

FoodSky: A Food-oriented Large Language Model that Passes the Chef and Dietetic Examination

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Abstract—Food is foundational to human life, serving not only as a source of nourishment but also as a cornerstone of cultural identity and social interaction. As the complexity of global dietary needs and preferences grows, food intelligence is needed to enable food perception and reasoning for various tasks, ranging from recipe generation and dietary recommendation to diet-disease correlation discovery and understanding. Towards this goal, for powerful capabilities across various domains and tasks in Large Language Models (LLMs), we introduce Food-oriented LLM FoodSky to comprehend food data through perception and reasoning. Considering the complexity and typicality of Chinese cuisine, we first construct one comprehensive Chinese food corpus FoodEarth from various authoritative sources, which can be leveraged by FoodSky to achieve deep understanding of food-related data. We then propose Topic-based Selective State Space Model (TS3M) and the Hierarchical Topic Retrieval Augmented Generation (HTRAG) mechanism to enhance FoodSky in capturing fine-grained food semantics and generating context-aware food-relevant text, respectively. Our extensive evaluations demonstrate that FoodSky significantly outperforms general-purpose LLMs in both chef and dietetic examinations, with an accuracy of 67.2% and 66.4% on the Chinese National Chef Exam and the National Dietetic Exam, respectively. FoodSky not only promises to enhance culinary creativity and promote healthier eating patterns, but also sets a new standard for domain-specific LLMs that address complex real-world issues in the food domain. An online demonstration of FoodSky is available at <http://222.92.101.211:8200>.

Index Terms—Food Computing, Large Language Models, Instruction Tuning, Retrieval Augmented Generation.

I. INTRODUCTION

Food is fundamental to human survival and culture, closely linked to social values and personal habits [1], [2]. The rich diversity not only enhances our gastronomic experience but also contributes to the complex world of food data [3], [4]. As society continually evolves, so does the complexity of the food system, leading to the accumulation of vast amounts of data related to culinary practices [5], [6], consumption patterns [1], [7], [8] and nutritional content [9], [10]. Food computing has emerged as a key interdisciplinary field towards

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food intelligence, which leverages this wide range of data to enables critical applications from farm to fork [11]–[13], such as agricultural advice [14]–[16], food robot control [17]–[19], culinary creation [20]–[22], dietary tracking [23], [23] and chronic disease prevention [24]–[26].

Within the broad spectrum of food computing, cuisine and nutrition stand out as two critical topics due to their direct impact on people's daily lives and well-being. Recent studies have explored various tasks, such as ingredient recognition [27]–[29], recipe retrieval [5], [30], [31] and nutrition assessment [32]–[34]. For example, ingredient recognition based on the Transformer model has achieved promising results and empowered fine-grained food perception in various applications [35]. However, the topics of culinary and dietary are complex, as they are closely related to and interact with real-world factors such as cuisine culture and chronic diseases. Previous studies have usually addressed these areas separately, ignoring the potential benefits their integration could bring to food computing research and applications.

Driven by the growth of food systems, the transition from analyzing local data to accumulating massive global datasets is providing new solutions in food computing [36], [37]. This shift supports the implementation of Large Language Models (LLMs), which have demonstrated superior ability to address complex real-world problems in different domains [38], such as medicine [39], [40], education [41], [42], and finance [43], [44]. Through extensive pretraining and instruction fine-tuning on massive datasets, these models can precisely understand and generate natural language, making them well-suited for tasks involving knowledge and reasoning, such as medical diagnosis [45] and clinical report generation [46]. The success in these areas highlights the potential of a food-specific LLM. The food-specific LLM could leverage massive datasets to deliver precise information perception, understanding and reasoning capabilities tailored to the food domain, addressing critical challenges such as dietary analysis, food recommendations, nutritional diet and cooking advice. This integration of food computing and LLM aims to deliver data-centric insights in food research, enhance user experiences in food applications, and pave one possible way for food intelligence.

Despite the growing interest in LLMs, there have been limited efforts to develop reliable LLMs specifically designed for the culinary and dietetic fields. Recently, some researchers have recognized the potential of LLM in the food domain and have begun applying LLMs in the development of dietary assistants. One notable example is FoodGPT [47], which proposed a framework to build a knowledge base through

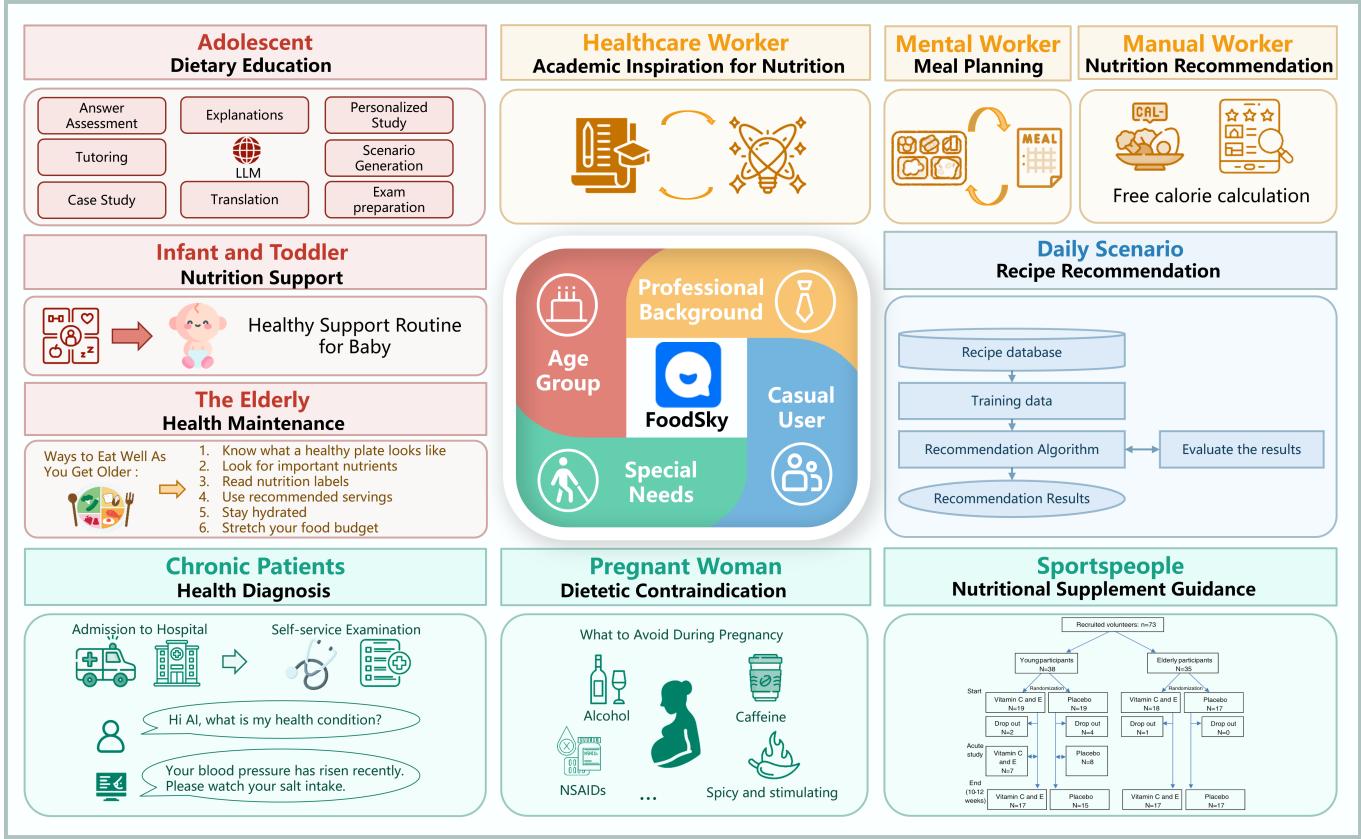


Fig. 1. The potential applications of the proposed food-oriented LLM FoodSky in different scenarios.

a knowledge graph and develop an LLM specific to food. However, FoodGPT has not released a fully-trained model for further development by other researchers. Another study [48] focused on establishing a dietary assistant with the functions of ingredient substitution and recipe recommendation using a food-oriented language model. Furthermore, FoodLMM [49] expands on these efforts by creating a multi-task dietary assistant that recognizes food and estimates nutrition simultaneously based on existing multimodal foundation models. These studies highlight the growing interest in using LLMs to address challenges in the food domain and demonstrate the potential for further development of dietary assistants.

