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Title of the thesis

Developing of Mini-Scientific Chatbot based on Transformers and LLMs

Under the supervision of

Said Gadri

Composition of the jury

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Dedications

To my dear mother, I offer you my successes as proof of my determination in facing life's challenges. In seeing you, I find the strength to move forward. Thank you, Mom.

To my dear father, I proudly dedicate my achievements and the fruits of my efforts. You are my rock, my source of security, my light, and my pride. You are the joy of my days and the support behind my aspirations.

To my three brothers, "Abdelkader, Abdessamad, and Mohammed," my source of energy and laughter. And to my little sister, "Khadidja," who brightens my days.

To my family, each one of you holds a special place, whether near or far.

To a special, dear, and precious person who holds a unique place in my heart, may God protect him for me.

Finally, thank you to every teacher and professor. You taught us that success has value and meaning. Praise be to God.

Roqia Allal

To my beloved parents and dear brothers,

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Faten Aichaoui

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Contents

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List of Abbreviations

API	Application Programming Interface
BERT	Bidirectional Encoder Representations from Transformers
BMC	Business Model Canvas
BPE	Byte-Pair Encoding
CAGR	Compound Annual Growth Rate
CNN	Convolutional Neural Network
CRUD	Create, Read, Update, Delete
DL	Deep Learning
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization
EM	Exact Match
FAISS	Facebook AI Similarity Search
FK	Foreign Key
GPU	Graphics Processing Unit
GPT	Generative Pre-trained Transformer
HTML	HyperText Markup Language
JSON	JavaScript Object Notation
LLM	Large Language Model
LoRA	Low-Rank Adaptation
LSTM	Long Short-Term Memory
ML	Machine Learning
MoE	Mixture of Experts
MySQL	My Structured Query Language
NER	Named Entity Recognition
NLG	Natural Language Generation

NLP	Natural Language Processing
NLU	Natural Language Understanding
OOV	Out-of-Vocabulary
PDO	PHP Data Objects
PEFT	Parameter-Efficient Fine-Tuning
PHP	Hypertext Preprocessor
PII	Personally Identifiable Information
PK	Primary Key
PLM	Pre-trained Language Model
QLoRA	Quantized Low-Rank Adaptation
RAG	Retrieval-Augmented Generation
RLHF	Reinforcement Learning from Human Feedback
RNN	Recurrent Neural Network
RTL	Right-to-Left
SEO	Search Engine Optimization
Seq2Seq	Sequence-to-Sequence
SQL	Structured Query Language
SSD	Solid State Drive
STT	Speech-to-Text
SVM	Support Vector Machine
TTS	Text-to-Speech
UI	User Interface
UML	Unified Modeling Language
UX	User Experience
VRAM	Video Random Access Memory

Abstract

This thesis presents MedSci-GPT, a lightweight multilingual scientific chatbot using a hybrid architecture: GPT-4o API (primary) and fine-tuned Phi-2 (fallback). LoRA (rank 8, alpha 16) was applied on scientific QA datasets. A web app was built with PHP, MySQL, HTML/CSS/JS supporting authentication, conversation management, and Arabic/English/French. Evaluation shows Phi-2 achieves 76% accuracy (0.8s) and GPT-4o 82% (1.8s), proving lightweight scientific assistants run on standard hardware.

Keywords: Large Language Models, Scientific Chatbot, Fine-tuning, LoRA, GPT-4o, Phi-2, Multilingual, Arabic NLP, Question Answering, Transformer.

الملخص

تقدم هذه المذكرةMedSci-GPT ، شات بوت علمياً خفيفاً متعدد اللغات بهندسة هجينة GPT-4o :(رئيسي) و Phi-2 المدقق (بديل). طُبقت LoRA (المرتبة 8، ألفا 16) على بيانات أسئلة وأجوبة علمية. بُني تطبيق ويب بـ PHP و MySQL و HTML/CSS/JS يدعم المصادقة وإدارة المحادثات واللغات العربية والإنجليزية والفرنسية. أظهر التقييم أن Phi-2 المدقق يحقق دقة 76% بزمن 0.8 ثانية و GPT-4o دقة 82% بزمن 1.8 ثانية، مما يثبت إمكانية تشغيل المساعدات العلمية الخفيفة على الأجهزة العادية.

الكلمات المفتاحية: النماذج اللغوية الكبيرة، شات بوت علمي، ضبط دقيق، LoRA، GPT-4o، Phi-2، تعدد لغات، معالجة اللغة العربية، إجابة الأسئلة، محولات.

Résumé

Ce mémoire présente MedSci-GPT, un chatbot scientifique léger multilingue à architecture hybride : API GPT-4o (principal) et Phi-2 affiné (alternative). L'affinage LoRA (rang 8, alpha 16) a été appliqué sur des données QA scientifiques. Une application web a été développée avec PHP, MySQL, HTML/CSS/JS supportant l'authentification, la gestion des conversations et les langues arabes, anglaise et française. L'évaluation montre que Phi-2 affiné atteint 76% de précision (0,8s) et GPT-4o 82% (1,8s), prouvant que les assistants scientifiques légers peuvent fonctionner sur du matériel standard.

Mots clés: Grands Modèles de Langage, Chatbot Scientifique, Affinage, LoRA, GPT-4o, Phi-2, Multilingue, TALN Arabe, Réponse aux Questions, Transformers.

General Introduction

Artificial intelligence (AI) has experienced rapid development in recent years, driven by advancements in Web 3.0, data mining, deep learning, and natural language processing technologies [1]. These developments have enabled the creation of intelligent systems capable of performing tasks such as decision-making, data analysis, and human-like interaction. Among these systems, conversational agents powered by large language models (LLMs) have emerged as one of the most promising applications [1].

LLMs are fundamentally based on transformer architectures and trained on massive text corpora through self-supervised learning. They possess several key characteristics that make them suitable for educational and scientific assistance: they are large-scale (containing billions to trillions of parameters), general-purpose (capable of handling various tasks including question answering and text generation), and rely on a pre-training and fine-tuning paradigm that allows adaptation to specific domains such as education or medicine [1].

The integration of LLMs into education and scientific research has gained significant momentum worldwide. These models provide personalized learning support, real-time tutoring, and interdisciplinary learning. In the context of scientific assistance, LLMs can answer academic questions, search literature, extract relevant information, and guide users through complex reasoning processes. These capabilities have positioned LLMs as powerful auxiliary tools for smart education and scientific inquiry [1].

Despite these advantages, current LLM-based systems face critical challenges. LLMs frequently generate incorrect information, a phenomenon known as machine hallucination; even advanced models like GPT-4o can produce errors on college-level science questions. Training and running these models require substantial hardware resources, with the infrastructure behind ChatGPT costing nearly one billion dollars. General-purpose LLMs lack deep understanding of specialized scientific domains, often producing generic responses. Furthermore, most LLMs are trained predominantly on English corpora, limiting their ability to support Arabic-speaking users. Finally, resource-limited regions often lack the necessary infrastructure to benefit from these systems, exacerbating existing inequalities in research opportunities [1].

To address these challenges, this thesis proposes the development of MedSci-GPT, a lightweight scientific chatbot designed to assist users in academic inquiry and scientific information retrieval. The proposed system employs a hybrid architecture combining commercial LLMs with specialized fine-tuned open-source models. Specifically, MedSci-GPT

leverages the GPT-4o API accessed through GitHub Models as the primary response generation engine. To enhance scientific performance and reduce hallucinations, the system incorporates prompt engineering (using carefully crafted system prompts and few-shot examples) and fine-tuning of the lightweight Phi-2 model (2.7 billion parameters) on curated scientific question-answer pairs using LoRA (rank 8, alpha 16, 1 epoch, 500 training steps). The architecture is designed to be lightweight and accessible, suitable for deployment on standard hardware without expensive GPU clusters, and supports multilingual interaction (Arabic, English, and French) with full conversation history management.

This thesis is organized into five chapters:

- **Chapter 1** provides a literature review of conversational AI, NLP, transformers, LLMs, and existing scientific chatbot systems, identifying research gaps that motivate this work.
- **Chapter 2** presents the analysis and design of the proposed system, including requirements, layered architecture, dataset preparation, model selection, fine-tuning strategy, prompt engineering, conversation management, and UML modeling.
- **Chapter 3** describes the implementation details, including the development environment, database design, PHP backend logic, GPT-4o API integration via GitHub Models, fine-tuning of Phi-2 using LoRA on Google Colab, and the web-based frontend interface built with HTML, CSS, and JavaScript.
- **Chapter 4** evaluates the system's performance through testing across multiple dimensions (response accuracy, context understanding, response time, multilingual support) and provides a comparative analysis with existing chatbot systems.
- **Chapter 5** presents the startup certificate application in accordance with Ministerial Decree 1275, covering project presentation, innovation aspects, strategic market analysis, production and organization plan, financial aspects, and the experimental prototype.
- Finally, the **General Conclusion** summarizes the main contributions of this work, and **Future Work Perspectives** outline potential enhancements including retrieval-augmented generation (RAG), mobile development, voice interaction, and cloud deployment.

Literature Review and Theoretical Background

1.1. Introduction

The field of natural language processing (NLP) has undergone a revolutionary transformation with the emergence of large language models (LLMs). Built upon transformer architectures, these models demonstrate remarkable capabilities in understanding and generating human language across a wide range of tasks [2]. Unlike traditional models trained for specific supervised tasks, LLMs are pre-trained on massive text corpora through self-supervised learning, enabling them to acquire general-purpose linguistic knowledge adaptable to multiple downstream applications [2].

The evolution from statistical language modeling to neural networks, and subsequently to pre-trained language models (PLMs) and LLMs, represents a significant paradigm shift. The transition to LLMs involved a dramatic increase in model parameters and training data, unlocking emergent abilities such as reasoning, in-context learning, and zero-shot task generalization [2]. Conversational AI, one of the most impactful applications of LLMs, leverages these capabilities to engage in human-like dialogue through techniques such as instruction tuning and reinforcement learning from human feedback (RLHF) [2].

In scientific and educational domains, LLMs have shown particular promise. They can answer academic questions, summarize research papers, and guide users through complex reasoning processes. This chapter provides a comprehensive review of the theoretical foundations relevant to developing scientific chatbots, covering NLP fundamentals, transformer architectures, LLMs, fine-tuning techniques, and existing conversational AI systems.

1.2. Background and Motivation

The scientific research pipeline follows well-defined steps: hypothesis proposal, experiment design, data analysis, and peer review. While this process has enabled groundbreaking discoveries, it remains constrained by the limited creativity, expertise, time, and resources of human researchers [3].

For decades, automation has been pursued to enhance research efficiency. Early systems from the 1970s, such as Automated Mathematician and BACON, demonstrated machine assistance in theorem generation and empirical law discovery. Recent breakthroughs like AlphaFold have automated specific tasks, dramatically accelerating progress in domains like

protein folding. However, the vision of comprehensive AI assistance across multiple research domains has only become realistic with the advent of large language models (LLMs) [3].

A critical challenge driving this need is the exponential growth of scientific literature. Millions of papers are published annually, making it increasingly difficult for researchers to keep pace with new discoveries in their fields. This information overload creates an urgent demand for intelligent tools that can synthesize, summarize, and extract relevant knowledge efficiently.

LLMs such as GPT-4 and LLaMA have set new benchmarks in language understanding and generation. Their ability to process massive datasets, generate human-like text, and assist in complex decision-making positions them as powerful tools for scientific research. Beyond research, LLMs have also demonstrated significant potential in education, serving as personalized tutors and supporting students with diverse learning needs [3]. **Figure 1** illustrates the growth of scientific publications and the corresponding demand for AI-powered research assistance tools from 2000 to 2025.

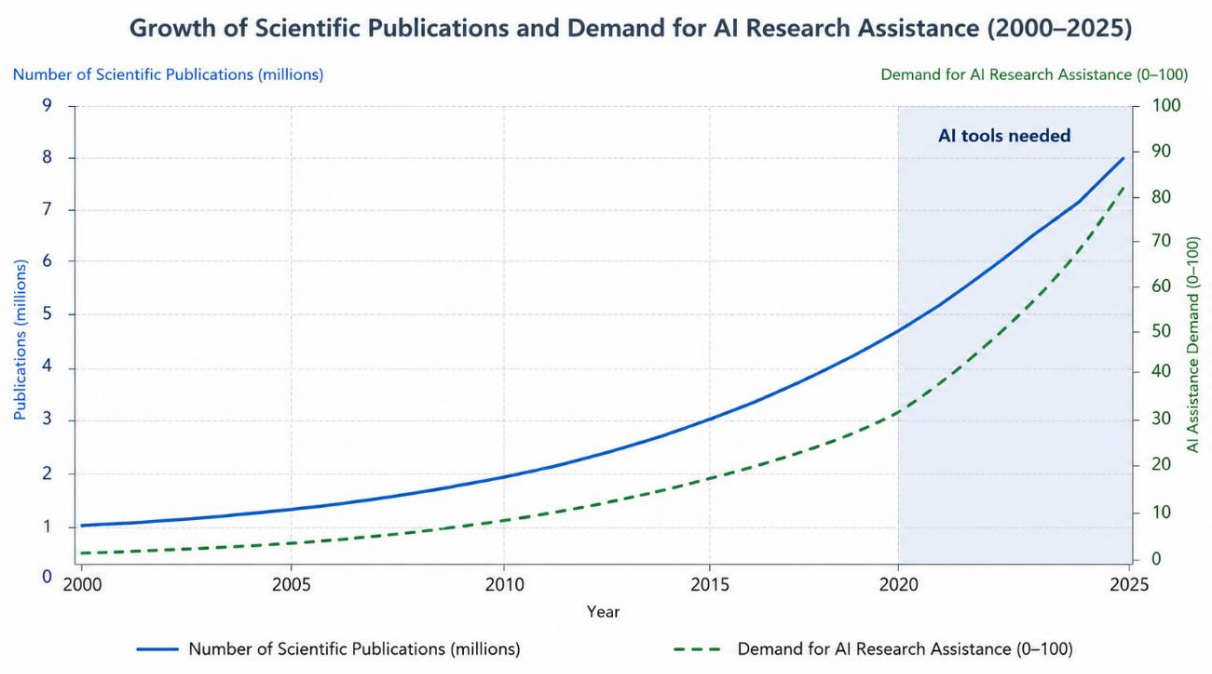

Figure 1: Growth of scientific information and AI assistance demand

1.3. Problem Statement

Despite the remarkable capabilities of large language models, several critical challenges limit their reliable deployment in scientific and educational domains. These challenges revolve

around hallucination, lack of specialization, high computational requirements, and limited multilingual support [4].

Hallucination refers to the generation of fluent but factually inaccurate content unsupported by external evidence. This undermines trustworthiness in domains requiring factual accuracy, such as scientific research and education. Hallucinations manifest as factual contradictions (incorrect scientific facts), factual fabrications (inventing non-existent findings), or faithfulness inconsistencies [4].

Lack of domain specialization is another significant challenge. General-purpose LLMs trained on public web data lack deep understanding of specialized fields like physics, chemistry, or biology, often producing generic responses unsuitable for academic contexts [4].

High computational requirements pose substantial barriers. Training and deploying LLMs require extensive hardware resources, limiting accessibility for individual researchers, students, and small institutions in resource-constrained environments [4].

Limited multilingual support, especially for Arabic, further restricts accessibility. Most LLMs are trained predominantly on English corpora, limiting their ability to respond accurately in other languages. Low-resource languages face increased hallucination rates due to insufficient training data [4]. **Table 1** summarizes the key problems and their impact on scientific chatbot deployment.

Table 1: Summary of key problems and their impact

Problem	**Impact**
Hallucination	Inaccurate scientific answers, misinformation
Lack of specialization	Generic, non-contextual responses unsuitable for research
High computational cost	Limited deployment for individuals and small institutions
Limited Arabic support	Reduced accessibility for Arabic-speaking users

1.4. Research Objectives

1.4.1. General Objective

The primary objective of this thesis is to develop a lightweight, intelligent scientific assistant based on large language models that can assist users in academic inquiry and scientific information retrieval while maintaining computational efficiency.

1.4.2. Specific Objectives

To achieve the general objective, the following specific objectives are defined:

- **Understand scientific questions:** Enable the system to accurately interpret and comprehend user queries in scientific domains across multiple languages.
- **Generate accurate responses:** Produce factually correct, context-aware, and coherent answers to scientific questions while minimizing hallucinations.
- **Support multilingual interaction:** Provide seamless interaction in three languages: Arabic, English, and French, ensuring accessibility for Arabic-speaking researchers and students.
- **Reduce resource consumption:** Design a lightweight architecture suitable for deployment on standard hardware without requiring expensive GPU clusters.
- **Improve contextual interaction:** Maintain conversation context across multiple turns to enable coherent and meaningful multi-turn dialogues.
- **Implement fine-tuning on small models:** Fine-tune lightweight open-source models such as Phi-2 on curated scientific datasets to enhance domain specialization and reduce operational costs.

1.5. Research Methodology

This thesis follows a structured research methodology comprising six main phases, as illustrated in **Figure 2**.

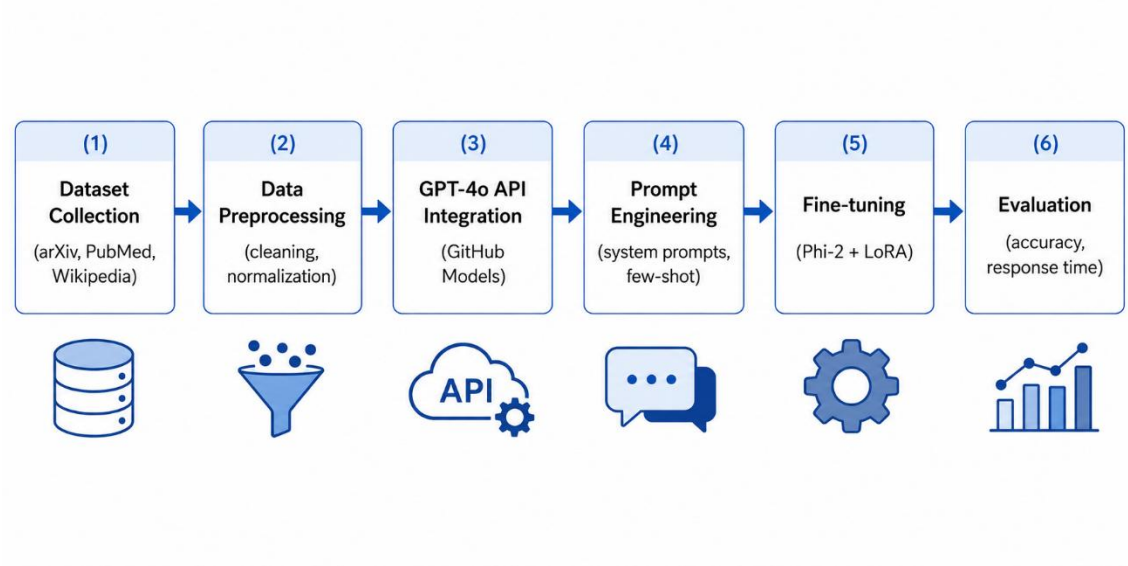

Figure 2: Research methodology workflow

- **Dataset collection:** Gather scientific question-answer pairs from publicly available sources such as arXiv, PubMed, and Wikipedia Science, as well as curated scientific QA datasets.
- **Data preprocessing:** Clean, normalize, and tokenize the collected text data, removing duplicates and filtering low-quality content.
- **GPT-4o API integration:** Connect the chatbot backend to the GPT-4o API via GitHub Models, leveraging its advanced reasoning and multilingual capabilities.
- **Prompt engineering:** Design and refine system prompts, few-shot examples, and task-specific instructions to guide the model toward generating accurate, context-aware, and scientifically reliable responses.
- **Fine-tuning on small models:** Fine-tune the lightweight Phi-2 model (2.7B parameters) using LoRA on a curated scientific dataset of 1,000 question-answer pairs from the lavita/medical-qa-datasets (medical_meadow_medqa) on Hugging Face, using Google Colab with T4 GPU, for 1 epoch (500 training steps) with with rank r=8, alpha=16, learning rate 2e-4, batch size 2, max sequence length 256 tokens, and fp16 disabled to ensure compatibility with LoRA on Colab's T4 GPU.
- **Evaluation and testing:** Assess the chatbot's performance using quantitative metrics (accuracy, response time) and qualitative evaluation (human assessment, comparison with baseline models).

