IntakeAI

Ondrej Vesely

Neuro 140: Biological and Artificial Intelligence

Dr. Gabriel Kreiman

May 13, 2025

Abstract

Access to mental health treatment faces large barriers when it comes to the intake process. It is often highly inefficient as a result of administrative bottlenecks resulting in missed calls and denied access to treatment. This project explores whether a conversational AI agent can be used to streamline intake for mental health treatment centers by handling calls, collecting key patient information, and conducting a brief screening. I built and deployed a voice-based AI intake bot using Bland.AI and built a backend system to securely store caller data and screening results. I then evaluated the bot's performance using an adapted version of the 3-bot evaluation framework with GPT-4o acting as users with different personas. The results showed a high reliability in data collection accuracy, clarity, tone, and role adherence. These findings suggest that conversation AI can be a highly useful tool in reducing barriers to care at the earliest stages of the intake process.

1. Introduction

1.1. Background and Motivation

Over the last decade, the prevalence of serious mental health disorders has rapidly increased, particularly among adolescents and young adults (Twenge, 2019). In line with this, the demand for mental health services such as therapy and inpatient treatment centers has also risen, placing a massive burden on the mental health care system. According to the National Center for Health Statistics, the percentage of U.S. adults who received any form of mental health treatment increased from 19.2% in 2019 to 23.9% in 2023 (Briones & Giri, 2024). That is roughly one in four adults seeking some sort of mental health care.

However, the ability of treatment centers to support this increase in treatment demand has not sufficiently scaled at the same rate. Treatment seekers often face a long and complicated process when they first decide to seek help. They must contact multiple treatment centers and frequently encounter long wait times or no response at all. Even when contact is made, seekers may get turned away because they don't meet the eligibility criteria of the center, or the center may be at full capacity. This often results in seekers making little to no progress in securing care and having to restart the search elsewhere, leaving them stuck in a vulnerable state and exacerbating feelings of hopelessness. A recent large-scale mystery shopper study found that only 18.5% of psychiatrists contacted across five U.S. states were available to see new patients, with median wait times of 67 days for in-person appointments and 43 days for telepsychiatry (Sun et al., 2023).

These inefficiencies on the part of the treatment centers also stem from insufficient administrative capacity. Many treatment centers lack the intake staff needed to handle the high volume of incoming calls driven by growing demand. As a result, patients experience long hold times, unanswered calls, or delayed callbacks. The same study found that the most common reason for unavailability was that providers were not accepting new patients (53.9%), and 17.1% of clinics could not be reached at all, highlighting how such administrative bottlenecks are one of the biggest barriers for patients who require care (Sun et al., 2023).

These delays in care can have potentially disastrous outcomes for treatment seekers. Mental health crises are time-sensitive, and an individual's motivation to seek care can be brief and limited. When individuals face long wait times or repeated barriers during intake, their willingness or ability to follow through on seeking treatment can be severely reduced (Reichert & Jacobs, 2018). Moreover, these delays extend how long an individual has to suffer, and they may also increase the severity of symptoms and make it more difficult to treat later down the line when treatment becomes available (Reichert & Jacobs, 2018). In the worst-case scenarios, the effort required to navigate a complicated system becomes overwhelming, leading them to stop seeking care entirely (Reichert & Jacobs, 2018).

1.2. Hypothesis

This project investigates whether this inefficient intake process at mental health treatment centers could be improved through using a conversational AI system to ease administrative burden. Specifically, I explore the feasibility of using an automated agent to handle incoming calls on behalf of a treatment center, collect essential patient information, and conduct a short screening to assess eligibility and urgency. My hypothesis is that this system, which would always be available, can address the core issues in the current intake system by reducing missed calls and streamlining data collection, which is necessary for treatment centers to be able to handle intake efficiently and provide seekers with clear information about availability, status, and eligibility. Rather than deploying my prototype in practice, I tested this hypothesis by evaluating its performance in ability to gather and store relevant information, its response clarity, and other aspects of user experience simulating the early stages of intake communication.

