

Sólo Escúchame: Spanish Emotional Accompaniment Chatbot

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Abstract. According to the World Health Organization (WHO), suicide was the fourth leading cause of death in the world for individuals aged 15 to 29 in 2019. Given the rapid increase in mental health issues, providing psychological support is both crucial and urgent. In this paper: (1) we propose Sólo Escúchame, the first open-source Spanish emotional assistance chatbot, based on LLaMA-2-7b-Chat. (2) We introduced the HEAR (Hispanic Emotional Accompaniment Responses) dataset, compiled from multiple English sources translated into Spanish, as well as generic data generated using ChatGPT-3.5-Turbo. Finally, (3) we propose an evaluation metric based on two semi-automatic assessment methods. Our system outperforms a range of state-of-the-art models in providing psychological assistance in Spanish. Our models and datasets are publicly available to facilitate reproducibility.

Keywords: Emotional assistant, spanish chatbot, hispanic emotional accompaniment responses.

1 Introduction

Research on conversational chatbots for mental health has grown significantly in recent years [13, 18, 36]. These chatbots offer a promising avenue to address the rising mental health concerns, particularly in the wake of the COVID-19 pandemic [9, 12]. The pandemic's drastic impact on routines [28], including the rise of remote work and home schooling, has been linked to increased rates of anxiety, depression, and even suicide among individuals aged 15 to 29 globally [7, 44, 23, 27, 32]. However, existing resources to combat these issues are often limited or closed-source, hindering their effectiveness [39]. Despite the impressive capabilities of current Language Models (LLMs) such as Chinchilla [16], PaLM [11], LLaMA [42, 43], ChatGPT [31, 1], BARD [25], Mistral [19], and Gemini [3], it is noteworthy to mention that they have not been explicitly designed or optimized for tasks related to emotional support.

Table 1. Some samples of emotion recognition dataset. **Note that the samples in our dataset are in Spanish.**

Text	Label
Every negative experience is an opportunity to grow and learn.	Optimism
I found a recipe that will make cooking chicken noodle soup easy for a class I am teaching	Admiration
It bothers me that you always behave aggressively and cannot have a civilized conversation	Anger

Furthermore, the predominant focus of these models on the English language presents a significant barrier to non-English speakers, limiting their accessibility and effectiveness in providing emotional support to individuals speaking different languages. To bridge these gaps, we propose “Sólo Escúchame (Just Listen to Me)”, an open-source Spanish emotional assistance language model. Inspired by similar psychological support chatbots [29, 38], Sólo Escúchame aims to provide accessible support, particularly for those who may not have immediate access to a professional psychologist due to personal or financial limitations. It is important to emphasize that Sólo Escúchame serves as a supplementary tool or a resource for psychologists, and does not replace professional mental healthcare. Our contributions include:

- We introduce HEAR (Hispanic Emotional Accompaniment Responses) dataset, specialized in emotional accompaniment. Our dataset is publicly available to facilitate future research.
- We propose “Sólo Escúchame”, a chatbot trained on our HEAR dataset and runs efficiently on CPUs. To the best of our knowledge, it is the first open-source Spanish chatbot designed for psychological assistance.
- We designed efficient prompts for (1) generating generic data using GPT-3.5-Turbo, and (2) training the Sólo Escúchame model through instruction-following demonstrations.
- We introduce semi-manual evaluation metrics for fair model comparison.

2 Related Work

Psychological Support Chatbots. Due to the COVID-19 pandemic, numerous chatbot solutions have emerged to provide psychological support. Chatbots have proven effective in reducing symptoms of depression and anxiety [21, 26]. These chatbots are often available as mobile applications, such as Woebot [13], Wysa [18], Tess [36] and Youper [15]. Woebot Health offers an enterprise solution that improves access to mental health support by enhancing emotional regulation skills and aiding in mood monitoring and management. Wysa AI Coach is an AI-driven service that provides emotionally intelligent responses to users’ emotions, assisting individuals with low mood, stress, or anxiety. Tess, another mental health chatbot, is created to help individuals dealing with panic attacks or those who need to discuss their thoughts before sleeping.

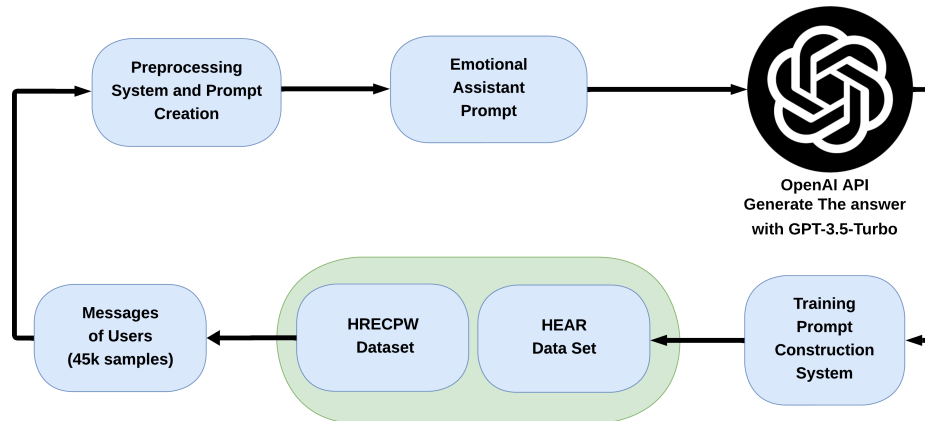


Fig. 1. Overview of the procedure to generate generic data using GPT-3.5.