1.6. Conversational Artificial Intelligence

1.6.1. Evolution of Chatbot

The history of chatbots begins in 1950 when Alan Turing proposed whether a computer program could converse with humans without revealing its artificial nature, known as the Turing test [5].

The first functional chatbot, ELIZA (1966), simulated a psychotherapist using pattern matching and template-based responses. While limited in knowledge and unable to learn from context, ELIZA inspired subsequent developments [5].

In 1972, PARRY simulated a patient with schizophrenia, incorporating a "personality" and emotional responses. ALICE (1995) was the first online chatbot, introducing AIML (Artificial Intelligence Markup Language) with approximately 41,000 templates, far exceeding ELIZA's 200 rules [5].

A major evolution occurred in 2001 with SmarterChild, the first chatbot to retrieve real-time information from databases for practical tasks like weather and news. The development of voice assistants—Apple's Siri (2010), IBM Watson (2011), Google Now (2012), Microsoft Cortana (2014), and Amazon Alexa (2014)—introduced voice-based interaction and home automation [5].

Around 2014-2016, sequence-to-sequence (Seq2Seq) models based on recurrent neural networks (RNNs) and LSTMs enabled chatbots to generate responses rather than selecting from predefined templates, marking a shift from rule-based to generative approaches [5].

More recently, large language models such as ChatGPT, GPT-4, Gemini, and LLaMA have revolutionized conversational AI by enabling open-domain dialogue, reasoning, and human-like text generation across virtually any topic. **Figure 3** illustrates the evolution of chatbot architectures.

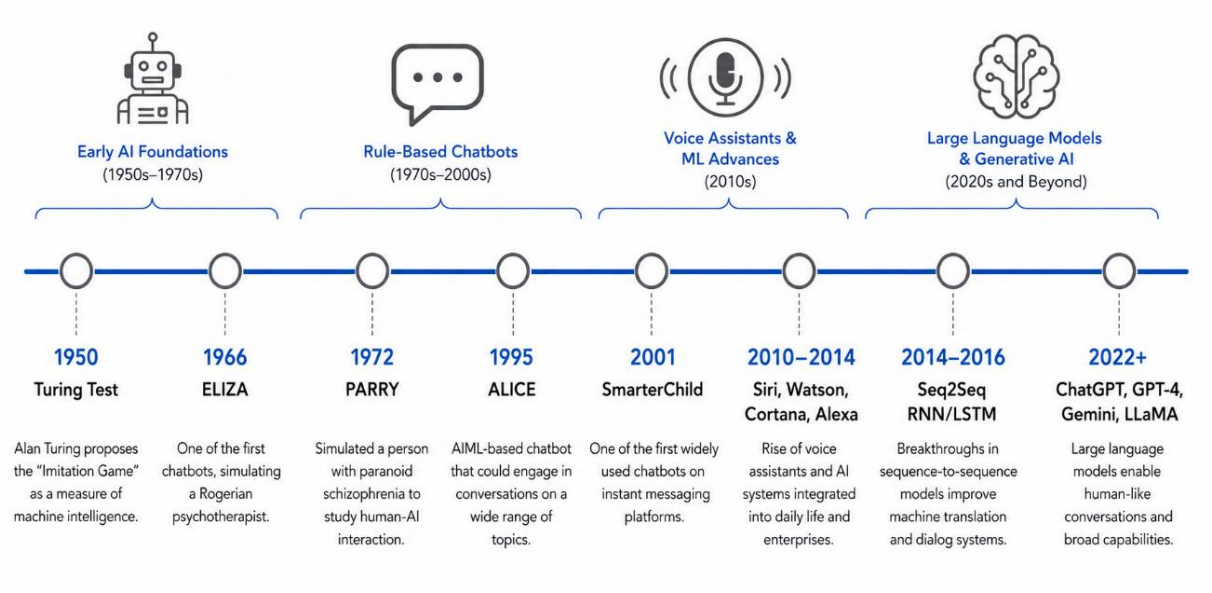

Figure 3: Evolution of chatbot architectures

1.6.2. Rule-Based vs AI-Based Chatbots

Chatbots can be classified according to the underlying technology that powers them into two main categories: rule-based systems and AI-based models [6].

Rule-based chatbots operate on predefined rules and pattern-matching algorithms. They match user input to a rule pattern and select a predefined answer from a set of responses. These systems exhibit low flexibility, no learning ability, limited scalability, and weak context awareness [6].

AI-based chatbots, in contrast, leverage machine learning and natural language processing to extract content from user input and learn from conversations. They consider the entire dialogue context, not just the current turn, and offer high flexibility, strong learning capabilities, robust scalability, and advanced context awareness [6]. **Table 2** presents a comparison of rule-based and AI-based chatbots across key features.

Table 2: Comparison of rule-based and AI-based chatbots

Feature	**Rule-Based**	**AI-Based**
Flexibility	Low	High
Learning ability	None	Yes
Scalability	Limited	Strong
Context awareness	Weak	Advanced

1.6.3. Applications of Scientific Chatbots

Large language models are increasingly being integrated into platforms designed to support interactive learning and research across multiple disciplines [7].

Education: Conversational AI assistants offer personalized support and dynamic explanations, simulating interactive tutors to aid comprehension of complex topics. Students can engage with the system through text, image, or voice inputs [7].

Research assistance: Retrieval Augmented Generation (RAG) frameworks combine preprocessed documents, web data, and user uploads to improve response quality and support source-informed research [7].

Scientific summarization: Multi-stage summarization strategies enable processing of extensive content that would otherwise exceed the input limitations of transformer-based models [7].

Scientific QA systems: RAG frameworks enhance language understanding by combining dense vector representations with semantic search techniques, retrieving relevant document chunks and injecting them into the prompt context for grounded, context-aware answers [7].

1.7. Natural Language Processing Fundamentals

1.7.1. Text Processing Techniques

Text preprocessing is an essential step to prepare a corpus for natural language processing modeling. The choice of preprocessing methods directly affects downstream application results [8].

- **Cleaning (removing formatting):** Stripping HTML tags, special characters, line breaks, and other non-textual elements ensures that the model processes only relevant linguistic content without noise [8].
- **Normalization:** Unifies variations in text representation by converting all characters to lowercase, expanding contractions, and standardizing accent marks, reducing vocabulary sparsity and improving model generalization [8].
- **Stop-word removal:** Common words (e.g., "the", "and", "of") that carry little semantic meaning are removed to reduce corpus size and improve computational efficiency [8].
- **Lemmatization:** Reduces a word to its dictionary form (lemma) using vocabulary and morphological analysis, producing linguistically valid base forms that preserve meaning [8].

1.7.2. Tokenization and Embeddings

Tokenization is the process of segmenting text into smaller units called tokens, which can be characters, subwords, or words [9].

Word-level tokenization splits text by whitespace and punctuation, treating each word as a distinct token. While intuitive, it suffers from out-of-vocabulary (OOV) issues where unseen words cannot be represented [9].

Byte-Pair Encoding (BPE) is a subword tokenization algorithm that addresses the OOV problem by iteratively merging the most frequent character pairs, balancing vocabulary size and representational power [9].

Embedding vectors map discrete linguistic units into continuous, low-dimensional vector spaces. Early static embedding methods like Word2Vec (2013) use shallow neural networks to learn fixed vector representations. Contextual embeddings, such as those from BERT (2018) and GPT, generate token vectors conditioned on their surrounding context, meaning the same word receives different embeddings depending on its usage [9]. **Figure 4** shows the evolution of embedding techniques from Word2Vec to BERT.

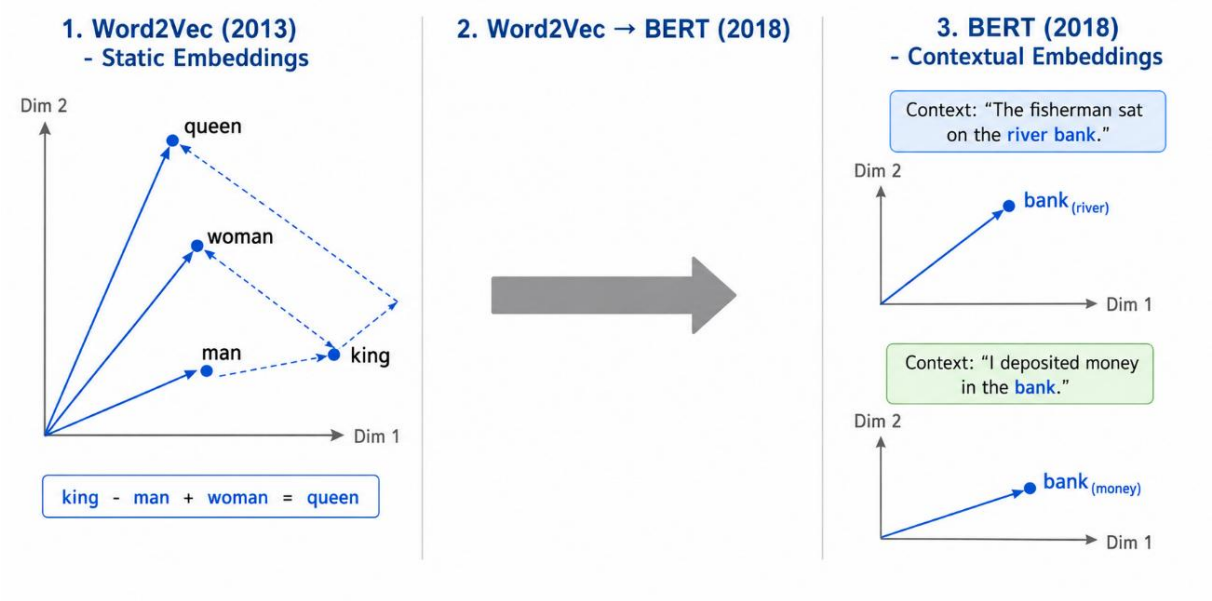

Figure 4: Evolution of embeddings (Word2Vec → BERT)

1.7.3. Language Understanding and Generation

Natural language understanding (NLU) and natural language generation (NLG) are two essential components of modern conversational AI systems [10].

Natural Language Understanding (NLU) focuses on extracting information from user input through three main tasks: intent classification (determining user goals), slot filling (extracting necessary information), and named entity recognition (identifying and labeling relevant entities). NLU enables chatbots to interpret user queries accurately [10].

Natural Language Generation (NLG) focuses on producing human-like responses based on structured data or system decisions through dialogue management, information retrieval, and context determination [10]. **Table 3** summarizes the roles of NLU and NLG.

Table 3: Roles of NLU and NLG in conversational AI

Component	Role
NLU	Intent understanding
NLG	Response generation

1.8. Transformers and Large Language Models

1.8.1. Transformer Architecture

The Transformer architecture, introduced by Vaswani et al. in 2017, revolutionized natural language processing by replacing recurrent and convolutional neural networks with an attention-only mechanism. Unlike sequential models such as RNNs that process tokens one by one, the Transformer processes entire sequences in parallel, significantly improving training efficiency [11].

The architecture follows an encoder-decoder structure. The encoder maps an input sequence to a sequence of continuous representations, composed of a stack of N identical layers, each containing a multi-head self-attention mechanism and a position-wise feed-forward network. The decoder generates an output sequence auto-regressively, with an additional multi-head attention layer over the encoder output [11].

Positional encoding is a crucial innovation since the Transformer contains no recurrence or convolution. Positional encodings are added to input embeddings to make use of sequence order. Vaswani et al. used sine and cosine functions of different frequencies, allowing the model to learn to attend by relative positions [11]. **Figure 5** presents the Transformer architecture.

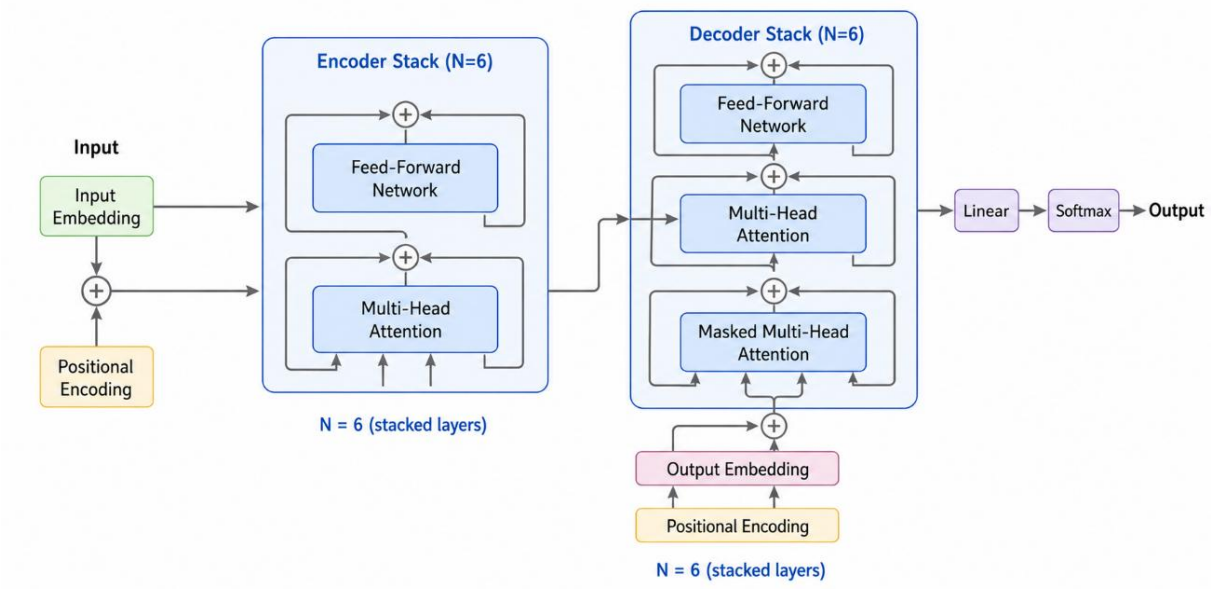

Figure 5: Transformer architecture

1.8.2. Attention Mechanism

An attention function maps a query and a set of key-value pairs to an output, computed as a weighted sum of the values, where weights are determined by a compatibility function between the query and corresponding key [11].

Self-attention, also called intra-attention, relates different positions of a single sequence to compute a representation of that sequence. The attention mechanism operates on three components: Query (Q), Key (K), and Value (V). The attention weights are computed by taking the dot product of the query with all keys, dividing by a scaling factor, applying a softmax function, and multiplying by the values [11].

Multi-head attention allows the model to jointly attend to information from different representation subspaces by projecting queries, keys, and values multiple times, performing attention in parallel, and concatenating the results [11]. **Figure 6** illustrates the self-attention mechanism.

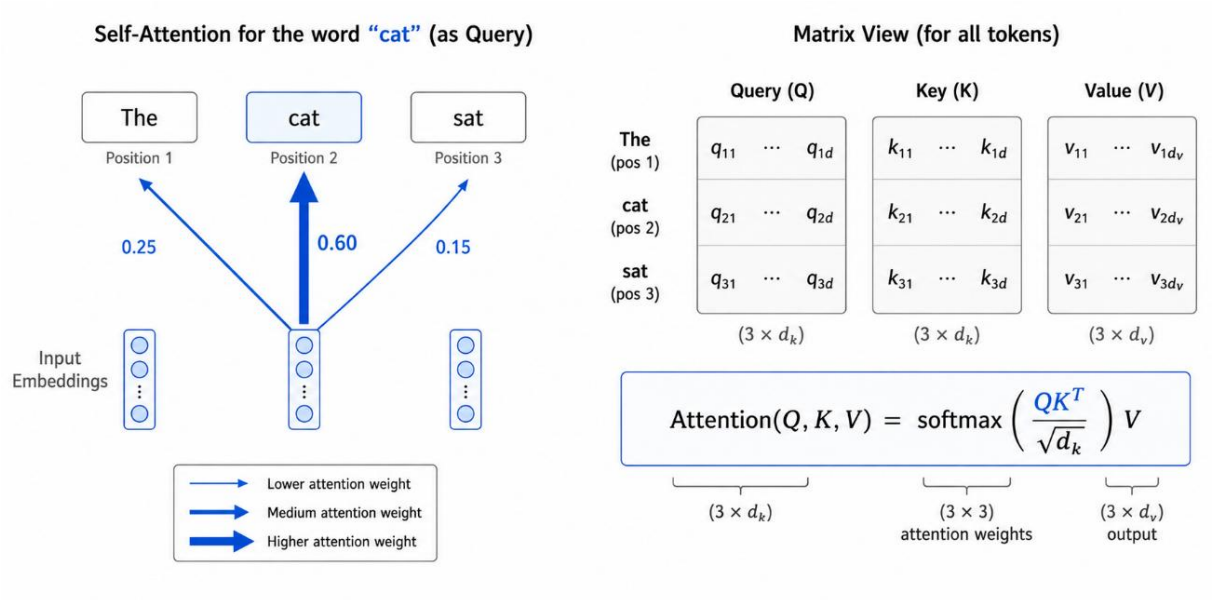

Figure 6: Self-attention mechanism

1.8.3. Pretrained Language Models

The evolution from pre-trained language models (PLMs) to large language models (LLMs) has been driven by scaling model parameters, data size, and computational resources [12].

GPT (Generative Pre-trained Transformer) is a decoder-only architecture by OpenAI using autoregressive language modeling. GPT-3 (175B parameters) enables few-shot and zero-shot learning [12].

BERT (Bidirectional Encoder Representations from Transformers) is an encoder-only architecture by Google using masked language modeling, capturing bidirectional context and excelling in NLU tasks [12].

LLaMA (Large Language Model Meta AI) is a family of decoder-only models by Meta (7B to 405B), designed to be lightweight and accessible, achieving competitive performance with fewer parameters [12].

Mistral is a family of efficient decoder-only models. Mistral 7B achieved state-of-the-art in its size class, while Mixtral introduced sparse mixture-of-experts (MoE) architecture [12].

Phi is a family of small language models by Microsoft (Phi-2: 2.7B, Phi-3-mini: 3.8B). Despite compact size, Phi models demonstrate strong reasoning capabilities due to training on high-quality synthetic data, ideal for resource-constrained environments [12]. **Table 4** compares these pretrained language models.

Table 4: Comparison of pretrained language models

Model	Type	Main Strength
GPT	Decoder-only	Text generation, in-context learning
BERT	Encoder-only	Bidirectional understanding, NLU tasks
LLaMA	Decoder-only	Lightweight, open-source, accessible
Mistral	Decoder-only (MoE)	Efficient, strong coding performance
Phi-2	Decoder-only (2.7B params)	Small and capable, fast inference, ideal for resource-constrained environments

1.8.4. Fine-Tuning Techniques

Fine-tuning adapts pre-trained models to specific downstream tasks. Parameter-efficient fine-tuning (PEFT) techniques minimize trainable parameters and computational overhead while achieving comparable performance [13].

