

# Emotional Nutritionist Chatbot with Hybrid Retrieval System

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## ABSTRACT

As demand for personalized nutrition grows, existing chatbots remain limited by generic advice and a lack of emotional awareness. In our midterm project, we developed a LLaMA 2-based chatbot, fine-tuned with LoRA and Kaggle datasets, and implemented a basic retrieval-augmented generation (RAG) pipeline to provide context-aware dietary suggestions. In the final project, we significantly enhance both performance and user experience: upgrading to GPT-4o for improved response quality, integrating a RoBERTa emotion classifier for emotion-aware prompt generation, and improving the RAG pipeline with adaptive PubMed retrieval. We further introduce a LangChain-based agent architecture with a router agent and tool calling, enabling modular, scalable, and task-specific interactions.

## 1 INTRODUCTION

As health-conscious individuals increasingly seek personalized nutrition guidance, many existing chatbot solutions remain limited by generic recommendations and a lack of emotional intelligence [5]. In our midterm project, we developed an AI-powered nutrition chatbot using LLaMA 2, fine-tuned with LoRA and Kaggle nutrition datasets. This early version integrated a stacked retrieval-augmented generation (RAG) framework to provide personalized, context-aware dietary recommendations by accessing both local and external nutrition data sources.

In this final project, we significantly enhance both the model performance and emotional intelligence of the system. We upgrade the core model to GPT-4o, leveraging its superior reasoning and generation capabilities to deliver higher-quality responses. We also integrate a RoBERTa-based emotion classifier, enabling the system to detect 27 emotion types and dynamically adjust responses through emotion-aware prompt engineering.

In addition, we enhance our RAG pipeline with stacked, adaptive retrieval leveraging scientific literature from PubMed. To improve relevance and efficiency, we use GPT-4o to distill complex user queries into targeted search terms—replacing the less effective LLaMA 2-based approach. We then apply TF-IDF scoring to rank abstract relevance and select the top 10 articles for the retrieval stack. This pre-filtering step ensures that only the most pertinent content is added to our stacked knowledge base.

We finally defines two retrieval tools used by the router agent (according to Prof Lin’s feedback during class presentation session): a web search module based on the Tavily API and a custom NCBI search. The former provides real-time search results from the open web, while the latter performs academic retrieval through a combination of local vector search and dynamic content fetching from NCBI. Both tools are registered for use within a LangGraph-based agent to support adaptive query routing based on the input type.

## 1.1 System Architecture

The architecture of the project consists of five core components designed to deliver emotionally aware and contextually grounded responses:

- **Emotion Detection:** A fine-tuned RoBERTa model classifies user sentiment into one of 27 emotional categories.
- **Emotion-Aware Prompting:** The detected emotional label is incorporated into the prompt to guide the language model in generating responses with appropriate tone and empathy.
- **AI Agent:** A dual-source search module combines real-time web results via the Tavily API with academic retrieval using local vector search and dynamic NCBI fetching.
- **Document Retrieval:** The system queries a local FAISS vector store built from NCBI articles. A fallback mechanism allows for dynamic ingestion of new content when relevant documents are insufficient.
- **Response Generation:** GPT-4o serves as the core response engine, enhanced with emotional context to produce personalized and empathetic responses.

In this report, Section 2 details the fine-tuning of the RoBERTa model and the implementation of Emotion-Aware Prompting. Section 3 provides an in-depth discussion of the Document Retrieval pipeline and the integration of GPT-4o in the chatbot system. Section 4 presents the design rationale behind the agent framework. Section 5 shows the experimental results and system outputs.

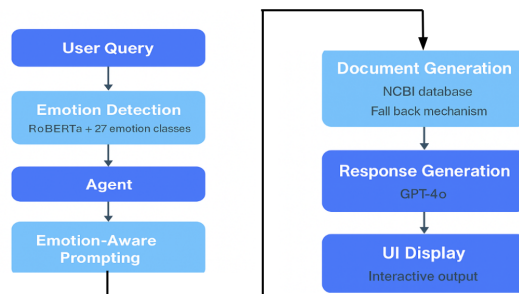


Figure 1: System Architecture

## 2 EMOTION AWARENESS VIA BEAM: FINE-TUNING & PROMPT REWRITING

### 2.1 RoBERTa Fine Tuning

To build an emotionally intelligent assistant, we developed a custom classifier called BEAM (Behavioral Emotion-Aware Model) by fine-tuning RoBERTa-base (125M parameters) on the GoEmotions dataset [2]. RoBERTa was chosen for its strong contextual language understanding and superior performance over BERT, especially

in capturing subtle emotional cues[4]. GoEmotions, a dataset curated by Google Research, contains over 58,000 Reddit comments labeled with 27 emotion categories such as joy, sadness, pride, and embarrassment[3]. We used the simplified 27-label version to balance granularity and inference efficiency, making it suitable for real-time emotional understanding in user-facing systems.