2. Literature Review

As significant advances have been made with chatbot technology over the past few years, there has been a large increase in their use in healthcare. They are useful in almost every aspect of the healthcare ecosystem, from AI-driven conversational agents in mental healthcare, medical information dissemination, appointment management, and lifestyle coaching (Barreda et al., 2025). This large range of functions shows that conversational agents are not only able to handle basic queries but are also being trusted more in sensitive domains that require empathy and precision. Thus, my use case for IntakeAI of supporting initial intake for mental health treatment centers has precedence given the use of conversational AI in other administrative and screening tasks within the healthcare industry.

These AI chatbots have different abilities and features. Two of the most important sets of features are whether it is open domain or closed domain, and whether the interaction type is intrapersonal or interpersonal (Adamopoulou & Moussiades, 2020). Most chatbots in healthcare are closed-domain systems, meaning they are tailored for a specific set of tasks, exactly like my idea for IntakeAI, which is designed to follow a carefully scripted intake protocol (Adamopoulou & Moussiades, 2020). My bot is also interpersonal rather than intrapersonal, meaning it engages with users in a real time conversation to extract all the relevant information. Such chatbots which are closed domain and interpersonal have proven success in supporting call centers and customer service teams by reducing human workload and increasing a system's capabilities to respond to inquiries (Adamopoulou & Moussiades, 2020). This is more precedence for IntakeAI since one of the most important bottlenecks in treatment access is the failure of call centers to follow up with treatment seekers.

In order to ensure that IntakeAI can be effective, it is important to verify that key clinical data such as symptom severity can be reliably assessed over the phone via an AI-driven phone interaction. Chatbots have already been used to conduct complex mental health assessments, however, extended conversations about mental health with chatbots can lead to user distrust (Schick et al., 2022). Therefore, I needed something verified and simple. To address this, I used the Patient Health Questionnaire-4 (PHQ-4) which is a clinically validated tool used to screen for symptoms of anxiety and depression in four short questions (Shields et al., 2021). The PHQ-4 has been shown to have strong psychometric validity even in remote formats such as over the phone (Shields et al., 2021). Therefore, by using PHQ-4 in my system, I was able to have a validated mental health screening process and keep the interaction short, showing that IntakeAI can be an effective simulator of an intake coordinator, at least initially.

In terms of the technical implementation of IntakeAI, I used Bland.AI, a platform specifically designed for building voice-based conversational agents. Although there has not been extensive research on Bland.AI specifically as it is a quite new tool, the designs of the platforms aligned with best practices for conversational UX, and it has been successfully deployed in similarly high-sensitive sectors such as healthcare and banking.

Finally, to evaluate IntakeAI in a rigorous way that also preserves privacy, I drew on the AI evaluation framework proposed by Choo et al. (2024). This uses simulated patient bots and evaluator bots to benchmark healthcare chabot performance. This framework has been proven to be effective in measuring a chatbot's ability to collect relevant information, maintain appropriate tone, and follow protocol without requiring real human data. As discussed more thoroughly in the methods section, I adapted the original setup by incorporating live voice calls and adding in extra dimensions using GPT-4o.

These studies provide a solid foundation for the design and deployment of IntakeAI. They show that 1) chatbots can support administrative and clinical tasks in mental health care, 2) validated screening tools can be administered effectively via voice, 3) platforms like Bland.AI are technically capable of handling structured phone interactions, and 4) AI-based evaluation methods can be used to assess chatbot performance without compromising privacy. By using these studies and grounding my prototype in them, I was able to develop a system that is technically feasible and aligned with best practices in emerging mental health technologies.

3. Methods

3.1. System Design & Implementation

3.1.1. Voice AI Agent

In order to sufficiently simulate an intake coordinator, I needed to build a tool that can not only synthesize speech but also have granular control over dialogue flow and logic. I began the design process by researching existing voice AI agents that would meet these requirements.