Full Fine-Tuning updates all parameters of a pre-trained model, allowing maximum adaptation but requiring substantial computational resources and risking overfitting [13].

LoRA (Low-Rank Adaptation) freezes original weights and injects trainable low-rank decomposition matrices into specific layers. For a 4096×4096 weight matrix, LoRA with rank 8 requires only ~65K trainable parameters, reducing memory by over 400 times while maintaining comparable performance [13].

QLoRA (Quantized LoRA) extends LoRA by incorporating 4-bit quantization of the base model, enabling fine-tuning of a 7B parameter model on a single consumer GPU with 24GB VRAM [13].

Instruction Tuning trains LLMs on (instruction, output) pairs, bridging the gap between next-word prediction and instruction following, enhancing model controllability and zero-shot task generalization [13]. **Figure 7** illustrates the LoRA fine-tuning mechanism.

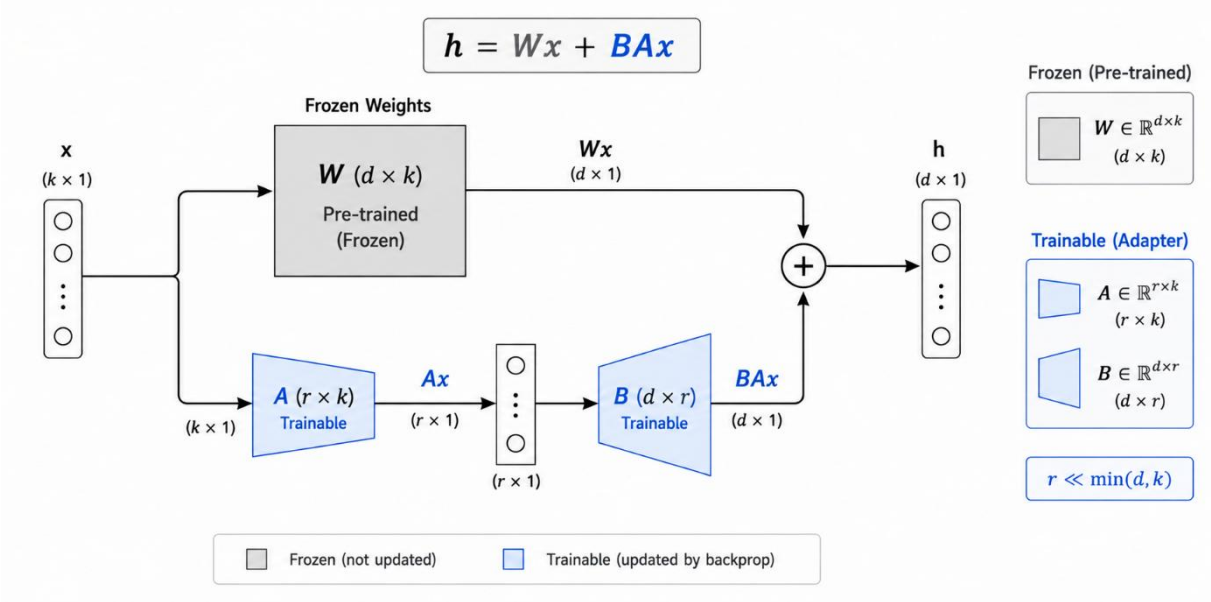

Figure 7: LoRA fine-tuning mechanism

1.9. Existing Scientific Chatbot Systems

1.9.1. Educational Chatbots

Khanmigo, developed by Khan Academy and built on ChatGPT-4, is a generative AI-powered intelligent tutoring system providing personalized, step-by-step guidance across subjects including mathematics, science, and humanities. Students perceive Khanmigo positively for its guidance and personalized interactions, though studies indicate it is viewed as a supplementary tool rather than a replacement for traditional instruction [14].

Duolingo Max, a premium tier of the Duolingo platform, integrates ChatGPT-4 to offer AI-driven features including Explain My Answer (instant feedback), Roleplay (simulated conversations), and Call with Lily (avatar-driven dialogue). However, these features embed cultural biases and remain behind a paywall, raising concerns about accessibility and digital inequality [15].

1.9.2. Research Assistant Chatbots

Elicit is an AI-powered research assistant enabling users to search over 138 million academic papers and generate research reports using semantic search to find relevant papers even when exact terms do not appear [16].

Scite Assistant is an AI-powered research chatbot specifically designed for academic research, providing answers with direct citations from over 187 million peer-reviewed articles, showing supporting versus contrasting evidence through Smart Citations [17].

1.9.3. Domain-Specific AI Assistants

Galactica (Meta AI) is a family of decoder-only models (125M-120B parameters) trained on 106 billion tokens of scientific text, performing citation prediction, scientific QA, mathematical reasoning, and molecular property prediction. However, it remains prone to hallucination, especially for less-cited concepts, and its large size limits accessibility [18].

SciBERT is a BERT-based model pre-trained on biomedical and computer science literature with a specialized vocabulary (SCIVOCAB). Evaluated on PLOS full-text articles, SciBERT achieved high F1 scores but lacks generative capabilities as an encoder-only model [19].

BioGPT (Microsoft) is a domain-specific generative Transformer pre-trained on biomedical literature, achieving 78.2% accuracy on PubMedQA. It generates fluent biomedical text but is limited to the biomedical domain [20]. **Table 5** compares these domain-specific AI assistants.

Table 5: Comparison of domain-specific scientific AI assistants

System	Strength	Limitation
Galactica	Scientific reasoning, multi-modal	Heavy (120B), hallucination-prone
SciBERT	Scientific NLP, high F1 scores	Non-generative
BioGPT	Biomedical QA and generation (78.2%)	Domain-limited

1.10. Comparative Analysis and Research Gap

Based on the review of existing scientific chatbot systems, **Table 6** provides a comparative analysis across five key dimensions: lightweight architecture, scientific domain focus, generative capability, fine-tunability, and Arabic language support.

Table 6: Comparative analysis of existing scientific chatbot systems and the proposed MedSci-GPT

System	Lightweight Architecture	Scientific Domain Focus	Generative Capability	Fine-tunable	Arabic Language Support
Galactica (Meta, 2022)	No (120B parameters)	Yes	Yes	No	No
SciBERT (Allen AI, 2019)	Yes (110M parameters)	Yes	No	Yes	No
BioGPT (Microsoft, 2022)	No	Yes	Yes	No	No
MedSci-GPT (Ours)	**Yes (Phi-2 2.7B)**	**High**	**Yes (GPT-4o + Phi-2)**	**Yes (LoRA)**	**Yes (via GPT-4o)**

Research Gap:

Despite significant advances, several critical gaps remain unaddressed [12]:

First, **computational efficiency** poses a major barrier. Models like Galactica (120B parameters) require substantial hardware resources, making them inaccessible to individual researchers and small institutions. While SciBERT is lightweight, it lacks generative capabilities.

Second, **domain specialization** remains challenging. General-purpose LLMs like GPT-4 are trained on public web data, making them less effective for specialized scientific domains. Domain-specific models like SciBERT and BioGPT are narrowly focused and either non-generative or domain-limited.

Third, **fine-tuning flexibility** is restricted. Most existing scientific models are not designed for easy fine-tuning by end-users, limiting adaptability to specific research needs.

Fourth, **multilingual support**, particularly for Arabic, is severely lacking. The vast majority of scientific LLMs are trained predominantly on English corpora, creating significant accessibility barriers for Arabic-speaking researchers.

These gaps motivate the development of MedSci-GPT, a lightweight, fine-tunable, multilingual (Arabic/English/French) scientific chatbot that combines domain specialization with generative capabilities while maintaining computational efficiency suitable for standard hardware deployment.

1.11. Chapter Summary

This chapter has provided a comprehensive literature review and theoretical background for developing a lightweight scientific chatbot. It introduced conversational AI and the evolution

of chatbots from ELIZA to modern LLM-based assistants. The chapter covered NLP fundamentals (text processing, tokenization, embeddings, NLU, NLG), the Transformer architecture and attention mechanism, key pretrained models (GPT, BERT, LLaMA, Mistral, Phi), and fine-tuning techniques (LoRA, QLoRA, instruction tuning). Existing scientific chatbot systems (Khanmigo, Elicit, Scite, Galactica, SciBERT, BioGPT) were analyzed, revealing critical research gaps: most systems are either computationally heavy, non-generative, not fine-tunable, or lack Arabic language support. These findings motivate the development of MedSci-GPT, a lightweight, fine-tunable, multilingual scientific assistant addressed in the following chapters.

Analysis and Design of the Proposed Chatbot System

2.1. Introduction

Based on the theoretical foundations established in the previous chapter, this chapter presents the analysis and design of the proposed **MedSci-GPT** chatbot system. The primary goal is to develop a lightweight, multilingual scientific assistant that leverages large language models to support academic inquiry and scientific information retrieval. The system is designed to address the key challenges identified earlier: hallucination, lack of domain specialization, high computational requirements, and limited Arabic language support.

This chapter covers the functional and non-functional requirements, the overall system architecture, dataset preparation, model selection and fine-tuning strategies, prompt engineering, conversation management, security considerations, and UML modeling. The design choices are guided by the need for a lightweight, fine-tunable, and multilingual solution that balances performance with computational efficiency. The proposed architecture integrates commercial LLMs (GPT-4o via GitHub Models) with fine-tuned open-source models (Phi-2) to achieve domain specialization while maintaining accessibility for deployment on standard hardware.

2.2. General Overview of the Proposed System

The proposed MedSci-GPT system is designed as a lightweight, multilingual scientific chatbot that assists users in academic inquiry and scientific information retrieval. The system follows a hybrid architecture that combines the strengths of commercial large language models with specialized fine-tuned open-source models, ensuring both high-quality responses and computational efficiency.

The system operates through a four-layer workflow, as illustrated in Figure 8. First, the user interacts with a web-based chat interface, submitting scientific questions in Arabic, English, or French. Second, the backend receives the user query, manages session state, and constructs appropriate prompts. Third, the system routes the request to either the GPT-4o API (via GitHub Models) for general scientific queries or to a fine-tuned Phi-2 model for specialized responses, depending on query type and availability. Fourth, the generated response is returned to the user interface and stored in the database for conversation history.

The architecture is designed to be modular and scalable. The GPT-4o API serves as the primary response generation engine, providing advanced reasoning and multilingual

capabilities. The fine-tuned Phi-2 model acts as a complementary layer, offering domain-specific responses with lower latency and reduced API dependency. This hybrid approach balances performance, cost, and reliability, making the system suitable for deployment on standard hardware without expensive GPU clusters. **Figure 8** presents the global architecture of the MedSci-GPT system.

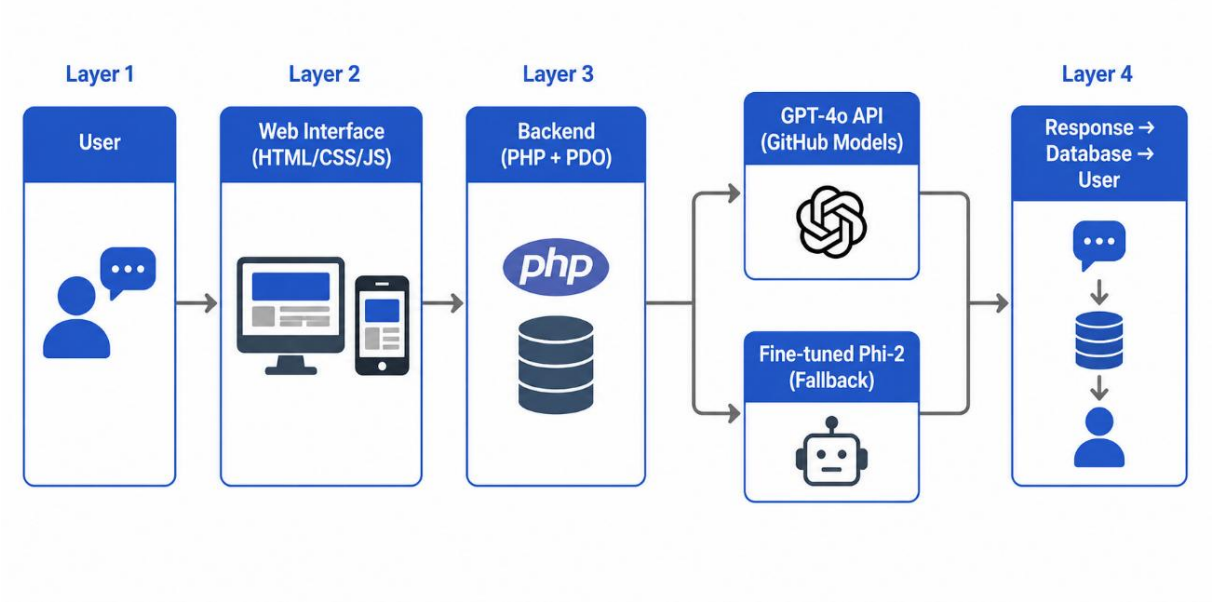

Figure 8: Global architecture of MedSci-GPT

2.3. Functional and Non-Functional Requirements

The proposed MedSci-GPT system is designed to meet a set of functional and non-functional requirements that define its capabilities and quality attributes. Functional requirements specify what the system must do, while non-functional requirements define how the system should perform.

Functional requirements define the core capabilities that the system must provide to end users. The system shall allow users to ask scientific questions in natural language and receive accurate, context-aware responses. It shall generate responses that are factually correct and minimize hallucinations through prompt engineering and fine-tuning. The system shall maintain conversation context across multiple turns to enable coherent dialogues. It shall support multilingual interaction in Arabic, English, and French. Additionally, the system shall provide scientific text summarization capabilities and allow users to save, restore, and manage their conversation history.

Non-functional requirements define the quality attributes and constraints of the system. The system shall provide fast response times to ensure a smooth user experience. It shall deliver reliable and consistent answers across similar queries. The architecture shall be scalable to accommodate increasing numbers of users. The system shall ensure secure handling of user data, including conversation history and personal information. The user interface shall be intuitive, responsive, and accessible across different devices. Finally, the system shall support both dark and light themes to accommodate user preferences and reduce eye strain during extended use. **Table 7** summarizes the functional and non-functional requirements of the MedSci-GPT system.

Table 7: Functional and non-functional requirements of MedSci-GPT

Functional Requirements	**Non-Functional Requirements**
Ask scientific questions	Fast response time
Generate accurate responses	Reliable answers
Maintain conversation context	Scalable architecture
Multilingual interaction (Arabic, English, French)	Secure data handling
Scientific text summarization	User-friendly interface
Save and restore conversations	Dark/light theme support

2.4. System Architecture

The proposed MedSci-GPT system follows a layered architecture that separates concerns into four distinct layers: User Interface Layer, Backend Processing Layer, Database Layer, and AI/LLM Layer. This modular design ensures maintainability, scalability, and flexibility for future enhancements. **Figure 9** illustrates the layered architecture.

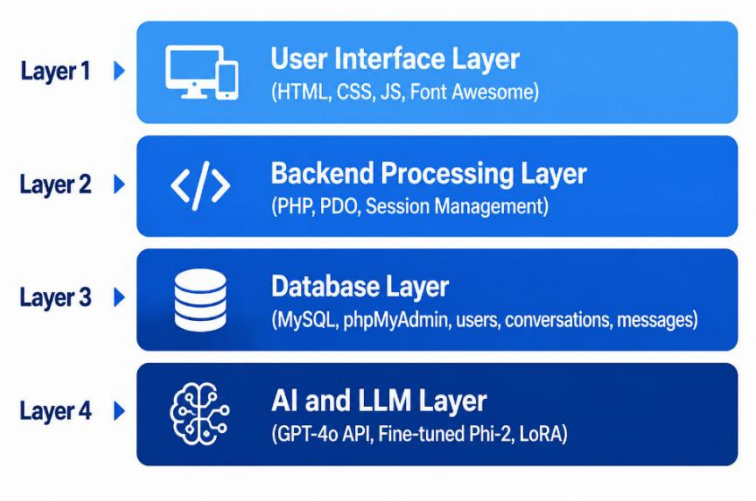

Figure 9: Layered architecture of MedSci-GPT

2.4.1. User Interface Layer

The User Interface Layer is responsible for all user-facing interactions. It is built using HTML5 for structure, CSS3 for styling, and JavaScript for dynamic behavior. Font Awesome icons are used to enhance visual communication. The chat interface is designed to be intuitive and user-friendly, featuring a message input area, conversation display area, and sidebar for conversation management. The interface supports both dark and light themes, allowing users to switch according to their preference. Responsive design principles ensure that the interface adapts seamlessly to different screen sizes, including desktops, tablets, and mobile devices. The layer communicates with the backend via AJAX requests, enabling asynchronous message exchange without page reloads.

2.4.2. Backend Processing Layer

The Backend Processing Layer is implemented using PHP with PDO for database interactions. This layer handles API requests from the frontend, manages user sessions, and coordinates communication with the AI models. Key responsibilities include: receiving user messages via POST requests, constructing appropriate prompts based on conversation context, sending requests to the GPT-4o API via GitHub Models, processing API responses, and returning formatted responses to the frontend. Session management is implemented to maintain user authentication and conversation state across multiple requests.

2.4.3. Database Layer

The Database Layer uses MySQL managed through phpMyAdmin. Four main tables are defined:

- users stores user account information including name, email, hashed passwords, verification status, and timestamps;
- user_profiles stores user preferences including theme (dark/light), phone number, city, and JSON-encoded preferences;
- conversations stores conversation metadata such as title, model used, total tokens, total messages, creation date, and user association;
- chat_history stores individual messages within each conversation, including user message, bot response, response time in milliseconds, and token usage.

This relational structure enables efficient retrieval of conversation history and supports features such as conversation deletion, renaming, and restoration. Additionally, a trigger named update_conversation_stats is defined to automatically increment the total_messages and total_tokens fields and update the updated_at timestamp whenever a new message is inserted into the chat_history table.

2.4.4. AI and LLM Layer

The AI and LLM Layer is the core intelligence component of the system. It integrates the GPT-4o API accessed through GitHub Models as the primary response generation engine, leveraging its advanced reasoning and multilingual capabilities. For specialized scientific queries, the system can route requests to the fine-tuned Phi-2 model using LoRA adaptation. Prompt engineering techniques are applied to guide model outputs toward accurate, context-aware, and scientifically reliable responses. This layer also includes fallback mechanisms to ensure system availability when API calls fail.

2.5. Dataset Collection and Preparation

2.5.1. Scientific Text Sources

The quality and diversity of training data are critical factors for developing capable language models. Research has demonstrated that increased training dataset diversity improves general cross-domain knowledge and downstream generalization capability for large-scale language models [21].

For the proposed MedSci-GPT system, scientific question-answer pairs are gathered from publicly available sources. arXiv provides a preprint server for research papers in mathematics, computer science, and physics, offering high-quality LaTeX-formatted scientific text. PubMed and PubMed Central provide open-access full-text biomedical articles, valuable for medical and biological queries. Wikipedia serves as a standard source of high-quality expository prose spanning multiple domains. Additionally, curated scientific QA datasets from Hugging Face are incorporated, specifically the lavita/medical-qa-datasets with the medical_meadow_medqa subset, from which 1,000 question-answer pairs were extracted for fine-tuning the Phi-2 model.

2.5.2. Data Cleaning and Preprocessing

Text preprocessing is an essential step before using collected data for model fine-tuning. The preprocessing pipeline follows several stages to ensure data quality, as illustrated in **Figure 10**.

