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Design and Development of a Hybrid Rule-Based and Controlled AI Chatbot for Digital Mental Health Services

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Abstract: Mental health issues have become increasingly prevalent, highlighting the need for accessible and integrated digital psychological services. Existing systems are often fragmented — communication, information delivery, and service management are separated across different platforms, creating operational inefficiencies. This study designs and develops a web-based hybrid chatbot system for digital mental health services at Corporate Psikologi Indonesia. The proposed system applies a hybrid approach combining keyword-based detection, a structured knowledge base, and controlled artificial intelligence to produce consistent and safe responses. A consultation booking feature is built into the same platform to support both informational and service-based interactions. The system was developed using a prototype-based approach and evaluated through functional testing and a preliminary user evaluation in a controlled environment. Results show that the system supports user interaction, delivers relevant mental health information, and facilitates consultation booking and service access effectively. The proposed hybrid chatbot architecture addresses service accessibility while maintaining response reliability. Future work will focus on broader user evaluation and stronger natural language understanding capabilities.

Keywords: Hybrid Chatbot; Mental Health; Keyword-Based Scoring; Digital Psychological Services; Prototype Model.

1. Introduction

Mental health has become a significant concern in modern society as individuals face growing psychological pressure from work, education, and social environments. Rapid lifestyle changes, technological demands, and economic uncertainty contribute to emotional stress and clinical mental health disorders. According to the World Health Organization (2023), conditions such as anxiety and depression affect a substantial portion of the global population, with consequences that extend beyond the individual to productivity, social relationships, and quality of life. Digital technology has changed how people access healthcare in response to this growing burden. Web-based platforms allow users to obtain information and support more flexibly, without geographical or time constraints, and systematic reviews confirm that digital mental health interventions reduce symptoms of depression and anxiety at a clinically meaningful level (Philippe *et al.*, 2022). Within this landscape, chatbot technology has attracted considerable attention as a delivery mechanism for mental health services — offering real-time interaction, continuous availability, and automated responses. Prior research shows that chatbot-based systems can support psychoeducation, early-stage communication, and self-guided mental health assistance (Abd-Alrazaq *et al.*, 2019; Casu *et al.*, 2024; He *et al.*, 2023; Li *et al.*, 2023; Nyakhar & Wang, 2025). Conversational agents also serve as a low-barrier entry point for individuals who avoid professional help due to stigma or privacy concerns — a problem that remains particularly persistent in mental health contexts.

These advantages, however, come with real limitations. Many chatbot implementations depend heavily on generative artificial intelligence, which can produce inconsistent or unverified outputs. In mental health settings, where response accuracy directly affects user safety, this represents a structural risk rather than a minor technical inconvenience (Casu *et al.*, 2024; Fiske *et al.*, 2019). Beyond response quality, most existing systems treat conversation as an isolated function. Communication, information delivery, and service management remain distributed across separate platforms, creating fragmented user experiences, increased administrative workload, and delayed responses. Users must move between systems to access information and schedule consultations — a process that reduces usability and overall service effectiveness. These conditions are directly observable at Corporate Psikologi Indonesia, where client-provider communication is still conducted manually through general messaging applications. Users contact administrators to obtain service information and scheduling details, a process prone to delays, inconsistencies, and scheduling conflicts that reduce service quality and user satisfaction.

Prior research on mental health chatbots has largely focused on conversational performance rather than system-level integration. Vaidyam *et al.* (2019) documented the potential of conversational agents to improve user engagement, while Cruz-Gonzalez (2025) examined the role of artificial intelligence in diagnosis, monitoring, and intervention. Neither line of work fully addresses the need to connect chatbot interaction with structured service components such as consultation management and verified information delivery. This gap motivates the present study, which proposes the design and development of a hybrid chatbot-based digital psychological service system using a structured knowledge base. The system combines keyword-based detection, database-driven responses, and controlled artificial intelligence to maintain consistency and reliability, with consultation booking and service management built into the same platform to enable end-to-end service delivery. The objectives of this study are: (1) to design a web-based hybrid chatbot system for mental health services; (2) to apply a structured knowledge base to improve response accuracy; (3) to connect consultation booking within a unified system; and (4) to evaluate the system through functional and user acceptance testing. The remainder of this paper is organized as follows: Section 2 reviews the relevant literature; Section 3 describes the methodology; Section 4 presents results and analysis; and Section 5 concludes the paper.

