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# LumiCHAT: An Expert-Based Mental Health Support Chatbot for Students

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***Abstract*** **- This study developed and evaluated an expert-based mental health support chatbot designed to provide accessible, confidential, and responsive assistance to students of Tagoloan Community College experiencing emotional distress, academic pressure, and psychological concerns. The system employed Artificial Intelligence and Natural Language Processing through RASA, supported by Laravel and React.js, to deliver empathetic conversations, assess risk levels, recommend coping strategies, and activate referral mechanisms to guidance counselors when necessary. Using the Agile Software Development Life Cycle, the platform integrated key features such as anonymous interaction, bilingual communication, automated appointment scheduling, and secure data handling compliant with the Data Privacy Act of 2012. System testing and usability evaluation using the System Usability Scale confirmed that the application is functional, user-friendly, and effective in reducing barriers caused by stigma, limited access to counseling services, and hesitation to seek help. The results demonstrate that the system enhances institutional mental health support by promoting early intervention, strengthening student-counselor communication, and fostering emotional well-being through a safe, inclusive, and technology-driven platform, contributing to a more responsive mental health support system within the academic environment.**

***Keywords - mental health chatbot, student support system, artificial intelligence, natural language processing, counseling referral, Agile SDLC, higher education mental health***

## I. INTRODUCTION

Mental health challenges among college students have increased due to academic pressure, social stressors, and limited access to professional support [1]. Although counseling services exist in many higher education institutions, they are often underutilized because of stigma, scheduling difficulties, and limited availability of mental health professionals [2]. As a result, many students do not receive timely intervention, negatively affecting their well-being and academic performance [3].

Recent studies indicate that AI-based chatbots can serve as effective supplementary tools for mental health support by providing anonymous, immediate, and nonjudgmental interactions [4], [5]. However, institutional deployment of such systems requires careful consideration of ethical responsibility, data privacy, and system reliability [6].

To address these concerns, this study developed LumiCHAT, an expert-based mental health support chatbot for Tagoloan Community College. The system functions as an initial support platform that provides coping guidance, self-care recommendations, and referral to institutional counselors when necessary. LumiCHAT was implemented

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using a web-based architecture with secure backend services and an interactive frontend, incorporating natural language processing to interpret user concerns and deliver expert-guided responses [7].

## II. RELATED WORK

Recent studies have demonstrated the growing role of conversational agents in supporting mental health and educational services. Prior research has focused on chatbot architecture, development platforms, natural language processing (NLP) integration, and evaluation strategies relevant to sensitive domains such as mental health **[8], [9].**

### A. Chatbot Architecture and Development Approaches

Agile-based development models are widely adopted in chatbot systems due to their flexibility and emphasis on iterative refinement. Skuridin and Wynn proposed an operational framework that links strategic objectives with Agile practices, highlighting the importance of continuous user feedback and rapid prototyping **[8]**. Similarly, Alegado et al. demonstrated the effectiveness of Agile SDLC in an academic chatbot system, reporting improved adaptability and usability through iterative testing **[9]**.

Advanced chatbot architectures have also incorporated knowledge-driven structures. Singla et al. introduced CAMI, which employed a knowledge graph to generate context-aware responses, enabling more precise and personalized recommendations **[10]**. These architectural strategies informed the modular and extensible design adopted in LumiCHAT.

### B. Development Tools and Platforms

The choice of chatbot development platform significantly affects scalability, transparency, and data control. Pérez-Soler et al. compared popular platforms such as Dialogflow, IBM Watson, and Rasa, concluding that open-source frameworks provide greater flexibility and deployment control **[11]**. Abdellatif et al. further highlighted that Rasa's modular architecture and customizable NLU pipelines make it suitable for research-oriented and privacy-sensitive applications **[12]**. These findings support the selection of open and locally deployable chatbot frameworks for institutional environments.