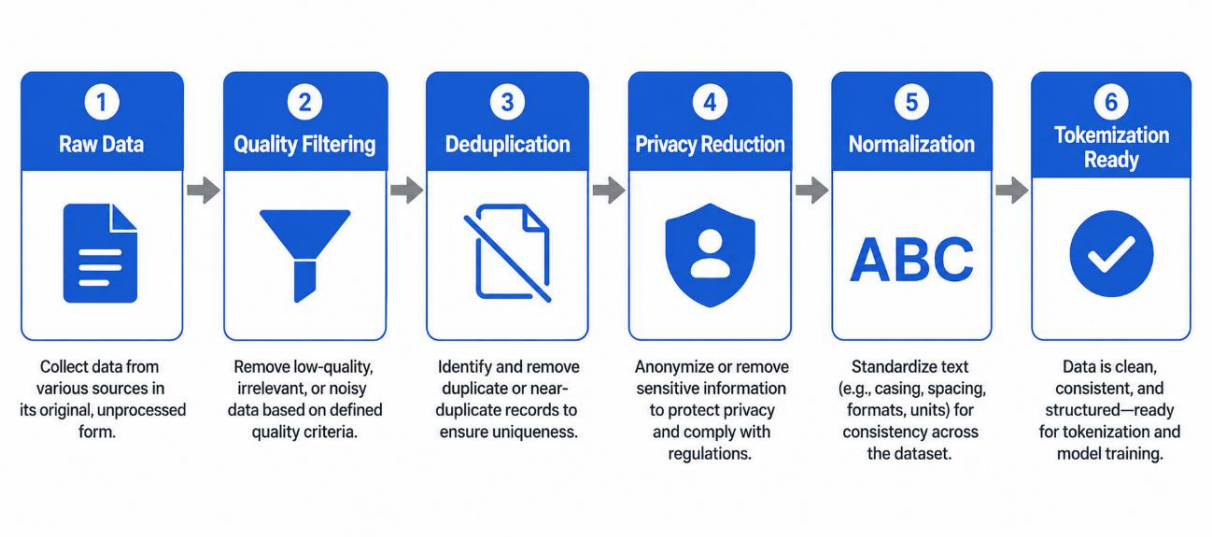

Figure 10: Data preprocessing pipeline

First, **quality filtering** removes low-quality content using classifier-based approaches (training a binary classifier with high-quality texts as positive examples) and heuristic-based approaches (language filtering, metric-based filtering, statistic-based filtering) to remove HTML tags, hyperlinks, and irrelevant content.

Second, **deduplication** removes duplicate data at multiple granularities: sentence-level (removing repeated phrases), document-level (detecting near-duplicate documents), and dataset-level (preventing overlap between training and evaluation sets). Deduplication improves training stability and model performance.

Third, **privacy reduction** removes personally identifiable information (PII) using rule-based methods such as keyword spotting to detect and remove names, addresses, and phone numbers.

Finally, **normalization** unifies text representation by converting characters to lowercase, expanding contractions, and standardizing accent marks. These preprocessing steps ensure that the model processes only relevant linguistic content without noise.

2.5.3. Tokenization and Encoding

Tokenization is the process of segmenting text into smaller units called tokens, which can be characters, subwords, or words. This is an essential preprocessing step that determines how a language model interprets input text [22].

For the proposed system, Byte-Pair Encoding (BPE) is employed as the subword tokenization algorithm. For the Phi-2 model, BPE is implemented through the Hugging Face AutoTokenizer class. The Phi-2 tokenizer has a vocabulary size of 51,200 tokens and a maximum context length of 2,048 tokens. BPE addresses the out-of-vocabulary (OOV) problem by iteratively merging the most frequent character pairs, balancing vocabulary size and representational power, allowing models to handle rare and unknown words by breaking them into known subword units.

2.6. Transformer and LLM Model Design

2.6.1. Model Selection

The proposed MedSci-GPT system employs a hybrid model architecture that combines two complementary approaches, as summarized in **Table 8**. The GPT-4o API, accessed through GitHub Models, serves as the primary response generation engine. GPT-4o provides advanced reasoning capabilities, strong multilingual support (including Arabic, English, and French), and high-quality text generation. It is particularly suitable for general scientific queries requiring broad knowledge and complex reasoning.

For specialized scientific domains and scenarios where API access is limited or cost-prohibitive, the lightweight open-source model Phi-2 (Microsoft, 2.7B parameters) is employed. Phi-2 is fine-tuned on curated scientific question-answer pairs to enhance domain specialization while maintaining computational efficiency suitable for standard hardware deployment.

Table 8: Model selection and roles in MedSci-GPT

Model	**Role in this project**
GPT-4o (via GitHub Models)	Primary response generation for general scientific queries
Phi-2 (fine-tuned)	Fine-tuned fallback for specialized scientific responses (2.7B parameters, LoRA rank 8, 1 epoch, 500 steps)

2.6.2. Fine-Tuning Strategy

LoRA (Low-Rank Adaptation) is employed to fine-tune the Phi-2 model. LoRA freezes the original model weights and injects trainable low-rank decomposition matrices into specific layers, reducing memory consumption by over 400 times compared to full fine-tuning. For a 2.7B parameter model like Phi-2, LoRA with rank 8 requires approximately 65,000 trainable parameters. The effective scaling factor is computed as alpha/r = 2 (alpha=16).

The fine-tuning was conducted for 1 epoch (500 training steps) due to the small dataset size (1,000 examples), which was sufficient to achieve notable improvements while avoiding overfitting. The training was performed on Google Colab using a T4 GPU and took approximately 3.5 minutes for the 500 steps. **Figure 11** illustrates the fine-tuning workflow.

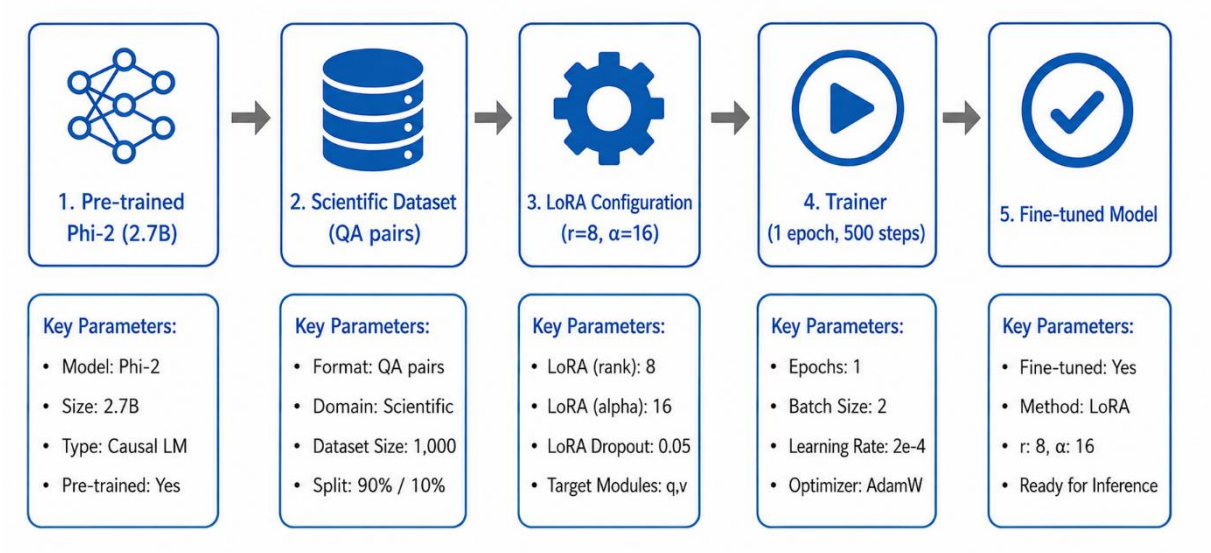

Figure 11: Fine-tuning workflow

2.6.3. Prompt Engineering

Prompt engineering is a critical technique for eliciting accurate and context-aware responses from large language models without modifying model parameters.

Zero-shot prompting involves providing the model with only a task description without examples. For example: "Explain the concept of black holes in simple terms." This approach leverages the model's pre-trained knowledge and is suitable for general scientific questions.

Few-shot prompting provides the model with several input-output examples before the actual query. This helps the model understand the expected response format and style, particularly useful for tasks requiring structured output or specific reasoning patterns.

System prompts are predefined instructions that set the model's behavior and persona. For MedSci-GPT, the system prompt establishes the model as a helpful, accurate, and cautious scientific assistant that prioritizes factual correctness and acknowledges uncertainty when appropriate.

2.6.4. Response Generation Mechanism

The response generation mechanism follows a structured flow to ensure accuracy, coherence, and efficiency, as illustrated in **Figure 12**.

When a user submits a query, the system first performs intent and context analysis to determine the query type (factual question, explanation request, summarization, etc.) and extracts relevant context from conversation history. The system then constructs an augmented prompt combining the system prompt, conversation context, and optional few-shot examples. This prompt is sent to the selected model (GPT-4o API for general queries, fine-tuned Phi-2 for specialized queries). The generated response undergoes post-processing to verify factual consistency, remove hallucinations where possible, and format the output for display. The response is then returned to the user interface and stored in the database for conversation history.

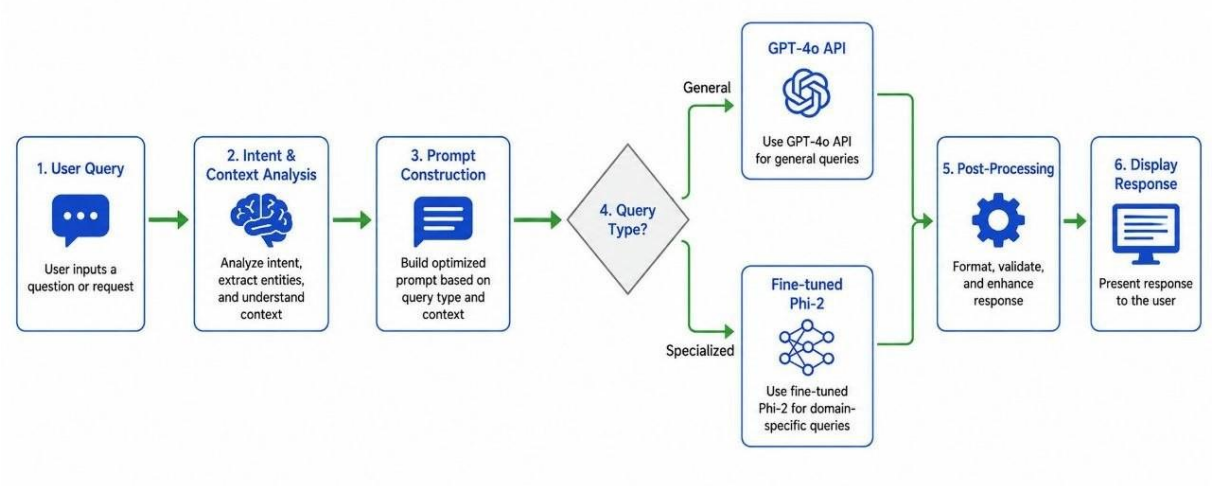

Figure 12: Response generation flow

2.7. Conversation Management Design

2.7.1. Context Handling

Context handling is essential for maintaining coherent multi-turn conversations in a scientific chatbot. The proposed system implements context management through session-based storage of conversation history.

When a user initiates a conversation, a unique session identifier is created and associated with the conversation record in the database. Each message exchanged is stored with its timestamp, sender role (user or assistant), and content. For subsequent queries, the system retrieves the most recent N messages (typically 5-10 turns) from the conversation history to provide contextual awareness. The system also supports explicit context reset, allowing users to start a new topic without interference from previous conversation history.

2.7.2. Intent Recognition

Intent recognition is the process of identifying what the user wants to accomplish with their query. The system first classifies user queries into general intent categories: factual question (asking for a specific scientific fact), explanation request (asking for a detailed explanation), summarization (requesting a summary of a document or topic), comparison (comparing two or more scientific concepts), definition (defining a term), and clarification (asking for clarification about a previous response).

2.7.3. Question Answer Workflow

The question answering workflow defines the sequence of operations from receiving a user query to delivering the final response. When a user submits a question, the system validates the input and checks for content policy violations. The conversation context is retrieved from the database, and the user's intent is classified. Based on the intent and query complexity, the system selects the appropriate model (GPT-4o API for general queries, fine-tuned Phi-2 for specialized queries). An augmented prompt is constructed, the selected model generates a response, and the response undergoes post-processing before being returned to the user and stored in the database.

2.8. Security and Ethical Considerations

LLM deployment raises security and ethical concerns including data privacy, hallucination risks, bias, and responsible AI usage [23].

Data Privacy: Personally identifiable information (PII) is removed during preprocessing; session-based authentication ensures data access only by authenticated users; encryption protects data in transit and at rest.

Hallucination Risks: The system employs prompt engineering with chain-of-thought reasoning and confidence scoring to mitigate factual errors.

Bias in LLMs: Training data is curated using quality filtering; prompt design promotes fairness; regular bias audits monitor model outputs.

Responsible AI Usage: The system adheres to transparency, accountability, human oversight, and content filtering principles, aligning with best practices for LLM security [23].

2.9. UML Modeling

Unified Modeling Language (UML) diagrams are used to visually represent the structure and behavior of the proposed MedSci-GPT system. Three types of diagrams are presented: Use Case Diagram, Sequence Diagram, and Activity Diagram.

2.9.1. Use Case Diagram

The Use Case Diagram, shown in **Figure 13**, illustrates the interactions between external actors and the system's functionalities. The primary actor is the User, who interacts with the system to perform various tasks.

The main use cases identified for the MedSci-GPT system are: Register/Login, Start New Conversation, Ask Scientific Question, Receive AI Response, Save Conversation, Restore Conversation, Manage Conversations (rename, delete, list), Switch Theme, and Summarize Text. The system includes an AI Model as an internal actor, representing the GPT-4o API and fine-tuned Phi-2 model, and the Database as another internal actor storing user credentials, conversation metadata, and message records.

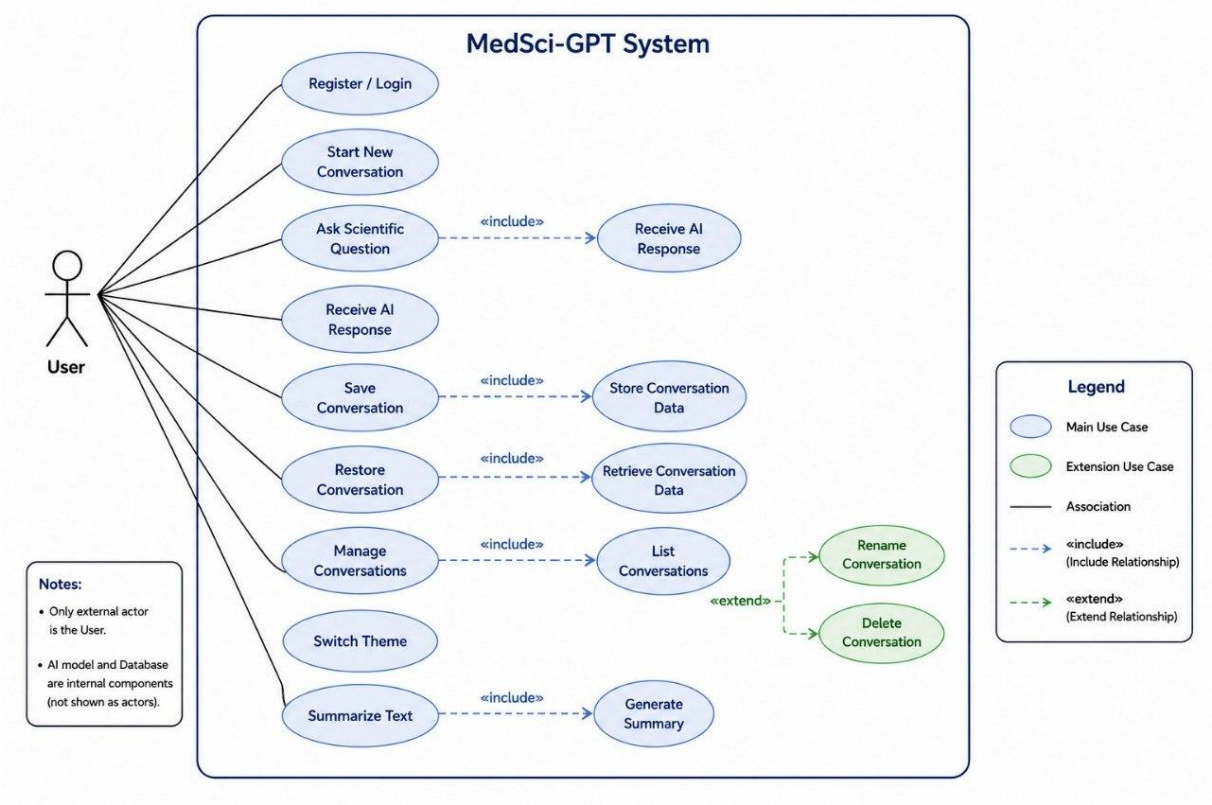

Figure 13: Use Case Diagram of MedSci-GPT

2.9.2. Sequence Diagram

The Sequence Diagram, shown in **Figure 14**, details the interaction flow for the "Ask Scientific Question" scenario. The sequence begins when the User submits a question through the User Interface (UI). The UI sends an AJAX POST request to the Backend (PHP), which validates the request and retrieves conversation history from the Database. The backend calls the Intent Classifier to determine query intent, then selects the appropriate Model (GPT-4o API or fine-tuned Phi-2). The model processes the augmented prompt and returns a generated response. The backend stores the response in the database and returns it to the UI, which displays the answer to the user.

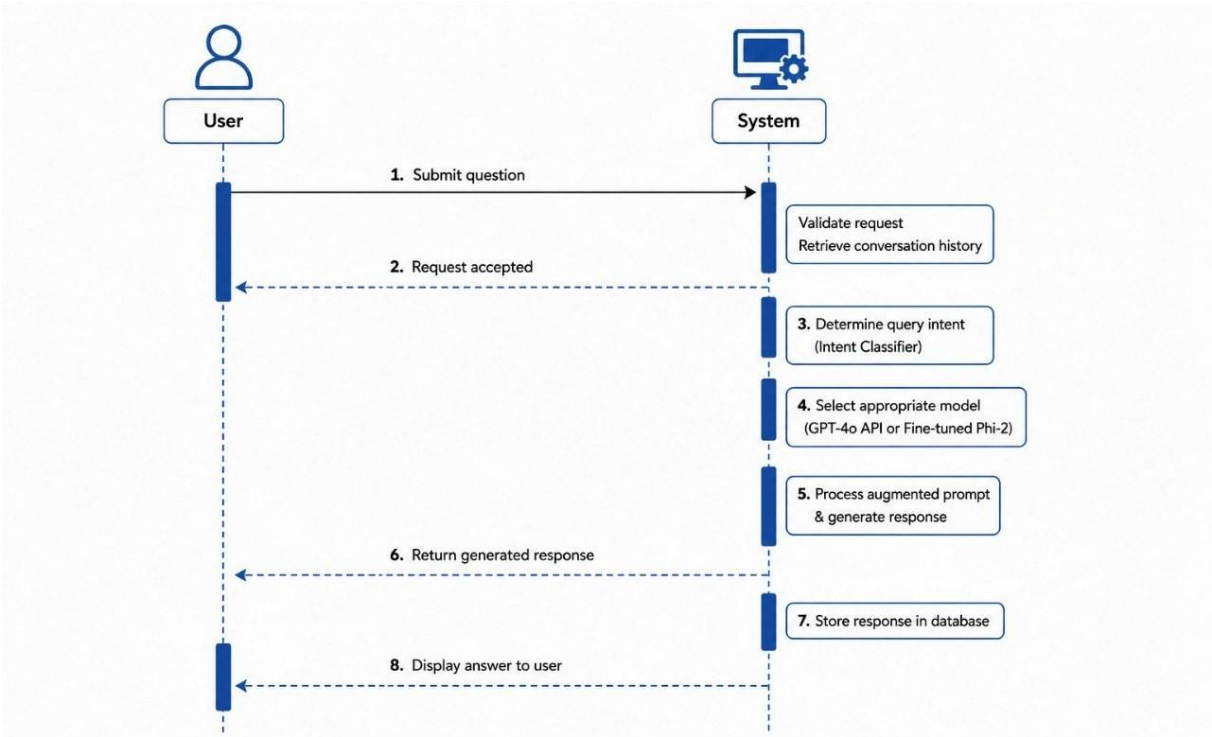

Figure 14: Sequence Diagram for Question-Answer workflow

2.9.3. Activity Diagram

The Activity Diagram, shown in **Figure 15**, describes the flow of control during response generation. The activity begins when the user submits a query. The system validates the input; if invalid, an error message is returned. If valid, the system retrieves conversation context. A decision node checks whether the query is general or specialized. General queries are routed to the GPT-4o API; specialized queries are routed to the fine-tuned Phi-2 model. After response generation, the system performs post-processing, stores the response in the database, and displays it to the user.