2. Related Work

This section reviews previous studies related to digital mental health services, chatbot technology, system limitations, and supporting technologies, with the aim of identifying current research developments and the gaps that motivate the proposed hybrid chatbot-based system.

2.1 Digital Mental Health Services

Digital mental health services have grown in prominence as demand for accessible psychological support continues to outpace the capacity of traditional clinical systems. The World Health Organization (2023) has called for mental health services to extend beyond conventional clinical settings through digital platforms, emphasizing that web-based systems allow users to access services without geographical restrictions. Cruz-Gonzalez (2025) conducted a systematic review confirming that artificial intelligence can support diagnosis, monitoring, and intervention processes in mental healthcare. Nyakhar & Wang (2025) found that chatbot-based interventions reduce symptoms of anxiety and depression, while Abd-Alrazaq *et al.* (2019, 2020) documented both the effectiveness and feature profiles of chatbot systems in mental health contexts. Torous (2020) made an early case for digital solutions as a means of expanding access to mental healthcare — an argument supported by Philippe *et al.* (2022), whose meta-analytic review demonstrated that digital mental health interventions produce measurable improvements in psychological outcomes, particularly for anxiety and depression. Taken together, these findings establish that digital platforms are not merely supplementary to traditional care — they address access gaps that conventional systems cannot resolve.

2.2 Chatbot Technology in Mental Health

Chatbots have been widely adopted as a mental health support tool, primarily because of their real-time availability and capacity for automated interaction. Vaidyam *et al.* (2019) reviewed conversational agents and found consistent evidence that chatbots improve accessibility and user engagement. Fitzpatrick *et al.* (2017) provided one of the earliest empirical demonstrations of chatbot efficacy through Woebot, a conversational agent that reduced symptoms of depression and anxiety in a randomized trial. Casu *et al.* (2024) confirmed that chatbots can deliver immediate and sustained support, though maintaining response consistency across varied user inputs remains an unresolved challenge. Laranjo (2018) reviewed conversational agents across healthcare domains more broadly and noted their potential while also pointing out that many systems lack rigorous evaluation and meaningful connection to clinical services — a limitation that persists in current implementations. Ethical and safety considerations add another layer of complexity, particularly in mental health contexts where user vulnerability makes response quality a matter of genuine consequence (Fiske *et al.*, 2019). On the development side, Arief *et al.* (2023) proposed a hybrid chatbot combining machine learning with generative artificial intelligence and reported improved response capabilities, while Ramayanti *et al.* (2023) demonstrated that Naïve Bayes and Random Forest algorithms can classify user emotional states from text with reasonable accuracy. Bickmore & Giorgino (2006) established early theoretical groundwork for conversational systems in health contexts, work that continues to inform current chatbot design.

2.3 Limitations of Existing Systems and Research Gap

Despite technical progress, existing chatbot systems share a common structural weakness: they treat conversation as the endpoint rather than one component of a broader service workflow. Casu *et al.* (2024) identified that generative AI-based chatbots frequently produce inconsistent or unverified outputs — a problem with direct safety implications in mental health settings. Miner *et al.* (2019) argued that AI in mental health must account for reliability and ethical responsibility, particularly when handling sensitive personal data. Studies such as Nyakhar & Wang (2025) focus primarily on intervention outcomes rather than system architecture, leaving the question of how to build well-integrated service systems largely unaddressed. Arief *et al.* (2023) and Ramayanti *et al.* (2023) addressed chatbot performance and emotion detection but did not extend their work to full service delivery. The pattern across these studies is consistent: the field has invested heavily in improving what chatbots say, but comparatively little in how chatbot interaction connects to the services users actually need. This gap — the absence of an integrated system that combines chatbot interaction, verified information delivery, and consultation management within a single platform — directly motivates the present study.