After researching and testing various systems, I chose Bland.AI since it was specifically designed for creating AI chatbots and had a very intuitive interface. It allowed me to construct conversational flows using a system of nodes, each one defining a specific interaction. For instance, node types range from default nodes, which are used to talk to the user based on a prompt, to nodes that send a webhook or transfer a call. These nodes can then be connected to create branching conversation pathways based on conditional logic.

The main design task was writing prompts for each node which control what the AI voice agent says at every step. They turned out to be the most complex and time-consuming part of the implementation. Since Bland uses prompt-based logic, the effectiveness of each prompt requires very specific and clear structure and instructions; any ambiguities could cause the bot to behave in unexpected ways. I encountered many issues in this process, where the bot would ask the wrong question, not ask it at all, skip over important guidelines, or misinterpret user responses.

This phase of development was very iterative. I would write a prompt, deploy it to a node, call the bot, and observe its behavior. Based on these tests, I would revise the prompt to make sure it was aligned with the intended behavior. As I got further into this process, I was able to develop a consistent prompt engineering strategy that generally led to a high system reliability. This included:

- Starting each prompt with clear context about the conversation state.
- Breaking down the desired interaction into step-by-step instructions for the bot.
- Including sample dialogue or phrasing to guide the bot's tone and phrasing.
- Defining explicit constraints and guardrails to prevent undesired behavior.

I included an example of a prompt for the very first node in Figure 1:

You are an AI intake coordinator for Vesely Wellness. The user just agreed to go through our quick intake screening process. Your primary goal at this stage is to ask the user to spell their first name.

You must follow these instructions step by step. Pay attention to the details regarding your behavior:
1. First, initiate the conversation by a smooth transition and request the user to spell their first name.
Dialogue Example - "Great! Could you spell your first name for me, please?"
Important things to consider at this step: The user will likely make pauses while spelling their first name. Do not interrupt them. Wait for at least 3 second long silence before you say anything after your question.

2. Then, always confirm that you got the user's first name right by spelling it back to them based on what you captured.
Dialogue Example: "Just to confirm, I got your first name as [Spell their first name back to them]. Is that right?"

3. If the user corrects you, kindly apologize, and acknowledge their correction. Then, confirm the updated information.
Dialogue example: "Sorry about that. So it is [Spell their first name back to them]?"

Figure 1: Initial Node Prompt

I managed the flow of the conversation using conditional logic. For example, at every node, the following path could vary based on whether a user answered a question in a certain way. I designed my prototype in a way that each node only had one outgoing node, so there was no need for branching out to different nodes based on the user's responses. What I mainly used to manage conversation logic was loop conditions, which ensured that the bot repeated or rephrased a question until it received an acceptable response. This was useful to ensure that the bot always validates whether it captured the user's response correctly to ensure data collection accuracy, such as name spellings, phone number precision, etc. This process required very careful fine tuning, just like the prompts, as there were certain cases where I would encounter infinite loops. I included the node tree structure for the conversation I developed in Figure 2:

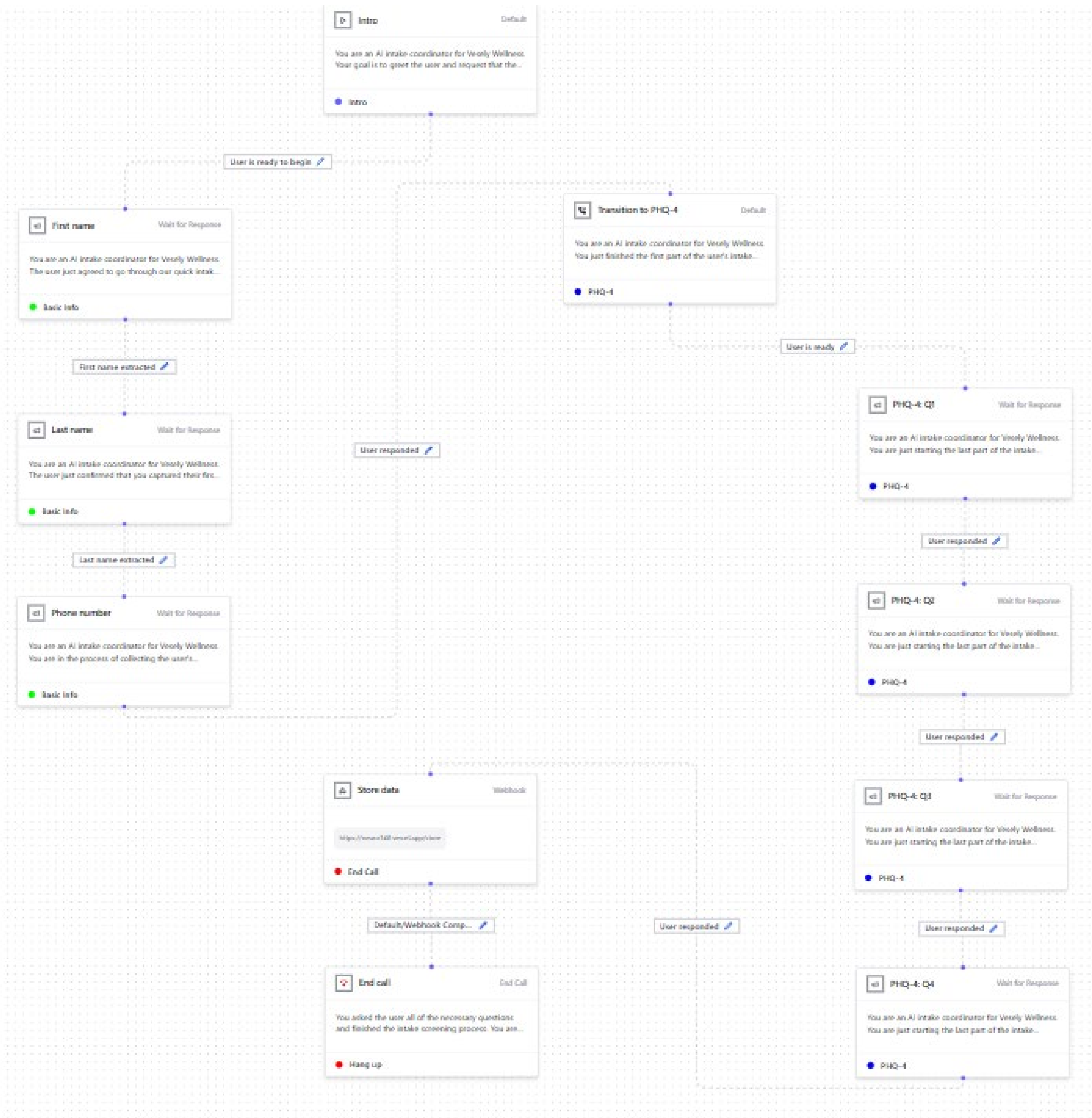


Figure 2: Tree Node Structure

In order to collect the data, I used variable extraction which allowed the system to save specific user responses as structured data. These variables formed the main part of the intake information collected during the call.

This modular, prompt-based system allowed me to simulate a real-world intake call as closely as possible, all in a controlled and testable way.

3.1.2. Intake Flow and Screening Logic

As discussed above, the intake bot was designed to guide users through a structured but streamlined process and collect both basic intake information and initial mental health screening data. The conversation begins with a brief introduction where the bot explains that it will assist the user through a quick intake process on behalf of the treatment center. I designed the tone to be professional and informative, but also empathetic with the hopes of establishing trust with the caller.