Although existing dietary assistants have made significant progress in areas such as multimedia dietary analysis and recommendation, they still have several limitations. First, previous food LLMs were developed based on general language models pre-trained in common scenarios, which can not fully understand and process the fine-grained characteristics of food information, resulting in inaccurate identification and analysis results. Specifically, the lack of certain culinary and dietary knowledge significantly limits their utility in practical food applications, such as ingredient substitution and nutrition assessment. Furthermore, current LLMs have not been adequately tailored to cover the extensive diversity of dietary practices and culinary traditions across various cultures. Recent research has shown that existing LLMs exhibit biases towards Western food knowledge, leading to potentially incorrect or culturally insensitive responses when handling queries from more diverse

backgrounds [50].

To address these problems, we introduced FoodSky¹, the first Chinese LLM specifically tailored to the food domain. The development of FoodSky, however, faced significant challenges. First, there is a lack of a large-scale food corpus. Unlike fields such as news and media, where data is abundant, food data is relatively limited and scattered across various sources including cooking websites, recipe databases, food blogs, etc. The quality of these data also varies, with spelling and grammar errors, duplicate invalid data, and irrelevant information that complicates the data cleaning process. Second, the food domain covers a wide range of topics including ingredients, cuisines, eating habits, and nutritional information, posing a challenge for the model to understand and handle these diverse topics comprehensively and effectively. Lastly, the cross-cultural nature of food requires the ability to process food-related knowledge across various cultural contexts. Different regions and cultures have distinct eating habits, taste preferences, and cooking traditions, which adds additional complexity for LLMs in handling food queries from various backgrounds.

To overcome these challenges, we first conducted comprehensive data collection and processing to build the first large-scale food-related Chinese corpus, FoodEarth. This corpus contains 811K instruction data from various authoritative sources such as e-books and websites, which were processed

¹As the old Chinese saying goes: food is the most important issue under the sky. Therefore, we name our constructed food-oriented LLM as FoodSky.

through multiple data filtering methods to obtain a high-quality dataset. To enable the model to understand comprehensive and diverse domain knowledge and effectively handle different topic tasks, we developed a Topic-based Selective State Space Model (TS3M) to capture fine-grained food semantics and adapt to diverse topics. Furthermore, we propose a Hierarchical Topic Retrieval Augmented Generation (HTRAG) mechanism to ensure that the model has better generalization and can handle food-related information from different cultural backgrounds based on knowledge enhancement.

Based on the FoodEarth database, TS3M and HTRAG, the proposed FoodSky demonstrates expert-level performance in both chef and dietetic examinations. In particular, FoodSky passes the National Chef Exam and the National Dietetic Examination in China with zero-shot accuracy of 67.2% and 66.4%, respectively. More experiments, including both qualitative and quantitative evaluations, further show that FoodSky achieves better performance compared to existing LLMs including InternLM2 [51] and ChatGPT-3.5 [52] on the Chinese National Chef Exam and the National Dietetic Exam, demonstrating its ability to provide reliable advice for various culinary and dietetic questions. As shown in Fig. 1, the proposed FoodSky aims to enhance culinary creativity, promote dietary health and benefit diverse groups of people across various scenarios and applications.

II. RELATED WORK

This section reviews studies on recent advances related to Large Language Models and food assistant.

A. Large Language Models

Language is a primary ability in human beings to express and communicate, which develops in early childhood and evolves over a lifetime [53]. However, machines cannot naturally understand and communicate with human language. Therefore, Language Models (LMs) are proposed to enable machines to read and write like humans [54]. LMs model the generative likelihood of word sequences, predicting the probabilities of future tokens. Research on LMs has gone through four stages: Statistical Language Models (SLMs), Neural Language Models (NLMs), Pre-trained Language Models (PLMs), and Large Language Models (LLMs) [55]. Initially, SLMs focused on enhancing task-specific methods by predicting probabilities and NLMs learned task-agnostic representations to reduce manual feature engineering. Furthermore, PLMs learned context-aware representations through large-scale pretraining. As the latest generation, LLMs stand out based on the scaling effect on model capacity.

Typically, LLMs refer to Transformer models that contain hundreds of billions (or more) of parameters, trained on massive textual data [56], such as GPT-3 [57], PaLM [58], Galactica [59], and LLaMA [60]. The concept of data-centered artificial intelligence (DCAI), initiated by Ng *et al.* [61], emphasizes the importance of data over model architecture. This concept is also known as data-centric thinking, where the size and quality of the data are the most crucial factors for developing powerful AI models [55].

Based on the data-centric concept, LLMs are having a significant impact on the AI community, triggering major transformations across multiple research areas [62], [63]. In the field of Natural Language Processing (NLP), LLMs are being used as general-purpose language task solvers. In Information Retrieval (IR), traditional search engines are challenged by AI-driven chatbots. In Computer Vision (CV), researchers are developing GPT-like Multimodal Large Language Models (MLLMs) to address multimodal issues [64]–[67]. Furthermore, LLMs have been employed in addressing various real-world challenges including medicine [39], [40], education [41], and finance [43]. In medicine, LLMs like ChatGPT have shown potential in medical education [68], radiologic decision-making [69] and clinical genetics [70]. Medical-specific LLMs such as Baize [45], Zhongjing [40] and Huatuo [46] are achieving better performance in these medical tasks. In education, LLMs can generate personalized content [38], [71], assist with homework [72], and provide real-time feedback in the process of self-study [42]. In finance, the financial LLMs, including FinMA [73], InvestLM [74], FinGPT [75], and BloombergGPT [44] are enhancing customer services and providing financial advisory in risk assessment, algorithmic trading and market prediction [75].

Different from these LLMs, FoodSky addresses the unique needs of the food domain through the understanding of the culinary arts and nutritional science. In addition, while general-purpose LLMs may struggle with diverse food topics and cultural backgrounds, the TS3M architecture in FoodSky enables it to capture fine-grained topic differences and the proposed HTRAG ensures the model with more precise and background-aware responses. This capability makes FoodSky stand out as a powerful tool that will influence culinary professionals, dietitians, and consumers, setting a new standard for the application of AI in food-relevant domains.

B. Food Computing

Food computing is an interdisciplinary field that uses computational methods to address food-related problems in the fields of medicine, biology, gastronomy, and agronomy, thereby playing an important role in academic research and industry applications [11]. Academically, food computing brings challenging research topics such as fine-grained recognition to the research community of machine learning [37], [76]. Industrially, food computing enables various key applications such as smart agriculture [4], [77], automated food processing [78], [79] and food recommendation [80], [81].

Among the tasks in the field of food computing, dietary assistant is one important application that can help consumers make smarter and healthier dietary choices [49], [82]. It enables intelligent methods in food scenarios like daily cooking, nutrition, and diet health, driven by advances in various research areas such as food recommendation [80] and recipe retrieval [5]. Closely related to dietary assistant, food recommendation is important for diet analysis and health management [83]–[86]. For example, Chu *et al.* [87] built a hybrid recommendation system by analyzing images in restaurant blogs, and Asani *et al.* [88] extracted food names

from user reviews to analyze dietary feelings. In addition, Ling *et al.* [89] made recommendations based on behavioral data of users who have successfully lost weight, and Ribeiro *et al.* [90] considered the nutrition, preferences, and budget of the elderly for meal recommendations. Recipe retrieval is another important research topic that provides recipe advice in culinary scenarios [91]–[94]. It is worth noting that Zhu *et al.* [30] and Guerrero *et al.* [95] use GAN to generate images and improve retrieval performance, and Salvador *et al.* [31] uses a classifier and a Transformer decoder to generate recipe content based on the input images, and obtains higher generalization than conventional retrieval methods.

As LLMs have shown the ability to address complex real-world issues related to knowledge reasoning in various fields, it has been recently explored in the dietary assistant domain. For example, Qarajeh *et al.* [96] evaluated the efficacy of different LLMs in identifying potassium and phosphorus levels in foods, and used LLMs to plan healthier diets to prevent complications such as hyperkalemia and hyperphosphatemia. Yin *et al.* [49] proposed a versatile dietary assistant FoodLMM based on the LLaVA [97]. FoodLMM has multi-tasking capabilities for food recognition, ingredient recognition, food segmentation, recipe generation, nutrition estimation and multi-round conversation. Nag *et al.* [98] proposed a personal health navigation framework that estimates current health status based on personal models, and guides the user towards their healthy goal.

Currently, there is no available comprehensive dataset for food recipe advice, food science popularization, diet recommendations and nutrition assessment. Therefore, we establish the first large-scale Chinese instruction dataset FoodEarth for the food domain. Specifically, unlike previous studies of other domains like medicine [39], [40] and education [41], [43], we adopted a multi-stage dataset construction pipeline that is designed to particularly address the diverse sources and complex raw data problems for Chinese food data. Based on this, the fundamental LLM FoodSky can be built to provide culinary insights and dietary guidance directly for users while boosting the research on dietary assistant and food computing.

