Artificial Intelligence in Menstrual Health: A Chatbot Approach to Personalized and Stigma-Free Conversations

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Abstract— This paper presents the Menstrual Health Chatbot, aimed at boosting awareness and access to information on menstrual health. It features advanced natural language processing and a healthcare-focused artificial intelligence model, specially refined to deliver individualized responses. The chatbot integrates personal medical histories to customize interactions, catering to conditions like PCOS and Endometriosis. Its architecture enhances user experience from sign-up to query resolution, fostering privacy and encouraging open dialogues on menstrual health. A critical aspect in the crafting of this model is the model refinement using Adapter Tuning with structured Question and answer pairs, highlighting Artificial Intelligence's role in bespoke healthcare. Additionally, the model has undergone fine-tuning with the Low Rank Adaptation(LoRA) technique. A comparison between the models trained using Adapter Tuning and LoRA is conducted, based on their responses.

Keywords— Menstrual Health, Artificial Intelligence, chatbot, personalized responses, Stigma Reduction, Fine-Tuning, Conversational AI.

I. INTRODUCTION

This chapter offers a thorough overview of the Menstrual Health Chatbot project, explaining its origins, main goals, and numerous uses. It highlights the project's creative application of AI to menstrual health and underscores its importance in closing gaps in healthcare.

A. Origin of the Problem

The Menstruation has always been associated with stigma and misconceptions; this is still the case today. Historically, certain times have been prohibited, which has created a culture of disinformation and silence. This stigma persists in spite of improvements in education and health care, making many people especially young girls feel uncomfortable or guilty about talking to doctors or other people about their menstrual health.

There are huge gaps in knowledge as a result of this unwillingness to ask for help or voice concerns regarding menstruation cycles. Without the proper knowledge or assistance, young women and girls frequently find themselves navigating their menstrual health. Their confidence and capacity to fully engage in social and educational activities are also impacted, in addition to their health, by this lack of open communication. It draws attention to the necessity of a more transparent, encouraging approach to communication and education on menstrual health.

B. Problem Statement

The Menstrual Health Chatbot Project confronts the critical challenge of providing empathetic, personalized menstrual health guidance. Many individuals, especially those with conditions like PCOS and Endometriosis, struggle to find a safe space for open discussion about their menstrual health issues. This project addresses the need for a supportive, stigma-free platform where users can receive tailored advice and engage in meaningful conversations about their menstrual well-being, informed by their unique health profiles.

C. Objectives

The Menstrual Health Chatbot Project's main goal is to create an AI-powered chatbot that can efficiently respond to specific questions about menstruation health. The chatbot's purpose is to have meaningful interactions with users by precisely understanding their needs and providing personalized responses that take into account health issues like Polycystic Ovary Syndrome (PCOS) and offer relevant recommendations. Making sure the chatbot offers a secure and friendly forum for conversations around menstrual health is a key goal. By providing a stigma-free atmosphere for users, it aims to remove the unpleasantness that is frequently connected to these discussions

D. Social Applications

- Encouraging Health Education on Menstruation
- Providing Accessible Health Information
- Personalized care based on data
- Strengthening medical support

II. PRELIMINARIES

This section explains the fundamental words and ideas used in the paper.

A. Menstrual Health

This encompasses a comprehensive approach to managing the menstrual cycle and its associated physical, mental, and social challenges. It involves not only the biological aspects but also the understanding and addressing of broader implications for an individual's overall quality of life. It also involves addressing societal attitudes and stigmas associated with menstruation. Proper menstrual health management is crucial for the well-being and empowerment of individuals, affecting various life aspects such as education, work, and social interactions.

B. Chatbot

A chatbot is an AI-driven software that simulates conversational interactions with users in natural language via text or voice. It operates as an interface, providing information and support without the need for live human agents, thereby offering a scalable and accessible solution for information dissemination. It eliminates the need for live human agents, offering a scalable, accessible solution for information dissemination. Chatbots also support diverse industries, from customer service and healthcare to education and entertainment, showing versatility in applications.

C. Natural Language Processing

Natural Language Processing (NLP) is a key AI technology enabling computers to understand, interpret, and respond to human language in a useful way. It underpins the ability of chatbots to engage in human-like conversations. NLP incorporates two primary components: Natural Language Understanding (NLU), which involves comprehending input in human language, and Natural Language Generation (NLG), which focuses on generating meaningful language responses. These components work together to facilitate interactive and realistic dialogues in chatbots.