### C. NLP and AI in Mental Health Chatbots

NLP and AI techniques enable chatbots to recognize user intent, analyze sentiment, and generate appropriate responses. Zhou et al. demonstrated that emotionally aware conversational systems, such as XiaoIce, can sustain meaningful user engagement through empathy-driven interaction metrics **[13]**. Large language models have further improved conversational depth and contextual understanding, reinforcing their suitability for mental health support applications **[10]**.

### D. Applications in Education and Mental Health

Several studies have confirmed the effectiveness of chatbots in educational and mental health contexts. CAMI successfully delivered evidence-based guidance to caregivers through a participatory design approach **[10]**. In academic settings, chatbots have been shown to influence student decision-making and trust in AI-assisted systems **[14]**. Locally, Cuevas et al. demonstrated the feasibility of NLP-enabled chatbots in Philippine public service systems, indicating strong user acceptance of conversational platforms **[15]**.

### E. Evaluation Strategies

Chatbot evaluation commonly combines usability testing, performance metrics, and quality models. Prior studies employed ISO/IEC 25010 to assess system quality across usability, reliability, and security dimensions **[9], [10]**. Additional metrics such as intent recognition accuracy, response latency, and conversation length have been used to quantify system effectiveness and engagement **[8]**.

### F. Research Gap

Although existing studies validate the effectiveness of chatbots in mental health and education, limited work has focused on institution-based, expert-guided chatbot systems deployed within Philippine higher education settings. LumiCHAT addresses this gap by integrating expert-validated mental health guidance, privacy-conscious system design, and usability evaluation tailored to student support services.

## III. METHODOLOGY

This study adopted the Agile Software Development Life Cycle (SDLC) model for the development of LUMICHAT, an expert-based chatbot for mental health support for students. Agile was selected for its iterative, collaborative, and user-centered nature, which enables continuous refinement based on stakeholder feedback and evolving user needs. The Agile cycle consists of planning, design, development, testing, deployment, and review phases, supporting responsiveness to change throughout the system lifecycle.

Figure 1.0 Agile lifecycle, adapted from Pratama & Kristiana


(2023)

The development of LUMICHAT involved active participation from guidance counselors, mental health professionals, and student users. Agile facilitated a participatory environment where functional components could be incrementally delivered, evaluated, and refined to ensure alignment with both technical and psychological requirements. This approach ensured that system accuracy and emotional appropriateness were addressed consistently across development phases [16].

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### A. Planning Phase

During the planning phase, the research team conducted structured interviews and consultations with guidance counselors and students to identify functional and emotional requirements for LUMICHAT. These activities aimed to surface challenges related to access to mental health support, emotional expression, anonymity, and availability.

This stakeholder-driven approach aligns with prior chatbot development studies in mental health contexts, where end-user participation significantly influenced system design and feature prioritization. Through co-design, key features such as anonymous interaction, mood tracking, and counselor referral booking were identified **[10].**

User requirements were translated into structured user stories following the format: *"As a [user role], I want [feature] so that [benefit]."* These user stories formed the initial product backlog and guided sprint planning.

To contextualize existing limitations, a manual process flowchart was created to document current counseling workflows and pain points, including long waiting times and limited counselor availability. Process visualization has been shown to effectively reveal inefficiencies and guide digital intervention design **[15].**

### B. Design Phase

The design phase focused on translating user stories into tangible system representations. Low- and high-fidelity wireframes were developed using Figma to visualize the user interface and interaction flow. The designs followed inclusive UX principles to ensure accessibility and emotional comfort across devices.

The interface design was informed by affective computing and emotionally aware UX guidelines, emphasizing clarity, reassurance, and trust in user–chatbot interactions **[8]**.

Use-case diagrams were created to model interaction scenarios such as initiating conversations, expressing emotional distress, receiving coping suggestions, and escalating to counselor support. These artifacts helped stakeholders validate functional coverage.

The emotional tone and phrasing of chatbot responses were reviewed based on best practices in empathetic conversational design, ensuring that responses acknowledged user emotions and avoided generic or dismissive language **[13], [17].**

### C. Development & Implementation (Tools and Software)

The development phase implemented LUMICHAT through iterative Agile sprints emphasizing modularity, collaboration, and continuous integration. The system was designed using a layered architecture that separated presentation, application logic, chatbot processing, and data management to improve maintainability and scalability [9].

