# Bridging AI and Psychology: A RAG-Driven Approach to Inhibitory Control and ADHD Interventions

**Julio R. S. Peixoto**[1,2], **João V. M. Lyra**[1,2], **Ana C. A. Passos**[1,2],
**Brena M. S. Pereira**, **Andrea C. H. B. Gouveia**, **Victor F. A. Araujo**[1,2,3]

[1] Interdisciplinary Research Group on Technology, Computing, and Society (GPITCS - Unit)

[2]Tiradentes University, UNIT, Sergipe

[3]National Institute of Science and Technology Social
and Affective Neuroscience (INCT-SANI)

***Abstract.*** *This study explores the integration of Retrieval-Augmented Generation (RAG) into Artificial Intelligence (AI) systems to enhance psychological support, particularly in ADHD interventions and Inhibitory Control assessment. To achieve this, the GPT-4o model was used in conjunction with structured databases of therapeutic dialogues to improve mental health intervention, cognitive evaluation, and professional training. In addition, prompt engineering was used as an inference technique through text-based instructions, and an experimental evaluation was conducted using a predefined set of prompts designed to measure contextual consistency, ethical compliance, and technical accuracy. The results indicate that integrating retrieval mechanisms improves AI-generated responses by providing more contextually relevant and accurate information, demonstrating the model's enhanced capability to process complex contextual queries.*

## 1. Introduction

The integration of Artificial Intelligence (AI) into psychological practice has transformed the landscape of mental health care, offering innovative solutions for assessment [Tutun et al. 2022], treatment [Nayinzira and Adda 2024], and clinical decision-making [MacIntyre et al. 2023]. From early conversational agents like ELIZA [Weizenbaum 1966] to modern AI-driven diagnostic tools, technological advancements have steadily improved the accuracy, accessibility, and efficiency of psychological services [Luxton 2014, Zhou et al. 2022]. Recent developments in AI, particularly Retrieval-Augmented Generation (RAG) [Das et al. 2025], present a promising frontier in augmenting clinical workflows by synthesizing and retrieving relevant information in real time, thereby enhancing the decision-making process of mental health professionals.

AI applications in psychology have expanded significantly in recent years, with notable advancements in clinical assessment, training, and treatment[Khalifa et al. 2024]. AI-powered systems can assist in diagnosing psychological disorders, reducing diagnostic errors, and providing evidence-based recommendations for treatment [Luxton 2014, Lee et al. 2021]. Virtual assistants and chatbots can play a crucial role in psychological triage, offering immediate support and guidance to patients while alleviating the burden on human professionals. Additionally, sophisticated AI models, including virtual human avatars [Sanjeewa et al. 2024a], enable personalized therapist training by simulating complex clinical interactions [Zhou et al. 2022].

Beyond diagnosis and training, AI has demonstrated potential in clinical decision support, offering data-driven insights to improve patient outcomes [Elhaddad and Hamam 2024]. Neural networks and machine learning algorithms can analyze large datasets to detect patterns and predict treatment responses for disorders such as depression, schizophrenia, and Alzheimer's disease [Durstewitz et al. 2019]. AI-powered decision support systems further mitigate the risks of misdiagnosis, ensuring more precise and effective interventions[Kleine et al. 2025].

In this study, we aim to evaluate the effectiveness of RAG-enhanced AI systems in psychological practice by comparing the performance of GPT-4.0 with and without RAG integration. A script, focusing on Inhibitory Control and Attention-deficit/hyperactivity disorder (ADHD) , was developed by a psychologist to assess psychological knowledge and contextual understanding, and its evaluations were conducted independently by two psychologists. By systematically analyzing the capabilities of these AI models, our research seeks to determine how RAG integration can enhance psychological assessments, treatments, and clinical decision-making. The findings aim to inform the development of AI systems that provide continuous support to psychologists and therapists, ultimately improving the quality and accessibility of mental health care.

## 2. Related Work

We address the literature study according to three aspects: RAG, AI in psychology, and Inhibitory Control/ADHD.

