Hermegency v0.1: A Chatbot for Mental Crisis Assistance

By Julien Ghali and Nobuhiro Inuzuka*

*NAGOYA INSTITUTE OF TECHNOLOGY, NAGOYA, JAPAN

Abstract
This paper introduces Hermegency v0.1, a chatbot designed to provide assistance to individuals experiencing schizophrenia crisis. By combining knowledge graphs and large language models, Hermegency v0.1 aims to offer personalized support to users during crises. In this initial version, the Chatbot incorporates only the Schizophrenia Knowledge Graph, in the PANSS format, and proposes two evaluations to measure its success, one with user satisfaction and another one.

Introduction
In recent years, Natural Language Processing (NLP) and artificial intelligence have seen remarkable progress in enabling chatbots to simulate human-like conversations and assist users across various domains. One critical application of this technology is supporting individuals experiencing mental health crises, where timely and empathetic intervention can be life-changing.

This paper presents Hermegency v0.1, an experimental chatbot focused on providing crisis assistance to individuals dealing with schizophrenia-related challenges. Leveraging advancements in NLP, Hermegency combines the power of knowledge graphs and large language models to engage users in natural conversations and offer personalized guidance. In this initial version, the chatbot's development will concentrates solely on integrating a Schizophrenia Knowledge Graph, which contains data related to schizophrenia symptoms, crisis management, and mental health support strategies.

As Hermegency v0.1 is an initial release, the scope is limited to evaluating user satisfaction and dialogue efficiency through an experiment. Users and experts will interact with the chatbot during simulated crisis scenarios, and their feedback will be used to assess the effectiveness and potential for improvement. The primary goal is to understand the chatbot's impact on users and gather valuable insights for further development.

In this paper, we describe the architecture and design of Hermegency v0.1, focusing on its Knowledge Graph integration with LLMs. Later, an experiment methodology is presented regarding two different metrics. We conclude by discussing the implications of this research and the roadmap for future iterations, aiming to expand the chatbot's capabilities and broaden its scope in mental health assistance by adding new knowledge graphs for different mental disorders.

Related work
The related work in the field of AI-based healthcare systems includes various approaches that leverage artificial intelligence, machine learning, and natural language processing techniques to provide efficient medical services and support for patients.

Khan et al. (2018) [1] propose an AI-based health physician system that interacts with patients, conducts diagnoses, and suggests appropriate remedies or treatments. Their system utilizes a decision tree algorithm, implementing a top-down searching approach to identify and diagnose patient problems. By employing a questionnaire-based approach, the system queries users about their symptoms, leading to informed decisions and recommended medications.

Chung and Park (2019) [2] present a chatbot-based healthcare service designed to offer rapid treatment for accidents in daily life and changes in chronic disease conditions. The chatbot acts as an intelligent conversation platform, interacting with users through a chat interface, and integrating with social network service messengers for easy access to diverse health services. Their framework, comprising data, information, knowledge, and service levels, ensures smooth human-robot interaction and facilitates efficient implementation of the chatbot healthcare service.

Welivita and Pu (2022) [3] introduced HEAL, a knowledge graph developed based on distress narratives and consoling responses gathered from Reddit. With 22K nodes representing various stressors, speaker expectations, responses, and feedback types, HEAL forms 104K connections between different nodes, each associated with one of 41 affective states. HEAL's statistical and visual analysis reveals emotional dynamics in distress-oriented conversations and identifies response patterns leading to emotional relief. Automatic and human evaluation experiments demonstrate that HEAL's responses are more diverse, empathetic, and reliable compared to baselines.

Le Glaz et al. (2021) [4] conducted a systematic review focusing on machine learning and NLP techniques in the context of mental health. Their study aims to summarize and characterize studies that employ these methods in mental health clinical practice. By exploring the potential use of AI and NLP techniques, this research addresses the growing importance of innovative approaches to mental health diagnosis and treatment.

Overall, these previous works highlight the growing interest and advancements in AI-driven healthcare solutions, with a focus on patient interaction, knowledge graph development, and the application of NLP and machine learning techniques to improve the quality and efficiency of mental health care.

Structure of the App

The following section will details how does Hermegency is build. We will go through the two part that makes an application: the front end and the back end. The **Fig 1.** Gives a first insights on how our application is build.