The first stage of the call involves gathering essential contact information. This includes first name, last name, and phone number. This information is incredibly important because it allows the treatment center to follow up with the treatment seeker after the call has ended. Thus, it was essential that the data was captured correctly and stored securely. This collected information is the minimum requirement for initiating any post-call action from the treatment center, whether that be putting the caller on a waitlist or starting the onboarding process for care.

The next stage after collecting basic identifiers was a brief standardized screening tool, the Patient Health Questionnaire-4 (PHQ-4). This is a very quick, validated tool used to assess symptoms of anxiety and depression (Kroenke et al., 2009). It consists of four questions which ask the user how frequently they have experienced key symptoms over the past two weeks. Each response is scored on a scale from 0 (not at all) to 3 (nearly every day). The results of each question are then added up to get a total score which indicated the likelihood and severity of anxiety and/or depression.

I decided to use the PHQ-4 because it was a validated method to assess the user's mental health in a very short amount of time making it perfect for my automated intake bot (Shields et al., 2021). In terms of triaging intake patients, this screening data is very valuable because it enables the treatment centers to assess the severity of the caller's condition early on and decide how best to allocate limited resources. Such post-call options include prioritizing higher-severity cases, categorizing calls into different care tracks, or managing waitlists more effectively. I used it to take an otherwise passive intake process into a more informed and responsive process.

Once the PHQ-4 is completed, the bot confirms that all necessary information has been collected and ends the call. The gathered data, including contact details and PHQ-4 responses, are securely stored for use by treatment center staff. This ensures that there is a seamless handoff from AI-driven intake to human-led care coordination.

3.1.3. Dynamic data storage

To support structured and accurate storage of intake data, I developed a backend pipeline that captures user responses from the voice interaction and stores them in a cloud database.

I began by setting up a Firebase Firestore database which was configured to store individual intake records as JSON documents. I generated and stored Firebase credentials securely in a .env file. This ensures that only my server can access the database. In order to ensure maximum trust in the system, it was important to emphasize privacy and security of very sensitive data.

Next, I built a lightweight Flask server with two endpoints:

- /store: a POST endpoint that handles the intake data submitted by Bland.AI.
- /: a GET endpoint that renders a simple HTML dashboard of stored entries.

The /store endpoint is the main executable component of the backend. It accepts JSON payloads from Bland.AI containing user responses. Upon receiving a request, the server:

- Validates and parses the input.
- Computes the total PHQ-4 score.
- Classifies the severity level based on clinical scoring guidelines.
- Determines whether the user is likely experiencing symptoms of anxiety, depression, or both.
- Stores the complete record — including a timestamp — in Firestore.

The second route is a simple dashboard interface for viewing the stored data. It essentially queries the intake records from Firestore and displays them in a basic HTML table. The dashboard includes features to sort entries by either severity or by the date of the phone call. I added this feature to give treatment center flexibility about how they want to prioritize their patient intake.

To make the server accessible from the Bland.AI workflow, I deployed the Flask app to Vercel after configuring a vercel.json file. This deployment meant that the server remains permanently on and can receive real-time intake data from completed calls. The full backend was designed to enable dynamic yet secure storage and display of intake information.

3.2. Evaluation Framework

In order to evaluate the performance of my intake bot, I used the AI-powered evaluation framework proposed by Choo et al. (2025). It is a 3-bot system for testing and validating early-stage health care chatbots. In this framework, simulated patient bots interact with the provider bot and the evaluator bots assess the quality of the interaction. It assesses it using predefined criteria. The original study found that there was a strong alignment between the AI evaluator scores and expert human reviewers, proving that this method is highly reliable. This allowed me to effectively evaluate the performance of my bot without having to deploy it in practice and reveal sensitive mental health data.

The original study relied entirely on AI-simulated interactions, but I modified this structure to incorporate live calls to the deployed bot. I did this to allow for a more realistic evaluation of voice quality, latency, and bot responsiveness over the phone. I was careful to ensure that this adaption retained the strength of the 3-bot framework whilst also capturing the additional complexity of audio-based user input.

