Analyzing Symptom-based Depression Level Estimation through the Prism of Psychiatric Expertise

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Abstract

The ever-growing number of people suffering from mental distress has motivated significant research initiatives towards automated depression estimation. Despite the multidisciplinary nature of the task, very few of these approaches include medical professionals in their research process, thus ignoring a vital source of domain knowledge. In this paper, we propose to bring the domain experts back into the loop and incorporate their knowledge within the gold-standard DAIC-WOZ dataset. In particular, we define a novel transformer-based architecture and analyse its performance in light of our expert annotations. Overall findings demonstrate a strong correlation between the psychological tendencies of medical professionals and the behavior of the proposed model, which additionally provides new state-of-the-art results.

Keywords: Depression estimation, psychiatrist annotations, external knowledge introduction.

1. Introduction

Mental illness is a serious issue with high social and economic cost, yet significant number of mental illness cases go undetected. Up to half of the patients with psychiatric disorders are not diagnosed as having mental illness by their primary care physicians (Higgins, 1994), a situation made worse due to shortage of medical professionals (Butryn et al., 2017). As a consequence, artificial intelligence in psychiatry has been emerging as a general term that implies the use of computerized techniques and algorithms for the diagnosis, prevention, and treatment of mental illnesses (Fakhoury, 2019). Within clinical settings, semi-structured interviews are the common practice for evaluating a person's mental health. These interviews usually act as inputs for training automated models with self-assessment scores being used as the final ground truth (e.g. Patient Health Questionnaire PHQ-8 for depression estimation). Throughout literature, different strategies have been proposed for the automated estimation of depression. Multimodal models combine inputs from different modalities (Ray et al., 2019; Qureshi et al., 2019). Multitask architectures simultaneously learn related tasks (Qureshi et al., 2019, 2020). Gender-aware models explore the impact of gender on depression estimation (Bailey and Plumbley, 2021; Qureshi et al., 2021). Hierarchical models process transcripts at different granularity levels (Mallol-Ragolta et al., 2019; Xezonaki et al., 2020). Attention models integrate external knowledge from lexicons (Xezonaki et al., 2020). Feature-based strategies compute multimodal characteristics (Dai et al., 2021). Graph-based systems aim to study complex structures within interview transcripts (Hong et al., 2022; Niu et al., 2021). Multiview architectures treat the input trasncripts as a combination of different text views (Agarwal et al., 2022). Symptom-based models treat depression estimation as an extension of the symptom prediction problem (Milintsevich et al., 2023). Domain specific language models are built (Ji et al., 2022) and large language models are prefix-tuned to automate depression level estimation (Lau et al., 2023).

Despite the multidisciplinary nature of the problem, most previous research initiatives have failed to include medical professionals in the learning process, except Yadav et al. (2020), who asked a psychiatrist to label tweets in terms of PHQ-9 symptoms. In this paper, we propose to follow this line of research by providing a clinically-annotated version of the gold-standard DAIC-WOZ dataset[1] (Gratch et al., 2014) to allow the integration of domain expertise in artificial models. We also define a novel transformer-based model and examine ways to utilize psychiatric annotations within its learning

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[1]The Distress Analysis Interview Corpus (DAIC) is the only publicly available resource for interview-based distress analysis.

process. Finally, we analogize the psychological tendencies of medical professionals against the proposed model in an attempt to validate its reliability as a predictive model in clinical settings. Overall results show that our model successfully aligns with medical experts thus being a trustful source of predictions for clinicians in psychiatry. Additionally, the proposed model provides new state-of-the-art results over the DAIC-WOZ test set.