### 2.1. RAG

Large Language Models (LLMs) have demonstrated remarkable success but still face limitations, particularly in domain-specific and knowledge-intensive tasks. One of the major challenges is the generation of factually incorrect content, commonly referred to as "hallucinations" [Gao et al. 2024]. To address this, Retrieval-Augmented Generation enhances LLMs by retrieving relevant information from external knowledge bases, improving factual accuracy and adaptability to dynamic environments. This integration has made RAG a key technology in chatbot development and real-world applications [Arslan et al. 2024]. In open-domain question answering, a common approach involves a two-step pipeline: a retriever selects relevant document passages, followed by a machine reader that extracts the correct answer [Karpukhin et al. 2020]. While effective, this method often suffers from performance degradation, highlighting the need for improved retrieval techniques. Pre-trained neural models encode a vast amount of knowledge but lack the ability to update or justify their outputs effectively. Unlike traditional models, RAG allows for flexible memory expansion and enhances interpretability, mitigating issues related to static knowledge storage and hallucinations [Lewis et al. 2021].

### 2.2. AI in Psychology

AI is becoming increasingly relevant in psychology, particularly in cognitive psychology, where it facilitates emotion recognition, behavioral therapy, and social interaction simulations [Walter 2024]. AI-driven systems can simulate human cognitive processes, supporting research and clinical applications [Irshad et al. 2022]. These advancements highlight AI's potential in psychological science, despite its underutilization by specialists in the field. In clinical practice, AI enhances psychological assessment and treatment through virtual assistants and chatbots. These tools help identify mental health disorders, provide basic psychological support, and reduce the workload of professionals [Vaidyam et al. 2019]. Additionally, AI-powered decision-support systems have the potential to analyze large datasets to improve diagnostic accuracy, reducing uncertainty and medical errors in detecting conditions such as depression, schizophrenia, and anxiety disorders [Zhou et al. 2022]. Virtual patient simulations further aid therapist training, refining diagnostic and treatment strategies [Elendu et al. 2024].

Conversational agents have demonstrated effectiveness in mental health care, improving diagnostic quality and therapeutic efficacy. However, challenges remain, including the need for standardized evaluation methods and broader representation of patient populations, such as pediatric cases and individuals with schizophrenia or bipolar disorder [Vaidyam et al. 2020]. Despite these limitations, AI-driven tools continue to expand access to mental health services, addressing global shortages of trained professionals.Machine learning and Natural Language Processing (NLP) further enhance mental health care by improving diagnosis, prognosis, risk assessment, and treatment adherence. These automated approaches can offer more cost-effective, scalable solutions for psychological evaluation and intervention [Le Glaz et al. 2021]. The integration of AI, particularly RAG, has the potential to refine clinical assessments, ensure access to real-time medical knowledge, and support mental health professionals in providing more effective care.

### 2.3. Inhibitory Control and ADHD

Inhibitory control, a core executive function, enables individuals to regulate their attention, behavior, thoughts, and emotions by suppressing dominant responses in favor of more appropriate actions[Kang et al. 2022]. This ability is essential for goal-directed behavior, allowing individuals to resist distractions, avoid impulsive actions, and adapt to dynamic environmental demands. A critical aspect of inhibitory control is attentional regulation, which involves selectively focusing on relevant stimuli while suppressing interference from competing information. This capacity, known as interference control at the perceptual level, is fundamental for maintaining concentration and avoiding cognitive overload in complex or dynamic settings [Kang et al. 2022]. Deficits in this function are often linked to difficulties in learning, problem-solving, and emotional regulation. ADHD, a chronic neurodevelopmental disorder affecting $\sim$5% of school-age children, is characterized by heterogeneous behavioral symptoms and cognitive impairments [Castellanos and Tannock 2002, Coghill et al. 2014, Sonuga-Barke et al. 2008]. Impairments in inhibitory control are particularly prominent, leading to difficulties in suppressing impulsive responses, sustaining attention, and regulating emotions, which significantly impact academic and social functioning [Kofler et al. 2018]. Closely related, self-regulation – the ability to manage impulses and delay gratification – plays a crucial role in stress management, social relationships, and long-term goal achievement [Kang et al. 2022]. These mechanisms underscore the importance of strengthening inhibitory control in psychological and educational interventions.