III. DATASET

This section details the construction of a large-scale Chinese instruction dataset for the food domain, which is illustrated in Fig. 2. The dataset was compiled from diverse Chinese authoritative sources, including nutrition databases, academic journals, and expert-endorsed websites. To ensure the data quality, we sort the sources of raw data by level, followed by a data annotation process to get the logical instruction data. In the data annotation process, we conduct semi-automated data filtering and semi-automated data annotation. To reduce the repetition rate in the dataset and increase the professionalism of the data, we finally completed the construction of the dataset with experts through similarity-based screening. The established dataset FoodEarth, consisting of 811,491 question-answer pairs, provides a robust foundation for fine-tuning LLMs in the food and nutrition domain.

A. Data Source Sorting

The main goal of our research is to provide professional consulting services in the domain of cuisine and diet. Our goal was to build a comprehensive knowledge base from six key areas of food expertise: Dietary science, Dietary advice, Food flavour profiles, Food safety measures, Food recipes and Healthy eating principles.

Textual data in the cuisine and diet domain is unique and complex due to its diverse sources. Data in fields like medicine and finance typically exhibit clear cause-and-effect relationships, such as in disease treatment mapping and economic regulation consulting. In contrast, food-related data vary in credibility and often present conflicting opinions. The complexity of cooking, diet, nutrition and science data arises from individual taste preferences, variations in food measurements, regional food diversity and different cooking methods.

To address these challenges, our textual dataset is built based on a wide range of authoritative sources, enhancing its reliability and comprehensiveness and providing a detailed understanding of this field. This diversity is crucial, as it captures the range of cooking techniques and personalized nutrition, making it different from datasets in other fields. The combination of information from various origins ensures that our dataset models the unique characteristics of the cuisine and diet domain, focusing on specific food challenges.

Currently, mainstream food data widely exists in professional books, authoritative nutrition papers, authoritative websites, public accounts and other online channels. As shown in Fig. 3, we divided the data sources into knowledge graph data source, authoritative data source, online databases and resources, and public Chinese instruction dataset, and then reorganized the data according to the authority and timeliness of the data.

In the food field, we accumulated millions of food nutrition and recipe knowledge graph data nodes through the above-mentioned authoritative website content as the core data content of this study. CNKI professional papers and authoritative websites in the field serve as secondary data sources including dietary recommendations, healthy eating principles, food safety measures, food flavor profiles and dietary science professional data. In addition, we also compiled other resources and generated data related to food and beverages through ChatGPT and public Chinese datasets as reference datasets to enrich our data scope. In the end, through multiple rounds of manual annotation, professional filtering, ChatGPT data processing and other data cleaning methods, we collected a pure text dataset of more than 2.5 billion tokens and completed the construction of a Q&A dataset with 811,491 pairs.

B. Data Annotation

In the process of constructing a high-quality dataset, we employed a semi-automated strategic combining automated processing and manual processing to ensure the quality and practicability of our established FoodEarth. Specifically, our processing procedure can be divided into two stages: semi-automated data filtering and semi-automated data annotation. During the semi-automated data filtering stage, we utilized the

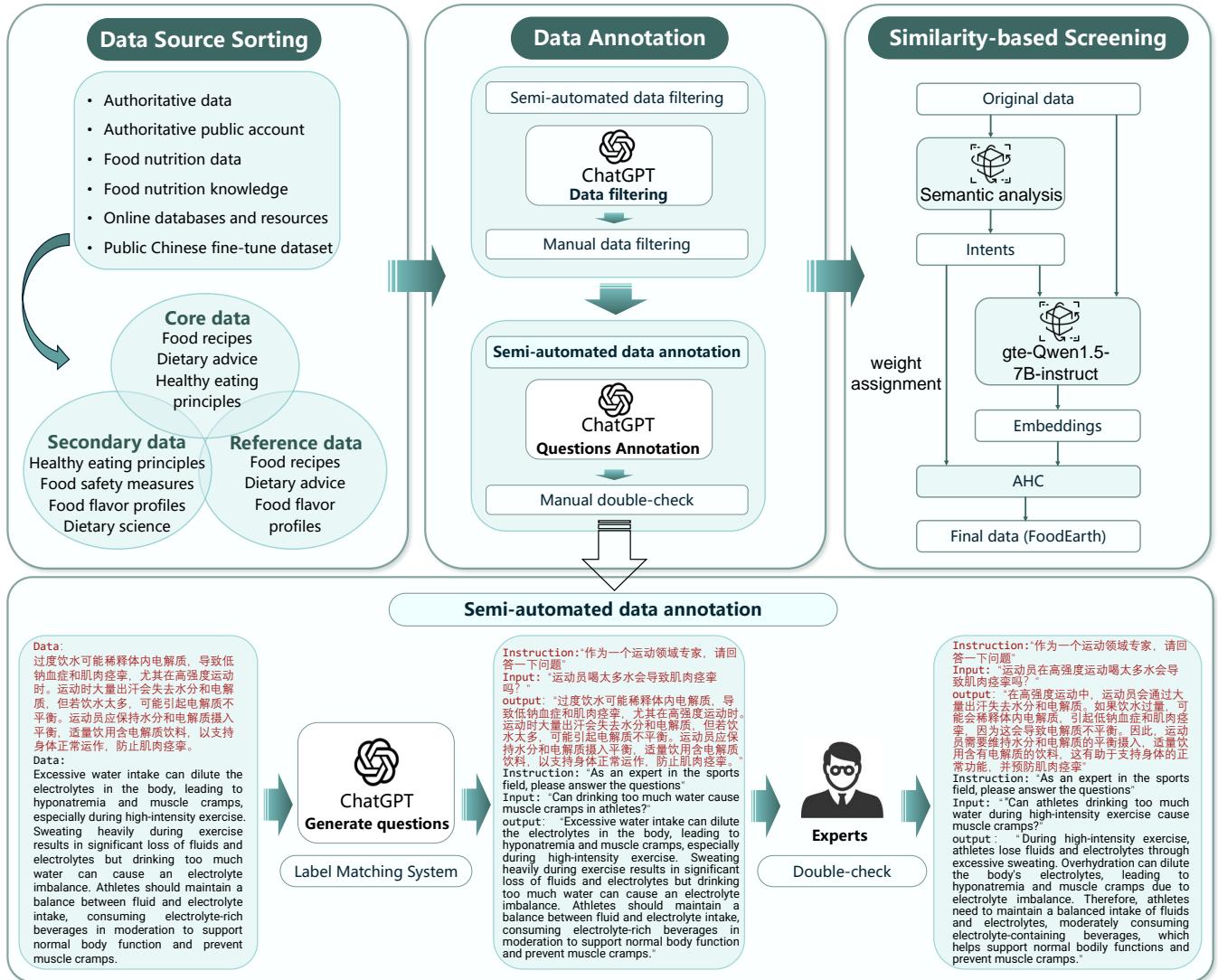


Fig. 2. The pipeline of establishing FoodEarth includes data source sorting, data annotation and similarity-based data screening. The semi-automated data filtering and annotation are the main procedures in data annotation. The AHC refers to the Agglomerative Hierarchical Clustering approach.

semantic understanding capabilities of ChatGPT to analyze the raw Chinese public question-answer dataset and identify food-related content, which reduced the workload of manual filtering. In the data annotation stage, we employed the ChatGPT API to generate diverse questions based on the filtered food-related raw data. Our annotation team then thoroughly reviewed each generated question and answer (Q&A) pair, validating the accuracy of the questions and answers. Any inaccurate or ambiguous Q&A pairings are improved or replaced to meet our strict standards. At each stage, we utilize ChatGPT to enhance efficiency, while incorporating manual verification and refinement by our expert annotation team to ensure accuracy.

1) *Semi-automated Data Filtering:* During the semi-automated data filtering process, we completed the work in three stages due to the wide variety of food text datasets, the wide range of sources, and the uneven levels of data quality. Initially, our team performed manual filtering based on pre-set quality criteria and relevance metrics. For example, we

first filtered out noise data such as irrelevant modal words and emoticons. This stage involved ten team members with data processing experience using the data mining system simultaneously. It took nearly a month to complete the preliminary data cleaning and store it in a dictionary format as the initial filtered data to facilitate subsequent processing.

Based on the manual filtering, we further enhanced the data filtering process by leveraging the ChatGPT API. As shown in Fig. 4, we set up a prompt mechanism to identify and remove irrelevant data, requiring ChatGPT to return 0 for text data that did not belong to the research topic as a negative sample, and return 1 for relevant text data as a positive sample. We then used the filtering system to judge the return value, filtering out the negative sample data and retaining only the positive sample data. We recorded this as secondary filtered data, which can reveal fine-grained correlation patterns that human filters may have missed.