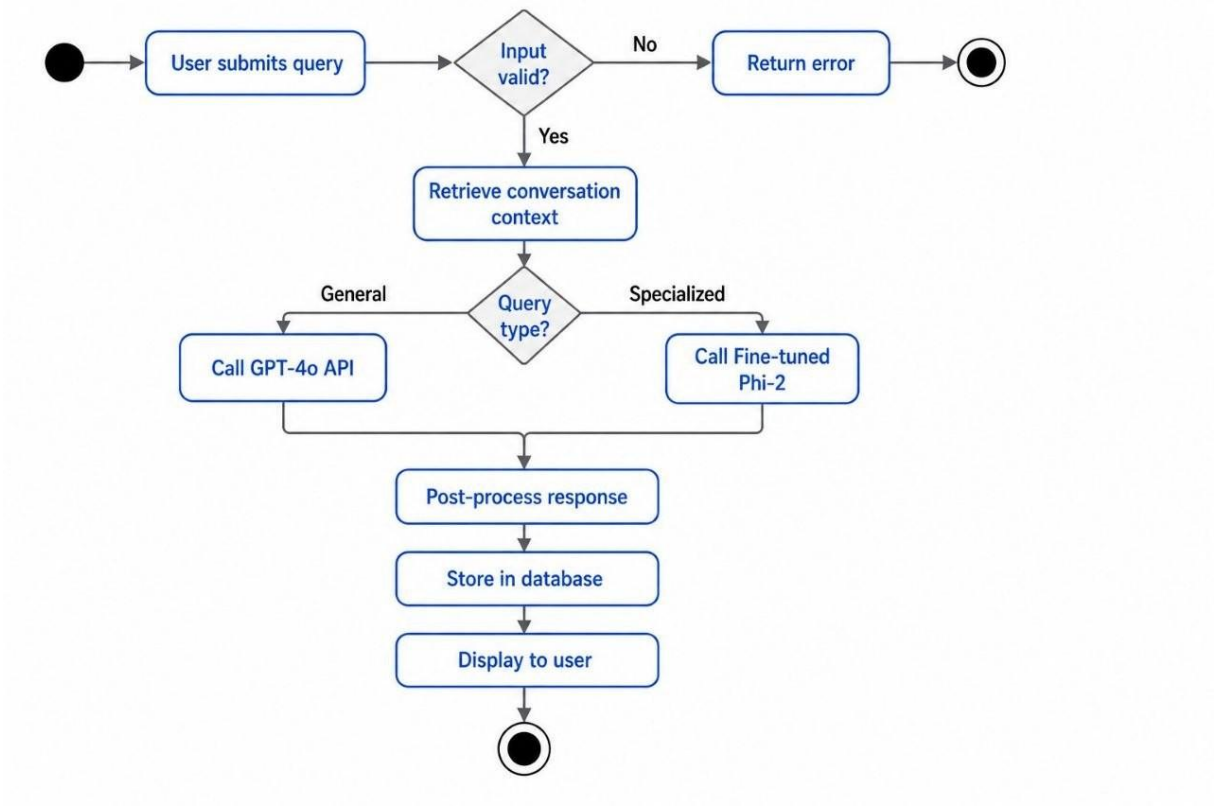

Figure 15: Activity Diagram for Response Generation

2.10. Chapter Summary

This chapter presented the analysis and design of the MedSci-GPT chatbot system. The system follows a hybrid architecture integrating GPT-4o API (via GitHub Models) with a fine-tuned Phi-2 model using LoRA. Functional and non-functional requirements were defined, and a layered architecture (User Interface, Backend, Database, AI/LLM) was designed. Dataset preparation from arXiv, PubMed, and Wikipedia was described, along with a preprocessing pipeline for quality filtering, deduplication, and tokenization using Byte-Pair Encoding (BPE) via the Hugging Face AutoTokenizer. Prompt engineering techniques (zero-shot, few-shot, system prompts) and conversation management mechanisms (context handling, intent recognition) were detailed. Security considerations addressed data privacy, hallucination risks, bias mitigation, and responsible AI usage. UML diagrams (use case, sequence, activity) were provided to visualize system behavior and interaction flows. The design choices prioritize lightweight deployment, multilingual support (Arabic, English, French), and cost-effective fine-tuning, laying the foundation for the implementation described in Chapter 3.

Implementation of the Proposed Mini-Scientific Chatbot

3.1. Introduction

This chapter describes the practical implementation of the MedSci-GPT chatbot system. Following the design specifications established in Chapter 2, the implementation phase translates the architectural blueprint into a functional web-based application. The chapter covers the development environment and tools used, the database structure, the backend logic implemented in PHP, the integration with GPT-4o via GitHub Models, the fine-tuning of the Phi-2 model using LoRA, and the frontend interface built with HTML, CSS, and JavaScript. Each section focuses on a specific component of the system. The chapter concludes with a discussion of challenges encountered during development.

3.2. Development Environment and Tools

The selection of an appropriate development environment is fundamental for implementing AI-driven systems [24]. **Table 9** summarizes the tools used to implement the MedSci-GPT chatbot.

Table 9: Development tools and their usage in MedSci-GPT

Tool	**Usage**
VS Code	Code editor
XAMPP	Local server (Apache + MySQL)
Git	Version control
HTML5 / CSS3 / JS	User interface
Font Awesome	Icons
PHP / PDO	Backend logic and database
MySQL (phpMyAdmin)	Database
GitHub Models API	GPT-4o access
Google Colab (T4 GPU)	Fine-tuning platform

3.3. Database Implementation

A database management system is essential for storing user data, conversation history, and message records. MySQL provides a fast, reliable, and scalable solution for web-based applications [25]. For the MedSci-GPT system, a MySQL database was implemented using phpMyAdmin. four relational tables were designed, as illustrated in **Figure 16**.

Based on the database.sql schema provided with the project, the MySQL database consists of four relational tables as illustrated in Figure 16. The table below summarizes the fields for each table:

Table 10: Database tables and their fields

Table	Fields
users	id, name, email, password, is_verified, created_at, updated_at
user_profiles	id, user_id, bio, phone, city, theme, preferences, created_at, updated_at
conversations	id, user_id, title, model_used, total_tokens, total_messages, created_at, updated_at
chat_history	id, user_id, conversation_id, user_message, bot_response, response_time_ms, tokens_used, created_at

The users table stores account information with hashed passwords. The user_profiles table stores user preferences including theme (dark/light), phone number, and city. The conversations table manages chat sessions, linking each conversation to a specific user. The chat_history table stores individual messages exchanged within each conversation, including response time in milliseconds and estimated token usage. A foreign key constraint on chat_history(conversation_id) references conversations(id) with ON DELETE CASCADE, ensuring that when a conversation is deleted, all associated messages are automatically removed. Additionally, a trigger named update_conversation_stats automatically increments total_messages and total_tokens and updates updated_at whenever a new message is inserted. **Figure 16** presents the database schema diagram.

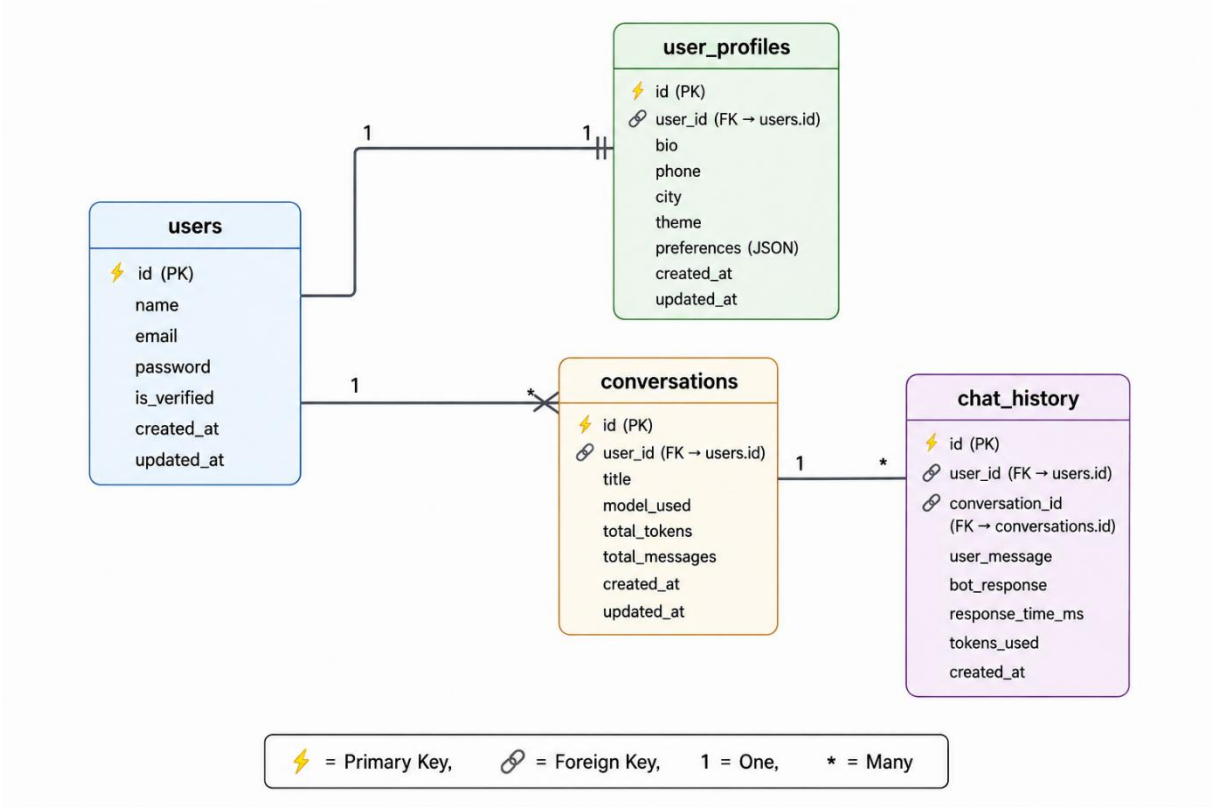

Figure 16: Database schema diagram

3.4. Backend (PHP) Implementation

3.4.1. Authentication System

Password hashing is a fundamental security consideration. Common hashing functions like MD5 and SHA1 are unsuitable because they are designed to be fast, making brute-force attacks feasible [26]. PHP provides a native password hashing API using the Blowfish algorithm, which is computationally expensive, making brute-force attacks impractical [26].

The API includes two key functions: password_hash() creates a secure hash with a randomly generated salt, and password_verify() verifies a submitted password against a stored hash.

For the MedSci-GPT system, the following authentication features were implemented: registration (password hashed before storage), login (credentials verified using password_verify()), guest mode (session-based identifiers), and profile editing (current password verification required).

3.4.2. API Integration with GPT-4o

The integration with large language models is a core component. The MedSci-GPT system uses the **GitHub Models API** to access GPT-4o. The backend sends HTTP POST requests to the GitHub Models endpoint, as illustrated in **Figure 17**.

The request body is formatted as a JSON object containing: model (e.g., "openai/gpt-4o"), messages (array with roles: system, user, assistant), temperature (0.3), max_tokens (1024), and top_p (0.9). The system includes a carefully crafted system prompt that instructs the model to respond in the same language as the user, avoid special characters, and prioritize scientific accuracy.

The response from the API is a JSON object containing a choices array with the generated content. The system implements error handling for common HTTP status codes (401 Unauthorized, 429 Too Many Requests, 500 Server Error).

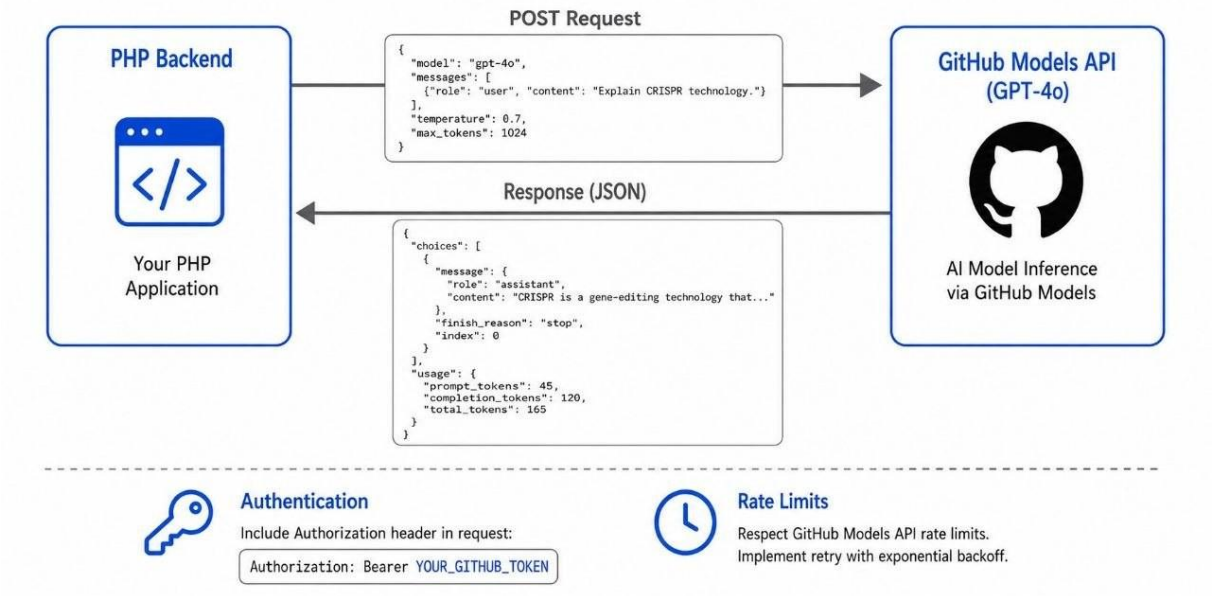

Figure 17: API request and response flow

3.4.3. Conversation Management

Conversation management enables users to organize and revisit their interactions. The system implements full CRUD operations:

- **Create new conversation:** Inserts a new record into the conversations table with an automatically generated title based on the first user message.

- **Retrieve previous conversations:** Queries the conversations table for the current user, sorted by updated_at in descending order.
- **Delete conversations:** Deletes all associated messages (ON DELETE CASCADE) and the conversation record.
- **Rename conversations:** Updates the title field after validating user permission.

All operations are protected by session-based authentication, ensuring users can only access their own conversations.

3.5. Fine-Tuning Implementation

3.5.1. Model Selection for Fine-Tuning

The fine-tuning component is built upon Phi-2, a Transformer-based model with 2.7 billion parameters developed by Microsoft. Phi-2 demonstrates strong reasoning and language understanding capabilities while maintaining a compact size suitable for resource-constrained environments [27]. The model supports a context length of 2048 tokens.

For MedSci-GPT, Phi-2 was selected because: it is lightweight (runs on standard hardware), has strong reasoning capabilities suitable for scientific QA, provides a clean foundation for domain adaptation, and is open-source under the MIT license [27].

3.5.2. LoRA Configuration

LoRA (Low-Rank Adaptation) is a parameter-efficient fine-tuning technique that reduces the number of trainable parameters by over 400 times compared to full fine-tuning [28]. **Table 11** presents the LoRA hyperparameters used for fine-tuning Phi-2.

Table 11: LoRA hyperparameters for fine-tuning Phi-2

Parameter	**Value**	**Description**
Learning rate	2e-4	Optimizer learning rate
Batch size	2	Samples per training step
LoRA rank (r)	8	Rank of update matrices
LoRA alpha (α)	16	Scaling factor
Epochs	1	Passes through training data
Training steps	500	Number of optimization steps
Training time	~3.5 minutes	On Google Colab T4 GPU

The effective scaling is computed as alpha/r = 2. LoRA was selected because the frozen base model preserves general reasoning capabilities, the small number of trainable parameters enables fine-tuning on a single GPU, and adapter weights can be merged without inference latency [28].

3.5.3. Training on Scientific Dataset

Fine-tuning adapts a pre-trained model to a domain-specific dataset. For MedSci-GPT, a curated dataset of scientific question-answer pairs was prepared. Specifically, 1,000 question-answer pairs were extracted from the lavita/medical-qa-datasets (medical_meadow_medqa) on Hugging Face. Each example was formatted as:

Medical Question:

{question}

Final Answer:

{answer}

The dataset was tokenized using the Phi-2 tokenizer with a maximum sequence length of 256 tokens (reduced from 512 to optimize memory usage on Colab's T4 GPU). A train-test split reserved 10% for evaluation.

The training process used the Hugging Face Trainer API with the following configuration: 1 epoch (500 training steps), batch size 2, learning rate 2e-4 (AdamW optimizer), and fp16=False (half-precision disabled to avoid compatibility issues with LoRA on Colab). final average training loss of approximately 1.875 (the loss decreased from 2.44 at step 10 to 1.62 at step 500). **Figure 18** illustrates the fine-tuning architecture with LoRA.