## 3. Methodology

In this section, we explain how we used RAG and the GPT-4o model[1] to build an architecture that can outperform existing systems and applications in the field of psychology,

[1]https://platform.openai.com/docs/models/gpt-4o

powered by a well-parameterized dataset. As shown in Figure 1, our architecture includes the following components: (i) dataset, (ii) vector database, (iii) retriever, (iv) embedding model, and (v) GPT-4o model. The RAG approach, combined with the GPT-4o model, integrates structured databases of therapeutic dialogues to address three key domains: clinical treatment, psychological assessment, and professional training. The system's validation focused on contextual coherence, ethical adherence, and technical accuracy, supervised by a psychology professional and aligned with computational psychological assessment guidelines.

### 3.1. Retrieval-Augmented Generation Workflow

The RAG pipeline (Figure 1) combines structured psychological data with generative AI for clinical relevance. The pipeline follows these steps:

*Psychology Dataset (I)*: Curated therapeutic dialogues, including patient queries and professional responses, are cleaned and structured to ensure relevance for clinical psychology applications; *Vector Database Integration (II)*: The cleaned data is converted into embeddings using a specialized text-embedding-3-small[2] model and stored in a Pinecone Vector Database[3], enabling efficient and scalable retrieval of information; *Embedding Model (III)*: Both user queries and dataset entries are transformed into semantic vectors, allowing for effective similarity matching and retrieval of relevant information; *Retriever Module (IV)*: For each incoming query, the retriever module identifies the top contextual matches from the vector database, ensuring that the most relevant information is retrieved for further processing; *Query*: User inputs are categorized into specific clinical domains, such as treatment, assessment, and training, using advanced keyword and intent analysis techniques; *Contextual Best Response*: The system prioritizes the best response candidates by filtering them through ethical guidelines and clinical validity checks, ensuring that the responses are both appropriate and accurate; *GPT-4o Generation (V)*: The retrieved context is fed into the GPT-4o model, which generates tailored, domain-specific responses that are contextually relevant and aligned with the user's needs; *System UI*: The final responses are delivered through an intuitive and accessible user interface (UI), designed to provide a seamless and user-friendly experience for both clinicians and patients.

### 3.2. Dataset Structure & Response Guidelines

The dataset used in the RAG pipeline consists of structured question-response pairs based on validated professional dialogues. It follows the format:

- **User Query**: Natural language input reflecting psychological concerns or therapeutic inquiries.
- **Expected Response**: Professionally curated replies providing guidance aligned with therapeutic principles.
- **Prohibited Responses**: Examples of inappropriate, unethical, or harmful replies, ensuring the model avoids biases and unsafe recommendations.

This organization approach ensures that responses maintain ethical and clinical integrity, preventing misinformation and reinforcing adherence to psychological best practices.

[2]https://platform.openai.com/docs/guides/embeddings
[3]https://www.pinecone.io/learn/vector-database/

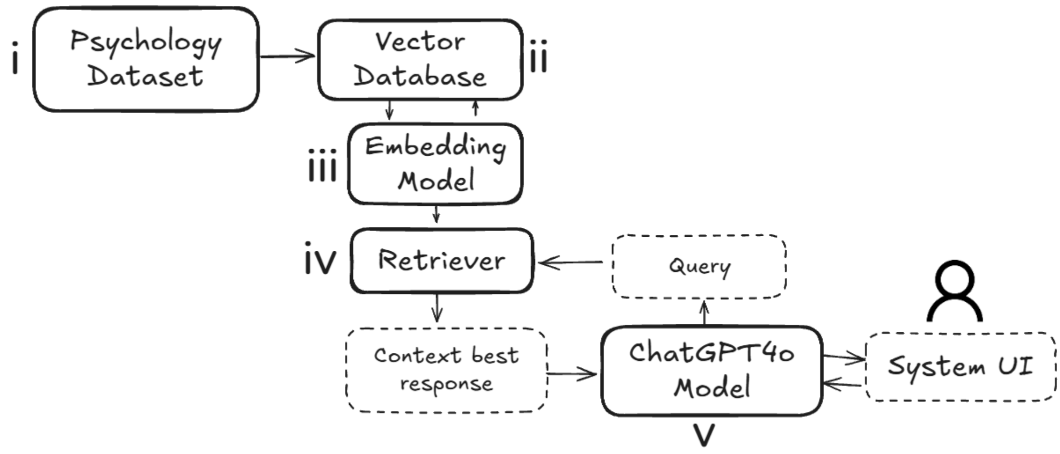


**Figure 1. RAG pipeline mentioned, illustrating the integration of a vector database for retrieval and GPT-4o for response generation for a better responses.**