2. Related Work

Different architectures and strategies have been used throughout the literature to build models capable of estimating patients' depression level based on patient-therapist interviews. One promising research area is to leverage inputs from different modalities into one learning modal. Qureshi et al. (2019) explore the possibility of combining audio, visual and textual input features into a single architecture using attention fusion networks. They further show that training the model for regression and classification simultaneously on the same dataset provides improvements in results. Ray et al. (2019) present a similar framework that invokes attention mechanisms at several layers to identify and extract important features from different modalities. The network uses several low-level and mid-level features from audio, visual and textual modalities of the participants' inputs. Another interesting approach aims at combining different tasks that share some common traits thus following the multi-task paradigm. Qureshi et al. (2020) propose to simultaneously learn both depression level estimation and emotion recognition on the basis that depression is a disorder of impaired emotion regulation. They show that this combination provides improvements in performance for the multiclass problem as well as the regression of the PHQ-8 score. Building on the success of hierarchical models for document classification, different studies (Mallol-Ragolta et al., 2019; Xezonaki et al., 2020) propose to encode patient-therapist interviews with hierarchical structures, showing boosts in performance. Xezonaki et al. (2020) further extend their proposal and integrate affective information (emotion, sentiment, valence and psycho-linguistic annotations) from existing lexicons in the form of specific embeddings. Exploring a different research direction, Qureshi et al. (2021) study the impact of gender on depression level estimation and build four different gender-aware models that show steady improvements over gender-agnostic models. In particular, an adversarial multi-task architecture provides best results overall. Along the same line, Bailey and Plumbley (2021) study gender bias from audio features as compared to (Qureshi et al., 2021), who target textual information. They find that deep learning models based on raw audio are more robust to gender bias than ones based on other common hand-crafted features, such as mel-spectrogram. Although most strategies rely on deep learning architectures, a different research direction is proposed by Dai et al. (2021), who build a topic-wise feature vector based on a context-aware analysis over different modalities (audio, video, and text). Niu et al. (2021) use graph structures within their architecture to grasp relational contextual information from audio and text modality. They propose a hierarchical context-aware model to capture and integrate contextual information among relational interview questions at word and question-answer pair levels. Milintsevich et al. (2023) treat binary classification as a symptom profile prediction problem and train a multi-target hierarchical regression model to predict individual depression symptoms from patient-therapist interview transcripts. Agarwal et al. (2022) highlight the importance of retaining discourse structure and define multi-view architectures that divide the input transcript into views based on sentence identities. The two views are processed both independently and co-dependently in order to account for intra-view and inter-view interactions. Building upon the success of language models in understanding textual data, Ji et al. (2022) fine-tune different BERT-based models on mental health data and provide a pre-trained masked language model for generating domain specific text representations. Lau et al. (2023) further account for the lack of large-scale high-quality datasets in mental health domain and propose the use of prefix-tuning as a parameter-efficient way of fine-tuning language models for mental health.

The gathering and assimilation of external knowledge into neural networks have garnered substantial attention in research endeavors in the domain of mental health. For the former case, Arseniev-Koehler et al. (2018) asked crowd workers to read excerpts of de-identified interview data from the DAIC-WOZ and rate how likely they thought a speaker had depression based on the transcribed utterances. Similarly, Yadav et al. (2020) work with twitter data and employ four native English speakers from multiple disciplines to independently annotate tweets into the 9 categories of PHQ-9. For the latter case, various strategies have been proposed for the integration of external knowledge into neural network training. Outside the mental health domain, Soares et al. (2019) and Boualili et al. (2020) use special tokens to highlight information directly within the input text and rely on fine-tuning pre-trained language models to understand the importance of marked text. Deshpande and Narasimhan (2020), (Stacey et al., 2022) and Wang et al. (2022) introduce additional loss terms during training as a means to guide the attention mechanism within the

Depression severity	Data split		
	Train	Val.	Test
No symptoms $[0..4]$	47	17	22
Mild $[5..9]$	29	6	11
Non-depressed Total	76	23	33
Moderate $[10..14]$	20	5	5
Moderately severe $[15..19]$	7	6	7
Severe $[20..24]$	4	1	2
Depressed Total	31	12	14
Total	107	35	47

Table 1: Number of interviews for each depressive class severity in the DAIC-WOZ dataset, distributed by train, validation and test sets.

neural networks towards the desired distributions. Within the mental health domain, only Xezonaki et al. (2020) generate custom context vectors using information from different lexicons, which are concatenated to word level representations.

3. Dataset and Psychiatric Annotations

3.1. Dataset

The Distress Analysis Interview Corpus (DAIC) is a multimodal corpus of semi-structured clinical interviews designed to simulate standard protocols for identifying people at risk of depression. Within our research, we focus on the textual input from the publicly available Wizard-of-Oz part of the corpus (DAIC-WOZ), which contains 189 interviews, where patients interact with an animated virtual agent controlled by a human therapist from a different room. Each session ranges from 7 to 33 minutes with an average time of 16 minutes. The dataset contains valuations for eight specific symptoms that are part of the PHQ-8 questionnaire: loss of interest, feeling of depression, sleeping habits, tiredness, loss of appetite, feeling of failure, lack of concentration and lack of movement. Table 1 shows the data splits between train, development and test sets, along with the class imbalance within DAIC-WOZ dataset.

3.2. Psychiatrist Annotations

In our attempt to reintroduce domain expertise into the learning process, we carried out the clinical annotation of the DAIC-WOZ dataset. In contrast to previous works that use crowd workers (Arseniev-Koehler et al., 2018) or native English speakers (Yadav et al., 2020) as annotators, we select mental health professionals for the annotation process. In particular, three psychiatrists from public hospitals were employed to undertake two major tasks: (1) span-based annotation of the transcripts and (2) PHQ-8 scoring based on interview transcripts.