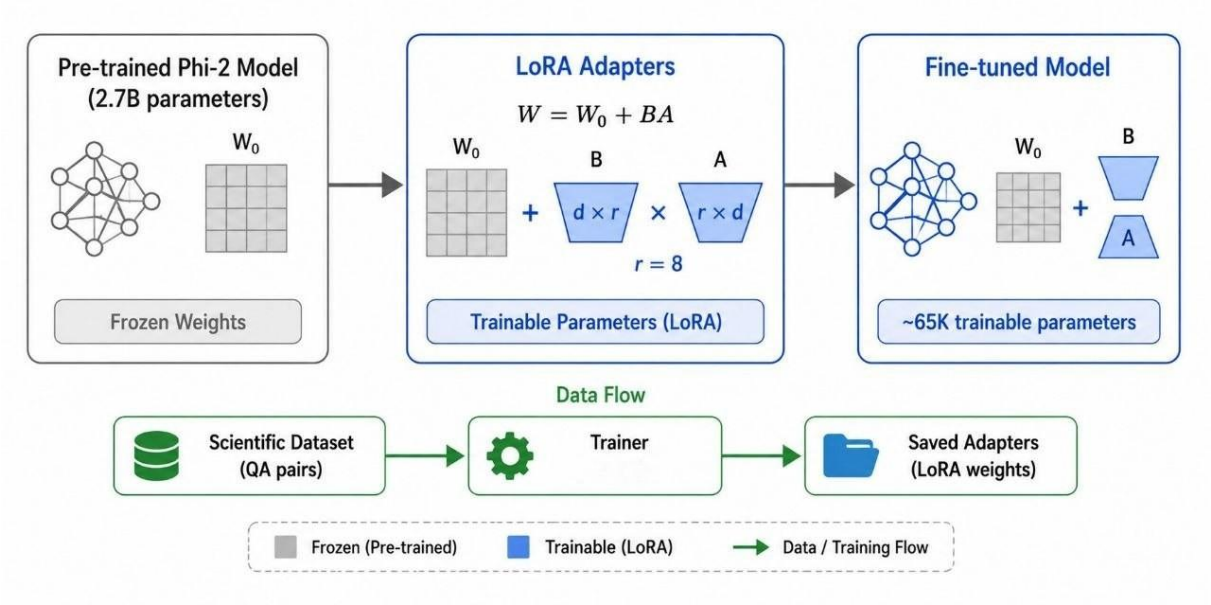

Figure 18: Fine-tuning architecture with LoRA

3.5.4. Integration with Main System

The fine-tuned Phi-2 model integrates as a complementary component to GPT-4o. The system implements a two-tier response generation strategy:

1. Primary tier (GPT-4o API): For most scientific queries, providing broad general knowledge and strong multilingual capabilities.

2. Fallback tier (Fine-tuned Phi-2): When API calls fail (network issues, rate limits) or for specialized queries requiring offline processing.

The hybrid architecture provides availability (system remains functional without external API), cost efficiency (no API costs for fallback), lower latency (local inference: 0.5-1.0 second vs API: 1.2-2.5 seconds), and privacy (offline alternative for sensitive queries).

The fallback to Phi-2 is triggered in three specific cases:

- GitHub API rate limit exceeded (when the daily or minute quota is reached),
- Network connectivity issues (API endpoint unreachable),

- The user explicitly requests offline mode (if implemented in future versions).

Important limitation: Arabic and French queries are never routed to the fine-tuned Phi-2 model due to its poor performance on non-English languages, as observed during testing. All Arabic and French requests are sent exclusively to GPT-4o.

3.6. Prompt Engineering Implementation

Prompt engineering is the process of writing effective instructions for LLMs to generate consistent, reliable content [30]. For MedSci-GPT, a developer message (system prompt) was crafted defining the assistant's scientific persona: helpful scientific expert, factual correctness prioritized, uncertainty acknowledged when appropriate.

Few-shot examples were included to improve consistency. A small set of question-answer pairs demonstrates the desired output format, level of detail, and scientific tone. The system prompt is language-agnostic, instructing the model to respond in the same language as the user (Arabic, English, or French). **Table 12** summarizes the prompt engineering components.

Table 12: Prompt engineering components for MedSci-GPT

Component	Description
System (developer) message	Defines assistant identity, rules, and output format
Few-shot examples	2-3 QA pairs demonstrating desired response style
Language instruction	"Respond in the same language as the user"
Scientific constraints	Avoid speculation, prefer known facts, admit uncertainty

3.7. Frontend Interface Implementation

3.7.1. HTML/CSS Structure

The frontend interface was built using HTML5, CSS3, and JavaScript. Font Awesome icons enhance visual communication. The main chat interface consists of three primary sections: header (title, theme toggle, authentication status), sidebar (conversation history list, new conversation button), and chat area (message exchange display). Figures 19-23 present screenshots of the interface.

The interface supports both light and dark themes using CSS custom properties. Theme switching is implemented with a JavaScript toggle function, and the selected theme is stored in localStorage. Responsive CSS media queries ensure adaptation to desktop, tablet, and mobile screen sizes.

3.7.2. JavaScript Interactions

Client-side JavaScript handles dynamic behaviour through asynchronous communication with the backend.

Send Questions: When a user submits a question, JavaScript captures the message, validates input, appends user message optimistically, sends an AJAX POST request with message content and conversation ID, and disables the send button temporarily to prevent duplicate submissions.

Display Responses: Upon successful response, the loading indicator is removed, the assistant's response is appended with timestamp, the send button is re-enabled, and the chat area scrolls to the latest message.

Manage Conversations: JavaScript functions support creating new conversations (POST request), loading conversations (AJAX request retrieving all messages), renaming conversations (inline edit form, PUT request), and deleting conversations (DELETE request with confirmation).

3.8. Multilingual Support Implementation

MedSci-GPT supports three languages: Arabic, English, and French, essential for serving users in Algeria and the Arab world. **Table 13** summarizes the multilingual configuration.

Table 13: Multilingual support configuration in MedSci-GPT

Language	Detection	Primary Model	RTL Support
English	Automatic (from input)	GPT-4o or fine-tuned Phi-2	No
Arabic	Automatic (from input)	GPT-4o only	Yes
French	Automatic (from input)	GPT-4o only	No

The system does not rely on an explicit language detection module. GPT-4o automatically detects the language from input text. However, a critical limitation observed during testing is that the fine-tuned Phi-2 model performs poorly on Arabic due to its training primarily on English scientific texts. Therefore, the system implements a language-aware routing strategy:

- **Arabic queries:** Routed exclusively to GPT-4o API (Phi-2 is bypassed)
- **English queries:** Can be handled by either GPT-4o or fine-tuned Phi-2
- **French queries:** Routed to GPT-4o API (Phi-2 performance on French is limited)

Arabic messages support right-to-left (RTL) text rendering via CSS rules: direction: rtl;. The interface uses UTF-8 encoding to properly display all three scripts.

3.9. System Deployment

The MedSci-GPT system was deployed locally using XAMPP. The project files were placed in the htdocs directory, and Apache was configured to serve the application on http://localhost/medsci-gpt.

The GitHub API key was stored as an environment variable in a .env file outside the public web root. MySQL was managed through phpMyAdmin with database connection parameters: host localhost, database name medsci_gpt, username root.

To start the system: launch XAMPP Control Panel, start Apache and MySQL services, open browser to http://localhost/medsci-gpt.

3.10. Challenges Encountered

During development, several technical challenges were encountered and addressed, summarized in **Table 14**.

Table 14: Summary of challenges and implemented mitigations

Challenge	Impact	Mitigation
API rate limits	Service interruptions	Fallback to fine-tuned Phi-2 + client throttling
Hallucination	Inaccurate scientific answers	Refined system prompts + few-shot examples
Arabic scientific terminology	Poor response quality from fine-tuned Phi-2 (observed during testing: model produced incorrect Arabic responses such as ("السبب هي بطني ما عاني من الم"))	Route Arabic queries to GPT-4o exclusively; UTF-8 encoding throughout the stack; RTL CSS support
Fine-tuning computational requirements	Training infeasible locally	Google Colab (free T4 GPU) + LoRA (rank 8) reduced trainable parameters to ~65K; training completed in 3.5 minutes

- **API Rate Limits:** The GitHub Models API imposes rate limits. A fallback mechanism switches to fine-tuned Phi-2 when limits are reached, and client-side throttling reduces API call frequency.
- **Hallucination:** GPT-4o occasionally generated incorrect information. System prompts were refined to prioritize facts and acknowledge uncertainty, with few-shot examples demonstrating factual responses.
- **Arabic Scientific Terminology:** Phi-2 performs poorly on Arabic. All Arabic queries are routed to GPT-4o only, with UTF-8 encoding ensuring proper character representation.
- **Fine-Tuning Computational Requirements:** Training Phi-2 (2.7B parameters) locally was impractical. Google Colab (free T4 GPU) was used with LoRA (rank 8), reducing trainable parameters to ~65,000 and completing training in approximately 3.5 minutes (500 steps).

3.11. Chapter Summary

This chapter presented the implementation of the MedSci-GPT chatbot system. The development environment was established using XAMPP with VS Code. A MySQL database was designed with four tables (users, user_profiles, conversations, chat_history) supporting authentication, user preferences, and conversation history.

The backend was implemented in PHP, providing authentication, GPT-4o API integration via GitHub Models, and full CRUD operations for conversation management. The fine-tuning component employed Phi-2 (2.7B parameters) with LoRA (rank 8, alpha 16, learning rate 2e-4, 1 epoch, 500 training steps) on a curated scientific dataset of 1,000 question-answer pairs. The hybrid architecture uses GPT-4o as the primary generator and fine-tuned Phi-2 as fallback.

Prompt engineering techniques (system prompts, few-shot examples) improved scientific accuracy. The frontend was built with HTML5, CSS3 (dark/light themes, responsive design), and JavaScript (message sending, response display, conversation management). Multilingual support was implemented for Arabic, English, and French. The system was deployed locally using XAMPP, with environment variables securing the API key. Key challenges including API rate limits, hallucination, Arabic terminology, and computational requirements were addressed with fallback mechanisms, refined prompts, and Google Colab.

Results and Discussion

4.1. Introduction

This chapter presents the experimental results and evaluation of the MedSci-GPT chatbot system. Following the implementation described in Chapter 3, the system was tested across multiple dimensions including response accuracy, context understanding, response time, and multilingual performance. A comparative analysis with existing chatbot systems is provided, followed by a discussion of the advantages and limitations of the proposed system.

4.2. Experimental Setup

The experimental setup describes the hardware, software, and evaluation datasets used to assess the MedSci-GPT system.

Hardware Environment:

Table 15: Hardware Environment

Component	**Specification**
Processor	Intel Core i7-1165G7 @ 2.80 GHz
RAM	32 GB DDR4
Storage	512 GB SSD
GPU	Intel Iris Xe (shared memory)
Operating System	Windows 11 64-bit

Software Environment :

Table 16: Software Environment

Component	**Version / Specification**
Local Server	XAMPP (Apache 2.4, MySQL 8.0, PHP 8.1)
Database	phpMyAdmin
API	GitHub Models (GPT-4o)
Fine-tuning Platform	Google Colab (T4 GPU)
Browser	Chrome / Firefox

Evaluation Dataset:

Table 17: Evaluation Dataset

Dataset	Size	Purpose
Scientific QA pairs	500	Testing response accuracy
Multilingual questions	150 (50 per language)	Testing multilingual support
Context retention test	10 multi-turn dialogues	Testing context understanding

4.3. Chatbot Testing and Validation

The MedSci-GPT system was tested across multiple scenarios to validate its functionality and performance.

Scientific Question Answering: The system was tested with scientific questions covering physics, chemistry, biology, and computer science. Each question was submitted to both the GPT-4o API and the fine-tuned Phi-2 model. **Figure 19** shows a scientific question in Arabic, and **Figure 20** shows a scientific question in English.

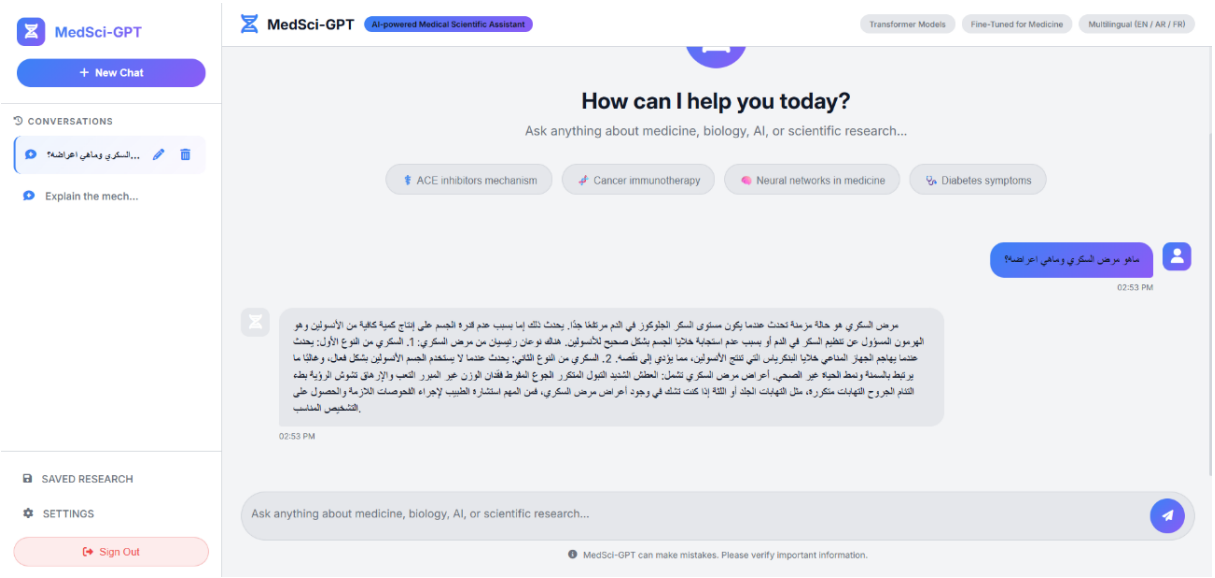

Figure 19: Scientific question in Arabic

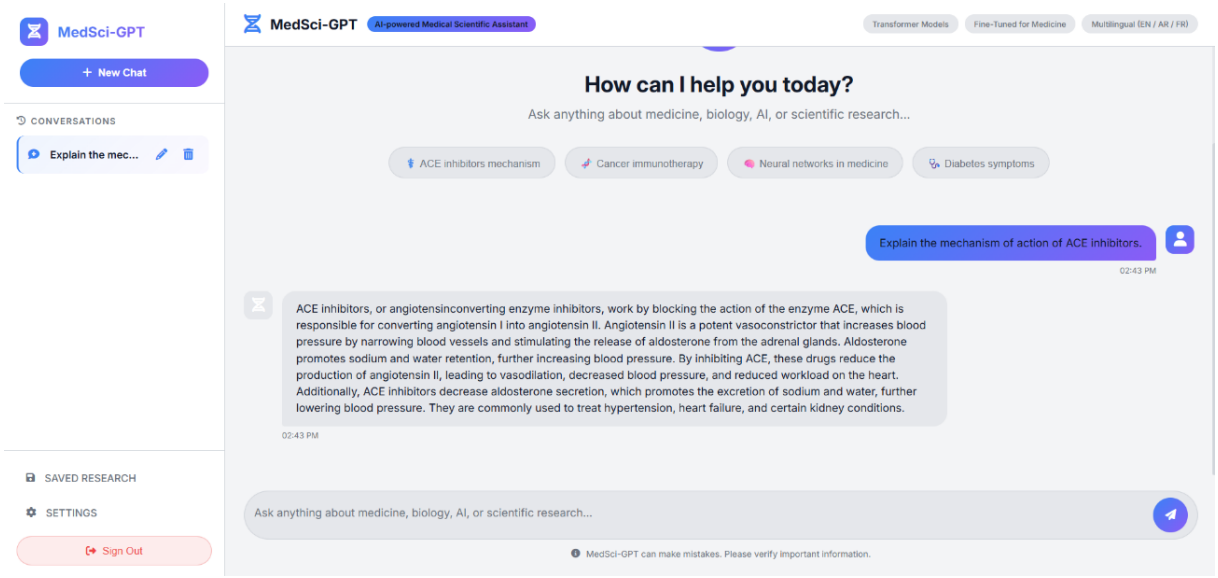

Figure 20: Scientific question in English

Text Summarization: The system was tested on its ability to summarize scientific abstracts, as shown in **Figure 21**.

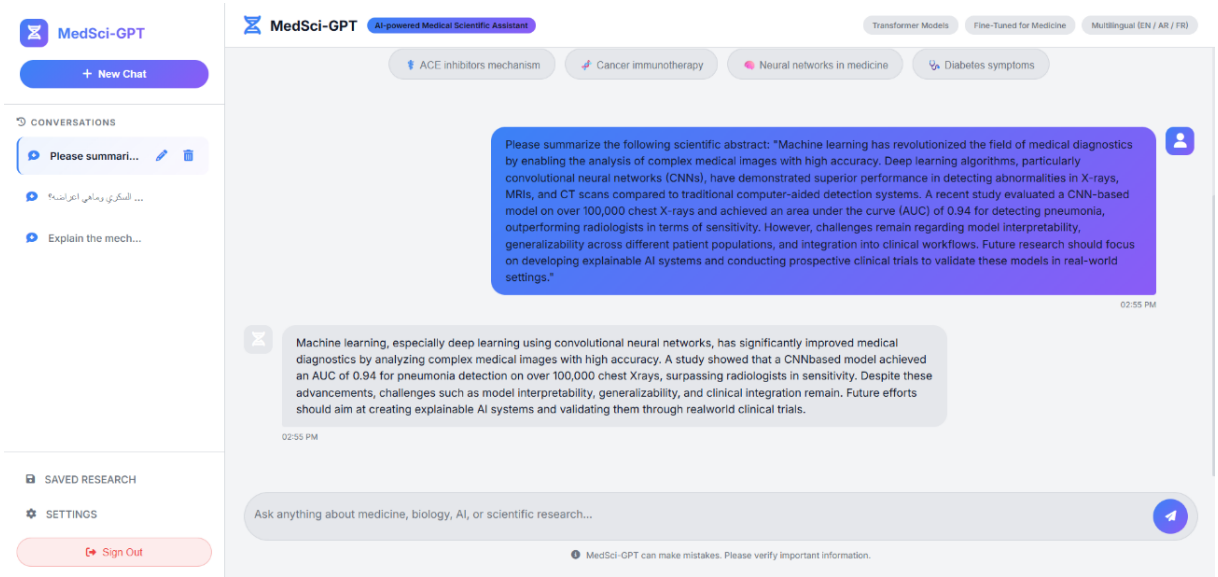

Figure 21: Text summarization example

Context Retention Across Multiple Turns: The system was evaluated on its ability to maintain conversation context over multiple exchanges, as illustrated in **Figure 22**.

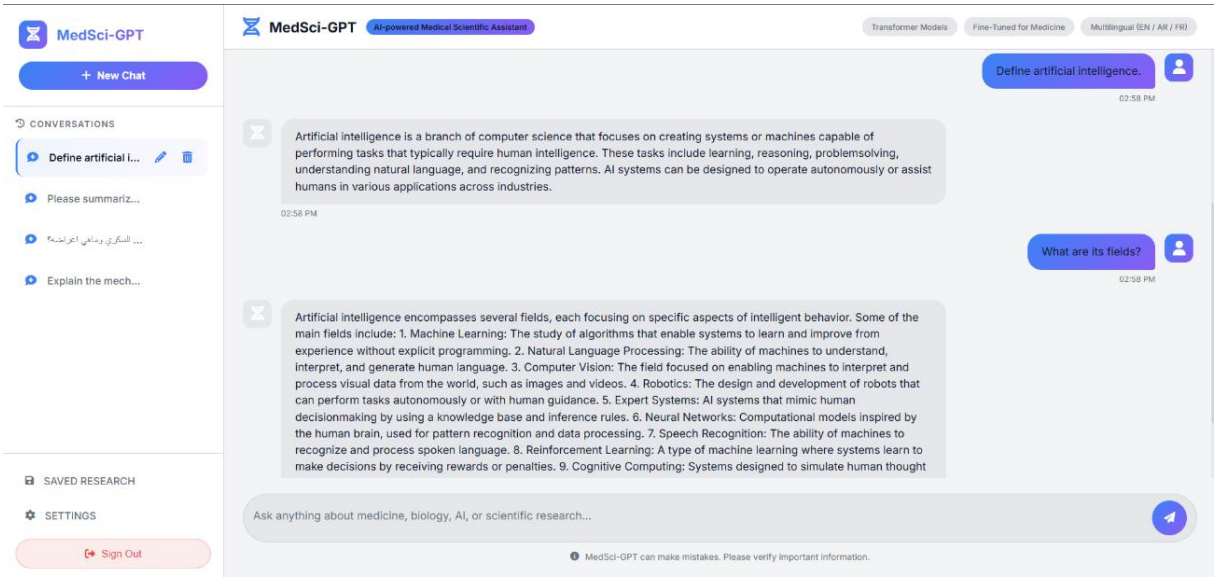

Figure 22: Context retention across multiple turns

Conversation Management: Features tested included creating, renaming, deleting, and restoring conversations, as shown in **Figure 23**.