After processing with ChatGPT, we submitted the dataset to three domain experts with deep expertise in food safety and

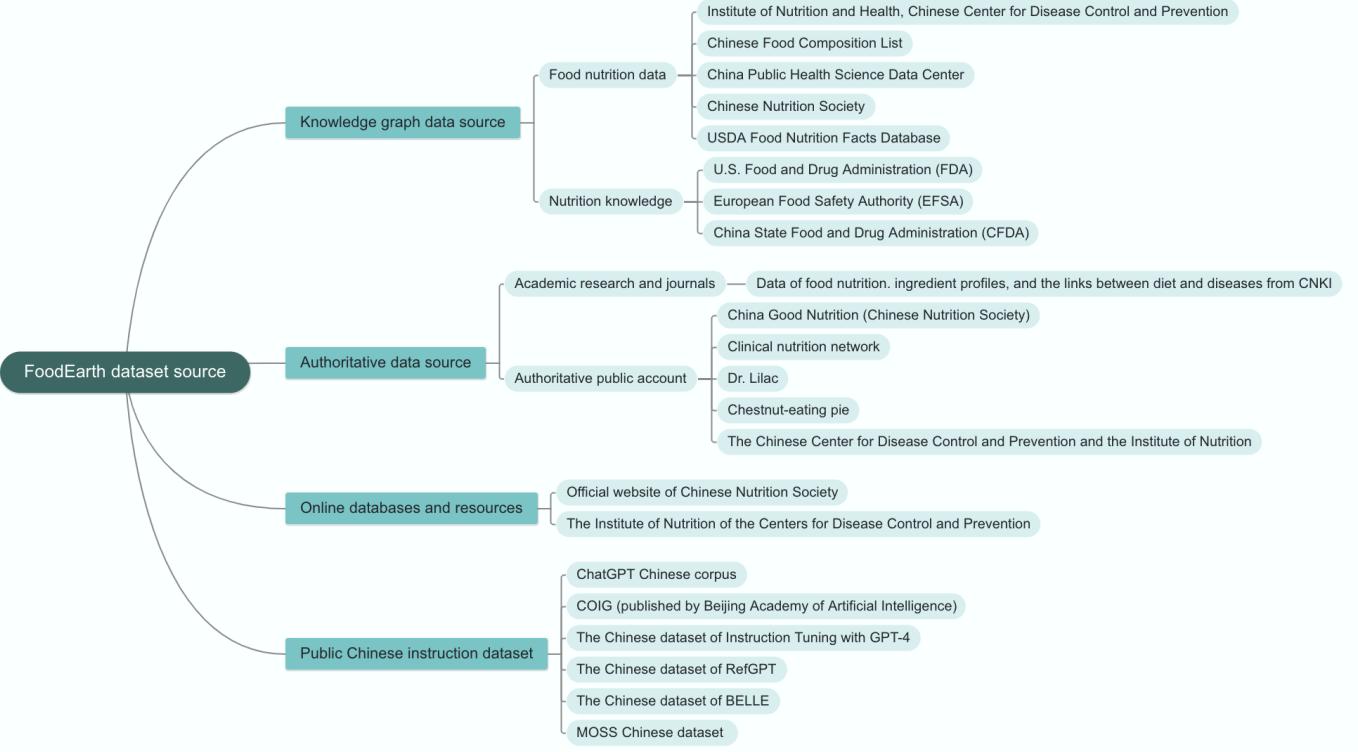


Fig. 3. The illustration of authoritative data sources of our FoodEarth.

TABLE I
DATA VOLUME PROPORTION AND DATA CONTENT OF EACH DATA SOURCE

Source Origin	Raw data	Instruction	Modalities	Data Types	License
Authoritative public account	25,482,971 tokens	8,401 pairs	text	news,article	CC BY-SA 3.0
Authoritative Data	22,680,536 tokens	12,424 pairs	text	report, academic papers, book	CC BY-SA 3.0
Knowledge graph data	6,480,672 tokens	538,376 pairs	structured data	knowledge graph	CC BY-NC 3.0
Public Chinese fine-tune dataset tokens	448,774,454 tokens	253,986 pairs	structured data	fine-tune dataset	Publish

nutrition. These experts conducted a comprehensive double-check on the filtered dataset, verifying its relevance and assessing the authenticity and trustworthiness of the data. They ensured the accuracy and usefulness of the dataset by comparing it with the latest literature and industry reports, ensuring fully cleaned final data. This step is important throughout the data preparation process, as the quality of the data may ultimately influence the health and physical well-being of users who rely on the information provided by the fine-tuned LLM.

2) *Semi-automated Data Annotation:* To effectively refine an LLM, we make more efforts to construct a comprehensive text-based question-answering (Q&A) training dataset, specifically tailored to the food domain. We carried out a dual process of automated generation and manual verification to ensure the quality of the dataset.

We used the ChatGPT API to automatically generate food-related question-answer pairs. By employing prompt engineering techniques, we carefully designed prompts that guided the model to create a diverse set of questions closely reflecting the information in the text. These prompts were iteratively

refined to ensure that the generated questions covered a broad range of information needs, from basic definitions to complex conceptual discussions. The prompts played a crucial role in directing the model to produce high-quality, relevant questions that aligned with the intended scope and depth of the dataset. After completing the construction of the question through ChatGPT, we used a simplified matching algorithm to accurately extract the text paragraph corresponding to the question from the dataset after completing the data filtering.

With the automated generation phase complete, our experienced annotation team conducts a thorough secondary inspection. This team, consisting of food science experts, engaged in a detailed review of each Q&A pair, validating the pertinence of the questions and the accuracy of the answers. Throughout the annotation process, any Q&A pairs deemed imprecise or ambiguous were directly refined or replaced to meet our exacting standards.

To further improve the quality of the established dataset, we carefully documented and reviewed the workflow of the annotation team to identify and reduce potential biases or errors.

Prompting GPT-3.5 to identify and eliminate irrelevant data

```

messages = [{"role": "system", "content": "::::
你是一位乐于助人的食品专家。你需要判断给出的文本是否包含了与人
有关的健康饮食、饮食文化与制作等和食品相关的内容，如果包含请你回
答1，如果不包含请你回答0。注意，你只需要回答一个数字::::"},

{"role": "user", "content": gpt_user_prompt}]

reply = client.chat.completions.create(
    model = "gpt-3.5-turbo-1106",
    messages = messages,
    max_tokens=1
).choices[0].message.content

```

The translation of Chinese prompt

::::
 You are a helpful food expert. You need to judge whether the given text contains content
 related to food like healthy eating, food culture and preparation, etc. If it does, please answer
 1, if it does not, please answer 0. Note that you only need to answer one number
 ::::

Fig. 4. The prompt used to automatically filter raw data based on ChatGPT in our semi-automated data filtering procedures.

This thorough review process was essential in establishing a high-quality, text-based question-answering training dataset specifically for the food domain. As shown in Fig. 5, the established dataset FoodEarth covers a wide range of food-related topics and has undergone strict quality assurance measures. As a result, FoodEarth can provide a strong foundation for fine-tuning the Chinese language model, ensuring that it is ready for complex, domain-specific applications.

C. Similarity-based Screening

After constructing FoodEarth, a large-scale food dataset that contains almost 1 million pairs of instruction data, we found that there are many semantically similar question and answer pairs, which made our model train on data that was repeated many times and failed to achieve good generalization performance. Therefore, to effectively process and deduplicate this large-scale dataset, we consider using the existing text representation model to encode the text for question and answer, and then use similarity to perform deduplication operations. We first sampled a mini-test set containing 506 pieces of data to evaluate and select the encoding model that best suits our similarity calculation task. We experimented with multiple text representation models on this mini-test set and selected the best-performing model for encoding the full dataset. Then we apply the selected encoding model to the entire dataset, transforming each piece of data into an encoding vector. By comparing the similarity of feature vectors between different data items, we use threshold setting and clustering methods to judge and identify duplicate data, and delete any data items with a similarity score higher than 0.9 with other centers of clustering in the dataset. Ultimately, this approach effectively

screens out the high-quality data by reducing data redundancy, which ensures the generalization performance of the proposed model.

1) *Mini-Test Set*: To determine the method of similarity-based screening that best fits our dataset, we first built a mini-test set to measure the performance of different embedding methods. The mini-test set consists of 506 samples, with two different sentences and a 0/1 label, representing whether the two texts are similar.

2) *Embedding Methods*: To determine the text similarity calculation method suitable for our dataset, and to better realize the similarity filtering task, we selected several models with the best text embedding performance at present and tested them on the mini-test set. We adopted several methods that currently rank high on C-MTEB, including gte-base-zh [99], gte-large-zh [99], gte-Qwen1.5-7B-instruct [99], bge-large-zh-v1.5 [100], acge_text_embedding [101], Baichuan-text-embedding [102], stella-mrl-large-zh-v3.5 [103] and puff-base-v1 [104]:

- gte-base-zh [99]: One of the GTE series models in Chinese, using the Dual Encoder framework. The model was initialized using the base model of the BERT model with 110M parameters.
- gte-large-zh [99]: One of the GTE series models in Chinese, using the Dual Encoder framework. The model was initialized using the large model of the BERT model with 330M params.
- gte-Qwen1.5-7B-instruct [99]: This model has been engineered starting from the Qwen1.5-7B LLM, drawing on the robust natural language processing capabilities of the Qwen1.5-7B model.