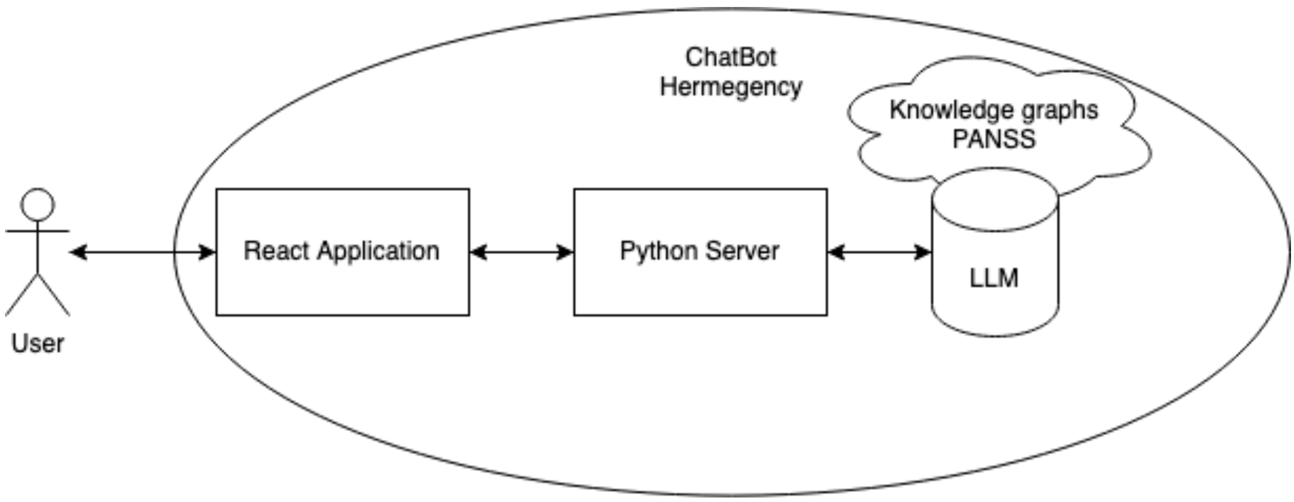

Fig 1. Structure of our Application

<u>Front-end</u>

React & React Native

React and React Native are JavaScript libraries developed by Facebook for building user interfaces. React is used for web applications, while React Native is used for mobile applications. Both libraries follow a component-based architecture, allowing developers to break the user interface into reusable building blocks. To build a chatbot, we can use React to create the web-based interface for the chatbot, and React Native to create the mobile app version. For the chatbot functionality, it is required to integrate it with a backend server that handles the natural language processing and responses to user queries. By combining React or React Native with our system, we can create a helpful chatbot for both web and mobile platforms.

Back-end

Llama 2

Llama 2 [5] is a large language model (LLM) that is based on the BERT [6] architecture. It has been trained on a massive dataset of text and code, which allows it to generate text, translate languages, write different kinds of creative content, and answer your questions in an informative way.

Llama 2 can be trained to be a chatbot that can understand and respond to Japanese language queries. To do this, it's necessary to train it using Japanese dialogue data, once it's done, the chatbot can interact with users in Japanese, therefore making it possible to help patients whom native language is Japanese. The chatbot will be able to understand and respond to a wide range of Japanese language queries, by enhancing it with knowledge graphs we can give it the ability reason in order to provide the adequate help for patients.

Knowledge graph

Integration of knowledge graphs with the Positive and Negative Syndrome Scale [7] (PANSS) for symptoms detection and measurement holds great promise in the domain of mental health assessment. Knowledge graphs offer a structured representation of domain-specific information, encompassing relationships and contextual knowledge. This structure allows to compensate for one of the biggest Large Language Models weakness, that be the incapacity to reason; for example, if you ask a Large Language Model « when did Einstein invented gravity », unless he is train to disagree, he will likely gives you an answer like « 1687 ». By combining PANSS, a widely-used clinical tool for evaluating schizophrenia symptoms, with a knowledge graph, we create a comprehensive framework to detect, quantify, and contextualize symptoms. The knowledge graph enriches the PANSS data by connecting symptoms to related clinical findings, risk factors, and treatment strategies.