### 3.3. Prompt Engineering

We used prompt engineering, which is an inference technique through a text-based directive that guides the model to behave in a way that improves its output quality and relevance. The system employs strategic prompt engineering to align GPT-4o's outputs with clinical standards and conversational objectives. Our dual-phase approach combines:

1. **System-Level Directives**: Foundational instructions shaping the AI's persona and ethical boundaries [Sanjeewa et al. 2024b].
2. **Contextual Templates**: Dynamic prompts integrating RAG-retrieved information with response format rules (e.g., prohibition of medical lists unless explicitly requested).
3. **Tone Calibration**: Lexical constraints (e.g., ”supportive”, ”fluid”) to ensure empathetic and natural dialogue.
4. **Structural Guardrails**: Rules to prevent inappropriate response patterns and ensure coherent outputs.
5. **Ethical Filters**: Mechanisms referencing the dataset's prohibited response taxonomy to avoid harmful or biased content.
6. **Context Injection**: Slots for integrating RAG-retrieved clinical evidence into the generated responses.

This architecture enables domain adaptation across treatment, assessment, and training scenarios while maintaining adherence to psychological communication protocols through prompt-controlled generation.

### 3.4. Experimental Design

To assess the performance of AI models in providing mental health support, particularly in the context of Inhibitory Control, a structured experiment was designed by a psychologist. The experiment involved a predefined script composed of prompts aimed at evaluating contextual coherence, ethical adherence, and technical accuracy. These prompts were systematically submitted to two AI models: GPT-4o and GPT-4o with RAG. This aligns with recent discussions on the potential of AI in psychological and behavioral therapies, where AI-driven approaches have shown promise in expanding access to mental health support [Walter 2024].

The prompts followed specific guidelines for prompt engineering, ensuring that the models adopted a role as a mental health assistant. The instructions emphasized maintaining a conversational and empathetic tone, structuring responses in a fluid and connected manner, and avoiding lists unless explicitly requested by the user. Additionally, responses were expected to integrate practical examples when relevant and prioritize natural dialogue over rigid formatting. Such applications of AI in psychotherapy are particularly valuable for individuals who might not have direct access to a professional, reinforcing the role of digital psychology in modern therapeutic practices [Walter 2024]. The RAG-enhanced model, in particular, was designed to maintain a humanized and empathetic discourse, ensuring that responses were not only contextually accurate but also emotionally supportive and engaging. By comparing the outputs of both models, the experiment aimed to determine whether RAG integration improved contextual accuracy, ethical consistency, and overall response quality while preserving a natural and welcoming communication style. The results of this comparison, including the scores assigned to each model's responses, are detailed in Table 1.

## 4. Results

The evaluation of responses followed structured guidelines, focusing on contextual coherence, ethical adherence, and technical comprehension. Each response was assessed for its alignment with the model's intended function as a mental health assistant, emphasizing natural conversational flow, empathy, and clarity. Reviewers provided qualitative feedback, highlighting strengths, errors, and areas for improvement. A numerical score from 0 to 5 was assigned based on the adequacy of the responses, ranging from completely inadequate to perfectly aligned with the intended purpose. This evaluation framework aligns with broader methodologies used in assessing language models in specialized domains, where structured qualitative analysis is complemented by quantitative scoring to ensure both accuracy and contextual appropriateness [Abraham , Brodeur et al. 2024].