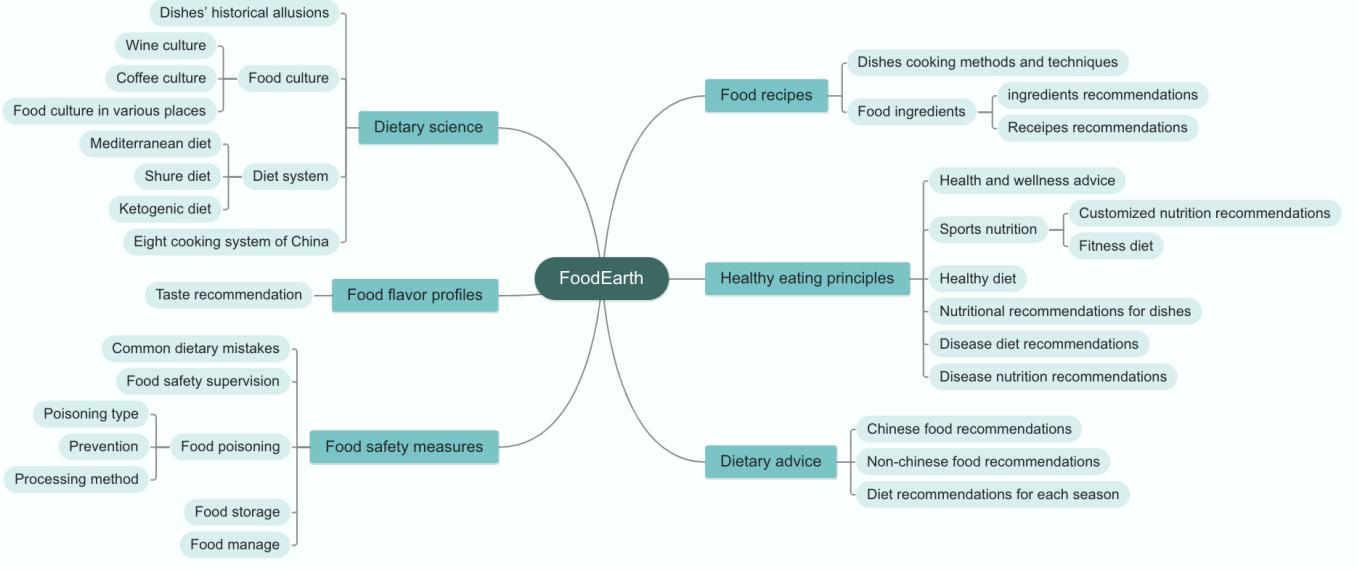


Fig. 5. Hierarchical structure of topics in our FoodEarth dataset.

- bge-large-zh-v1.5 [100]: BAAI General Embedding is a series of large embedding models open-sourced by Beijing Zhiyuan Artificial Intelligence Research Institute, referred to as BGE, and supports Chinese and English embedding. BGE-Large-zh is the Chinese vector large model with the largest parameter scale in the BGE series, with 326 million parameters. Input sequence 512, output dimension 1024.
- acge_text_embedding [101]: Compared with traditional pre-training or fine-tuning vertical domain models, the acge model supports the construction of general classification models in different scenarios, improves the accuracy of long document information extraction and has a relatively low application cost. It mainly uses the representation learning framework of Matryoshka Representation Learning (MRL).
- Baichuan-text-embedding [102]: The embedding model is self-developed by Baichuan Inc. It is pre-trained on high-quality Chinese data of more than 1.5T tokens and uses a self-developed loss function to solve the problem of contrastive learning methods relying on batch size.
- stella-mrl-large-zh-v3.5 [103]: This model is trained using the MRL method based on stella-large-zh-v3-1792d. Its main feature is variable vector dimensions.
- puff-base-v1 [104]: The Puff series of models are specifically designed for retrieval and semantic matching tasks, and pay more attention to generalization and the effect of private general test sets. The vector dimension of this model is variable and supports bilingualism in Chinese and English.

3) *Comparison of Different Embedding Methods:* To compare the performance of each model in terms of similarity calculation, we tested the above models on the mini-test set we constructed. The evaluation metrics used to assess the performance of the embedding methods include accuracy and

F1. These metrics are chosen because they effectively capture the similarity estimation performance and are widely used in the related literature.

$$\text{Accuracy} = \frac{|TP| + |TN|}{|TP| + |TN| + |FP| + |FN|} \quad (1)$$

$$F1 - score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (2)$$

We conducted experiments on several models on the mini-test set, and the experimental results are shown in Table II. The results show that each model shows excellent performance on the similarity assessment task. The accuracy rates all exceeded 98%, and only a few data were judged incorrectly, showing that existing text embedding models can understand the semantics of the food field well. Besides, The results show that the gte-Qwen1.5-7B-instruct model outperforms the other embedding methods on the mini-test set, achieving a 99.41% score of accuracy and a 99.41% score of F1. This indicates that the model is more suitable for capturing the semantic similarities between food items and distinguishing different semantics about food. Therefore, we selected this model for similar data filtering.

4) *Data Screening:* Based on the evaluation results, we use the gte-Qwen1.5-7B-instruct embedding method for data filtering and further clustering processing. We first tried to filter similar data by setting a threshold. This method first uses the gte-Qwen1.5-7B-instruct embedding model to obtain the embedding representation of all question and answer pairs in the dataset. Then we calculate the cosine similarity between each two data. We follow the threshold setting of experiments on the mini-test set and set the threshold to 0.9. When the value of cosine similarity is greater than the threshold, we regard the two pieces of data as similar data and remove the shorter data. However, this method is often inaccurate for many data whose text content is similar but the actual intention

TABLE II
COMPARISON OF SIMILARITY ESTIMATION PERFORMANCE OF DIFFERENT EMBEDDING METHODS (%)

Methods	Accuracy	F1
gte-base-zh	99.01	99.02
gte-large-zh	98.81	98.81
bge-large-zh-v1.5	99.01	99.00
acge_text_embedding	98.02	98.02
Baichuan-text-embedding	99.21	99.20
stella-mrl-large-zh-v3.5	99.01	99.02
puff-base-v1	97.43	97.50
gte-Qwen1.5-7B-instruct	99.41	99.41

is different. Therefore, we adopted a clustering method that jointly embedded representations of intentions and performed similarity filtering on the dataset. The process is given as follows:

- 1) Advanced language models are used to perform semantic analysis on question texts, identify their core intents and classify them into corresponding intent categories. These intent categories not only describe the topic of the question but also reflect its underlying user needs and goals.
- 2) The extracted intents to quantify the frequency and weight of various intents in the dataset are modeled to guide the subsequent clustering process. The model ensures that we fully understand the diversity and prevalence of intents through statistical analysis and probability distribution.
- 3) The processed question-answering data and its corresponding intent categories are input into the gte-Qwen1.5-7B-instruct text embedding model, which uses advanced text embedding technology to convert text into a high-dimensional vector representation, retain the original semantic information and reflect the semantic similarity between texts.
- 4) Agglomerative Hierarchical Clustering (AHC) is used to classify the data, after obtaining the embedding representation. AHC is a bottom-up method that forms a hierarchical structure by iteratively merging the most similar data points. We incorporate the intent distribution information into the clustering algorithm and ensure that the clustering results are based on both semantic similarity and the importance of each intent category through weight assignment. The weights are adjusted according to the probability and frequency in the intent distribution model, making data points of common intent categories more influential in the clustering.
- 5) The formation of the final data set depends on the selection of representative data points. This process takes into account the centrality of the data points in the micro-category to ensure that the data set is diverse and representative. The distance between each data point and the centre of the micro-category to which it belongs is calculated, and the data point with the smallest distance is selected to fully demonstrate the characteristics of each

category.

After completing the above steps, the dataset has been optimized to improve the quality and diversity of the dataset. We invite two experts to conduct secondary validation on this refined dataset to ensure the usability of each piece of final, thus resulting in the final version of FoodEarth with 811,491 Chinese instruction data, providing a solid foundation for further research and application.

IV. METHOD

In FoodSky, we propose two key algorithms, Topic-based Selective State Space Model (TS3M) to enhance the accuracy of the model by integrating topic-relevant information and Hierarchical Topic Retrieval Augmented Generation (HTRAG) to enable the generation of responses that are richer in informational content. The backbone model and instruction-tuning are first introduced to provide a technical background for the proposed algorithm.