The evaluation consisted of the following steps:

- Simulated Patients Using GPT-4o Voice

I initiated 15 test calls to the Bland.AI voice bot using GPT-4o to role play as users with different emotional tones and conversational styles. Some of these tones included anxious, frustrated, or calm users. I instructed GPT-4o to behave like a real user who was seeking treatment and to naturally respond to the bot's prompts. These interactions were designed to simulate the reality of the diverse range of types of call that an intake center would likely receive.

- Transcript Collection

All these interactions were logged and transcribed using Bland.AI's built-in call recording and transcript features. These transcripts captured the full sequences of each conversation and served as the main input for the overall evaluation.

- Evaluator Bot Using GPT-4o

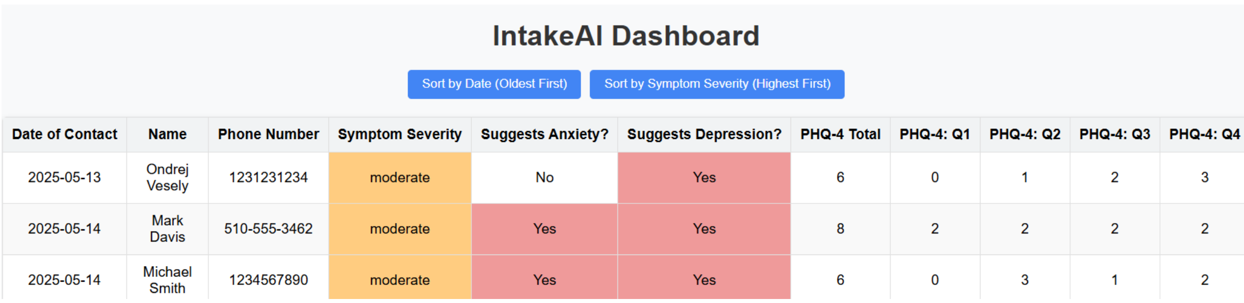
To evaluate performance, I used GPT-4o again, this time as an evaluator bot. Each transcript was fed into the model alongside a structured prompt which asked it to assess the conversation across a set of functional criteria. The criteria were as follows:

- Conversation Flow – Was the dialogue coherent and logically ordered?
- Instruction & Question Clarity – Were the questions asked by the bot easy to understand and appropriately phrased?
- Data Collection Accuracy – Did the bot correctly extract and log all necessary intake information (name, phone number, PHQ-4 answers)?
- Empathy and Tone – Did the bot maintain a supportive, respectful, and professional demeanor?
- Adherence to Role – Did the bot stay within its designed scope (did not give medical advice, followed the script, etc.)?
- User Experience – Was the overall interaction smooth, intuitive, and respectful of the user's state?

I adapted these criteria from the original evaluation framework but modified them to fit my context. For example, I retained some such as tone and role adherence because they are highlight relevant to therapeutic intake scenarios. However, I added others such as Data Collection Accuracy and User Experience to reflect the specific goals of the intake system which prioritized reliably capturing user information whilst also being empathetic and respectful.

3.3. Examples and Demo

You can find all relevant code at this link: https://github.com/veselyo/intakeai. To see all the node prompts that I used in Bland.AI, see the file called "bland_ai_nodes.json" in that same repository. Here, you can see a quick demo of how I performed the evaluation part: https://drive.google.com/file/d/1hfHiYx4BJibM7cMCApckBFdlsZ8ueJJ1/view?usp=sharing. Below, you can also find a snapshot of how the dashboard looks on the Vercel deployment server in Figure 3, which you can also access at this link: https://intakeai-pqzilbcr9-ovesely.vercel.app/.