D. Transfer Learning

Transfer learning's efficiency stems from its ability to leverage complex features learned in one domain, thereby reducing the need for large datasets in the new task. This approach is particularly useful when data availability is limited in the new task. Additionally, it significantly reduces training time and computational resources, making it a cost-effective solution. Furthermore, transfer learning allows for cross-domain applications, where insights from one field can enhance model performance in another, broadening its applicability across various disciplines.

E. Finetuning

Fine-tuning is a process that involves making slight adjustments to a pretrained model to adapt it to a specific task. In the context of AI chatbots, it involves adjusting the model to understand and respond to queries related to menstrual health more effectively. This fine-tuning step is crucial in bridging the gap between general AI capabilities and specialized, user-focused applications. This process refines the model's understanding of domain-specific nuances and vocabulary, thus enhancing its responsiveness and accuracy in that field.

III. EXISTING SYSTEMS

In this section, we examine the current state of menstrual health management systems and chatbots driven by artificial intelligence. This analysis sets the context for understanding the special contributions and innovations of the Menstrual Health Chatbot project in this field by offering insights into existing solutions, their capabilities, and their limits.

SurgicBERTa, a customized surgical language model presented in this study, developed from RoBERTa via focused pre-training on 7 million surgical terms. It has been discovered that there are benefits to further pretraining a model to make it domain specific. Accurate capture of ambiguous terminology in a variety of areas, including medicine, is made possible by contextual language models like BERT and RoBERTa, which are trained using deep neural networks with a masked language modeling target. A corpus of surgical texts was used to further train SurgicBERTa with a masked language modeling (MLM) objective. SurgicBERTa performs better in surgical language processing than the conventional RoBERTa model after additional pretraining, and it may be able to enhance surgical knowledge bases. [1]

In order to facilitate biomedical text mining, this paper presents BioBERT, a pre-trained biomedical language representation model. Its superior performance over BERT and previous models in biomedical text mining tasks highlights the significance of domain-specific pre-training in addition to its improved performance. With few architectural modifications, BioBERT can be applied to a wide range of downstream text mining applications. The study to improve BioBERT uses three common biomedical text mining tasks: Named Entity Recognition, Relation Extraction, and Question Answering. The finetuned model gives better responses to the domain specific tasks and questions highlighting the power of domain specfic finetuning. [2]

This study includes entering menstrual cycle data into ten period tracker applications for five women with varying cycle characteristics (constant 28-day cycle, average cycle lengths of 23, 28, and 33 days, and irregular cycle). This study focuses on accurate menstrual cycle prediction through the use of sophisticated algorithms and ovulation markers such as cervical mucus analysis and basal body temperature. Menstrual cycle tracking is made more accurate and dependable by the machine learning algorithms used here, which adjust and get better based on user data. The menstrual cycle information predicted by period tracker apps is inconsistent, particularly when it comes to ovulation days and viable windows. [3]

This study presents a major breakthrough in the field of medical artificial intelligence by examining the application of large language models (LLMs) to clinical settings. It also presents HealthSearchQA, a dataset of online medical queries. The study assesses the effectiveness of Flan-PaLM, a version of PaLM with 540 billion parameters, and PaLM, a 540 billion parameter LLM, on these datasets. Flan-PaLM has cutting-edge accuracy, as seen by its notable MedQA score of 67.6%. Human assessments, however, point out significant gaps in the model's answers. In order to solve these, the study presents instruction quick tweaking, which produces the more clinically-aligned model Med-PaLM. The potential of LLMs in medicine is emphasized by this research, but it also emphasizes the necessity of cautious assessment safety in clinical settings. [4]

IV. METHODOLOGY

This section outlines the systematic approach adopted for developing the Menstrual Health Chatbot. It delves into the selection of the AI model, the comprehensive description of the datasets utilized, and the detailed training process.

A. Model Selection

The base model selected for finetuning is 'medalpaca-7b', a variant of the Large Language Model Meta AI (LLaMA) [5]. Containing 7 billion parameters, medalpaca-7b stands out for its specialization in medical domain tasks, making it particularly suited for applications requiring nuanced understanding of medical dialogue and question-answering. The decision to select this model as the foundation for the chatbot is mainly because of its capacity to handle complex medical inquiries with a high degree of accuracy and contextual awareness. Its fine-tuning in medical contexts ensures that it can provide more precise and relevant responses to user queries, particularly important for a domain as specialized and sensitive as menstrual health.