A. Backbone Model

The backbone model serves as the foundation for our proposed extensions, including the Topic-based Selective State Space Model (TS3M) and Hierarchical Topic Retrieval Augmented Generation (HTRAG), which can further enhance the understanding ability of the proposed model and generate responses to food-related instructions and questions.

Specifically, our backbone model ϕ_w is an LLM (e.g. LLaMA-2) pretrained on the large-scale Chinese corpus and finetuned on Chinese instruction dataset from the general domain. We name this backbone as Chinese LLaMA-2 (CLLaMA2). To adapt the model to the specific challenges and characteristics of the food domain, we conduct food-specific finetuning. This stage involves training the model on the proposed FoodEarth dataset, which consists of food-related Chinese instructions, questions, and answers. The data covers various aspects of the food domain, including recipes, ingredients, nutrition, cuisines, and food safety. By focusing on food-specific data, the model learns to generate more accurate and informative responses to food-related queries.

B. Instruction Fine-tuning

Instruction fine-tuning plays a crucial role in adapting our backbone language model to follow instructions effectively and generate appropriate responses in the food domain. We employ an instruction fine-tuning approach with two stages: general instruction tuning and food-specific instruction tuning. Through the first stage of general instruction tuning on the large-scale general-domain dataset, we obtained the instructed-tuned backbone CLLaMA2-Alpaca. This model has the ability to understand and follow instructions in context, providing basic instruction-following capabilities.

After the general instruction tuning stage, the model has obtained a solid foundation in instruction-following. However, to specialize in the food domain, we proceed to the second stage: food-specific instruction tuning. In this stage, we further fine-tune the model using the food-related instructions and

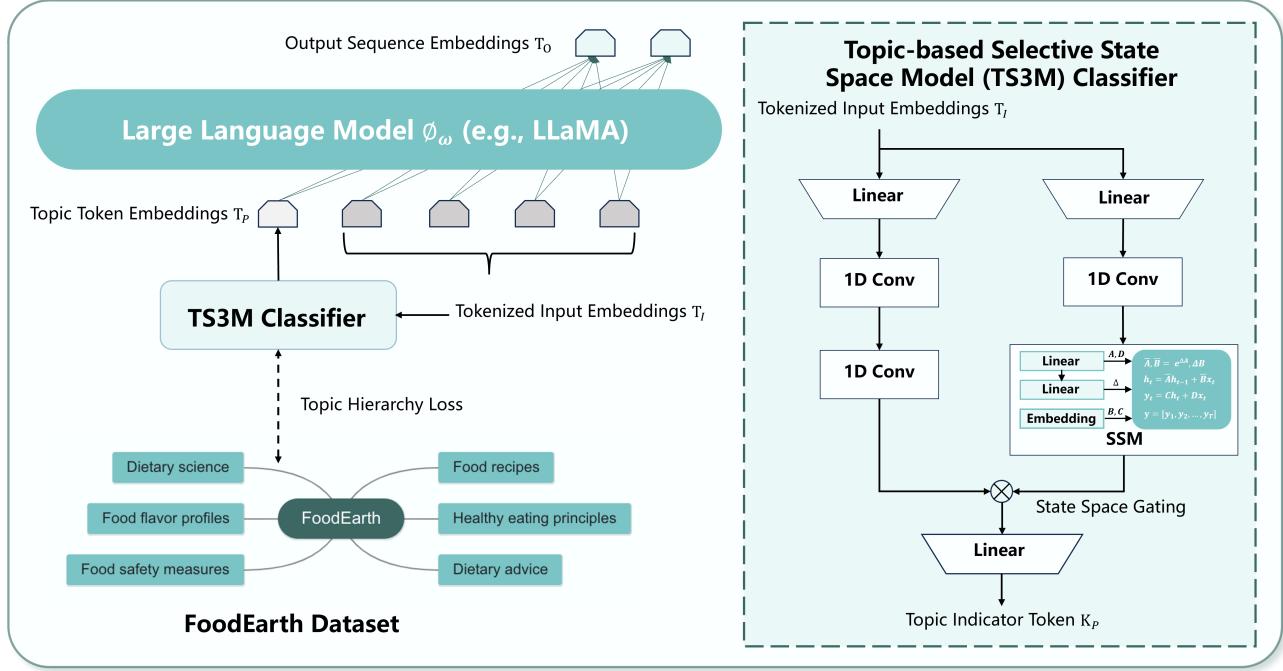


Fig. 6. The core model of the proposed FoodSky method. During the inference, the Hierarchical Topic Retrieval Augmented Generation (HTRAG) module uses the topic indicator token for food knowledge retrieval.

their corresponding responses in our proposed FoodEarth. This dataset covers a wide range of food-related topics, such as dietary science, cooking techniques, healthy eating principles, and food safety guidelines. By focusing on food-specific instructions, the model learns to understand and generate responses that are tailored to the unique terminology and challenges of the food domain, taking into account factors like ingredient properties, cooking methods, and dietary restrictions. To ensure the effectiveness of the food-specific instruction tuning, we employ several strategies:

- Data quality control: We carefully collect, process and double-check the FoodEarth dataset to ensure its accuracy, relevance, and diversity. This involves collecting data from reliable sources, such as culinary experts, food science publications, and reputable cooking websites. We also perform multiple data cleaning and preprocessing procedures involving an annotation team, automated methods, and experts to remove irrelevant or low-quality examples.
- Training techniques: During the general instruction tuning stage, we employ techniques such as masked language modeling (MLM) and next sentence prediction (NSP) to enhance the model's understanding of instructions and their relationships to the corresponding responses. MLM involves randomly masking a portion of the input tokens and training the model to predict the masked tokens based on the surrounding context. This helps the model learn to capture the semantic and syntactic patterns in the instructions. NSP, on the other hand, trains the model to predict whether a given response follows logically from the preceding instruction, improving its ability to generate coherent and relevant responses.

- Iterative fine-tuning: We employ an iterative fine-tuning approach, where we gradually increase the complexity and specificity of the food-related instructions during training. This allows the model to progressively adapt to the fine-grained characteristics and challenges of the food domain, improving its performance with more specialized capability.

C. TS3M Classifier

Fig. 6 also presents the Topic-based Selective State Space Model (TS3M). TS3M is designed to capture the semantic relationships between topic and content in the input instructions, enhances the output with prior knowledge of specific food topics, and enables the model to generate more coherent and informative responses.

TS3M takes the tokenized instruction embeddings $T_I \in \mathbb{R}^{n \times d_m}$ as input, where n represents the number of tokens and d_m is the embedding dimension of tokens. It employs a two-branch architecture consisting of a content representation branch and a topic state representation branch. The content representation branch combines linear and convolutional layers to refine semantic embeddings progressively through multiple layers. The topic state representation branch is designed to influence the output of the model with the selectively integrated internal state.

On the content representation branch, the initial layer first transforms the input token embeddings to adapt their dimensionality for convolutional processing:

$$X_L^1 = T_I W^1 + b^1, \quad (3)$$

where $W^1 \in \mathbb{R}^{d_m \times d_l}$ and $b^1 \in \mathbb{R}^{d_l}$ represent the weights and biases of the linear transformation, the dimension d_l of

the projected input. After the linear transformation, we obtain the projected input $\mathbf{X}_L^1 \in \mathbb{R}^{n \times d_L}$. Furthermore, a series of one-dimensional convolutional (1D Conv) layers refine these embeddings based on context relationships among tokens.

Specifically, two 1D Conv layers are implemented to model the relationships among tokens and downsample features:

$$\mathbf{X}_{C2}^1 = \sigma(\text{Conv}(\mathbf{X}_{C1}^1)) = \sigma(\text{Conv}(\sigma(\text{Conv}(\mathbf{X}_L^1)))), \quad (4)$$

where $\mathbf{X}_{C1}^1 \in \mathbb{R}^{n \times d_c}$ and $\mathbf{X}_{C2}^1 \in \mathbb{R}^{n \times d_c}$ are the output of 1D Conv layers, $\text{Conv}(\cdot)$ denotes the 1D convolutional operation and $\sigma(\cdot)$ denotes the non-linear operation of LeakyReLU [105].

On the topic state representation branch, TS3M incorporates the State Space Model (SSM) as its key technique, as outlined in Fig. 6, to selectively update the latent state based on the instruction input sequences projected through a linear transformation and 1D convolutional operation. The adjustment of the latent state is indirectly guided by the projected instruction token during the training, which can be described as:

$$\mathbf{h}(t) = \hat{\mathbf{A}}\mathbf{h}(t-1) + \hat{\mathbf{B}}\mathbf{x}(t), \quad (5)$$

where $\mathbf{h}(t)$ is the latent state at time t , $\mathbf{x}(t)$ denotes the projected instruction tokens at time t . \mathbf{A} and \mathbf{B} are matrices that define the state dynamics and input influence respectively. Δ_t is a timescale parameter.