At last, Youper chatbot app utilizes cognitive behavioral therapy (CBT) and positive psychology to aid users in managing anxiety and depression. It is worth noting that earlier emotional chatbots for healthcare were primarily designed for English speakers, as most available datasets in this field are in English [22, 24, 35, 41]. Thus, separate chatbots were developed for the Spanish-speaking community, although these remain very few. Among these, Perla [5] is a conversational agent specialized in conducting interviews based on the Patient Health Questionnaire-9 (PHQ-9).

Similarly, [47] developed a sentiment analysis chatbot designed to detect potential signs of mental health issues, intended for high school students typically aged 14 to 18 years old. Unfortunately, none of the prior Spanish language chatbots are open source. Fortunately, recent years have seen the emergence of open-source models [19, 43, ?], enabling free user customization and broadening access to advanced tools for mental health support. Moreover, these models have facilitated the development of more inclusive and versatile chatbots tailored to diverse linguistic and cultural needs. Next, we showcase some of the most powerful chatbots from both open-source and proprietary models, highlighting the enhancements achieved through the instruction-following demonstrations approach.

Large Language Models (LLMs). The development of chatbots reached a significant breakthrough with the introduction of the instruct-following demonstration approach [33]. This method aligns language models (LMs) with user intent, enabling chatbots to understand and execute specific instructions or commands from users. The significance of this approach became widely recognized with the release of ChatGPT-3.5 in 2022 [31]. ChatGPT-3.5, with its 175 billion parameters, marked the beginning of a new era in chatbot research.

This era has seen the emergence of powerful and close-source models such as BARD [25], Gemini-Ultra [3] (1.56 trillion parameters), Claude [4], and ChatGPT-4 [1] (1.7 trillion parameters). However, the large number of parameters in these models often requires substantial computational resources, making them difficult for small businesses and individuals to access. Consequently, some research has shifted its focus from solely generating accurate responses to developing smaller, more accessible

Table 2. Samples of HEAR dataset. **Note that the samples in our dataset are in Spanish.**

Input Text	Generic response
I was pleasantly surprised when I received a thank-you letter for my volunteer work.	What a beautiful surprise to receive a thank-you letter for your volunteer work! That shows how valuable you are to others. Tell me more about that letter; what did it say?
It irritates me when people do not respect my privacy on social media.	I'm sorry that some people do not respect your privacy on social media. Privacy is a fundamental right. Would you like to discuss more about your concerns and how you would like to protect your privacy online?

models [16], as well as creating open-source models [19, 41, 43]. Notable examples include LLaMA-1-2 [42, 43] (up to 70 billion parameters); Vicuna [41], an open-source chatbot with 13 billion parameters, fine-tuned from LLaMA; Mistral [19], based on a transformer architecture [45] with 7 billion parameters; and Mixtral8x7B [20], a sparse mixture of experts model. For our work, we have selected the LLaMA-2-7b-Chat model. This choice is based on two critical factors: it is an open-source model and, at the time of our experiments, it represents the state-of-the-art in its category.

3 Sólo Escúchame Language Model

3.1 Dataset

This is one of our main contributions and it is made of two stages. The first one is to create an Emotion Recognition Dataset where each sample $X = \{x, y\}$ contains a text x and a class $y \in \{\text{affection, happiness, admiration, anger, sadness, optimism, hate, surprise, fear, calm, disgust}\}$. The second stage takes the first dataset and creates the final dataset named HEAR, where each sample contains a text, its class, and a generic text generated by GPT-3.5-Turbo. We detail the two stages below:

Stage 1 : Create the Hispanic Emotion Recognition Based on Plutchik’s Wheel (HRECPW) Dataset. To build our Spanish dataset for emotion recognition³, we leveraged diverse English sources, including TweetEval [8], DailyDialog [24], HappyDB [6], and responses from 72 surveys we conducted with various individuals to capture a range of emotional examples and contexts. First, we preprocessed the dataset by removing all personal information and web links. At this stage, the dataset contained 13 classes of emotions: affection, achievement, joy, optimism, calm, anger, disgust, fear, sadness, surprise, love, hate and offensive. Second, we translated the datasets from English to Spanish and re-annotated the data using Plutchik’s Wheel of Emotions [34].

