Integrating Conversational Pathways with a Chatbot Builder Platform

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Abstract. MIRA, a Mental Health Virtual Assistant, is a task-oriented, rule-based chatbot connecting individuals seeking mental health support with trusted services and programs. Initially developed to support healthcare workers during the COVID-19 pandemic, experts in our multidisciplinary team designed a specific conversation flow to cater to them. The logic driving the system was primarily implemented in Python through an existing chatbot framework. Extending the functionalities of MIRA to cater to new populations, such as first responders, Veterans, Indigenous communities, or youth, required extensive modification of the conversation flow and thus necessitated extensive changes to the code base. The same would be true for extending MIRA to operate in other languages. To serve a broader audience and easily integrate additional conversational pathways without changes at the code level, we introduce the chatbot builder platform to simplify the creation and modification of conversational flows by non-experts.

Keywords: Chatbot Framework · Conversation Flow · Mental Health Assistant · Named Entity Recognition · Intent Extraction

1 Introduction

Recent studies reveal a concerning rise in mood disorders and mental health conditions [1–3]. Poor mental health can have a substantial effect on various aspects of an individual's life, including their behaviour, relationships, and workplace performance. The consequences can extend beyond individual well-being, affecting societal dynamics. If left unaddressed, individuals experiencing high levels of distress due to mental health conditions may be vulnerable to severe risks, including self-harm. Therefore, mental health awareness and access to mental health care services are crucial for building supportive environments and safe spaces that foster both individual and societal well-being.

Increasing evidence shows that the COVID-19 pandemic led to significant increases in the risks and burden of mental health illnesses [8–10]. The pandemic also exacerbated the adverse physical and psychological effects for those with pre-existing mental health conditions [11]. While this underscores an increased need for access to mental health services, several factors make it extremely difficult to seek help. Some of the most common challenges in accessing mental health services are not knowing what resources exist, not knowing where to seek help, extended wait times, shortage of mental health providers, and financial constraints due to inadequate coverage by insurance plans [7, 12].

Immediate access to information and support can be crucial in times of distress. It can be overwhelming for a person going through a crisis to find the right resources to seek help. The conversational nature of a chatbot and its ability to provide timely responses can make it a valuable tool in navigating mental health resources. Chatbots also offer an anonymous platform that can make it easier to talk about sensitive topics without fear of judgment or stigma.

Our study aims to complement and augment traditional mental healthcare with a conversational guidance system. Equity-deserving groups face numerous obstacles when they seek mental health support due to cultural stigma, inaccessibility to resources, lack of awareness, and financial challenges. Numerous studies have highlighted the pressing need for youth mental health services in Canada, predating the pandemic, with evidence indicating a decline in mental well-being among the youth [49]. We hope to address some of these challenges by extending the functionalities of MIRA to serve equity-deserving populations, including first responders, Veterans, Indigenous communities, children and youth, and French-speaking Canadians.

MIRA (Mental Health Intelligent Information Resource Assistant), the Mental Health Virtual Assistant, is an existing AI-based conversational agent that connects individuals seeking mental health support with trusted services and programs. Developed using the Rasa framework [17], the chatbot has been deployed and is currently operational [16], launched publicly by our team and former members. As a task-oriented chatbot, MIRA interacts with the user through a conversation and presents them with relevant resources from the existing MIRA Resource Library - a comprehensive database of catalogued and expertly vetted resources.

MIRA uses a hybrid approach combining Machine Learning (ML) and Natural Language Processing (NLP) techniques with a rule-based conversation flow. We leverage NLP to detect intents (general meaning of the sentence) and extract entities (additional information in the sentence that provides context) from the user's utterances. Experts on the team originally designed the conversational flow to assist healthcare workers.

The version of MIRA that catered to the needs of healthcare workers employed a rigid, hard-coded conversation flow structure. Altering this flow required direct changes to the underlying codebase. To make it easier to extend MIRA's programming and development accessibility to non-computer science experts in our team, we created a chatbot builder platform. The chatbot builder simplifies the creation and modification of conversational flows and integrates additional conversational pathways. The conversational flow is segmented into modules on the platform, each starting with a chatbot-initiated utterance and linking to connected modules or user pathways based on conditions. This tool enables individual members of our multidisciplinary team to adapt and extend a chatbot's functionality to support general audiences or particular groups of interest. Notably, while initially designed for MIRA, the platform serves as a valuable tool for any Rasa-based chatbot requiring rapid iterations and with continuously evolving needs.