Span-based annotation: This task consists of highlighting information within transcripts that influences a psychiatrist's decision during an interview. Since it is a subjective task that lacks a definitive right or wrong answer, a common consensus on importance of various utterances within the transcripts does not exist. Even within the field of medicine, professionals do not universally agree on the significance of various pieces of information, and subtle differences in opinion exist between psychiatrists based on their individual knowledge and experience. As such, after various meetings and discussions with the psychiatrists, it was agreed that the medical annotators should have complete freedom to annotate the transcripts without any constraints in order to capture their true judgement. As a consequence, we forgo defining detailed annotation protocols and rely on the annotators judgment as experts in the field for reliability of their annotations. However, they were encouraged not only to identify information that suggests the presence of depression, but also to pinpoint clues that indicate its absence. Furthermore, the inherent lack of consensus within the task eliminates the need for inter-annotator agreements. In case multiple annotators are assigned per transcript, a simple union of annotated spans would be used to capture knowledge from all assigned annotators. Unfortunately, at this stage of our research, only one annotator per transcript could be assigned due to the workload experienced by the annotators, particularly due to the radical increase of mental care demand after the covid pandemic coupled with the shortage of mental health professionals. The current annotation process lasted nearly 5 months and we anticipate this time frame to scale linearly with the increase in number of annotators per transcript.

For the annotation purpose, we designed an online tool based on the doccano[2] project which was hosted on servers from the herokou platform[3] enabling the entire annotation process to take place remotely for the convenience of the psychiatrists. The tool was designed to allow the psychiatrists to annotate any span of text (word, phrase, sentence, text) within the transcript and assign a label of importance to each span: highly important, important (default) or minimally important. Upon analysis, it was found that these labels did not provide any information since more than 99% of the spans were marked with the default label (important), and were therefore not used in any further analysis. The annotation process gave rise to an average of 36.12 annotations per transcript (35.18 for the non-depressed class and 38.28 for the depressed class) with a mean length of 7.45 words (7.74 for the non-depressed class and 7.17 for the