³huggingface.co/datasets/BrunoGR/HRECPW-Hispanic_Responses_for_Emotional_Classification_based_on_Plutchik_Wheel

Table 3. The proposed training prompt.

Below is an instruction that describes a task, paired with an input that provides further context. ### instruction: You are an emotional assistant, respond in Spanish in a respectful and appropriate way to the user’s emotional situation. If the user appears sad or upset, the assistant should respond empathetically and offer words of encouragement. ### input: input_text ### response: response_text /s

This led to merging some classes (love into affection, offensive into anger) and renaming others (achievement to admiration) for better alignment with the expressed emotions, resulting in a final set of 11 classes: 8 principal emotions (admiration, anger, disgust, fear, hate, joy, sadness, surprise) and 3 compound emotions (calm, optimism, affection). Refer to Table 1 for examples of dataset samples. The emotion recognition dataset was notably imbalanced, with a significant surplus of the affection class, which contained 32,837 samples.

In contrast, the disgust class had the fewest samples, totaling only 303. To address this issue, we employed under-sampling for the over-represented classes by randomly eliminating samples. This process reduced each class to a uniform size of 11,000 samples. This number per class was acceptable size to this dataset, and it was permissible to generate between 2,000 and 10,700 samples to over-sampling the less-represented classes.

At the end of this stage, we generated 48,500 generic samples for less-represented emotion sets, using the GPT-3.5-Turbo model [31]. Consequently, each of the 11 classes contains 11,000 samples in the training set, 200 samples in the validation set, and 120 samples in the test set. In total, this dataset contains 121,000 examples for training, 2,200 for validation and 1,320 for testing.

Stage 2: Create the Hispanic Emotional Accompaniment Responses (HEAR) Dataset. After balancing the dataset for emotion recognition across the 11 classes, we randomly extracted 3,771 samples for each emotion class from the training set, and kept the entire validation and test sets. Therefore, the final dataset comprises 41,481 training, 2,200 validation, and 1,320 test samples, respectively. We named this dataset HEAR⁴, which stands for Hispanic Emotional Accompaniment Responses dataset. We built it by generating generic responses to each user’s symptoms using GPT-3.5-Turbo, as illustrated in Fig. 1. Table 2 displays samples from the dataset. This finalized dataset was used to train the model for generating empathetic and suitable responses in emotionally supportive conversations.

3.2 Model

As previously stated, *Sólo Escúchame*^{5 6} is a fine-tuned version of LLaMA-2-7b-Chat, a model proposed by META [43]. One of the main novelties of this LLM is the improvement of the context length using Rotary Positional Embedding (RoPE) [40], and the use of Grouped-Query Attention (GQA) [2].

⁴huggingface.co/datasets/BrunoGR/HEAR-Hispanic_Emotional_Accompaniment_Responses

⁵github.com/BrunoGilRamirez/Just_HEAR_ME

⁶huggingface.co/BrunoGR/Just_HEAR.Me

Table 4. Final scores for psychological accompaniment evaluation in language models (LMs).

Model	Active Listening	Socratic Method
GPT2-124M [46]	32.57	30.68
Mixtral 8x7b [20]	84.52	61.60
LLaMA-2-7b-Chat [43]	87.42	66.45
GPT-3.5 [31]	87.62	67.84
Sólo Escúchame (ours)	90.67	77.12

We chose this open-source lightweight model for its balanced performance and speed. It is important for our model to run on a CPU to ensure accessibility to a wider audience. Therefore, we include quantized versions of our model with 2, 4, and 8 bits. To perform quantization, we used scripts provided by the llama.cpp project [14].

Fine-Tuning. We fine-tuned LLaMA-2-7b-Chat on our HEAR dataset using LoRA (Low Rank Adaptation)⁷[17]. LoRA consists in freezing the pre-trained Transformers weights, and only training small rank decomposition matrices instead, thus reducing considerably the total number of trainable parameters for downstream tasks.

We utilized Hugging Face’s Transformers library to train our model. Through extensive experimentation, we determined that the optimal parameters for our task are batch size = 15, micro batch size = 5, warmup steps = 300, learning rate = $5e^{-5}$. For the LoRA technique, we used the following key parameter values: $R = 64$, alpha = 128, dropout = 0.1.

Prompting. We follow the methodology introduced by [33] and the Alpaca model [41] to fine-tune our model using instruction-following demonstrations. Table 3 shows the prompt we propose to train the model.

4 Experiments

4.1 Evaluation Protocol

To evaluate the performance of our model Sólo Escúchame, we used the entire test set of the HEAR dataset, which contains 1,320 samples. The evaluation follows two sets of criteria: the active listening technique [37] and the Socratic method [30]. We selected these criteria because they are widely used by psychologists specializing in cognitive behavioral therapy [10]. Our chatbot’s goal is to make users feel heard and understood, and both methodologies include measures for these outcomes⁸.