The state transition is governed by the following procedures, which utilize an exponential matrix to update the state dynamically:

$$\hat{\mathbf{A}} = e^{\Delta_t \mathbf{A}}, \quad (6)$$

$$\hat{\mathbf{B}} = (\Delta_t \mathbf{A})^{-1} (e^{\Delta_t \mathbf{A}} - \mathbf{I}) \cdot \Delta_t \mathbf{B}, \quad (7)$$

Specifically, TS3M leverages Eq. (5) to update the latent state $\mathbf{h}(t)$ by combining the previous state $\mathbf{h}(t-1)$ with the current input $\mathbf{x}(t)$ through a linear transformation. This allows TS3M to selectively incorporate relevant information from the input instructions into the latent state based on the learned matrices \mathbf{A} and \mathbf{B} . This approach ensures that the model captures the most relevant information aligned with the topic of the input and generates accurate responses with improved quality and relevance for food and dietary advice tasks.

The latent state $\mathbf{h}(t)$ is further mapped to an output representation $\mathbf{y}(t)$ through another linear transformation defined by matrices \mathbf{C} and \mathbf{D} . This output representation captures the semantic information relevant to the current topic and can be used for the downstream generation task. The output generation is described by:

$$\mathbf{y}(t) = \mathbf{C}\mathbf{h}(t) + \mathbf{D}\mathbf{x}(t), \quad (8)$$

where $\mathbf{y}(t)$ represents the output at time t . \mathbf{C} and \mathbf{D} are matrices that map the latent state and input to an output space respectively.

The output sequence of topic state representation is constructed from the individual outputs over the sequence:

$$\mathbf{y} = [\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_T], \quad (9)$$

where \mathbf{y}_t corresponds to the output at each time step t , and T is the total number of time steps.

The integration of the content representation with the topic state representation is performed through state space gating $\text{Gate}(\cdot)$ to obtain the output topic sequence $\mathbf{T}_s \in \mathbb{R}^{n \times d_s}$, where d_s is the projected dimension.

$$\text{Gate}(\cdot) = \sigma(\mathbf{W}_{G1}\mathbf{X} + \mathbf{W}_{G2}\mathbf{Y}), \quad (10)$$

where $\mathbf{W}_{G1} \in \mathbb{R}^{d_s \times d_s}$ and $\mathbf{W}_{G2} \in \mathbb{R}^{d_s \times d_s}$. $\mathbf{X} \in \mathbb{R}^{n \times d_s}$ and $\mathbf{Y} \in \mathbb{R}^{n \times d_s}$ represent the content representation and topic state representation, respectively. This process ensures that the output is context-relevant and topic-focused, which provides the response about the specific food topic addressed in the input instruction. Finally, an indicator token encoder with a linear layer and a pooling layer downsamples the \mathbf{T}_s into the output topic indicator token:

$$\mathbf{K} = \text{GMP}(\mathbf{T}_s \mathbf{W}_o + \mathbf{b}_o), \quad (11)$$

where $\mathbf{K} \in \mathbb{R}^{1 \times P}$ and P is the topic numbers in the dataset. GMP represents a global maximum pooling operation, $\mathbf{W}_o \in \mathbb{R}^{d_p \times d_o}$ represents the transformation matrix, $\mathbf{b}_o \in \mathbb{R}^{d_o}$ represents the bias.

To combine with the reasoning procedure of the LLM, the upsampled topic token embeddings $\mathbf{T}_s \in \mathbb{R}^{1 \times d_m}$ is concatenated with the tokenized input embeddings $\mathbf{T}_I \in \mathbb{R}^{n \times d_m}$. The combined embeddings work as the final input for the LLM during the training and inference. The topic token embeddings upsampled from the topic indicator token \mathbf{K} provide the topic prior for generating responses.

TS3M offers enhanced capability in generating context-aware textual responses using topic knowledge from the Food-Earth Dataset. Moreover, TS3M can be integrated with the Hierarchical Topic Retrieval Augmented Generation (HTRAG) mechanism by the output Topic Indicator Token T_p . Based on the topic-specific knowledge provided by TS3M, HTRAG can further enhance the generation procedure.

During the training, the total training objectives are defined as \mathcal{L}_{Total} :

$$\mathcal{L}_{Total} = \lambda_1 \mathcal{L}_{NSP} + \lambda_2 \mathcal{L}_{TH}, \quad (12)$$

where λ_1 and λ_2 are weighting factors. As for iterative fine-tuning, a higher weight might be placed on \mathcal{L}_{NSP} in the beginning to establish foundational language understanding capabilities, with an increasing emphasis on \mathcal{L}_{TH} as the model becomes more proficient at handling basic language structures.

The NSP loss, denoted as \mathcal{L}_{NSP} , is important for training the LLM to predict the logical continuation of a text sequence, which is implemented using a binary cross-entropy loss function:

$$\mathcal{L}_{NSP} = -[\mathbf{y} \log(\hat{\mathbf{y}}) + (1 - \mathbf{y}) \log(1 - \hat{\mathbf{y}})], \quad (13)$$

where y is the ground truth label and $\hat{\mathbf{y}}$ is the model's predicted probability.

The Topic Hierarchy Loss \mathcal{L}_{TH} ensures that the model's output captures the topic-related information as encoded in the hierarchical graph of topics. It is formulated to penalize the distance between the model-generated topic indicator token

and the expected topic embeddings that follow the hierarchical relationships. The Topic Hierarchy Loss is given by:

$$\mathcal{L}_{TH} = e^{-d_{\text{graph}}(T, \hat{T})} \cdot \left(- \sum_{i=1}^P k_{i,T} \log(\hat{k}_{i,\hat{T}}) \right), \quad (14)$$

where T is the true topic associated with the input, and d_{graph} represents the shortest path distance in the hierarchical graph between the predicted topic \hat{T} and T .

D. HTRAG

HTRAG is proposed to enhance the generation capabilities of the instruction-tuned model by integrating retrieved information during the inference. It aims to provide the model with relevant and context-specific knowledge, to improve the accuracy and information richness of generated responses.

HTRAG operates through a multi-step process that hierarchically retrieves and integrates topic-relevant information from an external knowledge base, which includes food encyclopedias, recipe databases, nutritional information, and culinary techniques. The knowledge base is preprocessed and indexed by FAISS [106] to facilitate efficient retrieval based on the input instructions. The gte-Qwen1.5-7B-instruct is implemented as the embedding model for retrieval.

The first step in HTRAG involves passing the input instruction tokens X_q through the Topic-based Selective State Space Model (TS3M) to obtain the topic indicator token \mathbf{K} . Next, the topic indicator token obtained from TS3M is used to retrieve relevant information from the external knowledge base. The retrieval process employs a hierarchical approach that considers both the overall context of the input instructions and the specific topics identified by TS3M.

The retrieval process begins by matching the \mathbf{K} against the indexed knowledge base \mathbf{D} while calculating the similarity between the input queries and the content corresponding to the index using cosine distance. This initial retrieval step identifies a subset of relevant documents or passages that are semantically related to the input instructions. The retrieved information is then further processed and filtered based on the specific topics and their importance within the instructions.

Once the relevant information is retrieved, HTRAG integrates it with the original instruction representation. The integrated representation contains both the original instruction context and the supplementary knowledge retrieved from the external source. The augmented representation, which incorporates the retrieved topic-relevant information, is then passed to the LLM ϕ_ω for generating the final response \mathbf{T}_o :

$$\mathbf{T}_o = \phi_\omega(\text{Concat}(\mathbf{X}_q, \mathbf{R})), \quad (15)$$

where \mathbf{R} represents the integrated information from the retrieved documents, and $\text{Concat}(\cdot)$ denotes the concatenation operation. By hierarchically retrieving and integrating topic-relevant information, HTRAG enables the model to produce more informative and comprehensive responses to food-related queries. The integration of external knowledge enhances the model's ability to handle a wide range of food-related topics

and makes our approach perform better in addressing more complex and individualized queries in the food domain.

V. EXPERIMENT

A. Experimental Setup

1) Implementation Details: To investigate the impact of model size on performance, we experiment with two different backbone models: CLLaMA2-7B and CLLaMA2-13B. LLaMA-7B is a 7 billion-parameter model, while LLaMA-13B has 13 billion parameters, providing increased capacity for learning and generating responses. After the food-specific finetuning, we refer to the resulting models as FoodSky-7B for the 7B variant and FoodSky-13B for the 13B variant.