The LumiCHAT system is organized as a four-layer architecture (see Fig. 2.0). The presentation layer (React.js with Tailwind/Bootstrap) implements the responsive user interface — chat window, mood indicators, response cards, and counselor prompts — and enforces client-side accessibility and validation [8]. The application layer (Laravel) handles authentication, session management, business logic, and REST APIs that mediate client requests and backend services. The chatbot engine layer (Rasa) hosts the natural language understanding and dialogue management pipelines responsible for intent detection, policy-driven dialogue control, fallback handling, and response selection. (MySQL + artifact storage) stores pseudonymized logs, conversation histories, model artifacts, and administrative records while supporting secure retrieval and analytics for monitoring and model refinement.

During development the stack evolved from a locally hosted prototype to a live deployment: the Laravel application was hosted on a secure server, while the Rasa engine ran on a dedicated VPS and communicated with the application over authenticated HTTP endpoints; version control (GitHub) and CI practices ensured traceability and code quality.

Training data pipelines included text collection, cleaning, anonymization, counselor-validated labeling, conversion to Rasa YAML artifacts (nlu.yml, domain.yml, rules.yml), iterative training, and evaluation (precision / recall / F1 and confusion analysis) prior to production packaging. These processes supported progressive improvements in intent recognition and response relevance. [10] [11] [12]

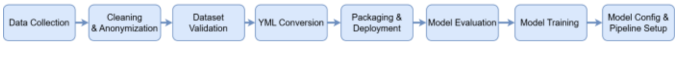


Figure 3.0 RASA NLU and Data Lifecycle Pipeline for LumiCHAT

The Rasa pipeline includes data preparation, YAML conversion, pipeline configuration (config.yml), training, evaluation, and packaging; datasets and anonymization steps were applied to training data [11].

### D. Testing Phase (planned measures)

Testing combined functional verification of end-to-end workflows and usability evaluation using the System Usability Scale (SUS). Planned evaluation metrics included SUS scores, intent-classification performance (precision, recall, F1-score), referral precision, and task-completion

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times [7]. Detailed test artifacts are provided in Figure 5.0 , Figure 6.0 and Table 1.0.

E. Deployment and Review

LUMICHAT was deployed to a secure live hosting environment to ensure accessibility beyond school hours. All interactions were anonymized and encrypted to protect user privacy. Deployment was supported by onboarding sessions, user guides, and in-app prompts.

The review phase involved collecting qualitative feedback from students and counselors through interviews and surveys. Feedback and system logs informed iterative improvements during sprint retrospectives, focusing on response tone, clarity, and escalation accuracy.

## IV. RESULTS & DISCUSSION

A. Implementation Outcomes

LUMICHAT was implemented with the core features defined during the design and development phases, including an NLU-driven conversational engine, anonymous interaction mode, appointment booking, and counselor administration tools. The deployed system was functionally evaluated through scenario-based testing conducted with student participants and guidance counselors to verify end-to-end workflow completion.

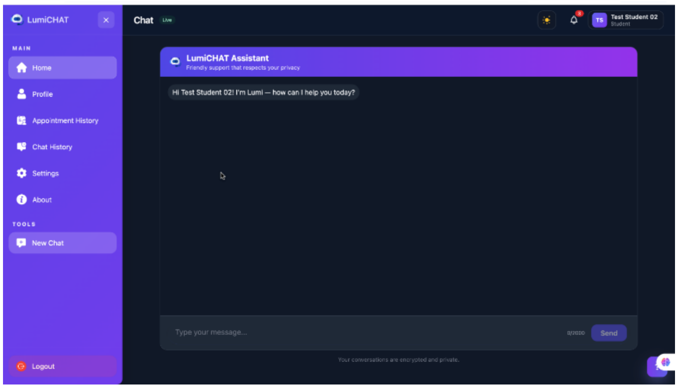


Figure 4.0 High Fidelity Web Interface for Chatbot Interface in LumiCHAT

Figure 4 shows the implemented student chat interface used during scenario-based testing. The interface supports core user tasks such as initiating conversations, receiving system responses, and accessing support features. Test observations indicate stable task completion with minimal operational issues, while user feedback highlighted areas for improvement in navigation clarity and the specificity of coping guidance.