We fully fine-tuned RoBERTa on 43,000 training examples using cross-entropy loss. The training was conducted over 3 epochs with a learning rate of  $2e-5$ , batch size of 32, and weight decay of 0.01. We tokenized the inputs using Hugging Face’s AutoTokenizer and selected the first label in multi-label examples. This setup led to a validation accuracy of approximately 70%, which is strong for multi-class emotion classification across fine-grained categories. The resulting classifier outputs the most probable emotion label along with a confidence score, providing a lightweight yet expressive signal for downstream applications.

Parameter	Value	Notes
Learning rate	$2 \times 10^{-5}$	AdamW optimizer
Batch size	32	Per-device train batch size
Epochs	3	Full fine-tuning
Weight decay	0.01	Regularization
Loss function	Cross-entropy	Single-label classification
Validation accuracy	~70%	On 27-class GoEmotions
Dataset size	43,410	GoEmotions training examples
Tokenizer	RoBERTa tokenizer	Hugging Face AutoTokenizer
Base model	RoBERTa-base	125M parameters

**Table 1:** Fine-tuning hyperparameters for BEAM

The primary goal of BEAM is to enable emotion-aware response generation. By detecting the user’s emotional state, we can condition the prompt sent to the response model (e.g., GPT-4o), resulting in answers that are not only factually accurate but also empathetic and tone-sensitive[2]. This is especially important in domains like nutrition, where users often express frustration, vulnerability, or urgency. BEAM allows us to embed this emotional context into the interaction pipeline, helping the system deliver responses that feel more supportive, personalized, and human-aligned.

## 2.2 Re-Prompting

To make the system emotionally responsive, we introduce a re-prompting step between emotion classification and response generation. After the user submits a query, the BEAM classifier detects their emotional state (e.g., “sadness”) and outputs a corresponding label with a confidence score. Rather than sending this raw query directly to the main GPT-4o model, we first pass it through an intermediate GPT-4o call that rewrites the prompt to incorporate the detected emotion.

This intermediate step uses a lightweight system prompt that instructs GPT-4o to rephrase the user’s input in a way that reflects their emotional tone. For instance, consider the user input: “I want to lose 10 pounds fast. I am very self-abased about my weight.” If BEAM detects an emotion such as self-consciousness or insecurity, the rewritten prompt becomes: “I have a strong desire to lose 10 pounds quickly because I feel self-conscious about my weight. Can you provide guidance that considers these feelings?” This emotionally aware prompt is then passed to the main RAG-based GPT model, along with relevant retrieved context, allowing the system

to generate responses that are both factually informed and emotionally aligned.

This modular re-prompting mechanism allows us to inject emotional intelligence into the response pipeline without modifying or fine-tuning the main generation model. It ensures that final outputs are not only grounded in relevant content but also sensitive to the user’s emotional state—an essential capability for promoting trust, empathy, and engagement in nutrition-focused applications.

### Emotion-Aware Query Processing Pipeline

*“I’m struggling to lose weight despite trying so many diets.”*

→ [LOG] Emotion detected: sadness (0.48)

#### Rewritten Prompt for Main AI:

**User Input:** *I want to lose 10 pounds fast. I am very self-abased about my weight.*

**Emotion-Aware Rewrite:** *I have a strong desire to lose 10 pounds quickly because I feel self-conscious about my weight. Can you provide guidance that considers these feelings?*

**Figure 2:** RoBERTa Prompt Engineering

## 3 CHATBOT SYSTEM DESIGN

### 3.1 Architecture Overview

The Emotional Nutritionist Chatbot adopts a GPT-4o for processing user queries and stacked retrieved database with a dynamic retrieval-augmented generation (RAG) framework. The system consists of the following key components:

- (1) **LLM Backbone (GPT-4o)** The chatbot leverages GPT-4o, provided by OpenAI, as its primary generative model. This model is responsible for producing fluent and coherent responses and is enhanced through prompt engineering to incorporate emotional and contextual cues.
- (2) **Query Processing Pipeline** User input is first processed through a RoBERTa-based emotion classifier, which detects emotional states across 27 predefined categories. The query is then rewritten using emotion-aware prompting techniques to incorporate emotional context, enabling more empathetic and user-aligned responses.
- (3) **Hybrid Knowledge Retrieval** The retrieval module interfaces with the NCBI database to provide access to up-to-date nutritional research. It follows a stack-based knowledge expansion strategy: if the local knowledge base contains sufficiently relevant information, the chatbot responds directly; otherwise, it performs real-time retrieval from NCBI and dynamically integrates newly acquired articles into the knowledge base.
- (4) **RAG Mechanism** A two-stage retrieval process in RAG system. The pipeline first queries a local FAISS index using dense similarity search and filters documents exceeding a predefined threshold (e.g., 0.65). If the number of qualifying documents is insufficient, a secondary keyword-based search is triggered to fetch additional content from NCBI, which is then embedded and indexed for immediate use.

### 3.2 Retrieval Architecture and Workflow

The retrieval component of the RAG chatbot employs a hybrid architecture characterized by two distinct workflows:

**First-Time Queries:** The system initiates a retrieval process from the NCBI database to obtain relevant articles, from which a response addressing the user’s query is generated.

**Subsequent Queries:**

- (1) If the existing knowledge base adequately covers the user’s query, the chatbot generates a response directly from previously retrieved materials.
- (2) If existing information proves insufficient, the system initiates real-time retrieval from the NCBI database, fetching new relevant articles, which are then incorporated into the knowledge base to enhance future responses.

This retrieval and integration approach adheres to a **Stack Database design**, facilitating progressive knowledge expansion. Newly retrieved materials are **added to the original knowledge base**, ensuring incremental learning.[1] The system continuously expands and enriches stored information, allowing future queries to be addressed with stronger supporting evidence.

### 3.3 Hybrid Retrieval System

We implement a hybrid retrieval system to optimize both response quality and computational efficiency.

**3.3.1 NCBI Database.** The system accesses the NCBI PubMed database via the Entrez E-utilities API. It uses a two-step process: `esearch.fcgi` retrieves PubMed IDs (PMIDs) based on the query, followed by `efetch.fcgi`, which fetches up to 100 articles per query, including abstracts, titles, publication dates, and author information.

**3.3.2 Query for NCBI.** Since NCBI requires keyword-based queries, natural-language user inputs (e.g., “What is the impact of sugar on diabetes?”) are transformed into concise keyword formats (e.g., “Sugar & Diabetes”). To automate this, we employ **GPT-4o** with optimized prompts to extract keywords effectively and efficiently.

**3.3.3 Relevance Processing for NCBI Article Retrieval.** After retrieving 100 articles, the system applies a TF-IDF-based relevance ranking on their abstracts to assess alignment with the user’s query. The top 10 most relevant articles, based on TF-IDF scores, are selected to store in stacked knowledge base.

**3.3.4 Emotional Prompting.** Upon receiving a user’s query, the system invokes a RoBERTa-based model to perform emotion-aware prompt engineering. The model analyzes the input, assigns one of 27 emotional labels, and then reformulates the original question to reflect that emotion before forwarding it to GPT-4o. For example, if the user asks *How can I incorporate more antioxidants into my diet?* and the RoBERTa model detects *curiosity* with a confidence score of 0.60, the query is rewritten as *I’m curious about finding ways to add more antioxidants into my diet. What are some effective and enjoyable options I could try?* This emotionally tailored prompt is then submitted to GPT-4o for a more nuanced, context-aware response.

