear of being judged?
- Do physical symptoms like sweating or trembling accompany your fear in social settings?
- How does this fear impact your personal or professional life?

Substance Abuse

- Do you use any substances like drugs or alcohol regularly?
- How often do you find yourself using these substances?
- Have you noticed any negative impacts on your health, work, or relationships due to substance use?
- Do you feel a strong desire or compulsion to use these substances?
- Have you tried to cut down or stop using these substances in the past?

B.2 Personality

Agreeableness

- Do you often find yourself making compromises to maintain harmony in your relationships?
- How likely are you to volunteer your time to help others?
- Would you describe yourself as someone who is generally trusting of others?
- How often do you get into arguments with people?
- Do you tend to empathize easily with others?

Conscientiousness

- How often do you set and achieve long-term goals?
- Do you prefer having a set schedule or being spontaneous?
- How would you rate your ability to resist temptations or distractions?
- Do you take pride in the accuracy and detail of your work?
- How do you handle important deadlines?

Extraversion

- Do you enjoy being the center of attention in social gatherings?
- How often do you initiate conversations with people you don't know?
- Do you prefer group activities or solitary activities?
- Do you feel energized when interacting with a large group of people?
- How would you describe your level of assertiveness in social situations?

Neuroticism

- Do you often feel anxious or worried about various aspects of your life?
- How do you react to stressful situations?
- Do you frequently feel mood swings or emotional instability?
- Do you often have trouble sleeping due to worrying?

– How often do you experience feelings of sadness or depression?

Openness

– Do you enjoy trying new activities and visiting new places?
– How often do you engage in creative activities like writing, painting, or playing music?
– Do you enjoy discussing abstract concepts and ideas?
– How do you feel about change and variety in your life?
– Would you say you are open to new and diverse perspectives or opinions?

B.3 Therapeutic

Family History

– Do you feel you have a strong and positive relationship with your family members?
– Do you manage conflicts or disagreements within your family effectively?
– Is there a history of mental health issues or substance use in your family?
– Do you believe your family background has significantly influenced your current life choices and behaviors?
– Do you feel supported and understood by your family?

Trauma History

– Have you ever experienced a traumatic event such as physical, emotional, or sexual abuse?
– How do you feel this event has affected your life?
– Do you often think about or have flashbacks to this traumatic event?
– How do you typically cope with reminders of the trauma?
– Have you sought any professional help to deal with the aftermath of this traumatic experience?

Resilience

– How quickly do you recover from setbacks or disappointments?
– Do you often find positive aspects in negative situations?
– How do you usually cope with stress and pressure?
– Do you feel confident in your ability to handle new challenges?
– How often do you bounce back from hardships stronger than before?

B.4 Direct

PHQ-8

– How much are you experiencing little interest or pleasure in doing things?
– How likely are you to volunteer your time to help others?
– How much are you feeling down, depressed, or hopeless?
– How much are you having trouble with falling or staying asleep, or sleeping too much?
– How much are you feeling tired or having little energy?
– How much are you experiencing poor appetite or overeating?
– How much are you feeling bad about yourself, or that you are a failure or have let yourself or your family down?
– How much are you having trouble concentrating on things, like reading the newspaper or watching television?
– How much are you moving or speaking so slowly that other people might have noticed, or the opposite – being so fidgety or restless that you've been moving around a lot more than usual?

PCL-C

– How much are you re-experiencing disturbing memories, thoughts, or images of a stressful experience from the past?
– How much are you experiencing repeated, disturbing dreams of a stressful experience from the past?
– How much are you suddenly acting or feeling as if a stressful experience were happening again (as if you were reliving it)?
– How much are you feeling upset when something reminded you of a stressful experience from the past?
– How much are you having physical reactions (e.g., heart pounding, trouble breathing, sweating) when something reminded you of a stressful experience?

- How much are you avoiding thinking about or talking about a stressful experience from the past or avoiding having feelings related to it?
- How much are you avoiding activities or situations because they remind you of a stressful experience?
- How much are you having trouble remembering important parts of a stressful experience?
- How much are you losing interest in activities that you used to enjoy?
- How much are you feeling detached or estranged from others?
- How much are you feeling emotionally numb or being unable to have loving feelings for those close to you?
- How much are you feeling as if your future will somehow be cut short?
- How much are you having trouble falling or staying asleep?
- How much are you feeling irritable or having angry outbursts?
- How much are you having difficulty concentrating?
- How much are you being 'super alert' or watchful or on guard?
- How much are you feeling jumpy or easily startled?

C Ablating the questionnaires

LMIQ utilizes questionnaires from four domains: DSM-inspired clinical conditions, Five Factor Model personality traits, therapeutic aspects, and the original questions from the PHQ-8 and PCL-C assessments. By systematically omitting each domain, we analyze their individual and collective contributions to diagnostic accuracy using a RandomForest pipeline.

The results are presented in Table 4. Evidently, the direct questions are the most important for PTSD prediction, where the contribution of other domains is less significant, and they cannot replace the direct questionnaires when these are removed. In the case of Depression, the other three domains (combined) can lead to reasonable results even in the absence of the direct questionnaires and contribute more significantly to the test performance.

Questionnaire Domain				# Features	Performance on PHQ		Performance on PTSD	
M. Health	Personality	Therapuetic	Direct		Dev MSE	Test MSE	Dev MSE	Test MSE
✓	✗	✗	✓	95	22.62	22.05	134.31	177.15
✗	✗	✓	✓	40	24.60	21.00	142.25	168.62
✗	✓	✗	✓	50	26.08	20.26	143.87	166.62
✗	✗	✗	✓	25	26.32	22.74	136.96	188.26
✓	✓	✓	✓	135	23.87	20.42	144.17	192.93
✓	✓	✗	✗	95	26.17	24.95	164.11	195.17
✓	✗	✗	✗	70	24.88	25.44	167.94	195.81
✓	✓	✓	✗	110	25.85	23.76	173.30	230.40
✓	✗	✓	✗	85	25.34	23.45	177.68	229.44
✗	✓	✗	✗	25	32.13	29.47	204.92	252.67
✗	✗	✓	✗	15	32.68	26.87	238.84	255.28

Table 4: An ablation study regarding the contribution of the various domains.