2.4 Integrated Digital Psychological Service Systems and Supporting Technologies

Addressing the fragmentation of existing systems requires a platform that handles communication, information delivery, and service management within a unified environment rather than distributing these functions across separate applications. Cruz-Gonzalez (2025) argued for the importance of connecting artificial intelligence to broader mental healthcare systems, and the World Health Organization (2023) has similarly called for scalable, integrated solutions at the global level. Most existing systems have not achieved this degree of integration, leaving a practical gap between chatbot interaction and operational service components such as consultation booking and administrative management. The proposed system addresses this gap through a hybrid approach supported by natural language processing, machine learning, and web-based architecture. NLP enables the chatbot to process user input through keyword detection and text classification to identify user intent and emotional conditions — techniques whose role in healthcare applications has been documented by Jiang *et al.* (2017). Machine learning approaches, as demonstrated by Ramayanti *et al.* (2023), can classify emotional states from textual input, though purely AI-based methods require large datasets and may produce variable results under real-world conditions. The hybrid approach adopted in this study combines keyword-based detection, database-driven responses, and controlled artificial intelligence to maintain response consistency while preserving conversational flexibility. Web-based architecture supports accessibility and scalability, enabling the system to serve users across locations without requiring dedicated software installation. This combination of technologies provides the technical foundation for an end-to-end digital psychological service platform applicable in organizational contexts such as Corporate Psikologi Indonesia.

3. Methodology

This study adopts the Prototype model to design and develop a hybrid chatbot-based digital psychological service system at Corporate Psikologi Indonesia. The Prototype model supports iterative development — the system is refined continuously based on evaluation results and user feedback, rather than being built to a fixed specification and tested only at the end. The proposed system applies a Hybrid Multi-Layer Architecture that combines keyword-based detection, a structured knowledge base, and controlled artificial intelligence to produce responses that are consistent, contextually relevant, and safe — properties that rule-based systems alone cannot achieve, and that generative AI systems alone cannot guarantee.

3.1 Research Method

The system development follows five sequential stages. In the Requirement Analysis stage, interviews with administrators and psychologists at Corporate Psikologi Indonesia, combined with direct observation of existing service workflows, were conducted to identify system requirements and user needs. Based on these findings, the System Design stage produced the system architecture, chatbot workflow, database structure, and user interface specifications. A functional Prototype was then built to implement core features — chatbot interaction and consultation booking. The prototype was subsequently subjected to Testing, which involved functional testing and a preliminary evaluation in a controlled environment with 10 participants who assessed usability and user experience using a 5-point Likert scale via a Google Forms questionnaire. Finally, the Refinement stage addressed weaknesses identified during testing through iterative revision of system components. The evaluation was designed to provide initial performance insights; a more thorough user study with a larger and more diverse participant pool is recommended for subsequent research.

3.2 System Architecture

The system is built as a web-based application using a client-server architecture. The frontend is developed in React.js to provide a responsive and user-friendly interface, while the backend runs on Python Flask to handle system logic and communication between components. A structured database stores mental health content, keyword categories, response templates, user data, and consultation schedules. A controlled artificial intelligence component is connected to the response layer to improve conversational naturalness while keeping outputs within predefined boundaries set by the structured knowledge base. This design ensures that chatbot interaction, information delivery, and consultation services operate within a single platform rather than across separate systems that users must navigate independently.