### 3.4 RAG Mechanism for Hybrid Search

The retrieval-augmented generation (RAG) pipeline is orchestrated by the `hybrid_search` function in conjunction with the OpenAI embedding model (`text-embedding-ada-002`). Upon receiving a

user query, it is first embedded and normalized to unit length via `get_normalized_query_embedding`, ensuring consistent cosine similarity comparisons. A local FAISS search is then performed on the on-disk index (`faiss_index`), filtering for document embeddings whose similarity exceeds a configurable threshold (e.g., 0.65). If at least `top_k` results satisfy this criterion, they are returned immediately, minimizing latency for familiar topics. Otherwise (when  $k > 0$ ), the `processing_with_model` function is invoked: it extracts query keywords, executes a live NCBI lookup to retrieve and chunk up to  $k$  new articles, embeds these chunks with the same OpenAI model, and calls `build_vector_store` to merge them into the FAISS index. Finally, the union of local and newly ingested documents is passed as context to GPT-4o, which generates a response that is both up-to-date and grounded in the latest nutritional research. This stack-style RAG approach continuously enriches the local knowledge base—tracked via a PMID log file—so that subsequent queries (e.g., follow-ups on “antioxidants”) can leverage existing documents and require fewer external fetches over time.

## 4 ROUTER AGENT DESIGN

The router agent serves as the central decision-making component of our nutrition chatbot system, intelligently directing user queries to the most appropriate information retrieval tools. Our implementation leverages the LangGraph framework to create a reasoning and acting (ReAct) agent that can dynamically select and invoke tools based on query characteristics and user context. The router agent that can analyze users’ queries and route them to both our proposed hybrid retrieval system and real-time search powered by TavilySearchResults.

### 4.1 Tool Integration

The router agent integrates two primary tools for information retrieval:

- (1) **NCBI Tool:** A custom-built tool for retrieving academic and credible articles from NCBI databases. This tool implements a hybrid approach:
  - Performs local FAISS vector search with similarity threshold filtering
  - Returns local results if sufficient matches ( $\geq \text{top\_k}$ ) are found
  - Fetches and processes new articles when local results are insufficient
  - Combines local and fresh results for comprehensive coverage
- (2) **TavilySearchResults:** A real-time web search tool that provides access to current information, configured with a maximum of 2 results per query for efficiency.

### 4.2 Decision Logic

The router agent employs a sophisticated decision-making process that considers both query characteristics and emotional context. The agent follows these routing rules:

- (1) **Academic/Research Queries:** When users seek clinical studies, evidence summaries, or scientific references, the agent calls the `hybrid_search()` to retrieve peer-reviewed, credible sources.

- (2) **Real-time Information Queries:** For current dietary guidelines, emerging research, or trending health advice, the agent utilizes `TavilySearchResults()` to access up-to-date information.
- (3) **Crisis Situations:** Throughout emotion detection, the agent prioritizes real-time resources when detecting signs of danger (e.g., self-harm indicators, severe malnutrition symptoms), ensuring users receive actionable guidance.

### 4.3 Implementation Details

The router agent is implemented using the `create_react_agent` function with a carefully crafted prompt that incorporates emotion awareness. The system processes:

- User queries with detected emotional states
- Context-aware tool selection
- Sequential tool invocation when necessary
- Streaming response generation for real-time user feedback

The agent ensures that at least one tool is always called, preventing scenarios where users receive responses without external validation. This design guarantees that all nutritional advice is grounded in either academic literature or current authoritative sources.

### 4.4 Use Case

Fig. 3 showcases the routing criteria and workflow of the proposed ReAct Router Agent. The user first queries about the benefits of coffee and seeks recommendations for the best coffee shops in Long Island City. The ReAct Agent then initiates a feedback loop to assess the user’s needs and intents. In this case, the user requires both real-time and academic-oriented information. Thus, the agent will invoke appropriate tools based on these needs, followed by emotion detection to enhance empathetic responses and enable prompt crisis situation intervention. The ReAct architecture continuously observes the retrieved results and refines the response through several feedback loops. The results include both the benefits retrieved from NCBI via `hybrid_search()` and the coffee shop recommendations in LIC via real-time search. Fig 5 shows the full ReAct process in Appendix.

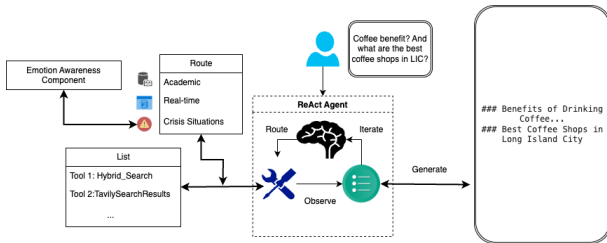


Figure 3: ReAct Router Agent

## 5 EMOTION-AWARE RAG EXPERIMENT

In the experiment in appendix, we showcase how an emotion-aware re-prompting layer integrates with our RAG pipeline and influences both retrieval and generation.