- **Active Listening.** Defined by Carl Rogers [37], it involves attentive listening to the full conversation, considering verbal and non-verbal cues, and expressing personal feelings. Some aspects, like non-verbal signs, are not evaluable in language models. Therefore, our assessment focuses on the following specific points for our model and other LMs:

⁷huggingface.co/BrunoGR/JUST_HEAR_ME-PEFT_Adapter

⁸Note that in the next two subsections, “→” means “answers the question”

Table 5. Active listening results. Best in bold.

	GPT-3.5	LLaMA-2-7b-Chat	Mixtral8x7b	GPT-2-124M	Solo Escúchame
Contextual Attention	1256	1260	1277	462	1240
Formulation of Clarifying Questions	776	718	531	199	913
Go Deeper into Conversation	1215	1240	1185	470	1254
Absence of Judgment or Criticism	1292	1278	1299	517	1300
Demonstration of Empathy	1246	1274	1287	502	1278

Table 6. Socratic method results. Best in bold.

	GPT-3.5	LLaMA-2-7b-Chat	Mixtral8x7b	GPT-2-124M	Solo Escúchame
Use of Inductive Questions	1077	1033	872	502	1224
Non-Imposition of Ideas	1236	1170	1200	536	1299
Expansion and Construction of Knowledge	1031	1071	972	473	1245
Generation of Cognitive Dissonance	45	36	34	16	69
Guided Discovery	1089	1076	988	498	1253

- Contextual Attention → Does the model demonstrate coherence in its responses, showing that it pays attention to the information provided earlier in the conversation?
- Formulation of Clarifying Questions → Does the model ask questions to obtain more details or clarifications about what has been said?
- Delving into the Conversation → Does the model encourage a deeper conversation while remaining consistent with the context provided by the interlocutor?
- Absence of Judgment or Critique → Does the model avoid expressing judgments or criticisms towards the interlocutor’s statements?
- Demonstration of Empathy → (1) Does the model empathetically respond, recognizing and reflecting the emotions expressed by the interlocutor? (2) Does the model acknowledge the emotions expressed by the interlocutor in its response?
- **Socratic Method:** Defined by the psychologist [30], it involves therapists guiding patients to formulate solutions through reflective questioning. Similar to the active listening technique, there are evaluation criteria that we cannot consider in the assessment of LMs. Consequently, we focus on the following five criteria.
 - Use of Inductive Questions → Does the model formulate questions that encourage reflection and critical analysis rather than providing direct answers?
 - Non-Imposition of Ideas → Does the model refrain from imposing ideas or solutions, by guiding the interlocutor to discover their own answers?
 - Knowledge Expansion and Construction → Does the model engage in knowledge construction through reflection and continuous dialogue?
 - Generation of Cognitive Dissonance → Does the model use dialogue to provoke cognitive dissonance, challenging the beliefs or ideas of the interlocutor?
 - Guided Discovery → Does the model primarily employ systematic questioning, guiding the interlocutor to discover their own beliefs and knowledge?

Table 7. Chatbot interaction snapshot.

User: Hola, me siento molesta el día de hoy

Chatbot: Hola Jannette, lamento que te sientas molesta. Si deseas compartir más sobre lo que sucedió, estoy aquí para escucharte.

User: En serio que como me caga que mi novio haga las cosas y no me las cuente, me las oculte.

Chatbot: Jannette, es comprensible que te sientas molesta cuando alguien no te comunica lo que está sucediendo en su vida. ¿Quieres hablar más sobre lo que está sucediendo con tu novio y cómo te hace sentir?

User: Es que siento que no confía en mí para contármelo, y eso me hace sentir excluida.

Chatbot: Es comprensible que te sientas excluida cuando alguien no te comunica lo que está sucediendo en su vida. La comunicación abierta y honesta es clave para un buen enfoque en una relación. ¿Has intentado hablar con tu novio sobre cómo te sientes?

User: ¿crees que él lo pueda entender?

Chatbot: Claro, Jannette. Entiendo que la comunicación abierta y honesta es clave en una relación. Si no has hablado con tu novio sobre cómo te sientes, tal vez sea una buena idea hacerlo. Recuerda que es importante expresar tus sentimientos y necesidades para mantener una relación saludable. ¿Quieres hablar más sobre cómo te sientes?

User: Creo que no, bueno, no al menos hasta hablar con él y saber su reacción. Pero gracias

Chatbot: ¡No hay problema! Estoy aquí para escucharte y brindarte apoyo.

The Socratic method and active listening are versatile tools that anyone can use, regardless of their training or experience. These techniques encourage dialogue, reflection, and deep understanding, making them suitable for diverse contexts such as education, therapy, and conflict resolution. They highlight the significance of ensuring that individuals feel acknowledged and comprehended.

Because these methods do not require extensive specialized knowledge, they are perfect for our model, which is designed to complement, not replace, a psychologist. By utilizing these approaches, we can evaluate the model's effectiveness based on its impact on users' emotional well-being, ensuring they feel genuinely supported.