2 Background

Chatbots are conversational agents that interact and engage with users through natural language conversations, either over text or voice-based interfaces, to perform various tasks or provide assistance. Chatbots are ubiquitous in recent times and have become widely popular for their convenience and utility. They are versatile, can scale operations, and can be programmed to be customized for users. There exists a broad range of chatbots, from customer service assistants that try to streamline customer interactions and provide customized support to voice-based assistants like Siri [18], and Alexa [19] to more cutting-edge innovations like ChatGPT [20], capable of engaging in more human-like conversations with users.

Typically, chatbots fall into two categories: those engaging in open-ended conversations or task-oriented interactions [23], or a combination of both [46]. Rule-based chatbots rely on pre-defined rules, responses, and actions [47]. Advanced chatbots employ generative models, creating natural real-time dialogues while executing tasks. Large Language Model (LLM) based chatbots like ChatGPT [20], Copilot [21], and Perplexity AI [22] excel in real-world scenarios given their ability to deal with noisy input and execute human instructions well, often through techniques like Reinforcement Learning from Human Feedback (RLHF). While LLM-based chatbots have surged in popularity in recent years, they have limitations. A notable concern is their potential to generate biased responses if the data used to train these LLMs is biased [14]. This can lead to discriminatory and harmful behaviour, posing ethical challenges.

They also tend to hallucinate to fill in gaps in their knowledge, generating factually incorrect or purely fictional information [15]. This can lead to erroneous decisions, spread misinformation, and reduce trust in AI. Furthermore, as these models grow in size and complexity, characterized by billions of parameters trained on massive amounts of data, their internal workings become increasingly opaque [14].

This makes it challenging to incorporate LLMs in domains like healthcare, where the accountability and transparency of decisions are crucial. Considering the sensitive nature of mental health, these limitations have the potential to be dangerous. With caution, we plan to explore using generative chatbots in the future once we enforce robust guardrails to ensure their reliability and safety.

2.1 Chatbot Builders

A previous study evaluated various chatbot development platforms (CDPs), including Amazon LEX, Dialogflow CX, ES (Google), LUIS, CLU (Microsoft), RASA, and Watson Assistant (IBM) to help users select the most suitable CDP for their needs [45]. They specified the criteria and assigned scores based on requirement assumptions. This study offered valuable insights relevant to our work. They found that the more recent versions of CDPs aimed to facilitate chatbot development without requiring coding. For example, Dialogflow introduced the CX edition featuring a visualized state machine known as the visual builder, while Microsoft developed Bot Framework Composer to build conversational AI applications [45]. In contrast, Rasa does not support any visual dialog management flow but offers stories, a text-based tool that replaces visual managers for designing dialog flows [45]. Despite this limitation, they claim Rasa is the most configurable and extensible among the CDPs due to its open-source nature. Additionally, Rasa's NLU implementation is transparent, allowing developers to make informed decisions about their choice of ML techniques [45]. While other commercial CDPs do not offer this level of transparency.

Another study analyzed three prominent chatbot building platforms: Google Dialogflow, IBM Watson Assistant, and Amazon LEX [44]. This work identifies a comprehensive set of desirable features and evaluates the utility of various chatbot development platforms. By comparing these platforms, the study provides insights to inform decisions on selecting the most suitable chatbot builder for specific use cases and requirements [44].

Although many visual chatbot builders are commercially available, there are few open-source platforms, with even fewer leveraging Rasa. We decided to develop our chatbot builder tailored specifically for Rasa, given its customizability and flexibility in controlling the chatbot's functions. While we developed the chatbot builder to expand on the initial version of MIRA, which used Rasa, our chatbot builder is a versatile tool applicable to any chatbot built on the Rasa framework.