| **Prompts** | **GPT4o + RAG** | **GPT4o** |
|---|---|---|
| How can I work on Inhibition Control with a 10-year-old child? | 5 | 4 |
| I am a child psychologist and would like to know how I can work on Inhibition Control with a 10-year-old child who exhibits aggressive behaviors in a school setting with peers and authority figures. | 4 | 4 |
| I am a psychologist working with Cognitive Behavioral Therapy and would like to work with emotional regulation techniques for a 10-year-old patient diagnosed with ADHD who has a deficit in Inhibition Control and reacts aggressively in a school setting when frustrated. | 3 | 4 |

| Prompts | GPT4o + RAG | GPT4o |
|---|---|---|
| I am a psychologist working with Cognitive Behavioral Therapy and would like to work with cognitive techniques for a 10-year-old patient diagnosed with ADHD who has a deficit in Inhibition Control and reacts aggressively in a school setting when frustrated. | 3 | 4 |
| I am a psychologist working with Cognitive Behavioral Therapy and would like to work with behavioral techniques for a 10-year-old patient diagnosed with ADHD who has a deficit in Inhibition Control and reacts aggressively in a school setting when frustrated. | 5 | 4 |
| I am a psychologist working with Cognitive Behavioral Therapy and would like to work with cognitive techniques for a 10-year-old patient diagnosed with ADHD who has a deficit in Inhibition Control and reacts aggressively in a school setting when frustrated, based on decisional balance and consequence analysis. | 4 | 4 |
| I am a psychologist working with Cognitive Behavioral Therapy and would like to work with behavioral techniques for a 10-year-old patient diagnosed with ADHD who has a deficit in Inhibition Control and reacts aggressively in a school setting when frustrated. | 5 | 4 |
| I am a psychologist working with Cognitive Behavioral Therapy and would like to explain what Inhibition Control is and its negative effects to a 10-year-old patient diagnosed with ADHD who exhibits aggressive behavior in a school setting when frustrated. | 5 | 4 |
| I am a psychologist working with Cognitive Behavioral Therapy and would like to work with cognitive techniques for a 10-year-old patient diagnosed with ADHD who has a deficit in Inhibition Control and reacts aggressively in a school setting when frustrated, based on decisional balance and consequence analysis. I would like to use scenes from children's films as a basis before applying them to his life situations. | 5 | 4 |
| I am a psychologist working with Cognitive Behavioral Therapy and would like to work on decisional balance, decision-making, and consequence analysis with a 10-year-old patient diagnosed with ADHD who has a deficit in Inhibition Control and reacts aggressively in a school setting when frustrated. Create a lighthearted story or parable that I can use. | 5 | 4 |

**Table 1:** GPT-4o and GPT-4o + RAG response comparison. The first column presents the prompts used, and the other two columns present the psychologist's evaluations

regarding the responses provided, respectively, by GPT4o + RAG and by GPT4o.

The evaluation results indicate that GPT-4o with RAG outperformed GPT-4o in terms of adequacy across the assessed criteria. The GPT-4o + RAG model achieved an average score of 4.4, suggesting that while some responses had room for improvement, the model consistently provided more contextually coherent, ethically aligned, and technically accurate answers. In contrast, GPT-4o achieved an average score of 4, reflecting stable but less dynamic performance, potentially indicating a more generalized approach without the enhanced retrieval capabilities of RAG. The superior performance of GPT-4o + RAG aligns with expectations that integrating retrieval mechanisms can refine response quality by providing more contextually relevant and precise information. Notably, in the last two questions, which demanded more elaborate and detailed context, GPT-4o + RAG demonstrated superior performance, achieving the highest scores. This highlights the model's ability to handle complex, context-dependent queries more effectively compared to GPT-4o without RAG.

## 5. Final Considerations

The integration of AI into psychological practice has improved mental health care, enhancing assessment accuracy, treatment effectiveness, and clinical decision-making. Therefore, this study explored the impact of RAG in psychological applications by evaluating the performance of GPT-4.0 with and without RAG integration, and our findings indicate that AI systems enhanced with RAG can improve the retrieval and synthesis of relevant psychological knowledge from a large volume of information, providing mental health professionals with more precise and context-aware support. However, as preliminary work, this study has limitations: (1) subjective evaluations lacking inter-rater reliability metrics (e.g., Cohen's kappa) or rigorous statistical analyses; (2) an opaque dataset with undisclosed size, diversity, or licensing details; (3) no clinical baseline comparison (e.g., junior psychologists or rule-based systems); and (4) insufficient discussion of ethical protocols, particularly privacy safeguards.