B. Dataset Description

The dataset utilized in this project comprises structured data, specifically a collection of question-and-answer pairs. These pairs were carefully selected to ensure relevance and accuracy in the context of menstrual health, forming a robust foundation for training the chatbot.

TABLE I. DATASET DESCRIPTION

Table Head	Table Column Head
Structured	{ *"input": "I am scared of talking about periods", "output": "It is understandable. But you do not need to be scared while sharing with me. Anything that you say is safe with me. I will not share it with anyone."* }

C. Training

The proposed idea to make the selected pretrained model undergo fine-tuning using two techniques: Adapter fine-tuning and Low-Rank Adaptation (LoRA). The effectiveness of each technique was evaluated by comparing the responses they generated, focusing on empathy, information accuracy, and the degree of personalization. The technique that excelled in these aspects was chosen for the final deployment of the model. This approach ensured the selection of the most effective fine-tuning method for optimizing the chatbot's performance in addressing menstrual health inquiries.

1) Adapter Tuning

This technique invovles selecting a small subset of the base models's parameters and updating them. In this way the model can adapt to the specific tasks wthout much computational cost of full model training. Let θ be full set of parameters $\emptyset$ of the pre-trained model. Adapter modules are introduced with parameters $\emptyset$, where $\emptyset \ll |\theta|$.

Forward pass function is $f\theta\left(\left(a\emptyset(x)\right)\right)$.

The objective function of the Adapter Tuning is defined below.

$$min\emptyset L\left(f\theta\left(\left(a\emptyset(x)\right), Y\right)\right) \quad (1)$$

where L is the loss function, x is the input, and y is the target output.

2) Low-Rank Adaptation

For a weight matrix W in the model, LORA introduces two low-rank matrices A and B, where the rank r is much smaller than the dimensions of W. The adapted weight matrix W' is calculated as

$$W' = W + AB^T \quad (2)$$

In the forward pass, the original weight W is replaced by W' in the computation. This allows the model to adapt its behavior based on the low-rank updates. The model is trained to optimize a specific objective (e.g., minimizing prediction error on a dataset) while keeping most of the original parameters frozen and only updating A and B.

D. System Architecture

The architecture diagram in the Fig. 1 gives an high level abstract overview of the whole system.

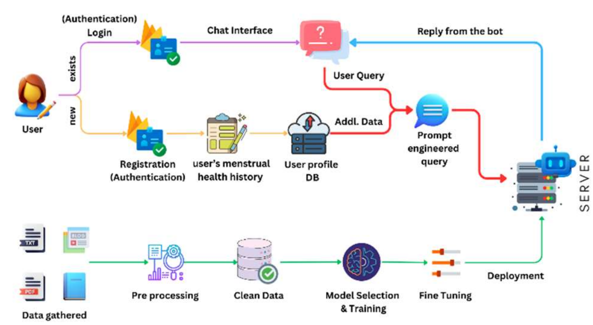

Fig. 1. Architecture diagram representing a outline of the structure of system

The architecture diagram in Fig. 1 illustrates the comprehensive workflow of a Menstrual Health Chatbot, from the initial user interaction to the final response delivery. It starts with the user, who can either log in if they have an existing profile or register as a new user, providing personal health details. Once authenticated, the user accesses the chat interface where they can pose queries. These queries, potentially enriched with additional data, are processed through a prompt-engineered system on the server. The system's backend involves collecting and preprocessing various textual data, selecting and training the model Medalapaca, and fine-tuning it. Finally, the trained and fine-tuned model is deployed to the server to provide real-time, personalized responses to user inquiries.

V. REQUIREMENTS

This section outlines the systematic approach adopted for developing the Menstrual Health Chatbot. It delves into the selection of the AI model, the comprehensive description of the datasets utilized, and the detailed training process.

A. Pytorch Library

This open-source machine learning library is pivotal for training the neural networks within the Menstrual Health Chatbot. Its dynamic computation graphing capabilities allow for flexible model adjustments during development.

B. *Transformer Library*

Transformers provides APIs and tools to easily download and train state-of-the-art pretrained models. Serving as the foundation for our chatbot's NLP functions, the Transformer library facilitates the implementation of attention mechanisms that are crucial for understanding the context in user dialogues.

C. *Hugging Face Platform*

This platform provides access to pre-trained models like Medalpaca, which form the backbone of our chatbot's understanding of medical language, and tools for model training and deployment.

D. *Azure ML Studio*

Leveraging cloud computing resources, Azure ML Studio enables scalable model training, and management, ensuring our chatbot is accessible and responsive at all times.