Evaluation Metrics. Our evaluation consists of two stages. Firstly, we employ the GPT-4-instruct model [1] to assess user conversations using a crafted prompt covering all evaluation criteria. GPT-4 provides feedback in JSON format, indicating if the conversations meet the criteria. Secondly, manual evaluation verifies GPT-4 assessments. This manual evaluation involves two human annotators: a computer science engineer, and a psychologist with over five years of experience in cognitive behavioral therapy. Both methodologies assign 20% weight to each of the five criteria, contributing to a total score ranging from 0% to 100%.

The value for each criterion is computed using Equation 1:

$$c_x = \frac{2}{n} \sum_{i=0}^n \text{Element}_i, \quad (1)$$

where x is the criterion being evaluated, n is the number of elements, and Element_i is the value of the criterion for the i^{th} element. The overall score is computed as shown in Equation 2:

$$\text{score} = \sum_{x=0}^m c_x, \quad (2)$$

where c_x is the value of the criterion x , and m is the criterion to add.

4.2 Compared Models

To evaluate the performance of our model, *Sólo Escúchame*, we compare it with the following state-of-the-art models:

- **LLaMA-2-7b-Chat** - Created by META [43], it demonstrates remarkable performance with just 7 billion parameters. We used it without further fine-tuning.
- **GPT-3.5** - Developed by OpenAI, this model stands as a significant milestone in the evolution of chatbot development [31]. We used it without further fine-tuning.
- **GPT2-124M** - This GPT-2 model with 124 million parameters is a LaMINI version [46]. We fine-tuned it with the HEAR dataset.
- **Mixtral 8x7b** - Sparse Mixture of Experts (SMoE) LM [20] with 7 billion parameters. We used it without further fine-tuning.

5 Results and Discussion

Results in Table 4 show that *Sólo Escúchame* outperforms state-of-the-art models in all tested configurations by a consequent margin. Indeed, it gains for the active listening and socratic method, respectively: 3.05 and 9.28 points against GPT-3.5, 3.25 and 10.67 points against LLaMA-2-7b-Chat, and 6.15 and 15.52 points against the most recent LLM Mixtral 8x7b. Further analysis is given below. Table 5 and Table 6 present detailed results obtained with the Active Listening and the Socratic methods, respectively. In both tables, we showcase the accuracy of each criterion by displaying the number of correctly classified samples. This approach allows for a more thorough understanding of the distinct strengths exhibited by each model:

- **GPT-3.5:** This model excels in active listening but encounters challenges when employing the Socratic method. For instance, the model presents limitations in generating questions that are designed to cause cognitive dissonance. Contextually and structurally, the responses are adequate, with an average of 77 tokens, effectively fulfilling the task.

- **LLaMA-2-7b-Chat:** The model exhibits language inconsistency, using English in 8 of 20 responses despite Spanish instruction. Responses are lengthy (average 111 tokens), and frequently initiates unprompted greetings, concluding conversations with farewell-like encouragement, hindering in-depth engagement.
- **GPT2-124M:** This baseline performs the worst and may not be suitable for the task. Despite Spanish fine-tuning. The model deforms names and introduces non-existent words. The coherence presented at beginning of the sentence fades away after 50 tokens. Average response length is 100 tokens.
- **Mixtral 8x7b:** Mixtral 8x7b outperforms GPT-3.5 in active listening, but lags in the Socratic method. Despite being over 10 times smaller, it performs exceptionally well, requiring only a satisfactory prompt and yielding responses with an average length of 78 tokens.
- **Sólo Escúchame:** Our model outperforms baselines in both methodologies. It leads in empathy with a score of 291, surpassing Mixtral. Consistently non-judgmental, well-structured responses with an average length of 78 tokens. While not perfect and shares limited empathy vocabulary with GPT-3.5, it satisfactorily fulfills the task.

5.1 Conversation Example

Table 7 illustrates a sample conversation between the user and the chatbot. It showcases the coherence of responses, empathetic interactions, and the respect the chatbot demonstrates for the user's expressed feelings.

6 Conclusions

Our model, Sólo Escúchame, outperforms the baseline models in both evaluation methodologies. It demonstrates empathy in responses, avoids judgment of user feelings, and maintains vigilance over user-expressed details throughout the conversation. Sólo Escúchame is a promising psychological assistant that can be installed locally, running on a CPU and providing flexibility for installation on various machines. Furthermore, HEAR is the dataset used to train Llama2-7b-chat for emotional accompaniment. This dataset is completely in Spanish, giving a new perspective of how to improve the performance on emotional accompaniment of models with similar capabilities as Llama2-7b-chat in this language. This dataset can highlight the capabilities of language to be more empathetic with users, taking into account their contexts and providing more appropriate attention to the situation.