2.2 Mental Health Chatbots

According to a 2022 study conducted by Statistics Canada, over 5 million Canadians were affected by mental health conditions in the previous 12 months [4]. The study also reported that youth (ages 15-24), especially women, were more susceptible to mood and anxiety disorders. In 2019, 5% of Canadian children between the ages 5-17 reported experiencing an anxiety disorder, while 2.1% reported experiencing a mood disorder [5]. The prevalence of these concerns is striking, with statistics indicating that by the age of 40, one in two Canadians will have experienced or will be actively experiencing a mental illness [6].

Digital Mental Health Interventions (DMHIs) aim to augment traditional care by improving access to mental health services and resources by adapting these interventions into digital formats [27]. They can encompass a range of applications, such as smartphone applications, web-based programs, online platforms, chatbots, virtual reality simulations, wearable devices or online support communities [26].

Chatbots are widely used in DMHIs within the mental healthcare domain. The findings from a study conducted in 2020 found that 39% of health chatbots were mental health chatbots [35]. This number continues to grow over time. They have been integrated to serve users with functions ranging from providing support, conducting screening, delivering therapeutic intervention, monitoring behaviour changes, and preventing relapses [28]. Efforts have been made to develop specialized chatbots to support individuals with specific mental health concerns such as depression and anxiety [29], autism [30], Attention-deficit/hyperactivity disorder (ADHD) [31], Post-traumatic stress disorder (PTSD), suicide prevention [32], mindfulness [33] and life coaching [34].

Previous research indicates that chatbots can improve mental health outcomes, with users reporting their experience with mental health chatbots mostly positively [36, 41]. This is supported by the ability of chatbots to offer increased accountability, such as daily check-ins [40], and behavioural intentions [39], promoting higher user engagement and lower dropout rates [38]. Towards improving care access, mental health chatbots have the benefit of being accessible round-the-clock and the ability to cater to the needs of users irrespective of their time zone or physical location [37]. Moreover, evidence suggests that the anonymity offered by chatbots, coupled with the absence of direct human interaction, allows users to express themselves more freely without the fear of judgment or stigma [42].

The findings from a comprehensive scoping review that evaluated 41 mental health chatbots indicate that the primary applications of chatbots in the mental health domain are for the delivery of therapy, followed by their use as training and screening tools [24]. Notably, the study revealed that a significant majority of these chatbots (92.5%) employed rule-based architectures, while only 7.5% were ML-based [24]. The study suggests the preference for rule-based frameworks is due to their ability to perform simple, well-defined, and structured tasks [25]. Additionally, rule-based chatbots are simpler to develop and prone to fewer errors. We employ a rule-based structure for MIRA's conversation flow to leverage our team's expertise in psychiatry.

Having a multidisciplinary team involved in the creation of new technology for mental health allows us to leverage their diverse perspectives, community insights, and expertise from various fields. Involving PLE and experts from fields such as psychiatry, youth services, or Indigenous communities is essential for developing technologies intended for their use. A chatbot builder facilitates the integration of new conversational pathways for non-computer science experts, allowing easy extension of existing chatbot frameworks. The platform simplifies the incorporation of insights for extensions to specific groups without rebuilding the entire system. Therefore, we developed a chatbot builder with a user-friendly interface for designing, updating, and managing the conversation flow.

3 Methodology

MIRA was developed using Rasa, an open-source conversational AI framework [17]. Our team chose Rasa due to its flexibility, ease of integration, and high level of customization compared to other platforms like Botkit, BotPress, and DeepPavlov [48]. Rasa's customization capabilities allow us to integrate advanced AI and NLP functionalities incrementally, fitting our project objectives [48]. This approach supports ongoing development and testing to continually enhance the chatbot's capabilities and adapt to evolving needs.

MIRA Resource Library is a database of resources, with over 1500 resources catalogued by volunteers from the Mood Disorders Society of Canada (MDSC). To ensure the quality and reliability of the resources, they are vetted and approved by a team of subject matter experts using an evaluation assessment form developed using a hybrid of validated tools [48]. At the end of an interaction with MIRA, the user is recommended resources from the MIRA resource library relevant to the context of the conversation.