### (1) User Input & Emotion Detection

The user submits:

“How can I incorporate more antioxidants into my diet?”

This query is first passed through our fine-tuned RoBERTa emotion classifier, producing:

[LOG] Emotion detected: curiosity (0.60)

### (2) Emotion-Aware Prompt Rewriting

We rewrite the raw query to embed the detected affective state:

“I’m curious about finding ways to add more antioxidants to my diet. What are some effective and enjoyable options I could try?”

This rewritten prompt guides GPT-4o to respond with an inquisitive and encouraging tone.

### (3) Hybrid Retrieval & Tool Routing

Because the FAISS index is empty, no local documents exceed our similarity threshold (0.65). The agent thus invokes the NCBI tool via `processing_with_model`, fetching and indexing ten new articles on antioxidants.

### (4) Response Generation

GPT-4o receives the emotion-aware prompt plus the retrieved documents as context, and produces a tailored answer (e.g., recommendations for berries, green tea, and dark chocolate), both informative and tonally aligned with “curiosity.”

### (5) Follow-Up Query & Stack RAG in Action

On the next question:

“Coffee and inflammation?”

the classifier logs:

[LOG] Emotion detected: admiration (0.50)

We rewrite the prompt to:

“What are the positive effects of coffee on inflammation, and why is it so admired for its potential benefits?”

Now, the FAISS index contains three antioxidant-related embeddings. The agent returns these and retrieves the remaining seven coffee-specific articles, demonstrating how the stack-style RAG approach incrementally enriches the local knowledge base.

**Key takeaway:** By inserting an emotion-aware rewriting step before both retrieval and generation, the agent produces responses that are simultaneously scientifically grounded and emotionally attuned to the user’s current state.

## 6 CONCLUSION

We have presented a hybrid retrieval-augmented generation framework for a nutrition-focused chatbot that seamlessly integrates emotion-aware prompting with a dynamic RAG pipeline. By combining a fine-tuned RoBERTa classifier for affect detection, GPT-4o for empathetic response generation, and a stack-style FAISS+NCBI retrieval mechanism, our system delivers advice that is both scientifically grounded and emotionally resonant. The hybrid search design continuously enriches the local knowledge base, reducing latency for repeat topics and progressively expanding domain expertise. Experimental interactions—such as the sequential “antioxidants” queries—demonstrate how the model reuses previously ingested documents and minimizes external lookups over time. Overall, this

architecture offers a scalable, adaptive solution for personalized, evidence-based nutritional guidance.

## REFERENCES

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# A APPENDIX: EXPERIMENT RESULTS

Device set to use cpu

👋 Welcome to the Nutritional RAG Chatbot!  
Ask me anything about nutrition, or click one of the sample questions below.

>>> You: How can I incorporate more antioxidants into my diet?  
...thinking...

===== Human Message =====  
I'm curious about finding ways to add more antioxidants to my diet. What are some effective and enjoyable options I could try?  
===== Ai Message =====  
To enhance your diet with more antioxidants, consider incorporating a variety of colorful fruits and vegetables, as they are typically rich in these beneficial compounds. Here are some delicious and effective options:  
1. **Berries**: Blueberries, strawberries, raspberries, and blackberries are all packed with antioxidants. You can enjoy them fresh, in smoothies, or as toppings for yogurt and  
  
\*\*\* \*\* \*\* \*\* \*\*  
>>> You: Coffee and inflammation?  
...thinking...