6.1 Limitations and Future Work

Sólo Escúchame is designed to be a supplementary tool for psychologists, offering accessible, non-judgmental support, particularly when professional services are unavailable. The model is still under research. In the near future, we plan to record conversations, allowing individuals to use them later in therapy if they wish.

These recordings can serve as reminders of the feelings experienced during moments of anxiety or depression. The authors chose automatic translation to ensure accurate Spanish text and to enhance the model's performance in this language. While automatic translation can introduce some limitations, we thoroughly review generated conversations to ensure their relevance and pertinence. We are committed to improving the translation process and increasing the dataset to enhance the model's performance.

The HEAR dataset, while sufficient for the model's for emotional accompaniment, limitations in the data prevent achieving this goal fully. Expanding the dataset with a larger and more diverse sample of responses would be beneficial. This would include a broader range of emotions typically found in conversations, allowing the dataset to train models for more extended and complex emotional scenarios. Additionally, future research aims to integrate voice input into the system, allowing users to express emotions through text or spoken interactions. The goal is to enhance the system's ability to understand non-verbal cues, discerning deeper emotions beyond explicit words.

References

1. Achiam, J., Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F. L., Almeida, D., Altenschmidt, J., Altman, S., Anadkat, S., Avila, R., Babuschkin, I., Balaji, S., Balcom, V., Baltescu, P., Bao, H., Bavarian, M., Belgum, J., Bello, I., Berdine, J., et al.: GPT-4 technical report (2023) doi: 10.48550/ARXIV.2303.08774
2. Ainslie, J., Lee-Thorp, J., de-Jong, M., Zemlyanskiy, Y., Lebron, F., Sanghai, S.: GQA: Training generalized multi-query transformer models from multi-head checkpoints. In: Proceedings of the Conference on Empirical Methods in Natural Language Processing, pp. 4895–4901 (2023) doi: 10.18653/v1/2023.emnlp-main.298
3. Anil, R., Borgeaud, S., Alayrac, J. B., Yu, J., Soricut, R., Schalkwyk, J., Dai, A. M., Hauth, A., Millican, K., Silver, D., Johnson, M., Antonoglou, I., Schrittwieser, J., Glaese, A., Chen, J., Pitler, E., Lillicrap, T., Lazaridou, A., Firat, O., Molloy, J., et al.: Gemini: A family of highly capable multimodal models (2023) doi: 10.48550/ARXIV.2312.11805
4. Anthropic's team: Claude (2023) www.anthropic.com/news/introducing-claude
5. Arrabales, R.: Perla: A conversational agent for depression screening in digital ecosystems. design, implementation and validation (2020) doi: 10.31234/osf.io/nfas4
6. Asai, A., Evensen, S., Golshan, B., Halevy, A., Li, V., Lopatenko, A., Stepanov, D., Suhara, Y., Tan, W. C., Xu, Y.: HappyDB: A corpus of 100,000 crowdsourced happy moments. In: Proceedings of the 11th International Conference on Language Resources and Evaluation (2018) doi: 10.48550/arXiv.1801.07746
7. Asarnow, J. R., Ougrin, D.: Editorial: Suicide and self-harm: Advancing from science to preventing deaths. *Journal of child psychology and psychiatry, and allied disciplines*, vol. 60, no. 10, pp. 1043–1045 (2019) doi: 10.1111/jcpp.13131
8. Barbieri, F., Camacho-Collados, J., Espinosa-Anke, L., Neves, L.: TweetEval: Unified benchmark and comparative evaluation for tweet classification. Findings of the Association for Computational Linguistics, Empirical Methods in Natural Language Processing, pp. 1644–1650 (2020) doi: 10.18653/v1/2020.findings-emnlp.148
9. Boettler, T., Newsome, P. N., Mondelli, M. U., Maticic, M., Cordero, E., Cornberg, M., Berg, T.: Care of patients with liver disease during the COVID-19 pandemic: EASL-ESCMID position paper. *JHEP Reports*, vol. 2, no. 3, pp. 100113 (2020) doi: 10.1016/j.jhepr.2020.100113