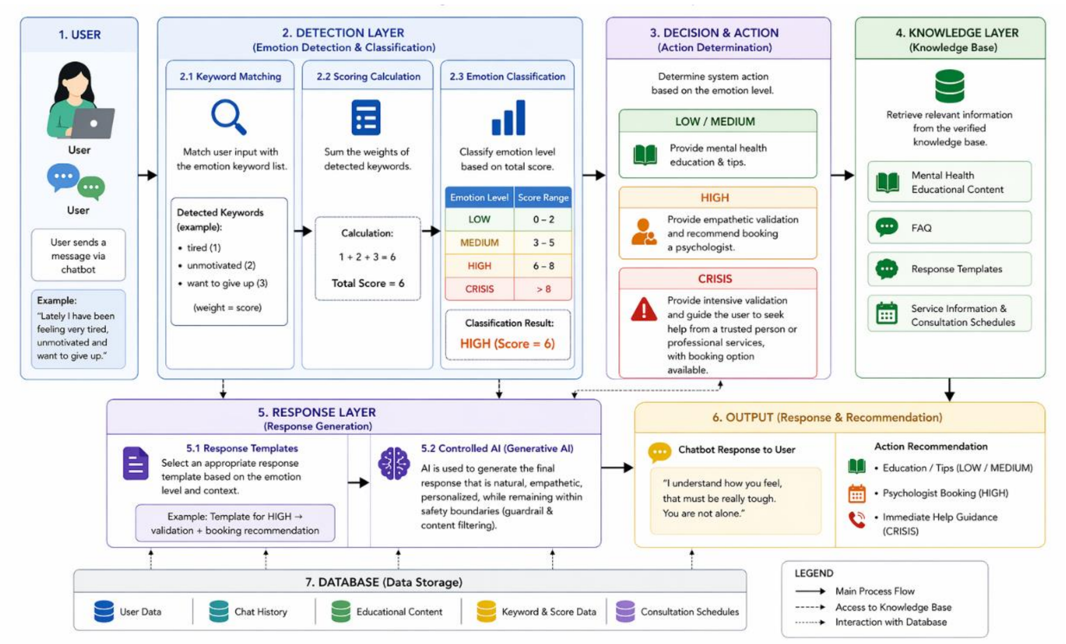

Figure 1. Hybrid Chatbot System Architecture

3.3 Hybrid Multi-Layer Model

The chatbot operates through a three-layer architecture. The Detection Layer analyzes user input to identify emotional conditions using keyword-based scoring. The Knowledge Layer retrieves relevant responses from the structured knowledge base. The Response Layer refines retrieved responses using controlled artificial intelligence to improve naturalness while maintaining consistency. The hybrid design combines rule-based processing with controlled generative capability — a combination that matters in mental health applications, where the cost of an inconsistent or inappropriate response is not merely a usability problem but a safety concern.

3.4 Keyword-Based Scoring Method

The system classifies user emotional conditions through a keyword-based scoring method. Keywords are drawn from mental health literature and adapted to reflect how users express emotional states in everyday conversation rather than clinical terminology. Each keyword is assigned a weight representing the severity of the associated emotional condition, grounded in the Kessler Psychological Distress Scale (K10) and refined through consultation with mental health practitioners at Corporate Psikologi Indonesia. Keywords associated with mild states (e.g., *"tired"*) receive lower weights, while those indicating moderate to severe distress (e.g., *"anxious," "hopeless"*) receive higher weights. Expressions associated with immediate risk — *"self-harm"* and *"suicide"* — receive the highest weights, reflecting their clinical significance. The total score is calculated as the sum of all detected keyword weights in a given user input, and the resulting score maps to one of four emotional levels: LOW (0–2), MEDIUM (3–5), HIGH (6–8), and CRISIS (>8). This mechanism produces classifications that are both consistent and explainable — a meaningful advantage over black-box machine learning approaches in a context where response rationale matters.

Table 1. Keyword Weighting Scheme

Keyword	Weight	Category
sad	2	mild
tired	1	mild
anxious	2	moderate
stressed	2	moderate
hopeless	3	severe
worthless	3	severe
want to give up	3	severe
self-harm	5	crisis
suicide	5	crisis

3.5 Dataset, Knowledge Base, and System Workflow

The dataset consists of primary data collected through interviews and workflow observations at Corporate Psikologi Indonesia, and secondary data drawn from mental health literature and related research. The knowledge base includes mental health educational content, emotional keyword lists, response templates, and service-related data — all structured to support consistent chatbot outputs. Formal clinical validation was not conducted at this stage, but content was reviewed against general mental health support guidelines and refined through practitioner consultation to minimize the risk of inappropriate responses. The system workflow begins when a user submits a message through the chatbot interface. The Detection Layer processes the input and calculates a keyword score to determine the emotional level. The Knowledge Layer retrieves the appropriate response, which the Response Layer then refines using controlled artificial intelligence before delivery. Users classified at the HIGH level receive a recommendation to book a consultation with a psychologist. Users classified at the CRISIS level receive explicit safety guidance directing them to seek immediate help from a trusted person or professional service. At this level, the system does not attempt to resolve the situation through automated conversation — human intervention takes priority over chatbot response.

4. Result and Discussion

4.1 Results

4.1.1 Implementation Results

The proposed system was successfully built as a web-based application supporting three user roles: users, administrators, and psychologists. Users interact with the chatbot to express their emotional conditions — the system processes each input through keyword-based detection, calculates a distress score, classifies the emotional level into one of four categories (LOW, MEDIUM, HIGH, CRISIS), and generates a structured response with appropriate recommendations. Administrators manage system data including mental health content, keyword lists, response templates, and consultation schedules. Psychologists access consultation data and manage appointments. The consultation booking feature allows users to schedule sessions directly through the platform, removing the need for manual coordination through external messaging applications. The system successfully implements all planned features and demonstrates feasibility as an integrated digital psychological service platform. Figures 2 and 3 present the chatbot interface and consultation booking interface, respectively.