Thus, future advances in this field are anticipated to lead to significant improvements. To this end, it is essential to expand the data set used, diversifying its sources to increase both the volume and the scope of available information, while also involving a greater number of specialists in system evaluation and validating its application through rigorous user testing. As a future prospect, the implementation of virtual humans is a promising perspective to enhance system humanization and foster a higher quality of user experience. Consequently, these advancements will contribute to AI systems that provide continuous support to psychologists and improve the standard and accessibility of mental health care.

## 6. Acknowledgements

This study was financed by the Conselho Nacional de Desenvolvimento Científico e Tecnológico - Brazil (CNPq) - Process Numbers 309228/2021-2; 406463/2022-0; 153641/2024-0 and funded by Foundation for the Support of Research and Technological Innovation the state of Sergipe (FAPITEC/SE) PROMOB, n° 01/2013.

## References

Abraham, T. M. Llms in medicine: Evaluations, advances, and the future.

Arslan, M., Ghanem, H., Munawar, S., and Cruz, C. (2024). A survey on rag with llms. *Procedia Computer Science*, 246:3781–3790. 28th International Conference on Knowledge Based and Intelligent Information and Engineering Systems (KES 2024).

Brodeur, P. G., Buckley, T. A., Kanjee, Z., Goh, E., Ling, E. B., Jain, P., Cabral, S., Abdulnour, R.-E., Haimovich, A., Freed, J. A., Olson, A., Morgan, D. J., Hom, J., Gallo, R., Horvitz, E., Chen, J., Manrai, A. K., and Rodman, A. (2024). Superhuman performance of a large language model on the reasoning tasks of a physician.

Castellanos, F. X. and Tannock, R. (2002). Neuroscience of attention-deficit/hyperactivity disorder: the search for endophenotypes. *Nature Reviews Neuroscience*, 3(8):617–628.

Coghill, D. R., Seth, S., and Matthews, K. (2014). A comprehensive assessment of memory, delay aversion, timing, inhibition, decision making and variability in attention deficit hyperactivity disorder: advancing beyond the three-pathway models. *Psychological medicine*, 44(9):1989–2001.

Das, S., Ge, Y., Guo, Y., Rajwal, S., Hairston, J., Powell, J., Walker, D., Peddireddy, S., Lakamana, S., Bozkurt, S., Reyna, M., Sameni, R., Xiao, Y., Kim, S., Chandler, R., Hernandez, N., Mowery, D., Wightman, R., Love, J., Spadaro, A., Perrone, J., and Sarker, A. (2025). Two-layer retrieval-augmented generation framework for low-resource medical question answering using reddit data: Proof-of-concept study. *Journal of Medical Internet Research*, 27:e66220.

Durstewitz, D., Koppe, G., and Meyer-Lindenberg, A. (2019). Deep neural networks in psychiatry. *Molecular Psychiatry*, 24(11):1583–1598.

Elendu, C., Amaechi, D. C., Okatta, A. U., Amaechi, E. C., Elendu, T. C., Ezeh, C. P., and Elendu, I. D. (2024). The impact of simulation-based training in medical education: A review. *Medicine*, 103(27):e38813.

Elhaddad, M. and Hamam, S. (2024). Ai-driven clinical decision support systems: An ongoing pursuit of potential. *Cureus*.

Gao, Y., Xiong, Y., Gao, X., Jia, K., Pan, J., Bi, Y., Dai, Y., Sun, J., Wang, M., and Wang, H. (2024). Retrieval-augmented generation for large language models: A survey.

Irshad, S., Azmi, S., and Begum, N. (2022). Uses of artificial intelligence in psychology. *Journal of Health and Medical Sciences*, 5(4).

Kang, W., Hernández, S. P., Rahman, M. S., Voigt, K., and Malvaso, A. (2022). Inhibitory control development: A network neuroscience perspective. *Frontiers in Psychology*, 13.

Karpukhin, V., Oğuz, B., Min, S., Lewis, P., Wu, L., Edunov, S., Chen, D., and tau Yih, W. (2020). Dense passage retrieval for open-domain question answering.

Khalifa, M., Albadawy, M., and Iqbal, U. (2024). Advancing clinical decision support: The role of artificial intelligence across six domains. *Computer Methods and Programs in Biomedicine Update*, 5:100142.