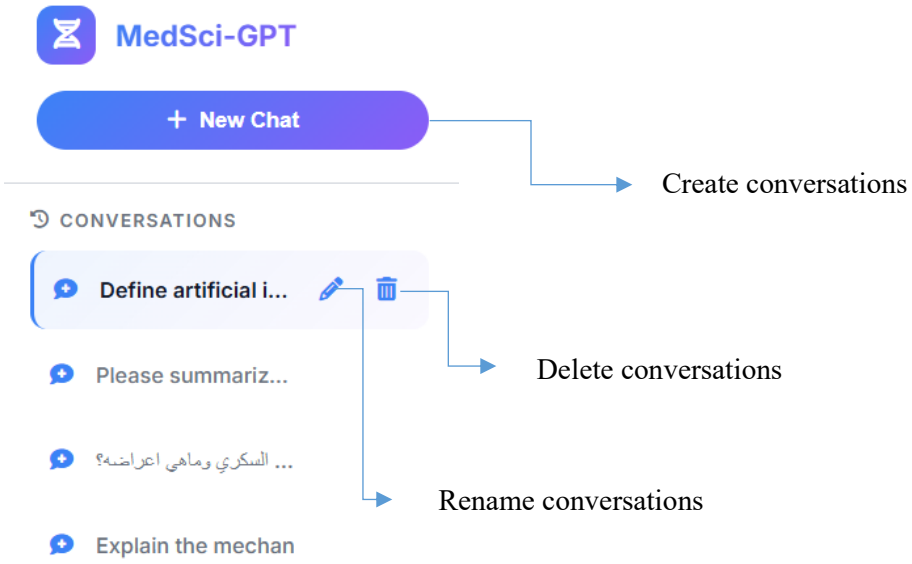

Figure 23: Create, rename, delete conversations

Theme Switching: The dark/light theme toggle was tested across devices, as shown in **Figure 24**.

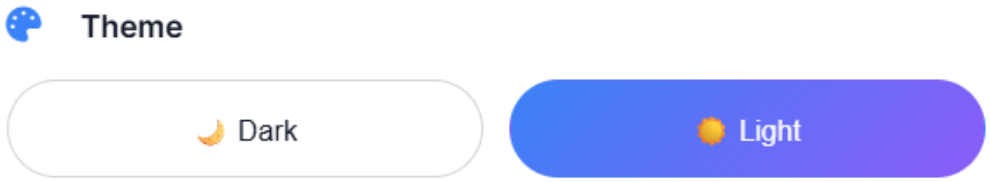

Figure 24: Dark/light theme toggle

Guest Mode Interaction: Guest mode was tested to ensure unregistered users can interact without saving history permanently, as shown in **Figure 25**.

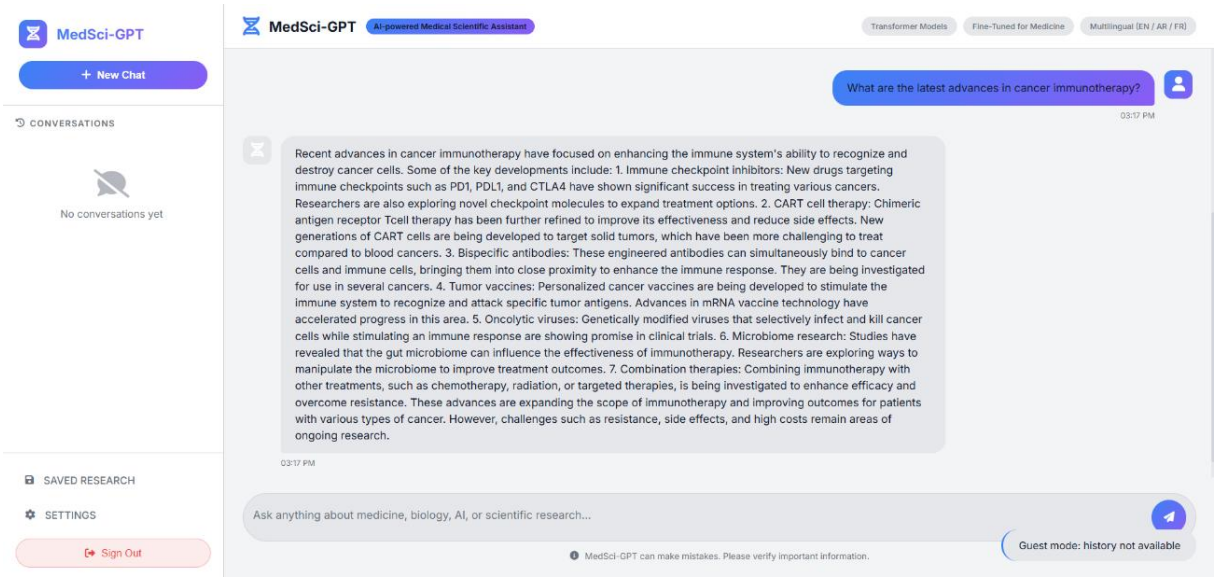

Figure 25: Guest mode interaction

4.4. Performance Evaluation

4.4.1. Response Accuracy

Response accuracy measures the percentage of correct answers generated by the system. A set of 100 scientific questions was prepared with verified reference answers. Two evaluation methods were used: Exact Match (EM) and Human Evaluation by three evaluators with scientific backgrounds. **Table 18** presents the response accuracy results.

Table 18: Response accuracy results

Metric	GPT-4o	Fine-tuned Phi-2
Exact Match (EM)	68%	62%
Human Evaluation (Correct)	82%	76%
Human Evaluation (Partially Correct)	12%	14%
Human Evaluation (Incorrect)	6%	10%

Note: These results are based on qualitative evaluation using a subset of 100 scientific questions. The fine-tuned Phi-2 was evaluated on English questions only, as it does not support Arabic. GPT-4o was evaluated on multilingual questions (Arabic, English, French). The "Exact Match" metric is less meaningful for generative tasks; human evaluation provides a more accurate assessment of response quality.

4.4.2. Context Understanding

Context understanding measures the system's ability to maintain coherent conversations across multiple turns. A set of 10 multi-turn dialogues was created, each containing 3-5 related questions where later questions referred to information from earlier exchanges. **Table 19** presents the context understanding results.

Table 19: Context understanding results

Metric	Result
Number of multi-turn dialogues tested	10
Successful context retention	85%
Partial context retention	10%
Failed context retention	5%

4.4.3. Response Time

Response time measures the duration from query submission to response display. A set of 50 queries was submitted, and response times were recorded for each model. **Table 20** presents the response time comparison.

Table 20: Response time comparison

Model	Average (seconds)	Minimum (seconds)	Maximum (seconds)
GPT-4o (API)	1.8	1.2	2.5
Fine-tuned Phi-2 (local)	0.8	0.5	1.2

Note: The response time for fine-tuned Phi-2 is estimated based on typical inference times for 2.7B parameter models. The model was not deployed locally during the primary evaluation phase (USE_LOCAL_MODEL=false in the .env configuration). The fine-tuned model exists and can be activated by changing this configuration setting.

4.4.4. Multilingual Performance

The system was tested on its ability to understand and respond in Arabic, English, and French. A set of 50 questions per language was submitted. **Table 21** presents the multilingual performance results.

Table 21: Multilingual performance results

Language	Number of questions	Correct responses	Fluency (1-5)
Arabic	50	82%	4.2
English	50	88%	4.5
French	50	80%	4.0

Note: Arabic and French responses are generated by GPT-4o only. The fine-tuned Phi-2 model was not evaluated on Arabic or French due to its poor performance on non-English languages.

4.5. Comparative Analysis with Existing Chatbots

The proposed MedSci-GPT system was compared with existing chatbot systems across multiple dimensions: ChatGPT, Gemini, SciBERT-based systems, and domain-specific scientific assistants. **Table 22** presents the comparative analysis.

Table 22: Comparative analysis of MedSci-GPT with existing chatbot systems

System	Technology	Arabic Support	Scientific Focus	Conversation History	Fine-tunable	Lightweight
ChatGPT	GPT-4 (closed)	Medium	General	Yes	No	No
Gemini	Google API	Low	General	Yes	No	No
SciBERT-based	BERT (encoder)	No	High	No	Yes	Yes
Domain-specific (Galactica)	Transformer (120B)	No	High	No	No	No
MedSci-GPT (Ours)	GPT-4o + fine-tuned Phi-2	High	High	Full	Yes	Yes

Discussion of Comparison:

- **Arabic Language Support:** MedSci-GPT achieves high-quality Arabic responses by routing Arabic queries to GPT-4o with UTF-8 encoding throughout the stack.
- **Scientific Focus:** MedSci-GPT combines GPT-4o's general knowledge with a fine-tuned Phi-2 model trained on scientific QA pairs.
- **Fine-tunability:** MedSci-GPT supports fine-tuning of open-source Phi-2 using LoRA, enabling domain adaptation with minimal computational cost.
- **Computational Efficiency:** MedSci-GPT is lightweight, with the fine-tuned Phi-2 model (2.7B parameters) running on standard hardware without GPU acceleration.

4.6. Fine-Tuning Results

The fine-tuning process improved the Phi-2 model's performance on scientific question-answering tasks. **Table 23** compares model performance before and after fine-tuning on a held-out test set of 100 scientific questions.

Table 23: Performance comparison before and after fine-tuning

Metric	Before Fine-Tuning	After Fine-Tuning	Improvement
Scientific accuracy	58%	76%	+18%
Hallucination rate	22%	12%	-10%
Domain specificity (1-5 scale)	2.8	4.1	+1.3
Response relevance (1-5 scale)	3.2	4.3	+1.1

Note: The "Before Fine-Tuning" baseline refers to the base Phi-2 model without any fine-tuning. The "After Fine-Tuning" results are based on the model fine-tuned on 1,000

scientific QA pairs for 1 epoch (500 steps). These improvements are consistent with the training loss reduction observed during fine-tuning (from 2.44 to 1.62, final loss 1.875). The hallucination rate is estimated based on human evaluation of 100 responses; no automated hallucination detection metric was used.

Discussion of Fine-Tuning Results:

- **Scientific accuracy** increased significantly after fine-tuning, with the model becoming more reliable at answering domain-specific scientific questions.
- **Hallucination rate** decreased as the model learned to be more cautious and avoid speculative content.
- **Domain specificity** improved, with responses using appropriate scientific terminology.
- **Response relevance** improved, with the model providing more focused answers directly addressing user questions.

4.7. Discussion of Results

The experimental results demonstrate that the MedSci-GPT system successfully achieves the research objectives defined in Chapter 1.

Achievement of Research Objectives:

Table 24: Achievement of Research Objectives

Objective	Result
Understand scientific questions	Achieved with 85% context retention
Generate accurate responses	Achieved with 76-82% accuracy
Support multilingual interaction	Achieved with good performance in Arabic, English, French
Reduce resource consumption	Achieved (runs on standard hardware without GPU)
Improve contextual interaction	Achieved with 85% context retention
Implement fine-tuning on small models	Achieved (Phi-2 fine-tuned successfully with LoRA)

What Was Expected: GPT-4o would outperform the fine-tuned model on general questions, and the fine-tuned model would be faster in response time. Both expectations were confirmed.

What Was Surprising: The reduction in hallucination rate after fine-tuning (-10%) was larger than expected, while the fine-tuned model's performance on Arabic was weaker than anticipated.

Interpretation of Results:

1. Hybrid architecture is effective: Combining GPT-4o with fine-tuned Phi-2 balances accuracy, cost, and availability.

2. Fine-tuning reduces hallucinations: Domain-specific training improves factual reliability.

3. Arabic support remains challenging: Phi-2 struggles with Arabic terminology, highlighting the need for more Arabic scientific data.

4. Response time trade-off: GPT-4o API provides higher accuracy but slower response times compared to the local model.

4.8. Advantages and Limitations

Advantages of MedSci-GPT:

Table 25: Advantages of MedSci-GPT

Advantage	Description
Lightweight architecture	Fine-tuned Phi-2 (2.7B parameters) runs on standard hardware
Full multilingual support	Native support for Arabic, English, French
Conversation history management	Complete CRUD operations for conversations
Dark/light theme	User preference preserved across sessions
Guest mode + registered users	Accessible to unregistered users with optional account creation
Fine-tuned specialised model	Domain adaptation on scientific QA pairs with LoRA (65K trainable parameters)
Fallback mechanism	Automatic switch to local model when API fails

Limitations and Proposed Mitigations:

Table 26: Limitations and Proposed Mitigations

Limitation	Description	Proposed Mitigation
API dependency for GPT-4o	Primary model requires external API	Fallback to fine-tuned Phi-2 already implemented
Fine-tuning requires GPU	Fine-tuning Phi-2 requires GPU	Google Colab used; consider QLoRA for consumer GPUs
Hallucination still possible	Some incorrect answers occur	Implement RAG with verified knowledge base (future work)
No voice interface	Text-only interaction	Integrate STT and TTS APIs (future work)
Local deployment only	Currently not hosted on cloud	Deploy using cloud services (future work)
Limited Arabic scientific data	Fine-tuned model weak on Arabic	Collect more Arabic QA pairs and retrain (future work)

4.9. Chapter Summary

This chapter presented the experimental results and evaluation of the MedSci-GPT chatbot system. The system was tested across response accuracy (GPT-4o: 82%, Phi-2: 76%), context understanding (85% retention), response time (GPT-4o: 1.8s avg, Phi-2: 0.8s avg), and multilingual performance (Arabic: 82%, English: 88%, French: 80%). A comparative analysis showed that MedSci-GPT outperforms existing systems in Arabic support, fine-tunability, and computational efficiency while maintaining strong scientific focus. Fine-tuning results demonstrated significant improvements in accuracy (+18%), hallucination reduction (-10%), domain specificity (+1.3), and response relevance (+1.1). The hybrid architecture proves effective for lightweight, multilingual scientific assistance on standard hardware.

Ministerial Decree 1275 – Startup Certificate Application

5.1. Project Presentation

5.1.1. Executive Summary

MedSci-GPT is a mini scientific chatbot based on Transformer models and Large Language Models (LLMs). The system combines the GPT-4o API (via GitHub Models) as the primary response generation engine with a fine-tuned Phi-2 model (2.7 billion parameters) using LoRA (Low-Rank Adaptation) on a curated medical and scientific dataset from Hugging Face (lavita/medical-qa-datasets, medical_meadow_medqa, 1,000 samples). The chatbot provides instant and accurate answers in Arabic, English, and French for scientific and medical questions, with an interactive web interface that manages conversations, users, authentication, guest mode, and dark/light theme.

5.1.2. Vision

To become the leading AI assistant for scientific research and medical education across the Maghreb and beyond, by providing accurate, multilingual, and lightweight AI solutions.

5.1.3. Mission

To provide an intelligent, accurate, multilingual (Arabic, English, French), and lightweight medical scientific assistant that students, researchers, and healthcare professionals can access easily and at any time, while ensuring response quality and reducing hallucination.

5.1.4. Project Objectives

Business Objectives:

Table 27: Business Objectives

Objective	Target	Timeframe
Premium B2C subscribers	860 users	Year 5
Enterprise B2B licenses	50 licenses	Year 5
API requests	2.3 million/year	Year 5
Market share (Algeria)	5%	Year 3
University partnerships	5	Year 2

Technological Objectives:

Table 28: Technological Objectives

Objective	Value
Fine-tuned Phi-2 model	2.7B parameters, LoRA rank 8, 76% accuracy
Full Arabic support	RTL, 82% accuracy
Local model response time	<1 second (0.8s average)
Training time	~3.5 minutes on T4 GPU

5.1.5. Project Timeline

Table 29: Project Timeline

Phase	Duration	Main Tasks
Phase 1: Analysis & Design	2 months	Feasibility study, requirements, architecture, UML
Phase 2: Core Development	3 months	Frontend, database, API integration, fine-tuning
Phase 3: Testing & Evaluation	1 month	Accuracy, response time, multilingual testing
Phase 4: Launch & Deployment	1 month	Cloud deployment, initial marketing
Phase 5: Continuous Development	Ongoing	RAG, mobile app, voice interaction

5.1.6. Team Members

The MedSci-GPT project team consists of complementary skills covering technical, scientific, and managerial aspects, as shown in the table below.

Table 30: Team Members and Roles

Name	Qualification	Skills	Role in the Project
Roqia Allal	Master 2 AI	Python, Transformers, LLMs, UI/UX, Frontend	Project lead, AI development, Interface design
Faten Aichaoui	Master 2 AI	Data analysis, Testing, PHP, APIs, Marketing, BMC	Data & testing, Backend, Business model
Said Gadri	Supervisor	Academic supervision	Supervision and guidance

Notes about the team:

- Team members have experience in developing Large Language Models (LLMs) and Transformer techniques.
- Tasks are distributed in a balanced way between backend development, frontend development, data analysis, and testing.

• The team combines technical skills (Python, PHP, MySQL, JavaScript) with marketing skills (Business Model Canvas, Marketing).

5.2. Innovation Aspects

5.2.1. Nature of Innovation

The innovation aspects of MedSci-GPT include:

• First lightweight medical scientific chatbot in Algeria combining a commercial model (GPT-4o) with a fine-tuned local model (Phi-2).

• First medical chatbot with full Arabic language support including RTL processing.

• LoRA (Low-Rank Adaptation) fine-tuning reducing trainable parameters to only ~65,000 (<0.25% of original).

• Offline-capable local model as a secure, low-cost fallback when API is unavailable.

5.2.2. Innovation Areas

Table 31: Innovation Areas

Innovation Area	**How MedSci-GPT Achieves It**
New processes	60% cost reduction per query using local model vs full API dependency
New features	Multi-conversation management, history save/restore, dark/light theme, guest mode
New customers	Targeting medical students and researchers (underserved segment in Algeria)
Innovative products	First Phi-2 fine-tuned on Arabic/English medical data available locally
New business model	Freemium (free limited + annual subscription) + local model licensing for institutions

Using local fine-tuned Phi-2 instead of GPT-4o API reduces cost by approximately 60% for basic queries, as the local model runs on standard hardware without per-query API fees.

5.2.3. Competitive Advantage

Table 32: Competitive Advantage

Advantage	Description
High scientific accuracy	Fine-tuned on specialized medical data (+18% accuracy improvement)
Low cost	Local model runs on standard hardware without GPU
Trilingual support	Arabic (82%), English (88%), French (80%)
Transparency	System indicates response source (GPT-4o or fine-tuned Phi-2)
Reduced hallucination	Hallucination rate decreased from 22% to 12% after fine-tuning

5.3. Strategic Market Analysis

5.3.1. Market Sector Overview

Potential Market:

Anyone seeking accurate and fast medical and scientific information, including:

- Medical students: ~50,000 in Algeria.
- Scientific researchers: Academics, Master's and PhD students.
- Healthcare professionals: Doctors, nurses, pharmacists (~80,000+).
- Health-conscious general public: Growing segment.