This integration facilitates a more holistic understanding of the user's condition and enables the chatbot to provide personalized and targeted support, guiding users towards effective management of their symptoms. Moreover, by continually expanding the knowledge graph with the latest research and expert insights, the chatbot's ability to detect and measure symptoms will continually improve, leading to more accurate and informed mental health assistance.

To provide an example, we detailed **Delusions** based on Kiran et al (2009) [8] article on the **Fig 2.**:

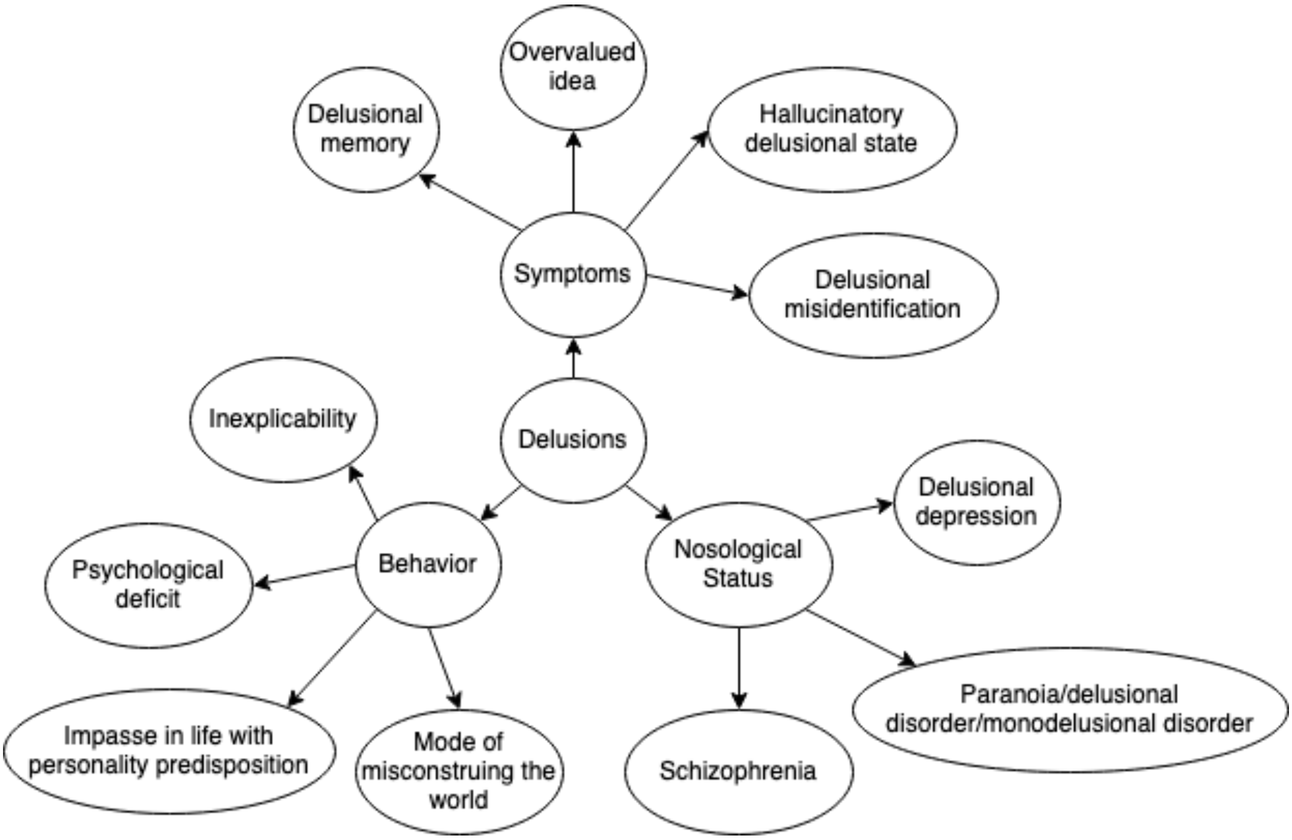

Fig 2. Sample of a knowledge graph of Delusions

Enhancing LLMs with knowledge graphs

KGs can enhance LLMs by providing external knowledge for inference and interpretability. While LLMs excel at language generation and generalization, they lack explicit access to factual knowledge, which is a strength of KGs. KGs provide a structured representation of rich factual knowledge and can be used to enhance LLMs by offering external knowledge for inference and interpretability. Pan et al. [9] proposed a roadmap detailing 3 different methods that used KG and LLMs, using those 3 different methods and looking at their results, we can achieved to build a chatbot able to use factual knowledge from medical sources, such as PANSS, to provide assistance to patients.