[2]https://github.com/doccano/doccano
[3]https://www.heroku.com/

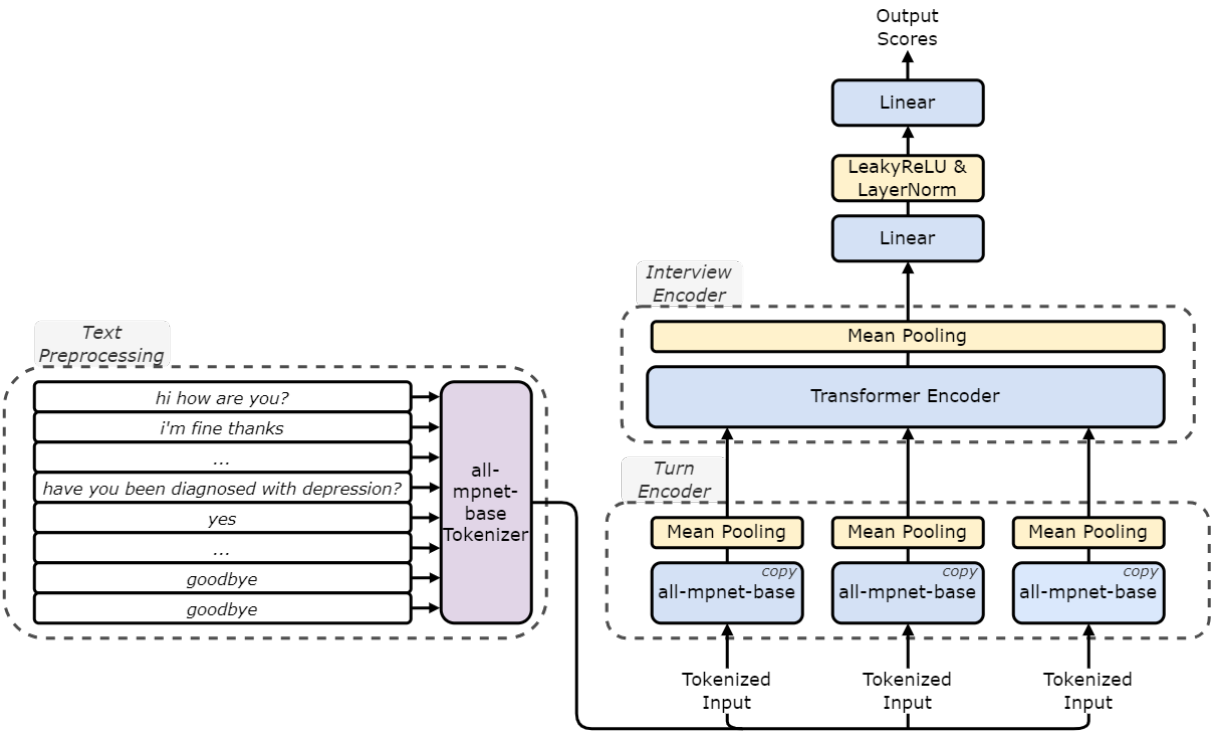


Figure 1: Hierarchical neural architecture for symptom-based prediction.

Span Level	Non-Depressed	Depressed
Word	467 (3.53)	227 (3.98)
Phrase	4101 (31.06)	1913 (33.56)
Sentence	0	0
Multi-sentences	77 (0.58)	42 (0.73)
Total	4645 (35.18)	2182 (38.28)

Table 2: Number of annotations for different levels of annotation spans. Figures in bracket indicate the average number of annotations per transcript.

depressed class). The distribution of the annotations by patient class and span level is given in Table 2. Interestingly, complete sentences were not annotated by any of the psychiatrists, who mostly followed a ngram-based strategy, with a small number of annotations focusing on multiple sentences. Furthermore, none of the psychiatrists highlighted questions within the dataset with all the annotations contained within patient responses.

PHQ-8 scoring: This task involves completing the self-assessment PHQ-8 questionnaire on behalf of each patient only based on their interview transcripts. Although the PHQ-8 screening tool is widely used as a measure of depression and has been found to be precise (Shin et al., 2019), it relies on the subjective assessment of the patient about his/her condition outside the context of the interview. As such, an interview transcript might not contain enough information to accurately express the intensity of individual symptoms. Furthermore, since the interviews are conducted with the aim of depression estimation and not specifically for fulfilling the PHQ-8 questionnaire, information on some symptoms might be missing altogether within individual transcripts depending on the questions asked during the interview. In order to verify these propositions, we asked the clinicians to fulfill the PHQ-8 questionnaires on behalf of each patient based on their understanding of the given transcripts. This task consists of evaluating each of the 8 symptoms within the PHQ-8 questionnaire on a Likert scale ranging from 0 to 3. The statistics about this task, illustrated in Table 3, show that 5 out of 8 symptoms (i.e. loss of interest, feeling of depression, sleeping habits, feeling of tiredness and feeling of failure) are steadily mentioned in most transcripts, while 3 of them (i.e. loss of appetite, lack of concentration and lack of movement) could not be measured reliably by the psychiatrists. This confirms our claims regarding the lack of symptom level information within individual interviews. This annotation task also acts as a human expert performance baseline, that defines an achievable learning goal for correctly inferring PHQ-8 scores for each symptom based on information present within the transcripts.

Symptoms	No interest	Depressed	Sleep	Tired	Appetite	Failure	Concentration	Movement
# annotations	178	188	179	160	47	176	48	10

Table 3: Nb. of psychiatrist scorings for each PHQ-8 symptom over the 189 interviews of the DAIC-WOZ.

ELLIE: *how close are you to your family*
PARTICIPANT: *@@ very close @@ even though i don't live with them @@ i try to see them as much as possible @@*
ELLIE: *mhm*
ELLIE: *how do you like your living situation*
PARTICIPANT: *uh it's ok*

Figure 2: Example of annotation marking.

4. Model and Mark-up Strategy

4.1. Neural Network Architecture

To learn the 8 symptom values of the PHQ-8, we design the transformer-based hierarchical model illustrated in Figure 1. The architecture is based on the model defined by Milintsevich et al. (2023), which has been updated to have access to sentence-level attention and take advantage of recent sentence representation models. In particular, the architecture has undergone two significant alterations compared to the definition in §3.2 of (Milintsevich et al., 2023): (1) the BiLSTM cells are replaced by a transformer-based encoder at the interview level (interview encoder), and (2) the pre-trained turn encoder is based on the all-mpnet-base model[4] in place of *S-RoBERTa*[5], both using a contrastive learning objective (Reimers and Gurevych, 2019). In particular, the model consists of two encoders: the turn encoder that encodes each sentence and the interview encoder that encodes sentence level representations into an interview level embedding. The interview level embedding is then passed through a feed-forward network that maps it to a prediction vector $m = [m_1, m_2, ..., m_8]$, where each predicted label $m_k \in [0, 3]$ represents a symptom score for the corresponding question in the PHQ-8 questionnaire. The interview encoder contains 4 layers containing 12 attention heads each with an intermediate size of 1536 and an hidden size of 768. This model acts as the base architecture for the different experiments and model configurations explored within our research and is referred to as the **Baseline model**.