The chatbot employs Rasa's Dual Intent and Entity Transformer (DIET) architecture for both intent detection and entity extraction tasks. This builds upon the prior work from our team [43], which involved exploring DIET, a transformer-based architecture designed to leverage the inter-dependencies between intents and entities for simultaneous detection. The DIET model consists of four components: featurization, transformer, named entity recognition (NER), and intent classification. The study showed that the DIET model outperformed other predictive models and architectures for both augmented and pre-augmented datasets [43].

Specifically, they were compared against Naïve Bayesian, Logistic Regression, Support Vector Machines (SVM), as well as various neural network configurations such as feed-forward neural networks, recurrent neural networks (RNNs), and long short-term memory networks (LSTMs). The results underscored the DIET model's effectiveness in improving performance across intent detection and entity extraction tasks, given the significant improvement in both metrics after data augmentation [43]. This meant that we could improve the functionality of MIRA without the need for extensive human-annotated data. The intents and entities extracted with the DIET classifier are used to trigger various functionalities, such as replying with a predefined message, writing to a database, or accessing an application programming interface (API) to complete the user's request. This allows MIRA to both easily drive the conversation based on user queries, and to extract relevant mental health concerns it can later use to serve the user resources.

Previously, MIRA relied heavily on the Rasa framework's rule-based system and custom Python actions to direct the conversation between topics and eventually to serve the user-relevant resources. Since MIRA heavily depended on custom actions, updating the code became cumbersome, requiring significant Python expertise to modify the chatbot beyond minor adjustments. Moreover, as these custom actions stretched the capabilities of the Rasa framework, developers had to take on more responsibility for managing the conversation state, increasing the risk of unnoticed errors causing disruptions in the flow of conversation. To address these challenges, the **Chatbot Builder** was developed as a solution.

3.1 Chatbot Builder

The chatbot builder provides a user-friendly interface for designing, updating, and managing the conversation flow. The conversational elements within the chatbot are segmented into modules in the chatbot builder, essentially a question-and-answer pair. These segments are termed *dynamic modules*, with their rule sets and actions. Each rule set can contain multiple logical rules that can conditionally trigger actions depending on the content of the user message. Once a conversation flow is designed, it is tested rigorously and refined iteratively by our team members and volunteers from MDSC.

The initial version of MIRA was pivotal, as it laid the groundwork for the subsequent iterations. This included establishing the foundations for MIRA using the Rasa framework, creating a portal for cataloguing and annotating the database of resources, constructing conversational flows using a flowchart tool, meticulously curating extensive training data for each intent, exploring various architectures for intent detection and entity extraction and developing strategies for data augmentation. While these efforts provided a strong foundation for MIRA's functionality, they also revealed limitations that required further improvement.

Firstly, the transitions between modules or *jumps* were occasionally unreliable, leading to errors and interruptions in the user experience. Secondly, scaling MIRA to extend to other audiences added challenges. To address these challenges, we abstracted the conversation flow and generalized the jumps between the modules. This was crucial to enable seamless transitions between different parts of the dialogue. Since the jumps were now generalizable and reliable, we needed a tool that would allow us to modify the conversation flow more efficiently. The tool led to the development of a chatbot builder, which served as the foundation for our subsequent goals.

The chatbot builder is built using Python and JavaScript, with Flask serving the frontend and backend operations. The web page is hosted directly through Gunicorn on a local server. JavaScript handles the bulk of the application, processes JavaScript Object Notation (JSON) within the browser, and saves computation on the server. When users save or export their conversation flow, the file is validated on the server with a simplified chatbot version. This chatbot verification is used exclusively for real-time tests before production deployment. Since the chatbot builder and the chatbot share the same server, the builder can directly update the active conversation file by serving a JSON file to the chatbot, ensuring immediate integration. Additionally, the chatbot builder can load the chatbot's current conversation flow.

Rasa Integration Rasa was altered to exclusively support custom Python actions responsible for loading and switching between conversation flows, processing dynamic modules, interfacing with the MIRA library for query management through an API, tracking conversation state through Rasa slots, and handling intent and entity detection through Rasa NLU. This shift eliminates reliance on Rasa's rule-based or story-based flows and the need for hard-coded custom actions. Additionally, the conversation flows are saved as simple JSON files that can be easily backed up and tracked in version control systems like Git. They can also be updated or reverted without any downtime.