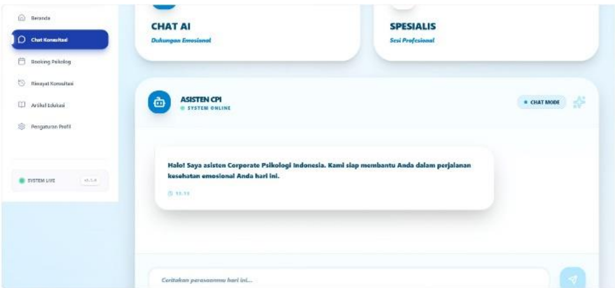

Figure 2. Chatbot Interface

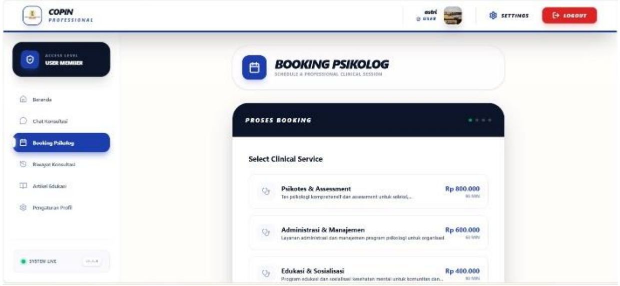

Figure 3. Consultation Booking Interface

4.1.2 Testing Results

System testing was conducted to evaluate whether all components function according to design specifications, covering functional testing, chatbot scenario testing, and user acceptance testing. Functional testing confirmed that each system component operates correctly. As shown in Table 2, all five core features — chatbot input, keyword detection, emotion classification, response generation, and consultation booking — passed testing without critical errors.

Table 2. Functional Testing Results

Feature	Description	Result
Chatbot Input	Users can input messages	Success
Keyword Detection	System detects emotional keywords	Success
Emotion Classification	System classifies emotional levels	Success
Response Generation	System generates appropriate responses	Success
Consultation Booking	Users can schedule consultations	Success

Chatbot performance was further evaluated across four input scenarios representing each emotional level (Table 3). The system correctly identified keywords, assigned the appropriate classification level, and generated contextually suitable responses in all tested cases.

Table 3. Chatbot Testing Results

No	User Input	Detected Keywords	Level	System Response
1	I feel tired today	Tired	Low	Provides encouragement
2	I feel anxious and stressed	anxious, stressed	Medium	Provides coping suggestions
3	I feel hopeless and want to give up	Hopeless	High	Recommends booking
4	I want to hurt myself	self-harm	Crisis	Suggests immediate help

For CRISIS-level inputs, the system delivers an explicit safety message rather than a generic automated response — for example: *"It sounds like you are going through a very difficult time. Please consider contacting a trusted person or a mental health professional immediately. You may also reach out to available mental health support services or crisis hotlines in your area."* This response acknowledges the user's situation while directing them toward real-world assistance. At this level, human intervention takes priority over continued chatbot interaction. A preliminary user acceptance evaluation was conducted with 10 participants in a controlled environment using a 5-point Likert scale (Table 4). All four evaluated aspects scored above 4.0, reflecting a generally positive reception. Response relevance received the lowest score among the four aspects — a finding that points directly to where further development is needed.

Table 4. User Acceptance Testing

Aspect	Mean Score	Category
Ease of Use	4.2	Good
Response Relevance	4.0	Good
Interface Clarity	4.3	Good
Feature Integration	4.1	Good

4.1.3 Performance Evaluation

System performance was assessed based on responsiveness and operational stability under normal testing conditions. As summarized in Table 5, the system achieved an average response time of 1.3 seconds, supporting near real-time interaction. No critical failures were observed throughout testing, indicating stable operation. These results reflect practical system performance rather than algorithmic optimization, which remains a direction for future work.