[4]https://huggingface.co/sentence-transformers/all-mpnet-base-v2

[5]https://huggingface.co/sentence-transformers/all-distilroberta-v1

Model	MAE	
	Dev.	Test
SOTA		
ASP MT. DLC+DLR+EIR (Qureshi et al., 2020)		3.69
HCAG-T (Niu et al., 2021)	3.73	-
SGNN (Hong et al., 2022)	3.76	-
Symptom prediction (Milintsevich et al., 2023)	3.61	3.78
Dual encoder (warm start) (Lau et al., 2023)	2.76	3.80
Our Configurations		
Baseline model	4.08	**3.52**
Marked-up model	3.49	3.60

Table 4: Comparison of overall model performance against current state-of-the-art results. The results are averaged over 5 random initializations.

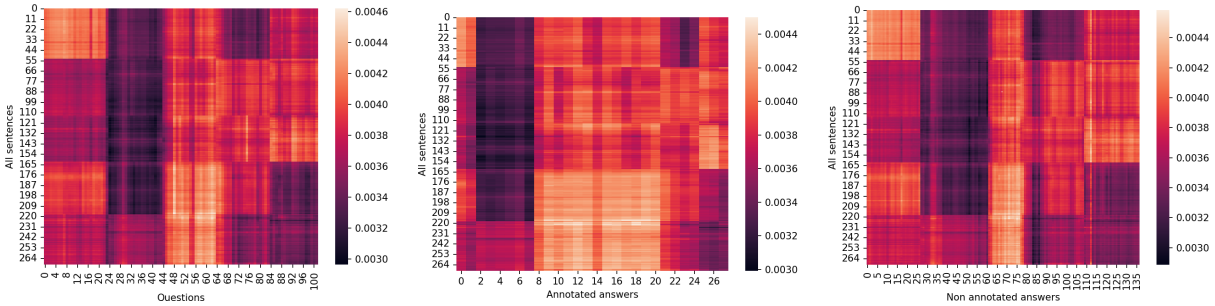
4.2. External Knowledge Integration

In our effort to reintroduce domain expertise into depression estimation task, we incorporate psychiatrist annotations into the learning process of our neural network model. We align our work with the research approach taken by Soares et al. (2019) and Boualili et al. (2020), and introduce special markers into the input text in order to directly highlight clinical annotations within the transcripts. The underlying idea is that explicitly marking spans in the input text may allow the model to carefully identify the annotations and make a more informed prediction. Consequently, all annotations provided by the psychiatrists are encompassed in between the @@ markers within the transcripts, giving rise to a marked-up corpus (example in figure 2). We use the Baseline architecture defined earlier and fine-tune it using the marked-up corpus. Specifically, the pre-trained *all-mpnet-base* model is fine-tuned by unfreezing only the final layer. The resulting model is referred to as the **Marked-up model**.

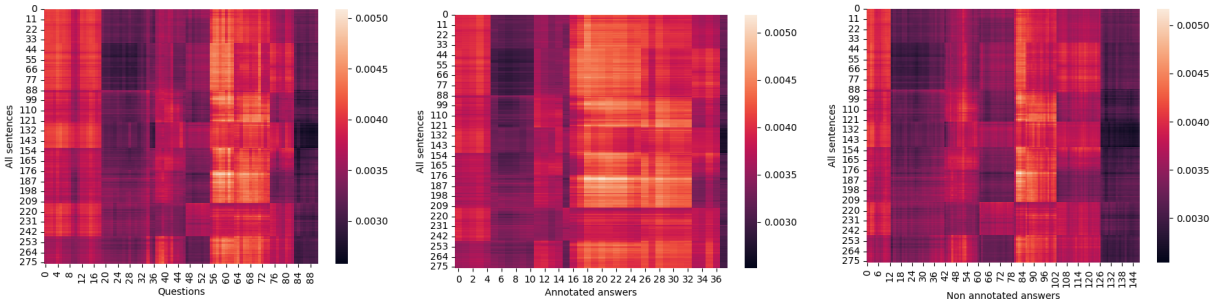
5. Overall Results

Table 4 provides overall results for the various model configurations considered in our experiments and puts them into perspective by comparison against current state-of-the-art results. Our baseline model provides new state-of-the-art performance for Mean Absolute Error (MAE) metric on the test set of the DAIC-WOZ on an average over 5 runs. It is interesting to notice that the marked-up model does not improve over the baseline model despite containing extra information, although it does out-perform all previous research initiatives. This issue is further discussed in details in §7.