B. NLP & Model Performance

The chatbot's natural language understanding model was evaluated using standard intent-classification metrics derived from a held-out test dataset. Performance results demonstrated acceptable precision, recall, and F1-scores across most defined intents, with stronger performance observed for clearly delineated categories (e.g., burnout and time management) and comparatively lower performance for semantically overlapping emotional intents.

Figure 5.0 summarizes the confusion matrix and intent-level performance metrics, highlighting instances where semantic overlap between emotional intents contributed to misclassification. These findings informed iterative refinements to training data and dialogue rules in subsequent development cycles.

Figure 6.0 the response selection results indicate consistent ranking accuracy for predefined response candidates, supporting reliable system behavior during conversational exchanges.

C. Usability & Task Performance

System usability was assessed using the System Usability Scale (SUS) following completion of predefined interaction tasks. Participants representing different user roles completed the SUS questionnaire after hands-on use of the system.

Table 1.0 Final SUS Score Computation for LumiCHAT

| Participant | Sum of Adjusted Scores (0–40) | Final SUS Score (0–100) |
|---|---|---|
| P-1 | 35 | 87.50 |
| P-2 | 30 | 75.00 |
| P-3 | 36 | 90.00 |
| P-4 | 29 | 72.50 |
| P-5 | 33 | 82.50 |
| P-6 | 20 | 50.00 |
| **Overall Average** | | **76.25** |

The aggregated SUS score indicated overall usability within the acceptable range. Analysis of task performance and participant feedback identified specific usability issues related to interface navigation and the clarity of suggested coping actions. These issues were addressed through iterative interface adjustments and response template refinement, demonstrating the effectiveness of the Agile feedback-driven development process.

D. Discussion (concise)

- The layered architecture with an on-premises Rasa deployment balanced privacy and institutional control while delivering acceptable NLU performance; improving detection of nuanced emotional intents will require larger and more diverse labeled datasets.
- Usability scores indicate the system is ready for limited roll-out while content personalization and

longitudinal outcome tracking are left for future work.

## V. CONCLUSION & FUTURE WORK

LUMICHAT is a practical, privacy-aware chatbot that complements campus counseling by providing early-intervention conversational support and an automated referral pathway to licensed counselors. The implemented system demonstrated acceptable usability and intent-classification performance sufficient for initial risk triage and limited roll-out.

Future improvements include (1) expanding and diversifying labeled datasets to improve detection of nuanced emotional intents, (2) adding personalization features while preserving user privacy, (3) integrating speech and other multimodal inputs, (4) implementing a continuous monitoring and model-update pipeline, and (5) conducting a longitudinal outcomes study to measure changes in help-seeking behavior and clinical impact.