===== Human Message =====  
What are the positive effects of coffee on inflammation, and why is it so admired for its potential benefits?  
===== Ai Message =====  
Tool Calls:  
NCBI (call\_2c9Xi0coU0lV1aMk02GV60pf)  
Call ID: call\_2c9Xi0coU0lV1aMk02GV60pf  
Args:  
query: positive effects of coffee on inflammation  
top\_k: 5  
===== Tool Message =====  
Name: NCBI  
["The aim of the study was to systematically review and analyze results from observational studies on coffee, caffeine, and tea consumption and association or risk of  
  
\*\*\* \*\* \*\* \*\*  
Staying awake...  
Staying awake...  
===== Ai Message =====  
Coffee is admired for its potential anti-inflammatory benefits due to several bioactive compounds it contains, such as chlorogenic acids, caffeine, and diterpenes like cafestol and kahweol. Research indicates that coffee consumption is associated with reduced inflammation and a lower risk of several inflammation-related conditions, such as cardiovascular diseases, diabetes, and certain cancers. Coffee's anti-inflammatory properties are primarily attributed to its ability to increase adiponectin levels, which in studies, have been linked to the consumption of filtered or medium and dark roasted coffee.  
  
Additionally, the Maillard reaction during coffee roasting enhances its overall antioxidant capacity, further contributing to reducing inflammation. This makes coffee a super functional food, helping in the fight against inflammatory diseases. The complex effects of coffee, including its influence on the expression of inflammatory markers like C-reactive protein (CRP), interleukin-6 (IL-6), and others, suggest that coffee can play a significant role in modulating inflammation.  
  
The admiration for coffee's potential benefits extends beyond its anti-inflammatory properties to possible protective effects against neurodegenerative diseases, liver conditions, and mood disorders, positioning coffee as a valuable dietary component in managing inflammation and related diseases.

Sample questions:

How can I incorporate more antioxidants into my diet?

What's the effect of sugar on overall health?

Are there any foods that can improve skin health?

Exit System. See You Next Time !

Your question:

Question:

Submit

[LOG] Emotion detected: curiosity (0.60)  
[LOG] Rewritten prompt: I'm curious about finding ways to add more antioxidants to my diet. What are some effective and enjoyable options I could try?  
[LOG] Emotion detected: admiration (0.50)  
[LOG] Rewritten prompt: What are the positive effects of coffee on inflammation, and why is it so admired for its potential benefits?

Figure 4: Emotion-Aware RAG Experiment with Agent

Device set to use cpu

Human Message

I'm curious about the benefits of drinking coffee. Could you also recommend some of the best coffee shops in Long Island City?

Tool Call

NCBI (call\_AYGgf5jyv9I3fDwgCMbYIKuL)  
call ID: call\_AYGgf5jyv9I3fDwgCMbYIKuL  
Args:  
query: benefits of drinking coffee  
tavily\_search\_results\_json (call\_8e54vFe5IPWtUwEWTnqBU3I)  
call ID: call\_8e54vFe5IPWtUwEWTnqBU3I  
Args:  
query: best coffee shops in Long Island City  
content: [{"title": "The 6 Best Coffee Shops in Long Island City - Two Sisters Abroad", "url": "https://twosistersabroad.com/the-6-best-coffee-shops-in-long-island-city/", "content": "Located right in the heart of Long Island City, just a few blocks from the Court Square subway, The Mill is a rustic, cozy coffee shop with great coffee and food options. The quaint cafe is peaceful and relaxing. It's the perfect location to grab a coffee and a snack with friends, or to visit on your own for a little caffeine pick-me-up. [...] The shop is small, but it does offer seating at four large round tables, which serve as the perfect location to chat, read or work on your laptop. The coffee is good, and also reasonably priced at \$2.50 for a small drip coffee and \$3.75 for a small cold brew. I regularly stop by The Mill for coffee to-go and have always had a great experience.\\n\\nEtto Espresso Bar [...] Their menu is also very reasonably priced - making the cafe stand out even more. Bagel sandwiches are about \$5.75 each, and you can get a combo with a bagel sandwich and a hot coffee for \$6.65. They have a wide variety of bagel flavors and toppings, so you're sure to find something you like. Keep in mind that they do have a no laptop policy from 8am-2pm, due to the small space. This is probably not the best"}]

Sample questions:

How can I incorporate more antioxidants into my diet?

What's the effect of sugar on overall health?

Are there any foods that can improve skin health?

Exit System. See You Next Time !

Your question:

Question: Or ask your own question

Submit

LOG

Emotion detected: curiosity (0.72)

LOG

Rewritten prompt: I'm curious about the benefits of drinking coffee. Could you also recommend some of the best coffee shops in Long Island City?