Components The platform consists of module-based building blocks that users can create and customize to implement rules and actions. Each rule set can include multiple logical rules, such as string comparison, entity or intent detection, or the state of flags. These rule sets fall into three categories: early rules (activated upon entry), inner rules (active during interaction), and exit rules (triggered upon exit). The rules prompt actions such as responding with a message, redirecting or *jumping* to another dynamic module that is relevant, setting flags or Rasa slots (entities), adding strings to a running query, sending that running query to the MIRA Library and displaying relevant resources. Finally, core rules are always active and can be used to interrupt the flow, regardless of the module. For instance, in MIRA, the core rules are always active and continuously detect if a user wants to end the conversation, indicates self-harm or suicidal intent, or is in an emergency.

Analogy of a Banking Assistant Since the effectiveness of the Chatbot builder is not limited to MIRA and applies to any Rasa-based general chatbot that requires ongoing iterations, we explain the components of the chatbot builder using the analogy of a banking assistant. Consider a task-oriented banking chatbot built to assist customers with banking transactions and inquiries. Here, the modules could correspond to various services the bank offers, presenting high-level choices for users such as transferring funds, applying for a loan or checking their balance. Depending on the user's preference, the conversation flow would direct them to relevant modules designed for that specific ask. For instance, if the user indicated wanting to apply for loans, the flow could lead the user to the `apply_loans` module, followed by `specific_loan_type` modules, then a `loan_eligibility_check` module, and so forth. The rules with each module may include verifying user credentials, detecting user intent, and identifying transaction details as particular entities. The chatbot executes actions such as retrieving account balances or redirecting users to a secure payment portal. If a user indicates a preference to speak with a human agent, the system detects this core rule and transfers control to a customer service agent.

4 Results and Discussion

The key advantage of the chatbot builder is its ability to serve as a conversation flow manager, allowing the transfer of contextual information from intents detected from current modules to intents detected in subsequent modules in terms of flags, slots, or entities. Additionally, the chatbot builder allows our team to address and create follow-up actions for modules within the conversation flow. This includes designing fallbacks and exit rules to handle scenarios where the chatbot may encounter uncertainties or reach the end of a conversation path. These features enhance our chatbot's overall robustness and adaptability, enabling smoother and more engaging user experiences while navigating through different conversation flows.

The chatbot builder proved beneficial in several ways:

1. It enables fast prototyping, resolution of bugs, and updates to the flow of the conversation.
2. It facilitates collaboration within an interdisciplinary team. The larger team does not need coding experience to make changes to the flow.
3. It makes it easier to add new pathways to the conversational flow. This, in turn, makes it easier to extend the functionalities of MIRA to serve more communities.

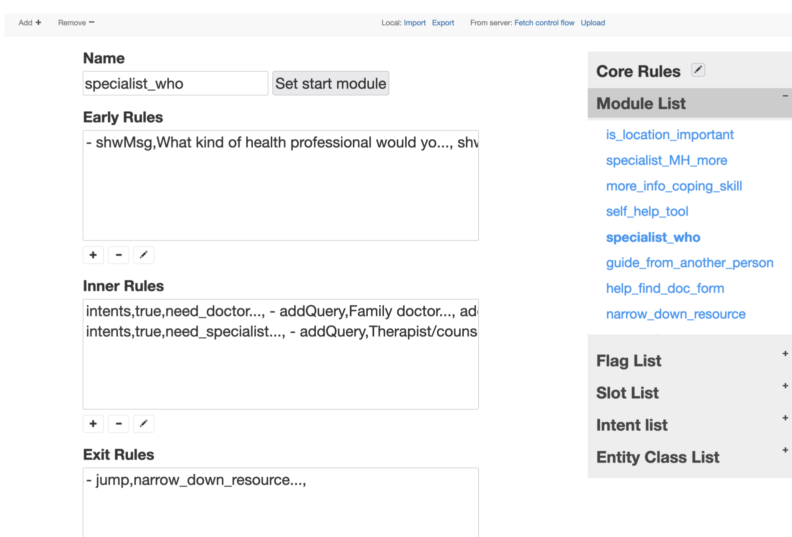
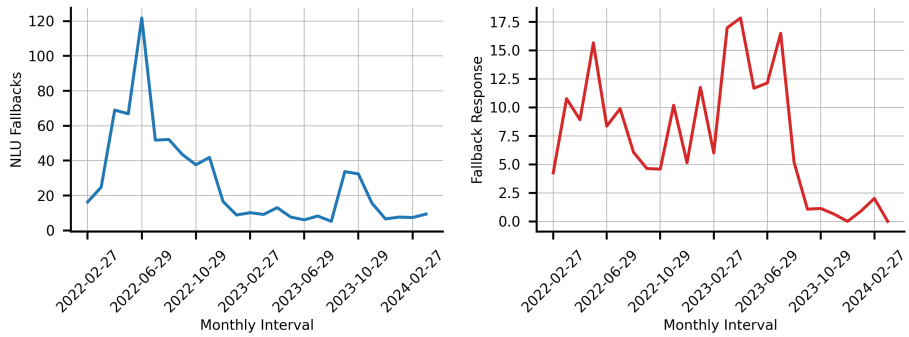