Ablation study: We conduct an ablation study to analyse the amount of information contained within



(a) Patient id: 335 (PHQ-8 = 12). Average attention scores (Q, A, N) = (1.994e-05, 2.030e-05, 1.966e-05)



(b) Patient id: 307 (PHQ-8 = 0). Average attention scores (Q, A, N) = (1.955e-05, 2.044e-05, 1.905e-05)

Figure 3: Heat maps of sentence level attention scores from the Baseline model for two different patients.

Ablation	MAE on Test set
Baseline model	**3.52**
Baseline$_{\text{ann.}}$ inference	4.02
Baseline$_{\text{non-ann.}}$ inference	3.84

Table 5: Ablation study with baseline model for exclusively non-annotated and annotated sentences.

the clinical annotations. Given the complete set of information required for estimating depression, we seek to understand the role played by our clinical annotations within this set. For that purpose, we define two new input configurations and use them with the trained baseline model at inference stage to generate new predictions over the modified inputs. The two versions in this input ablation study are defined as follows:

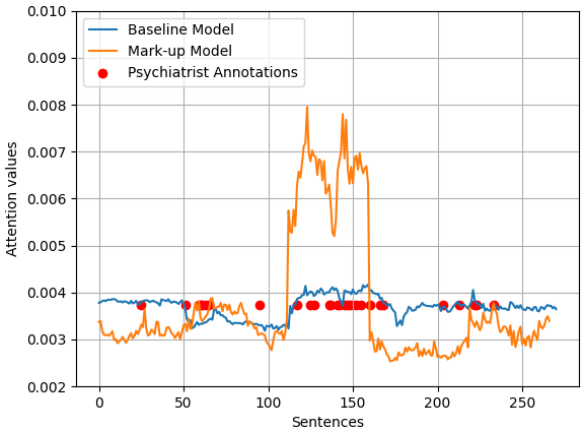
Baseline$_{ann}$ inference: only question-answer pairs with at least one annotation are kept within the input transcripts.

Baseline$_{non-ann}$ inference: only question-answer pairs without any annotation are retained within the input transcripts.

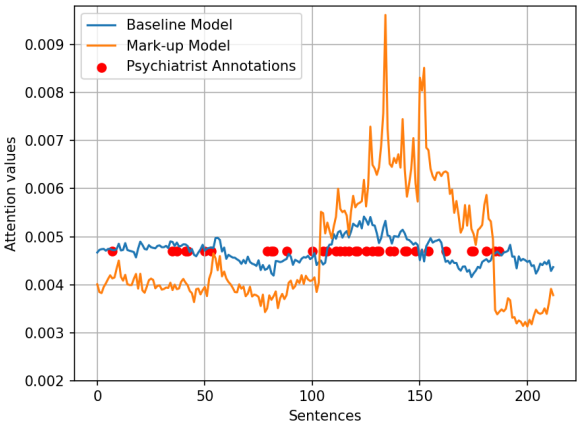
Results of the ablation study are shown in table 5. We see a significant drop in performance on removing annotated question-answer pairs from the input transcripts, highlighting the validity of the psychiatrists' annotations. Surprisingly, we also see a drop in performance when only annotated questions-answer pairs are used as inputs. This behaviour can be attributed to the fact that in this case the number of sentences within the interviews is severely reduced and as such the coherence of the discourse is undermined, affecting the performance of the automated models.

6. Attention and Annotated Spans

Psychiatrist annotations highlight text spans that hold relevance for depression estimation as per clinicians' knowledge and medical guidelines. Given their importance from the medical point of view, we propose to verify whether automated models attend to the same annotated text spans or look for information that complements clinical knowledge. Psychiatrist annotations are analysed against sentence-level attention scores from the model, sentence being the atomic textual element for this analysis. In particular, we focus on 3 different sentence types: questions (Q), non-annotated turns (N) that contains answers without any annotations and clinically-annotated turns (A) that contain patient responses with at least one annotation. Thus, each attention head $H^{s\times s}$ of the interview encoder is converted into three attention sub-matrices $H^{s\times q}$, $H^{s\times n}$ and $H^{s\times a}$, where s is the number of sentences in a given transcript, q the number of questions, a the number of annotated turns and n the number of non-annotated turns, such that $s = q + n + a$. For each interview, we average the sentence-level attention scores for Q, N and A sentence types for all attention heads contained in the interview encoder as defined in equation 1, where h and l stand for the number of heads and



(a) Patient id 335, PHQ-8 score 12



(b) Patient id 307, PHQ-8 score 0

Figure 4: Attention scores for the baseline and marked-up models plotted against clinical annotations.