E. *Firebase*

This platform is used for its robust backend services, including real-time databases for storing user profiles and chat histories, authentication, and hosting the web interface of the chatbot.

F. *Replicate*

Replicate is incorporated to maintain version control of the chatbot's deployment, allowing for consistent updates and rollbacks if necessary. The menstrual health chatbot is deployed on this platform. The API key provided by the platform is used to access the deployed chatbot.

G. *React Web Framework*

React is the library for web and native user interfaces. Build user interfaces out of individual pieces called components written in JavaScript. This JavaScript library is essential for building the user interface of the chatbot, ensuring a seamless and interactive experience for users across various devices and platforms.

VI. IMPLEMENTATION AND RESULTS

This section examines the functionalities delivered by the Menstrual Health Chatbot, assessing its performance in real-world applications and comparing the results of fine-tuning the model using Adapter fine-tuning and LoRA techniques. Outcomes from these assessments, captured through various means, including screenshots, will be showcased to illustrate the chatbot's practical impact.

A. *Comparision of Models*

The model responses obtained from using two fine-tuning techniques, namely Adapter fine-tuning and LoRA fine-tuning, are compared with the not fine-tuned model. Later, the best fine-tuned model, based on the quality of the model responses, is assessed with the prompt engineered query. The prompt engineered query is the combination of the user query and the user medical conditions gathered during the user registration and stored as the user profile in the database.

TABLE II. DATASET DESCRIPTION

Model and type of query	**Query and response**
User Query	Why are my periods so irregular?
Not finetuned model	Irregular periods can be caused by a variety of factors such as stress, hormonal changes, or lifestyle factors.
Finetuned model using Adapter Finetuning	1.Pregnancy: If you are pregnant, your periods may be irregular. 2. Breastfeeding: If you are breastfeeding, your periods may be irregular. 3. Stress: Stress can cause changes in your body that affect your period.4. Thyroid disease: Thyroid disease can cause your period to be irregular.
Finetuned model using LoRA	Irregular menstrual cycles could be a result of hormonal fluctuations. Common causes include significant weight changes, excessive exercise, or emotional stress. Consulting with a healthcare provider is recommended for a personalized diagnosis.
Prompt engnieered query	Why are my periods so irregular? Medical History: PCOS.
Best Finetuned model with prompt engineered query	As per your history, you have been diagnosed with PCOS. PCOS is a condition where the ovaries do not release an egg regularly. This leads to irregular periods. In addition, there is an increased production of androgens (male hormones) in PCOS which can cause acne, excessive hair growth, weight gain etc.

B. *Home Page*

The Menstrual Health Chatbot's home page offers a summary of its features and advantages and is made to be both friendly and educational. It has easy-to-use navigation that lets users log in or sign up depending on whether they are returning or new to the site. The page may include user reviews or testimonials to establish authenticity and trust, as well as important details about the chatbot's mission, such as its emphasis on tailored menstrual health care.

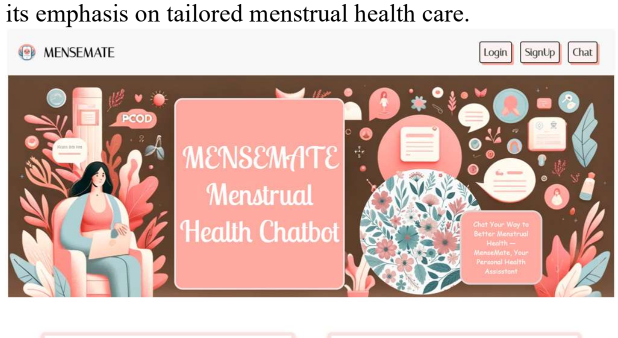

Fig. 2. The homepage which gives an overview of the website

C. *User Registration Form*

The user creates a user profile by registering herself on the website and providing information such as her name, age, email address, password, and menstrual health issues. The data gathered from the registration form is stored in the database and will be accessed for providing customized responses to the users. The layout of the user registration form is shown below in the Fig 3.

D. *User Profile in Frebase*

The Firebase database's user profile schema is given in Fig. 4. It outlines the specific fields and data types used to store user information. It's a crucial component for personalizing user experience.