10. Castellero-Mimenza, O.: Método socrático: Qué es y cómo se aplica en la psicología (2024) psicologiaymente.com/clinica/metodo-socratico
11. Chowdhery, A., Narang, S., Devlin, J., Bosma, M., Mishra, G., Roberts, A., Barham, P., Chung, H. W., Sutton, C., Gehrmann, S., Schuh, P., Shi, K., Tsvyashchenko, S., Maynez, J., Rao, A., Barnes, P., Tay, Y., Shazeer, N., Prabhakaran, V., Reif, E., et al.: PaLM: Scaling language modeling with pathways. *Journal of Machine Learning Research*, vol. 24, no. 1, pp. 1–113 (2024)
12. Ciotti, M., Ciccozzi, M., Terrinoni, A., Jiang, W. C., Wang, C. B., Bernardini, S.: The COVID-19 pandemic. *Critical reviews in clinical laboratory sciences*, vol. 57, no. 6, pp. 365–388 (2020) doi: 10.1080/10408363.2020.1783198
13. Darcy, A., Evers, M.: Woebot health (2023) woebothealth.com/
14. Gerganov, G.: llama.cpp (2023) github.com/ggerganov/llama.cpp
15. Hamilton, J.: Youper (2023) www.youper.ai/
16. Hoffmann, J., Borgeaud, S., Mensch, A., Buchatskaya, E., Cai, T., Rutherford, E., de-Las-Casas, D., Hendricks, L. A., Welbl, J., Clark, A., Hennigan, T., Noland, E., Millican, K., van-den-Driessche, G., Damoc, B., Guy, A., Osindero, S., Simonyan, K., Elsen, E., Vinyals, O., et al.: Training compute-optimal large language models. In: *Proceedings of the 36th International Conference on Neural Information Processing Systems*, pp. 30016–30030 (2024) doi: 10.48550/arXiv.2203.15556
17. Hu, E. J., Shen, Y., Wallis, P., Allen-Zhu, Z., Li, Y., Wang, S., Chen, W.: LoRA: Low-rank adaptation of large language models. In: *International Conference on Learning Representations*, pp. 1–13 (2022) doi: 10.48550/arXiv.2106.09685
18. Inkster, B., Janssen, C. A.: wysa (2023) www.wysa.com/team
19. Jiang, A. Q., Sablayrolles, A., Mensch, A., Bamford, C., Chaplot, D. S., de-las-Casas, D., Bressand, F., Lengyel, G., Lample, G., Saulnier, L., Lavaud, L. R., Lachaux, M. A., Stock, P., Scao, T. L., Lavril, T., Wang, T., Lacroix, T., Sayed, W. E.: Mistral 7B (2023) doi: 10.48550/ARXIV.2310.06825
20. Jiang, A. Q., Sablayrolles, A., Roux, A., Mensch, A., Savary, B., Bamford, C., Chaplot, D. S., de-las-Casas, D., Hanna, E. B., Bressand, F., Lengyel, G., Bour, G., Lample, G., Lavaud, L. R., Saulnier, L., Lachaux, M. A., Stock, P., Subramanian, S., Yang, S., Antoniak, S., et al.: Mixtral of experts (2024) doi: 10.48550/ARXIV.2401.04088
21. Košecká, D., Balco, P.: Use of a communication robot—chatbot in order to reduce the administrative burden and support the digitization of services in the university environment. *Developments in Information and Knowledge Management Systems for Business Applications*, pp. 597–629 (2023) doi: 10.1007/978-3-031-25695-0_26
22. Lambert, N., Schoelkopf, H., Gokaslan, A., Soldaini, L., Pyatkin, V., Castricato, L.: Self-directed synthetic dialogues and revisions technical report (2024) doi: 10.48550/ARXIV.2407.18421
23. Lee, S. A., Jobe, M. C., Mathis, A. A., Gibbons, J. A.: Incremental validity of coronaphobia: Coronavirus anxiety explains depression, generalized anxiety, and death anxiety. *Journal of Anxiety Disorders*, vol. 74, pp. 102268 (2020) doi: 10.1016/j.janxdis.2020.102268
24. Li, Y., Su, H., Shen, X., Li, W., Cao, Z., Niu, S.: DailyDialog: A manually labelled multi-turn dialogue dataset. In: *Proceedings of the Eighth International Joint Conference on Natural Language Processing*, vol. 1, pp. 986–995 (2017) doi: 10.48550/arXiv.1710.03957
25. Manyika, J.: An overview of Bard: An early experiment with generative AI (2023)
26. May, R., Denecke, K.: Security, privacy, and healthcare-related conversational agents: A scoping review. *Informatics for Health and Social Care*, vol. 47, no. 2, pp. 194–210 (2021) doi: 10.1080/17538157.2021.1983578
27. Mazza, M. G., de-Lorenzo, R., Conte, C., Poletti, S., Vai, B., Bollettini, I., Melloni, E. M. T., Furlan, R., Ciceri, F., Rovere-Querini, P., Benedetti, F.: Anxiety and depression in