Class	Metric	Q	N	A
Non-depressed	min.	12.84	12.93	13.60
	max.	137.50	136.76	135.35
	med.	42.03	42.10	**42.25**
	avg.	30.85	31.01	**31.25**
Depressed	min.	15.29	15.02	15.37
	max.	103.88	102.83	110.89
	med.	37.96	38.50	**38.82**
	avg.	12.18	12.18	**12.29**

Table 6: Sentence-level attention scores calculated over the DAIC-WOZ dataset for **Q**uestions, **N**on-annotated and **A**nnotated turns. Values are with precision of 10^{-4}. Med. and avg. stand for median and arithmetic mean.

layers respectively.

$$\overline{X} = \frac{1}{l.h} \sum_{l,h} \frac{1}{i.j} \sum_{i,j} H_{i,j}^{s \times x}, \forall x \in \{q, n, a\} \quad (1)$$

Finally, we average these values over the 189 interviews of the DAIC-WOZ to get the overall picture. Results with the baseline model are given in Table 6 and show that the transformer-based model focuses more on clinically-annotated spans compared to other parts of the transcripts, independently of the patient class. This provides first evidence that the baseline model targets clinically-motivated spans for its decision process without the introduction of any external knowledge or use of specific architectures tuned towards guiding the attention values.

To complement this analysis, figure 3 plots three attention heatmaps $\overline{Q}$, $\overline{A}$ and $\overline{N}$ with brighter regions representing higher attention scores. Plots are provided for a depressed patient as well as a non-depressed patient[6]. This illustration exemplifies overall results and shows that although model attention is distributed over all three categories, clinically-annotated turns receive higher average attention as compared to non-annotated turns and questions. Finally, figure 4 illustrates the attention scores in perspective of the psychiatrists' annotations for the same patients. Following the blue line corresponding to the baseline model, we observe an increase in attention scores in the vicinity of psychiatrist annotations, while the opposite is true in the absence of annotations. These plots represent a general trend observed throughout the dataset with some exceptions.

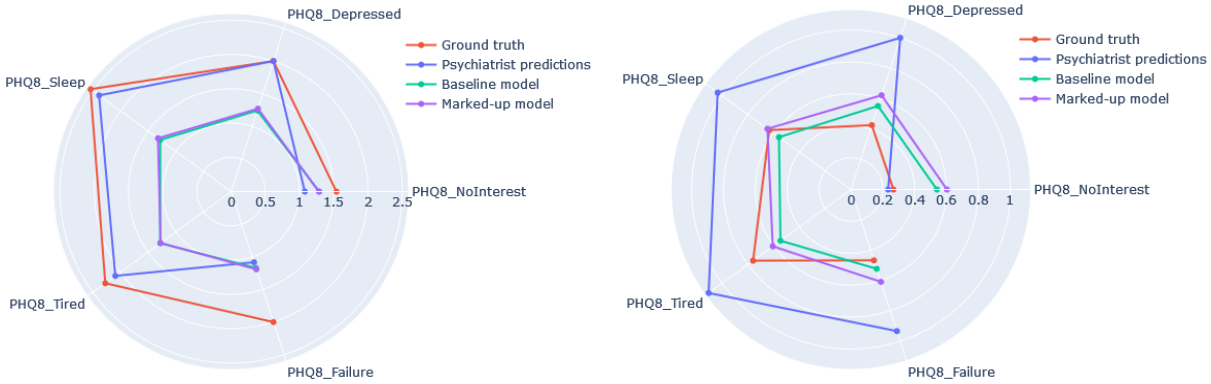
[6]More examples including exceptions will be added to the appendix in the final version upon acceptance.

7. Performance Analysis against Knowledge Introduction

Although the baseline model attends to parts of the interviews that psychiatrists find relevant, we explore the impact of the introduction of clinician expertise directly in the learning process and analyse the performance of the marked-up model. Overall results are illustrated in Table 7 and do not evidence gains in performance resulting from the knowledge added by the psychiatrist annotations. Indeed, the baseline model outperforms the marked-up model 5 times out of 8 for both the depressed and non-depressed classes. This confirms our previous findings from section §6, showing that the baseline architecture already attends to clinically-annotated sentences, thus reducing the impact of the marked-up strategy. Figure 4 compares both baseline and marked-up models, with plots showing similar behaviours of attending to the annotated sentences although with different amplitude. In particular, the marked-up model tends to pay high attention to the middle of the transcripts thus failing to highlight important information from other regions. This is not the case for the baseline model, which has more evenly distributed attention values, while still being consistent with psychiatrist annotations.