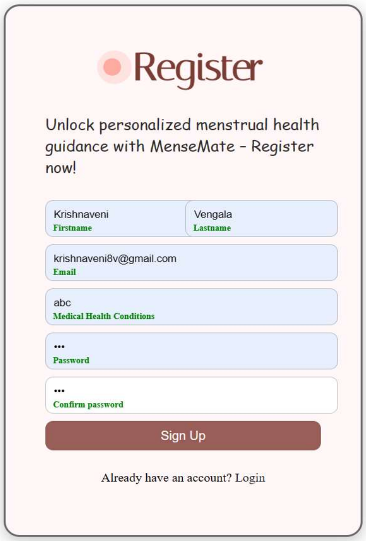

Fig. 3. The Registration page which collects the user data and the intital step to access the chatbot.

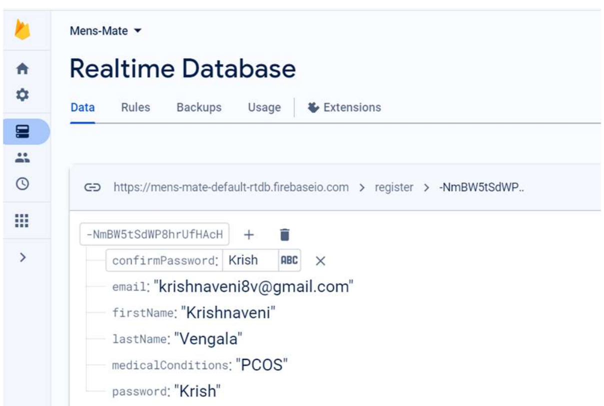

Fig. 4. User profile schema in Firebase.

E. User Login Form

Returning users can use the Menstrual Health Chatbot securely through the login page in Fig. 5 below. It has an easy-to-use interface that requests login information, usually a password and email address. It also includes necessary features like password recovery choices and reroutes new users to the registration page.

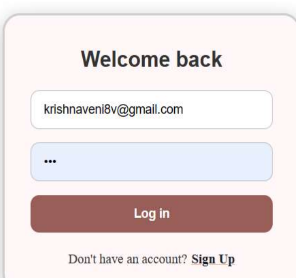

Fig. 5. The login page which provides authentication to the user.

F. Chat Page

The Menstrual Health Chatbot's chat website serves as its interactive hub, allowing users to have conversations with the AI. The UI of this page in Fig. 6 is simple and easy to use; it includes a chat window where users may type questions and get answers.

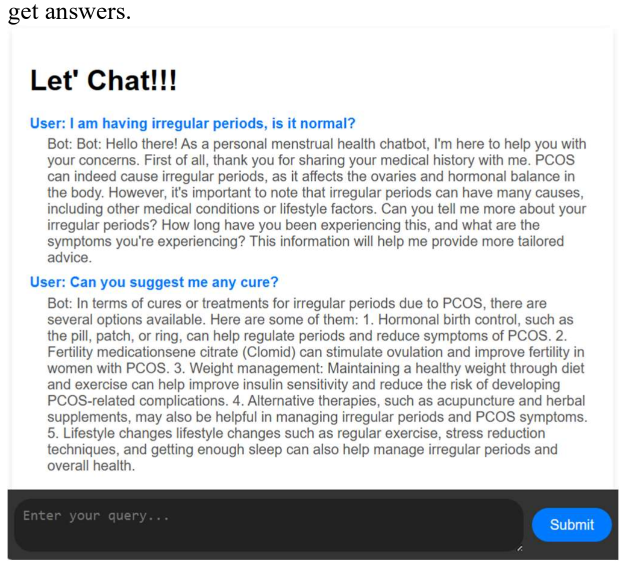

Fig. 6. The Chat page in which the user interacts with the menstrual health chatbot.

VII. CONCLUSION

The process of fine-tuning and prompt engineering was crucial, transforming the model to accurately address domain-specific questions. This exemplifies the potential of customizing AI models for specific content areas, enhancing both accuracy and practical applicability. The integration of user-specific context, such as medical history, into the chatbot's prompts marked a significant advancement, demonstrating the model's ability to deliver personalized and context-aware responses. This progression not only improves model accuracy but also paves the way for more sophisticated, user-focused AI applications.

VIII. FUTURE WORK

For future developments of the Menstrual Health Chatbot, key focuses include enhancing personalization through user profiles for tailored advice, fostering a supportive community platform, and forming partnerships with health professionals for expert guidance. Additionally, expanding educational resources, offering multilingual and global support, and integrating with health apps and devices are planned. Interactive tools, offline access, and awareness campaigns to combat menstrual health stigma are also on the agenda, broadening the chatbot's impact and accessibility.

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