- COVID-19 survivors: Role of inflammatory and clinical predictors. *Brain, Behavior, and Immunity*, vol. 89, pp. 594–600 (2020) doi: 10.1016/j.bbi.2020.07.037
28. Megahed, N. A., Ghoneim, E. M.: Antivirus-built environment: Lessons learned from COVID-19 pandemic. *Sustainable Cities and Society*, vol. 61, pp. 102350 (2020) doi: 10.1016/j.scs.2020.102350
 29. Narynov, S., Zhumanov, Z., Kumar, A., Khassanova, M., Omarov, B.: Development of chatbot psychologist applying natural language understanding techniques. In: *Proceedings of the 21st International Conference on Control, Automation and Systems*, pp. 636–641 (2021) doi: 10.23919/iccas52745.2021.9649825
 30. Oblitas, L. A.: *Psicoterapias contemporáneas*. Cengage Learning Editores (2008)
 31. OpenAI: *Introducing ChatGPT* (2022) chatgpt.com
 32. Oppenheimer, C., Silk, J., Jones, N., Butterfield, R.: Neural processing of social rejection and suicide risk. *Biological Psychiatry*, vol. 87, no. 9, pp. S420 (2020) doi: 10.1016/j.biopsych.2020.02.1072
 33. Ouyang, L., Wu, J., Jiang, X., Almeida, D., Wainwright, C. L., Mishkin, P., Zhang, C., Agarwal, S., Slama, K., Ray, A., Schulman, J., Hilton, J., Kelton, F., Miller, L., Simens, M., Askell, A., Welinder, P., Christiano, P., Leike, J., Lowe, R.: Training language models to follow instructions with human feedback. In: *Proceedings of the 36th International Conference on Neural Information Processing Systems*, pp. 27730–27744 (2024)
 34. Plutchik, R.: A general psychoevolutionary theory of emotion. *Theories of Emotion*, pp. 3–33 (1980) doi: 10.1016/b978-0-12-558701-3.50007-7
 35. Rajpurkar, P., Zhang, J., Lopyrev, K., Liang, P.: SQuAD: 100,000+ questions for machine comprehension of text. In: *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, pp. 2383–2392 (2016) doi: 10.18653/v1/D16-1264
 36. Raws, M.: Try tess today! (2023) www.x2ai.com/uprisehealth
 37. Rogers, C. R., Farson, R. E.: *Active listening*. Martino Fine Books (2015)
 38. Salhi, I., Guemmat, K. E., Qbadou, M., Mansouri, K.: Towards developing a pocket therapist: An intelligent adaptive psychological support chatbot against mental health disorders in a pandemic situation. *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 23, no. 2, pp. 1200 (2021) doi: 10.11591/ijeecs.v23.i2.pp1200-1211
 39. Shah, K., Kamrai, D., Mekala, H., Mann, B., Desai, K., Patel, R. S.: Focus on mental health during the coronavirus (COVID-19) pandemic: Applying learnings from the past outbreaks. *Cureus*, vol. 12, no. 3, pp. e7405 (2020) doi: 10.7759/cureus.7405
 40. Su, J., Ahmed, M., Lu, Y., Pan, S., Bo, W., Liu, Y.: Roformer: Enhanced transformer with rotary position embedding (2024) doi: 10.1016/j.neucom.2023.127063
 41. Taori, R., Gulrajani, I., Zhang, T., Dubois, Y., Li, X., Guestrin, C., Liang, P. B., Hashimoto, T. B.: Alpaca: A strong, replicable instruction-following model (2021) crfm.stanford.edu/2023/03/13/alpaca.html
 42. Touvron, H., Lavril, T., Izacard, G., Martinet, X., Lachaux, M. A., Lacroix, T., Rozière, B., Goyal, N., Hambro, E., Azhar, F., Rodriguez, A., Joulin, A., Grave, E., Lample, G.: LLaMA: Open and efficient foundation language models (2023) doi: 10.48550/ARXIV.2302.13971
 43. Touvron, H., Martin, L., Stone, K., Albert, P., Almahairi, A., Babaei, Y., Bashlykov, N., Batra, S., Bhargava, P., Bhosale, S., Bikel, D., Blecher, L., Ferrer, C. C., Chen, M., Cucurull, G., Esiobu, D., Fernandes, J., Fu, J., Fu, W., Fuller, B., et al.: LLaMA 2: Open foundation and fine-tuned chat models (2023) doi: 10.48550/ARXIV.2307.09288
 44. Troglio-da-Silva, F. C., Rolim-Neto, M. L.: Psychiatric symptomatology associated with depression, anxiety, distress, and insomnia in health professionals working in patients affected by COVID-19: A systematic review with meta-analysis. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, vol. 104, pp. 110057 (2021) doi: 10.1016/j.pnpbp.2020.110057

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45. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., Polosukhin, I.: Attention is all you need. In: Proceedings of the 31st Conference on Neural Information Processing Systems, pp. 1–15 (2017) doi: 10.48550/ARXIV.1706.03762
46. Wu, M., Waheed, A., Zhang, C., Abdul-Mageed, M., Aji, A. F.: LaMini-LM: A diverse herd of distilled models from large-scale instructions. In: Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics, vol. 1, pp. 944–964 (2024) doi: 10.48550/arXiv.2304.14402
47. Yáñez, E. A., Reyes, S. V., Gómez, J. F. R., Elizondo, P. V., Gonzalez, A. M., Hernández, A. G.: Implementation of sentiment analysis in chatbots in spanish to detect signs of mental health problems. In: New Perspectives in Software Engineering, vol. 576, pp. 196–214 (2022) doi: 10.1007/978-3-031-20322-0_14