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APPENDICES

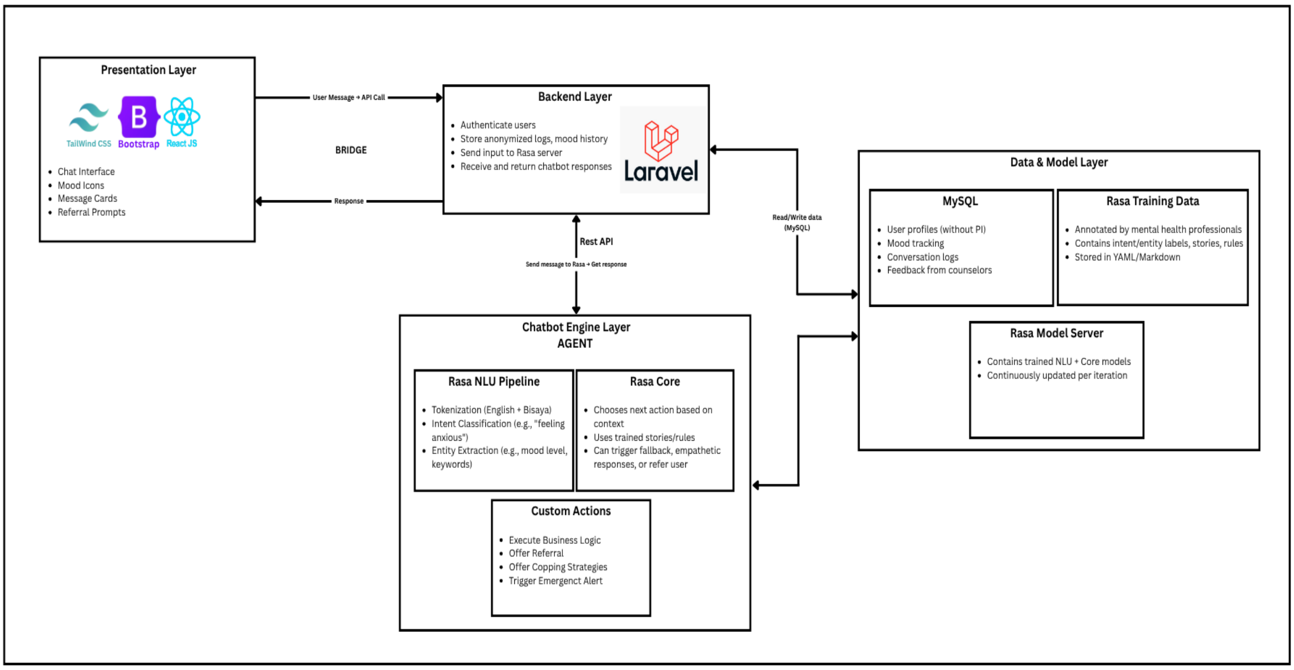


Figure 2.0 Layered Architecture for LumiCHAT