IntakeAI Dashboard

Sort by Date (Oldest First) Sort by Symptom Severity (Highest First)

Date of Contact	Name	Phone Number	Symptom Severity	Suggests Anxiety?	Suggests Depression?	PHQ-4 Total	PHQ-4: Q1	PHQ-4: Q2	PHQ-4: Q3	PHQ-4: Q4
2025-05-13	Ondrej Vesely	1231231234	moderate	No	Yes	6	0	1	2	3
2025-05-14	Mark Davis	510-555-3462	moderate	Yes	Yes	8	2	2	2	2
2025-05-14	Michael Smith	1234567890	moderate	Yes	Yes	6	0	3	1	2

Figure 3: IntakeAI Dashboard

Unfortunately, I haven't paid for a number for you to call the bot, so it is only able to send a call to a number that you specify within the Bland.AI platform. If you do that, this dashboard will automatically add an entry with the collected information after the call ends. As per the demo, "Mark Davis" was added there automatically.

4. Results

To evaluate the effectiveness of the system, I tested it across a range of simulated caller personas using the evaluation framework as described in Section 2.2. These personas were simulated by the GPT-4o voice feature, so it was calling the IntakeAI bot itself. Each test call was then transcribed and evaluated by the same GPT-4o agent to ensure that it remembers every interaction for more accurate evaluation. The GPT-4o evaluator bot then scored the calls across six key criteria as discussed in Section 2.2. Here are the results:

Criterion, Score (0–3): Justification

- Conversation Flow, 3/3: The bot consistently followed a logical and well-paced flow across all tested personas. It transitioned cleanly between stages of intake without skipping or looping unexpectedly.
- Instruction & Question Clarity, 3/3: Questions were clearly phrased and consistently understood across calm, anxious, and frustrated users. Even subtle prompts (e.g., confirming spelling) were handled well.
- Data Collection Accuracy, 3/3: All required fields (first name, last name, phone number, PHQ-4 responses) were successfully captured and confirmed. No errors were observed in field entry or logic.
- Empathy and Tone, 3/3: The bot maintained an appropriate, warm tone throughout. It remained patient and calm with anxious and frustrated users, never appearing robotic or insensitive.
- Adherence to Role, 3/3: The bot adhered precisely to its purpose: guiding intake without offering diagnoses, advice, or deviating from script. It stayed within clear boundaries as a non-clinical assistant.
- Overall User Experience, 3/3: Across all calls, the experience was smooth, user-friendly, and professional. There were no friction points that disrupted the conversation or caused user confusion.
- Total Score, 18 / 18: The intake bot performed with near-perfect consistency across a range of simulated caller behaviors. It collected information accurately, followed a clear and empathetic script, and maintained role integrity throughout.

These results suggest that the system is highly usable and ready for further testing or integration in intake workflows at mental health treatment centers.

5. Discussion

The results of this project show that IntakeAI is a highly effective tool for improving the intake process at mental health treatment centers. It had strong performance across all of the evaluation criteria, particularly in data collection accuracy, conversational clarity, tone, and adherence to its designed role. The bot was able to consistently capture the key intake information and conduct the screening without creating friction or confusion. It was able to do so consistently across the range of personas tested, including the angry persona that was used in the demo.

These findings support my original hypothesis that automated voice agents can be reliable first points of contact for treatment seekers due to their constant availability. As such they can reduce the burden on administrative staff in treatment centers, which is the current pain point when it comes to patient intake. As such, IntakeAI can help ensure that no call for help is missed and that treatment centers receive structured, actionable information about each treatment seeker. This is a really crucial improvement in a system where long wait times and missed calls are common.

I was able to successfully adapt the 3-bot evaluation framework, thus highlighting the promise of using LLMs to both build and also test and validate healthcare AI systems (Choo et al., 2025). My evaluation method simulates users and evaluated transcripts with GPT-4o, performing controlled and efficient validation processes without requiring real patients or deployment in actual centers. This is a really interesting avenue for future exploration when it comes to early stage development in highly sensitive areas such as mental health and healthcare more broadly.