Fig. 1: The UI of the chatbot builder platform shows the `specialist_who` module. The early rules prompts users to select a health professional, while the inner rules detect the `need_doctor` or `need_specialist` intents. On exit, as a fallback rule, it transitions to the `narrow_down_resource` module.



(a) Frequency of NLU fallback intent per 10,000 messages over time

(b) Number of fallback responses per 10,000 messages over time

Fig. 2: Trends in NLU fallbacks and response rates over a monthly interval (730-hour period)

The interface of the chatbot builder platform is depicted in Fig. 1. Since the development of the chatbot builder, we have expanded the scope of MIRA beyond healthcare workers to include the general audience, youth (14 years and older), French-speaking Canadians and Indigenous communities, broadening its accessibility and impact. However, the versions involving French and Indigenous communities are undergoing beta testing and will soon be publicly deployed.

We evaluate the effectiveness of the chatbot builder by assessing the improvements in the chatbot brought about by the chatbot builder. This includes measuring if there are fewer disruptions in the conversation flow and misclassified intents. A decrease in misclassified intents implies that the intent handling and routing to relevant modules have improved. A task that was previously challenging to resolve solely through code. Consequently, the chatbot builder gave us more control over managing intents and follow-ups, allowing us to extract intents better and establish clear conversation paths. To empirically estimate the chatbot builder's effectiveness, we conducted statistical analyses to determine if there were reduced interruptions in the conversational flow and fewer instances of misclassified intents. This evaluation aimed to quantify the improvements in chatbot performance enabled by the chatbot builder platform.

The NLU Fallback intent is triggered when the confidence level of a detected intent is below 60%, prompting the chatbot to send a fallback response requesting the user to rephrase their sentence. MIRA can also respond with an error response when the dialogue flow encounters an error or fails to progress. With the release of a version of MIRA that used the conversation flow designed with the chatbot builder, we observed a significant drop in the number of error responses generated by MIRA, as shown in Fig. 2a, and a decrease in the number of times the NLU Fallback intent was triggered, as shown in Fig. 2b. This indicates that the system is more stable and easier to troubleshoot and iterate since the entity and intent detection remain the same.

5 Conclusion and Future Work

This work addresses the need for a visual chatbot builder platform. The platform is valuable in a multidisciplinary environment to accelerate the development of a chatbot with rapidly evolving requirements. The chatbot builder is a solution that can remove the dependence on Rasa's rule-based and story-based flows and hard-coded custom actions, making it useful for any Rasa-based chatbot. The chatbot builder helped facilitate the expansion of the scope of MIRA beyond healthcare workers, broadening its accessibility and impact. This expansion has streamlined the development cycle, enabling quicker deployment of changes to MIRA. Through MIRA, we hope to improve accessibility by providing quality, controlled information on mental health services and programs tailored to individual queries. MIRA can help raise awareness through information about mental health programs and services. Our platform is constantly evolving to meet the requirements and needs of our team. In the future, we plan to collect further feedback from users about their satisfaction levels in modifying and designing chatbots from scratch within the framework. We aim to launch an open-source chatbot builder suitable for both Rasa-based and NLP-driven chatbots. This will help enable the creation of more advanced, less predefined, natural language-driven chatbots.

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