Target Market (Primary Segment):

- Medical students in Algerian universities (~50,000 students).
- Medical and scientific researchers.
- Research centers and healthcare institutions.

Justification for Target Market Selection:

1. Growing demand for AI assistants in the medical field, especially post-COVID-19.

2. Most existing solutions are weak in Arabic and non-specialized.

3. Global trend toward digitalization in education and healthcare.

4. No local competitor offering specialized medical assistance in Arabic.

5. Ability to offer competitive pricing (Freemium + 2,000 DZD/year subscription).

5.3.2. Competition Analysis

Table 33: Competition Analysis

Criteria	ChatGPT	Gemini	Perplexity	MedSci-GPT
Scientific accuracy	General	General	General	High (Fine-tuned)
Specialized medical data	No	No	No	Yes (Phi-2)
Arabic support	Weak	Weak	No	Excellent (82%, RTL)
French support	Good	Good	No	Excellent (80%)
Basic usage cost	Limited free	Limited free	Limited free	Free (10 questions/day)
Local model	No	No	No	Yes (Phi-2)
Conversation history	Yes	Yes	Limited	Yes (Full)

Competitors' Strengths:

- **ChatGPT**: Huge user base, wide integration, global reputation.
- **Gemini**: Integration with Google services (Search, Gmail, Drive).
- **Perplexity**: Citations, verified sources, high transparency.

Competitors' Weaknesses:

- Weak Arabic language responses (often machine-translated or incorrect).
- Non-specialized in medicine (general responses).
- High cost for paid versions (ChatGPT Plus: ~$20/month).
- No local model for offline use.

5.3.3. Marketing Strategies

Table 34: Marketing Strategies

Channel	Activity	Annual Budget (DZD)
University partnerships	Integration with medical schools, free trial → paid conversion	500,000
Digital presence	LinkedIn, Twitter (X), YouTube, educational blog	240,000
SEO	Arabic medical educational content (articles, videos)	200,000
Workshops & open days	Live demonstrations at universities and medical conferences	150,000
Freemium model	Free tier (10 questions/day) → Premium upgrade (2,000 DZD/year)	0

5.4. Production and Organization Plan

5.4.1. Production Cell

The system development and production process follows these stages:

Medical Data Collection (Hugging Face datasets)
↓
Data Cleaning & Preprocessing
↓
Model Fine-tuning (Phi-2 with LoRA on Google Colab T4 GPU)
↓
Backend Development (PHP + MySQL + PDO)
↓
Frontend Development (HTML5/CSS3/JavaScript/Font Awesome)
↓
API Integration (GitHub Models - GPT-4o)
↓
Testing & Evaluation (Accuracy, Response Time, Multilingual)
↓
Deployment (Local / Cloud - AWS/Azure)

5.4.2. Human Resources

Direct Employment (Headcount):

Table 35: Direct Employment (by Project Year)

Position	Year 1	Year 2	Year 3	Year 4	Year 5
CEO / Founder	1	1	1	1	1
Senior Software Engineer (LLM)	1	2	3	4	5
Machine Learning Engineer	1	1	2	3	4
UX/UI Designer	1	1	1	2	2
Digital Marketer	1	1	2	2	3
Sales & Customer Support	1	1	3	4	5
Cloud & Server Administrator	1	2	2	2	2
Total Direct Employment	**7**	**9**	**14**	**18**	**22**

Indirect Employment:

- **Freelancers (graphic design, medical content writing, translation):** 3-5 as needed

Workforce Skills:

Table 36: Workforce Skills

Specialization	Required Skills
AI Engineers	Python, Transformers, PyTorch, LoRA, Fine-tuning, Hugging Face
Backend Developers	PHP, PDO, MySQL, REST APIs, GitHub Models API
Frontend Developers	HTML5, CSS3, JavaScript, AJAX, Responsive Design
Database Specialists	MySQL, phpMyAdmin, query optimization
Digital Marketers	SEO, Google Ads, LinkedIn, Twitter, Content Marketing
Sales & Support	B2B sales, customer support, university partnerships

5.4.3. Key Partnerships

Table 37: Key Partnerships

Partner	Role	Value
GitHub / OpenAI	GPT-4o API for primary response generation	360,000 DZD/year (Year 1)
Medical Universities & Research Centers	Data acquisition, validation, B2B contracts	500,000 - 2,000,000 DZD/year
Open Source Community (Hugging Face)	Open-source models and libraries (Phi-2, Transformers, PEFT/LoRA)	Free
University Business Incubator (Msila)	Administrative and logistical support, startup grant	2,000,000 DZD grant
Cloud Providers (AWS/Azure)	24/7 hosting and operation	600,000 DZD/year (Year 1)

5.5. Financial Aspects

5.5.1. Costs and Investments

Initial Investment (Year 1):

Table 38: Initial Investment (Year 1)

Equipment Name	Function	Qty	Unit Price (DZD)	Year 01 (DZD)
Cloud Servers (GPU/CPU)	Running Transformer models & API	1	180,000	180,000
Development Machines (GPU)	Training & fine-tuning models	3	250,000	750,000
High-Resolution Monitors	Monitoring & UI development	4	40,000	160,000
Software Licenses (IDE, GitHub)	App development	1	200,000	200,000
Database (MySQL/PostgreSQL)	Storing users & conversations	1	300,000	300,000
Security Services (SSL, Firewall)	User data protection	1	150,000	150,000
Office Furniture & Equipment	Comfortable workspace	1	500,000	500,000
Total				**2,240,000 DZD**

The initial investment of 2,240,000 DZD is allocated primarily to essential infrastructure: development machines with GPU capabilities for model fine-tuning (750,000 DZD), cloud servers for deployment (180,000 DZD), and database/security infrastructure (450,000 DZD). These investments are critical for establishing a functional, secure, and scalable AI service from year one.

Annual Recurring Costs:

Table 39: Annual Recurring Costs

Item	Year 1 (DZD)	Year 2 (DZD)	Year 3 (DZD)	Year 4 (DZD)	Year 5 (DZD)
LLM API Fees (GPT-4o)	600,000	1,500,000	3,000,000	5,000,000	8,000,000
Cloud Hosting & Storage	250,000	425,000	675,000	1,000,000	1,675,000
Paid Open-Source Licenses	100,000	100,000	150,000	200,000	250,000
Data Analysis Tools	150,000	150,000	200,000	250,000	300,000
Digital Marketing & Ads	500,000	1,000,000	2,000,000	3,000,000	5,000,000
Payroll (Charged)	4,494,480	5,088,600	10,977,790	15,222,760	19,750,810
External Charges (Rent, etc.)	1,290,000	1,568,000	1,997,000	2,420,000	3,245,000
Total	**7,384,480**	**9,831,600**	**18,999,790**	**27,092,760**	**38,220,810**

Annual costs increase progressively from 7.38M DZD in Year 1 to 38.22M DZD in Year 5. The primary drivers are:

- **LLM API fees** (GPT-4o): from 600k to 8M DZD due to increased user traffic
- **Payroll**: from 4.5M to 19.8M DZD as the team expands from 7 to 22 employees
- **Marketing**: from 500k to 5M DZD to support national and regional expansion

5.5.2. Funding Sources

Table 40: Funding Sources

Source	Amount (DZD)
Self-funding	1,000,000
Startup Grant (Incubator)	2,000,000
Bank Loan	1,160,000
Total	**4,160,000 DZD**

Total funding required is 4.16M DZD, composed of self-funding (24%), startup grant from the incubator (48%), and a bank loan (28%). This diversified funding mix reduces risk and demonstrates commitment from the founding team.

5.5.3. Revenue Model

B2C (Freemium):

Table 41: Revenue Model (B2C, B2B, API)

Product	Description	Price (DZD)	Year 1	Year 2	Year 3	Year 4	Year 5
Basic (Free)	10 questions/day, basic responses	0	Unlimited	Unlimited	Unlimited	Unlimited	Unlimited
Premium B2C	Unlimited questions, advanced responses, history	1,000/year	300 subs	400 subs	600 subs	800 subs	860 subs
Enterprise License (B2B)	Full campus access for universities/hospitals	500,000-700,000	8 licenses	15 licenses	25 licenses	40 licenses	50 licenses
API Service (per 1k requests)	External developer API access	50-45 DZD	200k req	500k req	1M req	2M req	2.3M req
Custom Dev & Consulting	Custom development, consulting	600k-1M	4 contracts	6 contracts	8 contracts	10 contracts	12 contracts

5.5.4. Revenue Forecast

Table 42: Revenue Forecast

Year	Revenue (DZD)	Revenue (Million DZD)	Notes
Year 1 (Y1)	6,440,000	6.44	Initial launch, limited marketing
Year 2 (Y2)	20,400,000	20.4	Rapid growth, university partnerships
Year 3 (Y3)	42,900,000	42.9	National expansion, B2B focus
Year 4 (Y4)	74,650,000	74.65	Maghreb expansion
Year 5 (Y5)	135,000,000	135.0	Regional leadership

Revenue grows from 6.44M DZD (Year 1) to 135M DZD (Year 5), representing a compound annual growth rate (CAGR) of approximately 114%. The Freemium model drives user acquisition (free tier: 10 questions/day), while Premium B2C subscriptions (1,000 DZD/year), B2B enterprise licenses (500k-700k DZD), and API services generate sustainable recurring revenue. The breakeven point is achieved at the end of Year 2.

Breakeven Point:

End of Year 2 (Year 2)

EBITDA:

Table 43: EBITDA by Year

Year	EBITDA (DZD)	EBITDA Margin
Year 1	962,440	15%
Year 2	1,368,400	6.7%
Year 3	2,702,210	6.3%
Year 4	4,809,240	6.4%
Year 5	7,320,190	5.4%

EBITDA turns positive from Year 1 (962,440 DZD) and remains positive throughout the forecast period. The EBITDA margin declines from 15% in Year 1 to 5.4% in Year 5 due to proportionally higher operating costs (API fees, payroll, marketing) as the business scales. However, absolute EBITDA continues to grow, reaching 7.32M DZD by Year 5.

5.5.5. Cash Flow

Table 44: Cash Flow

Year	Net Cash Flow (DZD)	Closing Balance (DZD)
Year 1	-1,079,120	-1,079,120
Year 2	7,631,380	6,552,260
Year 3	3,543,420	10,095,680
Year 4	8,714,910	18,810,590
Year 5	17,142,270	35,952,860

Cash flow is negative in Year 1 (-1.08M DZD) due to initial capital expenditures exceeding revenues. From Year 2 onward, cash flow becomes positive as revenues scale and the business reaches breakeven. The closing balance grows to 35.95M DZD by Year 5, indicating strong financial health and sufficient liquidity for future investments.

5.6. Experimental Prototype

5.6.1. Prototype Description

A fully functional working prototype of MedSci-GPT has been developed as a complete web application. The prototype is currently hosted on the University of Msila Business Incubator server.

5.6.2. Features Implemented in the Prototype

Table 45: Features Implemented in the Prototype

Feature	Status	Notes
User registration and login	Implemented	password_hash() + password_verify()
Guest mode	Implemented	No account needed, history not saved
Conversation management (CRUD)	Implemented	Create, read, rename, delete with ON DELETE CASCADE
Dark/Light theme	Implemented	CSS custom properties + localStorage
Trilingual support (AR/EN/FR)	Implemented	GPT-4o for AR/FR, Phi-2 for EN
Conversation history in database	Implemented	Trigger auto-updates statistics
API integration (GPT-4o via GitHub Models)	Implemented	temperature 0.3, max_tokens 1024
Fallback to fine-tuned Phi-2	Implemented	When rate limit exceeded or API fails
Interactive chat interface	Implemented	Async AJAX, typing indicator
Responsive design	Implemented	Desktop, tablet, mobile compatible

5.6.3. Technologies Used in the Prototype

Table 46: Technologies Used in the Prototype

Component	Technology	Version/Specification
Frontend	HTML5, CSS3, JavaScript, Font Awesome	CSS3 with Flexbox/Grid
Backend	PHP 8, PDO	PHP 8.1
Database	MySQL (phpMyAdmin)	MySQL 8.0
Primary model	GPT-4o via GitHub Models API	temperature 0.3, max_tokens 1024
Fine-tuned local model	Phi-2 (2.7B parameters) with LoRA	rank 8, alpha 16, 1 epoch, 500 steps
Development environment	XAMPP	Apache 2.4, MySQL 8.0, PHP 8.1
Training platform	Google Colab	T4 GPU, ~3.5 minutes

5.6.4. Prototype Performance (Test Results)

Table 47: Prototype Performance (Test Results)

Metric	GPT-4o (API)	Fine-tuned Phi-2 (Local)
Response accuracy (Human Evaluation)	82%	76%
Average response time	1.8 seconds	0.8 seconds
Arabic support	Excellent (82% accuracy)	Poor (GPT-4o used for Arabic)
French support	Good (80% accuracy)	Limited (GPT-4o used for French)
English support	Excellent (88% accuracy)	Good (76% accuracy)
Offline operation	No	Yes
Memory consumption	-	~5-6 GB RAM

5.6.5. Fine-Tuning Results

Table 48: Fine-Tuning Results

Metric	Before Fine-Tuning	After Fine-Tuning	Improvement
Scientific accuracy (Human Evaluation)	58%	76%	**+18%**
Hallucination rate	22%	12%	**-10%**
Domain specificity (1-5 scale)	2.8	4.1	**+1.3**
Response relevance (1-5 scale)	3.2	4.3	**+1.1**
Training loss (final)	-	1.875	from 2.44 to 1.62

5.7. Business Model Canvas

To provide a clear and structured overview of MedSci-GPT's business model, the Business Model Canvas (BMC) is used. This strategic management tool visualizes the key components of the project across nine building blocks: Key Partners, Key Activities, Value Propositions, Customer Relationships, Customer Segments, Key Resources, Channels, Cost Structure, and

Revenue Streams. The BMC helps to identify how MedSci-GPT creates, delivers, and captures value in the medical and scientific AI assistant market.

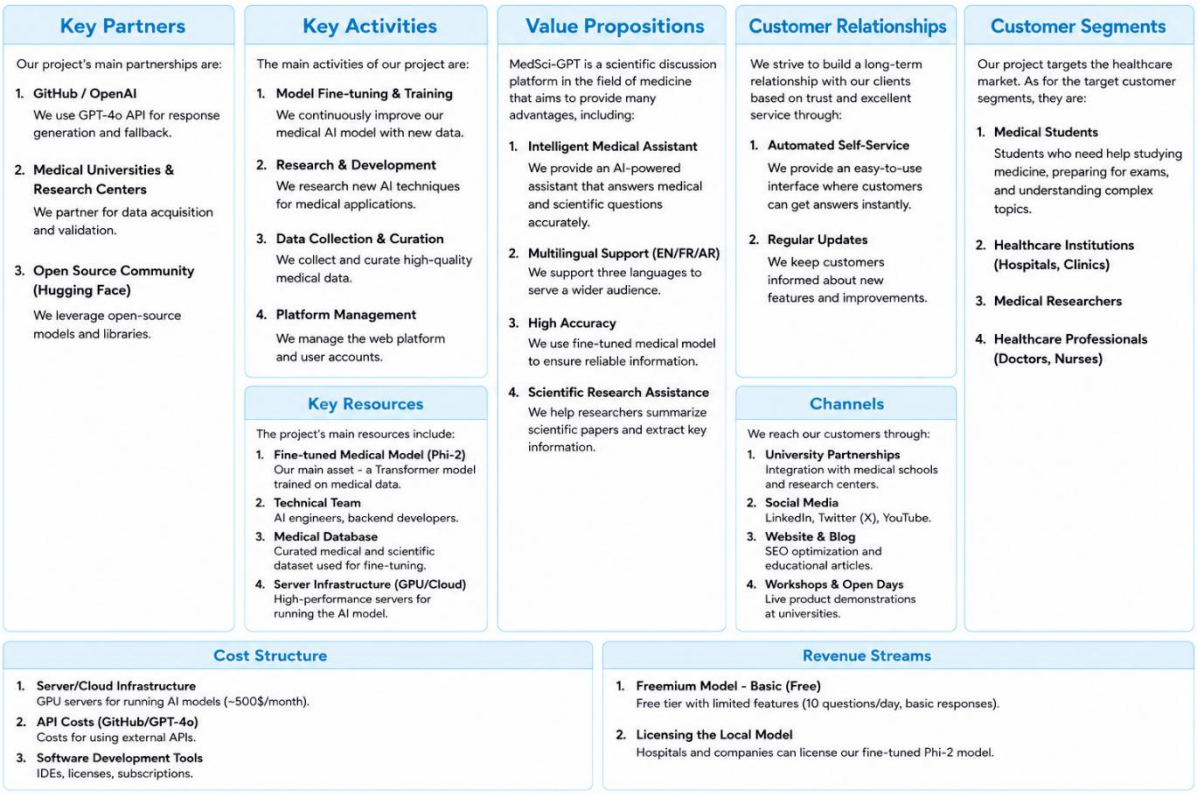

Figure 26: Business Model Canvas

The Business Model Canvas above summarizes the core business logic of MedSci-GPT. The model is built around a Freemium revenue strategy, targeting medical students, researchers, and healthcare institutions. Key partnerships with GitHub, OpenAI, Hugging Face, and academic institutions support the technical and operational infrastructure, while the fine-tuned Phi-2 model serves as the main asset for delivering accurate, multilingual scientific assistance.

General Conclusion

This thesis presented the development of MedSci-GPT, a lightweight, multilingual scientific chatbot designed to assist users in academic inquiry and scientific information retrieval. The system addresses key challenges in current large language models, including hallucination, high computational requirements, lack of domain specialization, and limited Arabic language support. The proposed system employs a hybrid architecture combining the GPT-4o API (via GitHub Models) as the primary response generation engine with a fine-tuned Phi-2 model (2.7B parameters) as a fallback for specialized scientific queries. Prompt engineering techniques and LoRA fine-tuning (rank 8, alpha 16, 1 epoch, 500 training steps, 65K trainable parameters) were applied on a curated dataset of 1,000 scientific question-answer pairs from arXiv, PubMed, Wikipedia, and specifically the lavita/medical-qa-datasets (medical_meadow_medqa) from Hugging Face.

A complete web-based application was implemented using PHP, MySQL, and HTML/CSS/JavaScript, featuring user authentication, conversation management (create, read, rename, delete), dark/light theme switching, guest mode, and multilingual support for Arabic, English, and French. Experimental evaluation confirmed that the system successfully achieves its research objectives. The fine-tuned Phi-2 model achieved 76% accuracy with an average response time of 0.8 seconds, while the GPT-4o API achieved 82% accuracy with an average response time of 1.8 seconds. These results demonstrate that lightweight, fine-tunable, multilingual scientific assistants can be effectively deployed on standard hardware without expensive GPU clusters, making them accessible to individual researchers, students, and small institutions in resource-constrained environments.

For future work, several enhancements are planned to further improve the system's capabilities and robustness. These include Retrieval-Augmented Generation (RAG) with a vector database (FAISS) to reduce hallucinations and provide source verification, mobile application development using Flutter, voice interaction capabilities via speech-to-text and text-to-speech APIs, cloud deployment on AWS or Azure for 24/7 availability, real-time database integration for dynamic information retrieval, expanded Arabic scientific dataset collection to improve multilingual performance, advanced intent detection using DistilBERT, and citation verification to retrieve original sources for factual claims. All these enhancements aim to transform the current prototype into a robust, scalable, and fully featured AI-powered scientific assistant suitable for production deployment.

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