Experiments

<u>User satisfaction</u>

The user satisfaction metric is a measure for evaluating the effectiveness and usability of the chatbot. This metric assesses users' overall satisfaction with the chatbot's support, and ability to address their specific needs during crisis situations. User satisfaction is typically gathered through feedback surveys or post-interaction questionnaires that allow individuals to rate their experience with the chatbot. Questions may inquire about the chatbot's responsiveness, accuracy in understanding symptoms, clarity of guidance, and overall helpfulness.

The metric can incorporate qualitative feedback, allowing users to provide detailed insights into their interactions with the chatbot. By analyzing user satisfaction, we can identify areas for improvement and iterate on the chatbot's design to enhance its performance and user experience, ensuring it provides valuable and supportive assistance to individuals in need.

Dialogue efficiency metric

The dialogue efficiency metric is a tool for assessing the performance of the chatbot designed to provide crisis assistance to individuals experiencing schizophrenia. This metric aims to evaluate the chatbot's ability to engage in effective conversations with users while addressing their specific crisis needs. A health expert, well-versed in schizophrenia and crisis intervention, can perform this evaluation by engaging in conversations with the chatbot. In these interactions, the expert takes on the role of the user seeking assistance.

Through these role-playing scenarios, the expert can assess the chatbot's capacity to accurately detect and comprehend symptoms, offer appropriate guidance, and exhibit empathy in its responses. Additionally, the health expert can analyze real-world interactions with actual users to gather feedback and insights, which will further validate the chatbot's effectiveness. By leveraging the expertise of a health professional, the chatbot's dialogue efficiency can be fine-tuned, ensuring it delivers high-quality and personalized support to individuals experiencing schizophrenia crises.

Conclusion

In conclusion, the development of this chatbot, combining the power of Large Language Models and Knowledge Graphs, holds potential to revolutionize the assistance provided to individuals experiencing schizophrenia crises. By leveraging the vast knowledge graph inspired by PANSS and incorporating the capabilities of advanced language models, the chatbot can offer personalized and empathetic support to users, assisting in crisis evaluation and guidance. With its ability to understand user symptoms by interacting with him, the chatbot's potential to provide timely and accurate pre-diagnoses, as well as deliver appropriate guidance, has the capacity to positively impact the mental health support landscape.

By using knowledge graphs as a tool to reason, we actually are able to enlarge our chatbot capabilities by adding more knowledge graphs associated with other mental disorders. Our paper here presents a v0.1, focusing on Schizophrenia, but future versions might include new mental disorders until its reach can provide assistance to every patients.

References

[1] Khan, R. S., Zardar, A. A., & Bhatti, Z. (2018). Artificial intelligence based smart doctor using decision tree algorithm. arXiv preprint arXiv:1808.01884.

[2] Chung, K., & Park, R. C. (2019). Chatbot-based heathcare service with a knowledge base for cloud computing. Cluster Computing, 22, 1925-1937.

[3] Welivita, A., & Pu, P. (2022, June). HEAL: A knowledge graph for distress management conversations. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 36, No. 10, pp. 11459-11467).

[4] Le Glaz, A., Haralambous, Y., Kim-Dufor, D. H., Lenca, P., Billot, R., Ryan, T. C., ... & Lemey, C. (2021).

[5] Touvron, H., Martin, L., Stone, K., Albert, P., Almahairi, A., Babaei, Y., ... & Scialom, T. (2023). Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.

[6] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

[7] Kay, S. R., Fiszbein, A., & Opler, L. A. (1987). The positive and negative syndrome scale (PANSS) for schizophrenia. *Schizophrenia bulletin*, *13*(2), 261-276.

[8] Kiran C, Chaudhury S. Understanding delusions. Ind Psychiatry J. 2009 Jan;18(1):3-18. doi: 10.4103/0972-6748.57851. PMID: 21234155; PMCID: PMC3016695.

[9] Pan, S., Luo, L., Wang, Y., Chen, C., Wang, J., & Wu, X. (2023). Unifying Large Language Models and Knowledge Graphs: A Roadmap. *arXiv preprint arXiv:2306.08302*.