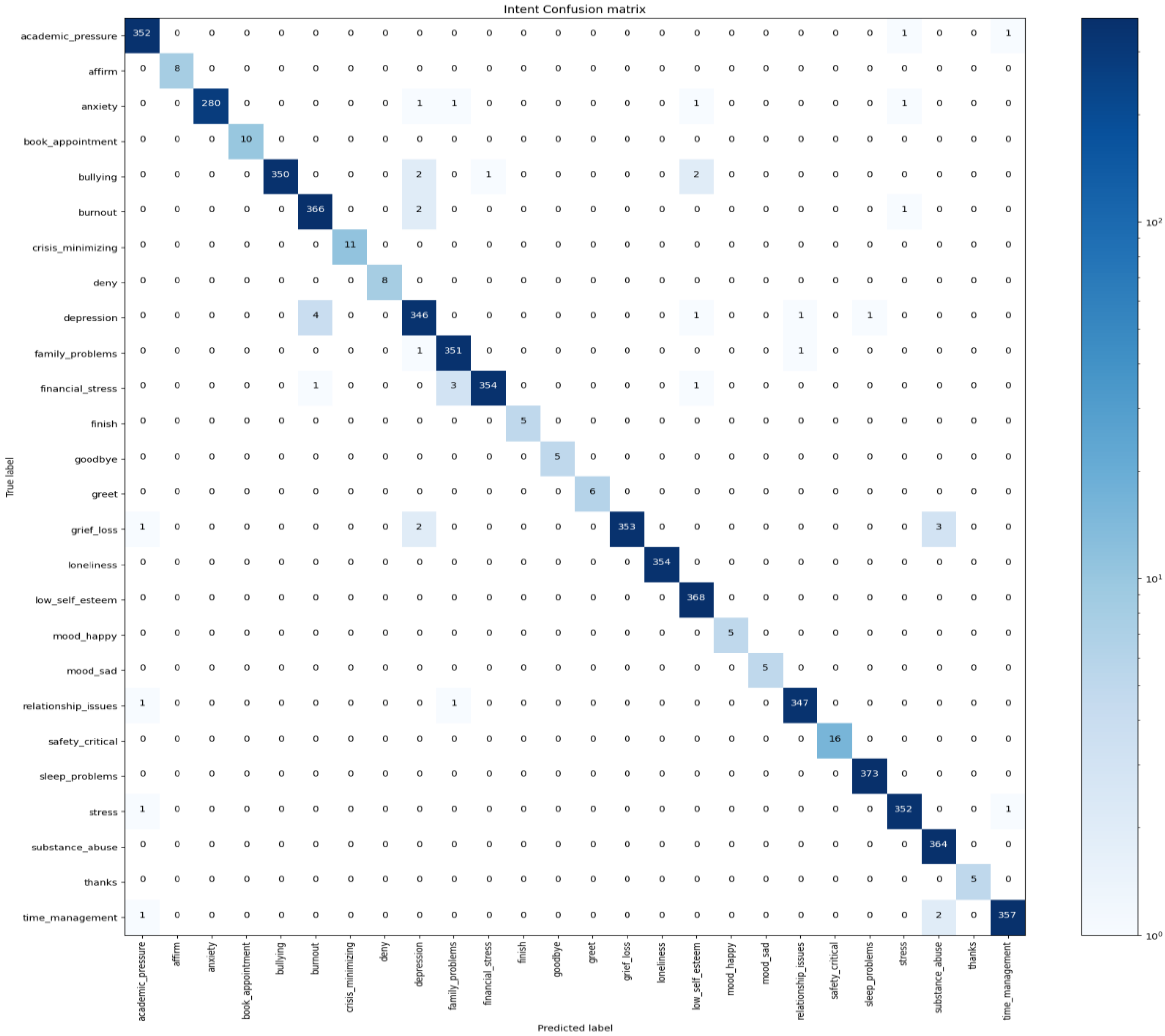


Figure 5.0 Model Evaluation (Intent Confusion Matrix)

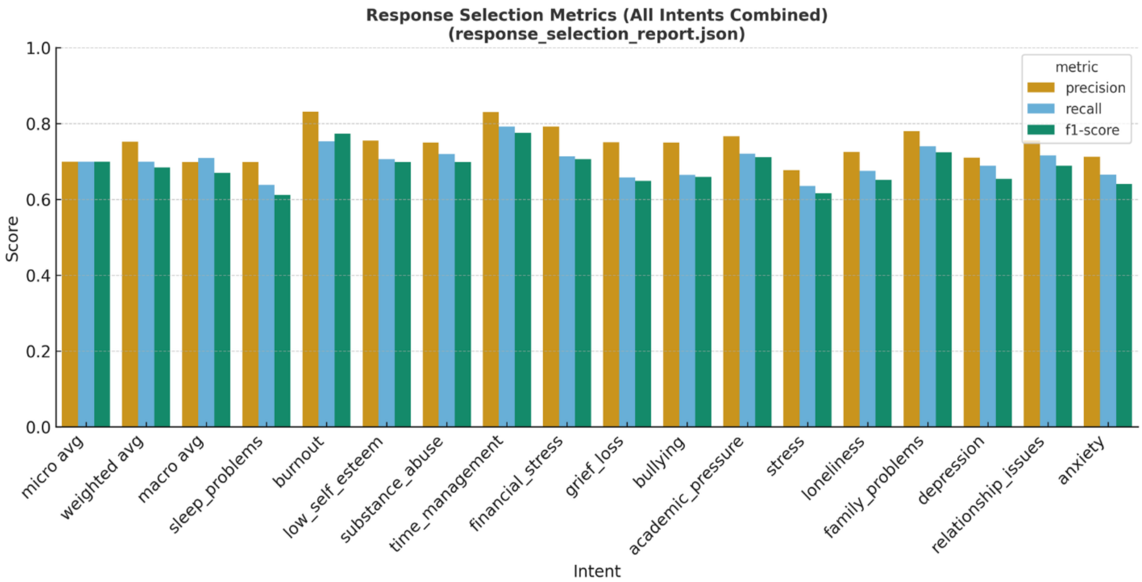


Figure 6.0 Model Evaluation (Response Selection Metrics)