Kleine, A.-K., Kokje, E., Hummelsberger, P., Lermer, E., Schaffernak, I., and Gaube, S. (2025). Ai-enabled clinical decision support tools for mental healthcare: A product review. *Artificial Intelligence in Medicine*, 160:103052.

Kofler, M. J., Irwin, L. N., Soto, E. F., Groves, N. B., Harmon, S. L., and Sarver, D. E. (2018). Executive functioning heterogeneity in pediatric adhd. *Journal of Abnormal Child Psychology*, 47(2):273–286.

Le Glaz, A., Haralambous, Y., Kim-Dufor, D.-H., Lenca, P., Billot, R., Ryan, T. C., Marsh, J., DeVylder, J., Walter, M., Berrouiguet, S., and Lemey, C. (2021). Machine learning and natural language processing in mental health: Systematic review. *Journal of Medical Internet Research*, 23(5):e15708.

Lee, E. E., Torous, J., De Choudhury, M., Depp, C. A., Graham, S. A., Kim, H.-C., Paulus, M. P., Krystal, J. H., and Jeste, D. V. (2021). Artificial intelligence for mental health care: Clinical applications, barriers, facilitators, and artificial wisdom. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, 6(9):856–864.

Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., Küttler, H., Lewis, M., tau Yih, W., Rocktäschel, T., Riedel, S., and Kiela, D. (2021). Retrieval-augmented generation for knowledge-intensive nlp tasks.

Luxton, D. D. (2014). Artificial intelligence in psychological practice: Current and future applications and implications. *Professional Psychology: Research and Practice*, 45(5):332–339.

MacIntyre, M. R., Cockerill, R. G., Mirza, O. F., and Appel, J. M. (2023). Ethical considerations for the use of artificial intelligence in medical decision-making capacity assessments. *Psychiatry Research*, 328:115466.

Nayinzira, J. P. and Adda, M. (2024). Sentimentcarebot: Retrieval-augmented generation chatbot for mental health support with sentiment analysis. *Procedia Computer Science*, 251:334–341.

Sanjeewa, R., Iyer, R., Apputhurai, P., Wickramasinghe, N., and Meyer, D. (2024a). Empathic conversational agent platform designs and their evaluation in the context of mental health: Systematic review. *JMIR Mental Health*, 11:e58974.

Sanjeewa, R., Iyer, R., Apputhurai, P., Wickramasinghe, N., and Meyer, D. (2024b). Empathic conversational agent platform designs and their evaluation in the context of mental health: Systematic review. *JMIR Ment Health*, 11:e58974.

Sonuga-Barke, E. J., Sergeant, J. A., Nigg, J., and Willcutt, E. (2008). Executive dysfunction and delay aversion in attention deficit hyperactivity disorder: nosologic and diagnostic implications. *Child and adolescent psychiatric clinics of North America*, 17(2):367–384.

Tutun, S., Johnson, M. E., Ahmed, A., Albizri, A., Irgil, S., Yesilkaya, I., Ucar, E. N., Sengun, T., and Harfouche, A. (2022). An ai-based decision support system for predicting mental health disorders. *Information Systems Frontiers*, 25(3):1261–1276.

Vaidyam, A. N., Linggonegoro, D., and Torous, J. (2020). Changes to the psychiatric chatbot landscape: A systematic review of conversational agents in serious mental illness: Changements du paysage psychiatrique des chatbots: une revue systématique des agents conversationnels dans la maladie mentale sérieuse. *The Canadian Journal of Psychiatry*, 66(4):339–348.

Vaidyam, A. N., Wisniewski, H., Halamka, J. D., Kashavan, M. S., and Torous, J. B. (2019). Chatbots and conversational agents in mental health: A review of the psychiatric landscape. *The Canadian Journal of Psychiatry*, 64(7):456–464. PMID: 30897957.

Walter, Y. (2024). Digital psychology: Introducing a conceptual impact model and the future of work. *Trends in Psychology*.

Weizenbaum, J. (1966). Eliza—a computer program for the study of natural language communication between man and machine. *Communications of the ACM*, 9(1):36–45.

Zhou, S., Zhao, J., and Zhang, L. (2022). Application of artificial intelligence on psychological interventions and diagnosis: An overview. *Frontiers in Psychiatry*, 13.