Device set to use cpu

Tool Message

Name: tavily\_search\_results\_json  
[{"title": "The 6 Best Coffee Shops in Long Island City - Two Sisters Abroad", "url": "https://twosistersabroad.com/the-6-best-coffee-shops-in-long-island-city/", "content": "Located right in the heart of Long Island City, just a few blocks from the Court Square subway, The Mill is a rustic, cozy coffee shop with great coffee and food options. The quaint cafe is peaceful and relaxing. It's the perfect location to grab a coffee and a snack with friends, or to visit on your own for a little caffeine pick-me-up. [...] The shop is small, but it does offer seating at four large round tables, which serve as the perfect location to chat, read or work on your laptop. The coffee is good, and also reasonably priced at \$2.50 for a small drip coffee and \$3.75 for a small cold brew. I regularly stop by The Mill for coffee to-go and have always had a great experience.\\n\\nEtto Espresso Bar [...] Their menu is also very reasonably priced - making the cafe stand out even more. Bagel sandwiches are about \$5.75 each, and you can get a combo with a bagel sandwich and a hot coffee for \$6.65. They have a wide variety of bagel flavors and toppings, so you're sure to find something you like. Keep in mind that they do have a no laptop policy from 8am-2pm, due to the small space. This is probably not the best location to come to get work done - but it is an awesome breakfast spot!\\n\\nThe Mill", "score": 0.9205687}, {"title": "The 50 best coffee shops and best cafes in Long Island City", "url": "https://wanderlog.com/list/geoCategory/288013/best-coffee-shops-and-best-cafes-in-long-island-city", "content": "The 50 best coffee shops and best cafes in Long Island City - 1 Partners Coffee - 2 Sweetleaf Coffee Roasters - 3 Coffee Project New York | East Village - 4", "score": 0.8995547}]

AI Message

## Benefits of Drinking Coffee  
Research shows that coffee consumption is associated with several potential health benefits:  
  
- \*\*Type 2 Diabetes and Metabolism:\*\* Coffee consumption has been linked to a reduced risk of type 2 diabetes, as well as improvements in glucose tolerance and insulin sensitivity. This is believed to be due to compounds such as chlorogenic acids in coffee.  
  
- \*\*Cardiovascular Health:\*\* Coffee consumption is associated with a lower risk of cardiovascular disease (CVD), including coronary heart disease and stroke. However, excessive coffee consumption may have adverse effects, such as raising cholesterol levels and affecting blood pressure.

Sample questions:

How can I incorporate more antioxidants into my diet?

What's the effect of sugar on overall health?

Are there any foods that can improve skin health?

Exit System. See You Next Time !

Your question:

Question: Or ask your own question

Submit

LOG

Emotion detected: curiosity (0.72)

LOG

Rewritten prompt: I'm curious about the benefits of drinking coffee. Could you also recommend some of the best coffee shops in Long Island City?

Device set to use cpu

While moderate coffee consumption (about 3 to 4 cups a day) appears beneficial for most adults, it may cause side effects like anxiety and insomnia in some individuals. Pregnant women should be cautious due to potential risks.

## Best Coffee Shops in Long Island City  
If you're looking for great coffee spots in Long Island City, here are some options:  
  
1. \*\*The Mill\*\*\*: A cozy, rustic coffee shop with a peaceful atmosphere. Great for grabbing a coffee or snack with friends.  
2. \*\*Etto Espresso Bar\*\*\*: Known for its reasonably priced menu and delicious bagels. Perfect for breakfast, though it has a no-laptop policy during busy morning hours.  
3. \*\*Partners Coffee\*\*\*: Known for its quality coffee and inviting atmosphere.  
4. \*\*Sweetleaf Coffee Roasters\*\*\*: Popular for its artisanal roasts and unique coffee blends.  
5. \*\*Coffee Project New York\*\*\*: A place to enjoy experimental and classic coffee drinks in a chic setting.  
Feel free to explore these spots to find your new favorite coffee hangout in Long Island City!

Sample questions:

How can I incorporate more antioxidants into my diet?

What's the effect of sugar on overall health?

Are there any foods that can improve skin health?

Exit System. See You Next Time !

Your question:

Question: Or ask your own question

Submit

LOG

Emotion detected: curiosity (0.72)

LOG

Rewritten prompt: I'm curious about the benefits of drinking coffee. Could you also recommend some of the best coffee shops in Long Island City?

Figure 5: ReAct Agent Tooling