There are limitations in this study, primarily the fact that even though the bot was evaluated under varied user personas, the testing occurred only in a simulated environment. When it comes to the real world, there may be a number of additional challenges such as noisy environments, diverse accents, and emotional difficulties beyond what the bot was trained to handle. Another limitation is that the bot currently operates with fixed prompt logic without incorporating active learning or dynamic personalization. These would both be valuable next steps.

In terms of future work, it would be really interesting to explore integration with electronic health records, multilingual support, and more sophisticated triage models that have more advanced risk detection features. As mentioned above, testing in real-world scenarios which include feedback from actual users and clinical staff would also be important to fully assess the system.

To conclude, IntakeAI has proven to have strong early-stage feasibility as a tool to automate and streamline treatment center intake processes. Further validation is required before real-world deployment, however, this prototype has shown that AI can play a meaningful role improving access and reliability of care for those who need it most.

References

Twenge, J. (2019, March 14). Mental Health Issues Increased Significantly in Young Adults over Last Decade. American Psychological Association. https://www.apa.org/news/press/releases/2019/03/mental-health-adults

Briones, E. M., & Giri, A. (2024). QuickStats: Mental health treatment trends among adults aged ≥18 years, by age group - United States, 2019–2023. *MMWR. Morbidity and Mortality Weekly Report*, 73(50), 1150. https://doi.org/10.15585/mmwr.mm7350a5

Sun, C.-F., Correll, C. U., Trestman, R. L., Lin, Y., Xie, H., Hankey, M. S., Uymatiao, R. P., Patel, R. T., Metsutnan, V. L., McDaid, E. C., Saha, A., Kuo, C., Lewis, P., Bhatt, S. H., Lipphard, L. E., & Kablinger, A. S. (2023). Low availability, long wait times, and high geographic disparity of psychiatric outpatient care in the US. General Hospital Psychiatry, 84, 12–17. https://doi.org/10.1016/j.genhosppsych.2023.05.012

Reichert, A., & Jacobs, R. (2018). The impact of waiting time on patient outcomes: Evidence from early intervention in psychosis services in England. *Health Economics*, *27*(11), 1772–1787. https://doi.org/10.1002/hec.3800

Barreda, M., Cantarero-Prieto, D., Coca, D., Delgado, A., Lanza-León, P., Lera, J., Montalbán, R., & Pérez, F. (2025). Transforming healthcare with chatbots: Uses and applications—A scoping review. DIGITAL HEALTH, 11. https://doi.org/10.1177/20552076251319174

Adamopoulou, E., & Moussiades, L. (2020). An Overview of Chatbot Technology. IFIP Advances in Information and Communication Technology, 584(1), 373–383. https://doi.org/10.1007/978-3-030-49186-4_31

Schick, A., Feine, J., Morana, S., Maedche, A., & Reininghaus, U. (2022). Validity of Chatbot Use for Mental Health Assessment: Experimental Study. JMIR MHealth and UHealth, 10(10), e28082. https://doi.org/10.2196/28082

Shields, R. E., Korol, S., Carleton, R. N., McElheran, M., Stelnicki, A. M., Groll, D., & Anderson, G. S. (2021). Brief Mental Health Disorder Screening Questionnaires and Use with Public Safety Personnel: A Review. International Journal of Environmental Research and Public Health, 18(7), 3743. https://doi.org/10.3390/ijerph18073743

Choo, S., Yoo, S., Endo, K., Truong, B., & Son, M. H. (2025). Advancing Clinical Chatbot Validation Using AI-Powered Evaluation With a New 3-Bot Evaluation System: Instrument Validation Study. *JMIR Nursing*, *8*, e63058–e63058. https://doi.org/10.2196/63058

Kroenke, K., Spitzer, R. L., Williams, J. B. W., & Löwe, B. (2009). An Ultra-Brief Screening Scale for Anxiety and Depression: The PHQ–4. Psychosomatics, 50(6), 613–621. https://doi.org/10.1016/s0033-3182(09)70864-3