Table 5. System Performance Metrics

Metric	Description	Result
Response Time	Average chatbot response time	1.3 seconds
System Stability	System reliability during testing	Stable
Feature Functionality	All features operate correctly	Functional
User Satisfaction	Overall user perception	Positive

4.2 Discussion

The results show that the proposed hybrid chatbot system performs adequately across the dimensions tested: system functionality, usability, and service integration. Compared to purely generative AI-based systems, the hybrid approach produces more controlled and consistent responses — a difference that becomes most consequential in crisis scenarios, where the cost of an inappropriate response is highest. The user evaluation results, with all usability aspects scoring above 4.0, reflect a generally positive reception, though the relatively lower score for response relevance signals that the current response generation mechanism has room for improvement.

The keyword-based scoring method provides structured and explainable classification of user emotional conditions. This is not a trivial advantage. In mental health applications, the ability to trace why a system produced a particular response — and to verify that the response is appropriate — carries more weight than raw conversational fluency. Purely generative systems offer the latter but cannot reliably guarantee the former. The four-level classification scheme (LOW, MEDIUM, HIGH, CRISIS) allows the system to calibrate responses to user conditions rather than applying a uniform approach. The CRISIS level is the most consequential: by directing users toward immediate professional help rather than attempting to manage the situation through automated responses, the system acknowledges the boundary between what a chatbot can appropriately do and what requires human judgment. The connection between chatbot interaction and consultation booking addresses a structural problem that most existing systems leave unresolved. Users who receive a recommendation to consult a psychologist can act on that recommendation immediately, within the same platform, without switching to a separate application or contacting an administrator manually. This reduces friction and removes a coordination burden that, as observed at Corporate Psikologi Indonesia, has historically contributed to delays and scheduling errors.

Several limitations remain. The keyword-based method does not capture indirect or complex expressions — sarcasm, understatement, or mixed emotional signals will likely be misclassified or missed entirely. This is consistent with findings from Feng *et al.* (2025), who noted that AI-based conversational agents continue to struggle with context-dependent user inputs. The controlled AI component has not been compared experimentally against fully generative alternatives, so the performance advantage of the hybrid approach remains descriptively supported but not formally quantified. The evaluation sample of 10 participants is sufficient for preliminary insights but insufficient for generalizable conclusions. Future work should address emotion detection through more advanced NLP techniques, expand the keyword dataset to cover a broader range of expressions, and conduct comparative evaluations against alternative chatbot architectures with a larger and more representative user sample.

5. Conclusion and Recommendations

This study designed and developed a web-based hybrid chatbot system for digital mental health services at Corporate Psikologi Indonesia, with results that support four substantive conclusions. The system successfully delivers an integrated platform combining chatbot interaction, mental health information delivery, and consultation booking within a single environment — addressing the fragmentation that characterizes most existing digital psychological service systems. The structured knowledge base enables consistent and controlled response generation, reducing the risk of inappropriate outputs that remain a documented weakness of purely generative AI approaches. The consultation booking feature eliminates the manual coordination process previously conducted through external messaging applications, directly reducing administrative workload and scheduling errors. Functional testing and user acceptance evaluation confirm that the system operates as designed and is received positively by users, with mean scores above 4.0 across all evaluated usability aspects. The primary contribution of this study is an integrated hybrid chatbot architecture that connects structured knowledge, controlled response mechanisms, and service management within a unified platform — a combination that existing systems have addressed only partially. The keyword-based scoring method, grounded in the Kessler Psychological Distress Scale and refined through practitioner consultation, provides explainable emotional classification across four severity levels, with the CRISIS level designed to redirect users toward immediate professional help rather than sustain automated interaction.

Two limitations deserve honest acknowledgment. The keyword-based method handles straightforward expressions reasonably well but struggles with indirect, ambiguous, or contextually complex inputs — a constraint that affects real-world applicability given that distressed users do not always communicate in direct terms. The controlled AI component has not been benchmarked against fully generative alternatives, leaving the performance advantage of the hybrid approach empirically unquantified. The evaluation sample of 10 participants, while adequate for a preliminary study, cannot support broad generalizations about system performance. Future research should pursue three directions: advancing emotion detection through more sophisticated NLP methods capable of handling contextual and implicit expressions; expanding the keyword dataset to reflect greater linguistic diversity; and conducting comparative evaluations against alternative chatbot architectures with a larger, more representative user sample. These steps are necessary to move the system from a working prototype toward a clinically deployable solution.

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