Symptoms	Psychiatrist Pred.		Baseline model		Marked-up model	
	Depr.	Non-Depr.	Depr.	Non-Depr.	Depr.	Non-Depr.
Loss of interest	0.615	0.366	**0.611**	**0.431**	0.699	0.485
Feeling of depression	0.571	0.696	**0.884**	**0.443**	0.939	0.465
Sleeping habits	0.615	0.533	0.761	**0.691**	**0.651**	0.808
Tiredness	0.727	0.689	**0.797**	0.711	0.812	**0.666**
Feeling of failure	1.083	0.800	0.820	**0.543**	**0.786**	0.573
Lack of concentration	-	-	**1.332**	0.521	1.361	**0.475**
Loss of appetite	-	-	**0.932**	0.745	1.037	**0.628**
Lack of movement	-	-	1.008	**0.105**	**0.964**	0.125

Table 7: MAE calculated against patients self-assessments scores by symptoms over the DAIC-WOZ test set. Results are averaged over 5 runs for the automated models. Psychiatrist prediction evidences the difference between the patients' assessments and the psychiatrists' ones.



(a) Depressed class

(b) Non-Depressed class

Figure 5: Radar plots showing symptom-wise average scores for the different automated models, the patient self-assessments and the psychiatrists' ratings over the test set of the DAIC-WOZ. Note that only 5 symptoms are illustrated, which refer to the ones that psychiatrists could reliably annotate.

In order to put prediction results into perspective, we calculate the Mean Absolute Error (MAE) between the psychiatrists PHQ-8 scores and patients' self-assessments. Results in Table 7 show that psychiatrist predictions outperform automated models in most cases, albeit by a small margin for most of the symptoms (feeling of failure being an exception where baseline model performs better). Further analysis of psychiatrist scoring confirms findings from the medical domain (Domken et al., 1994), showing that clinicians tend to under-evaluate the PHQ-8 scores for the depressed class, while over-evaluating those for non-depressed class. Intriguingly, we observe the same behaviour for the automated models as illustrated in Table 8. The figures show that both the baseline model and the marked-up model exhibit the same behavior as psychiatrists, which further strengthens our claim of shared psychological tendencies between our proposed model and psychiatrists. As expected, the number of transcripts misdiagnosed by the automated models far exceeds those misdiagnosed by psychiatrists. This is due to the fact that models generate floating point predictions whereas psychiatrists' predictions are based on a Likert scale ranging from 0 to 3.

Symptoms	Depr.		Non-Depr.	
	Over	Under	Over	Under
Psychiatrist Prediction				
Loss of Interest	1	5	3	6
Feeling of depression	3	3	16	2
Sleeping habits	3	3	10	2
Tiredness	2	3	12	5
Feeling of failure	1	8	13	5
Baseline Model				
Loss of Interest	4	9	24	5
Feeling of depression	2	12	24	9
Sleeping habits	1	12	19	10
Tiredness	1	10	14	14
Feeling of failure	1	11	20	9
Marked-up model				
Loss of Interest	4	9	27	3
Feeling of depression	3	11	26	7
Sleeping habits	1	12	19	11
Tiredness	1	10	15	14
Feeling of failure	2	10	23	7

Table 8: Number of over- and under-evaluated transcripts in the test set for the baseline model, the marked-up model and the psychiatrists' scorings.

In order to further analyse the behaviour of over and under evaluation, we plot the symptom-wise average scores for the different automated models, the patient self-assessments and the psychiatrists' ratings in figure 5. The illustrations show high correlation between the results from the two automated

models. Both baseline and marked-up models generate the same average scores for the depressed class while for the non-depressed class the values are very close. This confirms that the introduction of annotations into the learning process through the markup strategy does not provide significant performance gain. These plot also support the claims of over and under evaluation of PHQ-8 scores, and showcase a similar pattern as seen in table 8.

8. Conclusion

In this paper, we examine automated depression estimation through the prism of psychiatric expertise and compare the behaviour of automated models against clinical annotators. The analysis of sentence-level attention scores shows that the baseline model learns to analyse the transcripts in ways similar to trained psychiatrists despite the lack of medical knowledge in the training process. Our analysis further establishes a strong correlation between the psychological tendencies of our automated model and medical professionals, thus validating its role as a credible source of predictions for clinicians in psychiatry. Additionally, the proposed architecture provides new state-of-the-art results over the DAIC-WOZ test set. The source code and the clinically-annotated DAIC-WOZ dataset will be publicly released upon acceptance.

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