We train FoodSky-13B on a server with 8 NVIDIA A100 (80G) and train FoodSky-7B on a server with 8 NVIDIA V100 (32G), respectively. Our methods are trained using a Low-Rank Adaptation (LoRA) parameter-efficient tuning method [112]. We use the transformers² and the peft³ libraries based on Pytorch. To make a trade-off between the training efficiency and performance, we implement fp12 precision with ZeRO-3⁴ and gradient accumulation strategy based on DeepSpeed⁵. We limit the length of a single response (including history) to 1,500. We use a dropout rate of 0.1, 10^{-5} and a cosine learning rate scheduler based on Adam [113]. We evaluate the last convergent checkpoint as the final result.

2) Baseline Methods: We compare FoodSky with representative state-of-the-art LLMs:

- ChatGLM2-6B [114]: A 6B-parameter open bilingual LLM optimized for Chinese QA and dialogue. The model is trained for about 1 trillion tokens of Chinese and English corpus.
- Mistral-7B [108]: A 7B-parameter open LLM released by Mistral AI. The model is a carefully designed language model that provides both efficiency and high performance on various tasks to enable real-world applications.
- InternLM2-7B [51]: A 7B-parameter open-source LLM tailored for practical scenarios. The model is trained on over 2 trillion high-quality pre-training corpora. It leverages trillions of high-quality tokens for training to establish a powerful knowledge base.
- Vicuna-v1.5-7B and Vicuna-v1.5-13B [109], [115]: 7B-parameter and 13B-parameter open chatbots trained to replicate ChatGPT's behavior. The models are fine-tuned from Llama 2 with supervised instruction fine-tuning. The training data is around 125K conversations collected from ShareGPT.com.
- Baichuan2-7B [102]: A 7B-parameter multilingual LLM released by Baichuan Intelligence. The model is trained on a high-quality corpus with 2.6 trillion tokens.
- Qwen-7B [111]: A 7B-parameter open-source LLM released by Alibaba Group, demonstrating superior performance in multiple downstream tasks. The model is

²<https://huggingface.co/docs/transformers/>

³<https://github.com/huggingface/peft>

⁴https://huggingface.co/docs/accelerate/usage_guides/deepspeed

⁵<https://github.com/microsoft/DeepSpeed>

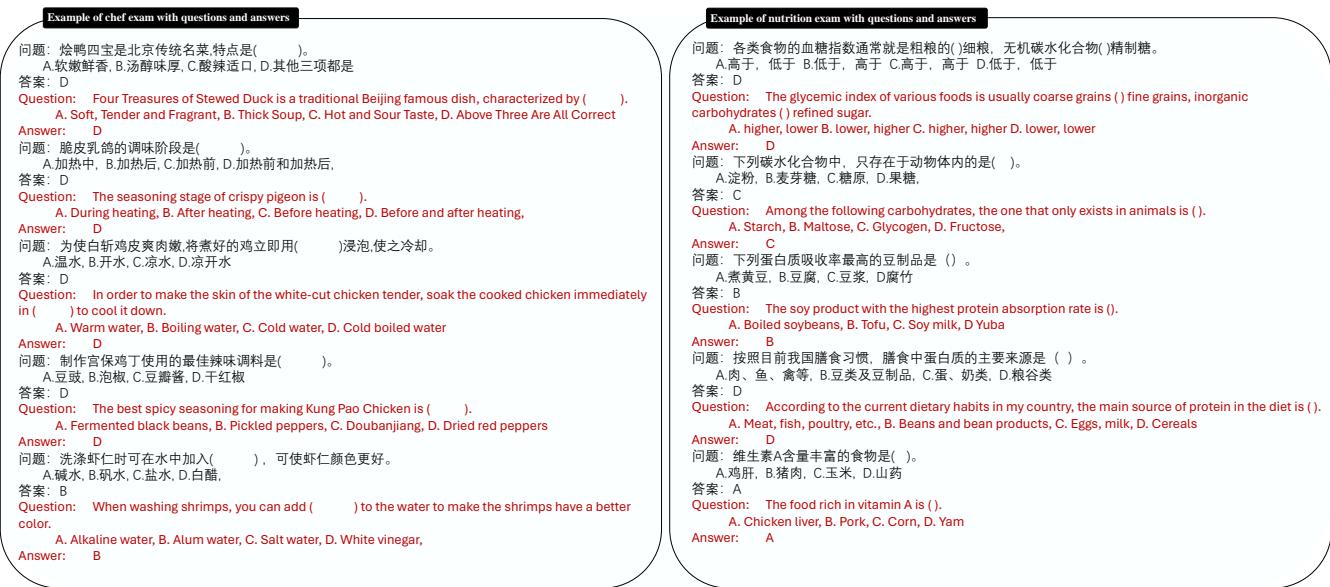


Fig. 7. Examples of questions and answers in CDE benchmark with the corresponding English translation.

TABLE III
THE ZERO-SHOT AND FEW-SHOT (5-SHOT) PERFORMANCE OF DIFFERENT LLMs ON THE CDE BENCHMARK EVALUATED BY THE ACCURACY (%).

	Zero-shot			Few-shot		
	Chef Exam	Dietetic Exam	Total	Chef Exam	Dietetic Exam	Total
ChatGLM-6B [107]	49.1	42.9	43.8	44.5	47.4	47.0
Mistral-7B [108]	30.9	42.4	40.7	44.5	48.2	47.6
Vicuna-v1.5-7B [109]	42.5	36.7	36.5	40.9	45.6	44.9
Baichuan2-7B [102]	53.6	51.5	51.8	70.0	59.0	60.6
CLLaMA2-7B [110]	39.7	40.9	39.9	41.9	35.4	41.0
InternLM2-7B [51]	55.8	68.2	57.6	63.0	75.4	64.8
Qwen-7B [111]	49.0	42.7	48.0	59.3	75.0	60.6
Vicuna-v1.5-13B [109]	44.5	44.4	44.4	52.7	47.5	48.3
CLLaMA2-13B [110]	48.2	53.6	52.7	44.0	45.3	48.2
ChatGPT-3.5 [52]	54.4	57.3	54.8	52.1	68.2	54.5
FoodSky-7B (Ours)	62.0	60.1	61.7	62.2	62.8	62.4
FoodSky-13B (Ours)	67.2	66.4	67.1	69.5	70.9	69.7

pretrained for up to 3 trillion tokens of multilingual data with a wide coverage of domains.

- ChatGPT-3.5 [52]: The chatbot developed by OpenAI. The model is trained using reinforcement learning from human feedback and fine-tuned from GPT-3.5.
- CLLaMA2-7B [110]: A 7B-parameter Chinese pre-trained version of the open-source LLM LLaMA [60]. A method to augment LLaMA with capabilities for understanding and generating Chinese text and its ability to follow instructions is utilized in pre-training and fine-tuning process.

3) *Evaluation:* To comprehensively evaluate different LLMs, we first employ the accuracy as the main metric to compare the performance on the CDE benchmark. Then, a range of automatic evaluation metrics are commonly used

in natural language generation tasks. These include BLEU-1, BLEU-2, BLEU-3 and BLEU-4 [116], which measure the n-gram overlap between the generated and reference answers; ROUGE-1, ROUGE-2, and ROUGE-L [117], which assess the unigram, bigram, and longest common subsequence overlap, respectively; and GLEU [118], which is a variant of BLEU that correlates better with human judgments. Additionally, Distinct-1/2 [119] assesses the textual diversity of the generated answers by calculating the ratio of distinct unigrams and bigrams. We also use GPT-4 as the judge to subjective scores of fluent score, logic score, professional score, informative score on FoodQA.

We test the baseline models and FoodSky on the Chef and Dietetic Examinations (CDE) benchmark, Food Long Conversation (FoodLongConv) benchmark and Food Question

TABLE IV
PERFORMANCE COMPARISON OF DIFFERENT MODELS ON DIFFERENT TOPIC SUBCATEGORIES (%).

	Dietary Science	Food Flavor Profiles	Food Safety Measures	Food Recipes	Healthy Eating Principles	Average
Baichuan2-7B [102]	56.1	59.8	46.8	49.0	60.1	51.8
CLLaMA2-7B [110]	40.8	45.8	33.0	37.9	42.4	39.9
InternLM2-7B [51]	60.5	58.9	61.7	51.9	70.0	57.6
Qwen-7B [111]	50.3	57.0	45.7	45.8	43.9	48.0
ChatGPT-3.5 [52]	66.9	56.1	57.4	48.7	59.1	54.8
FoodSky-7B (Ours)	70.1	62.6	62.8	56.3	62.1	61.7
FoodSky-13B (Ours)	68.3	68.2	67.0	65.6	73.1	67.1

TABLE V
PERFORMANCE COMPARISON OF DIFFERENT MODELS ON FOODLONGCONV BENCHMARK (%).

	BLEU-1	BLEU-2	BLEU-3	BLEU-4	GLEU	ROUGE-1	ROUGE-2	ROUGE-L	Distinct-1	Distinct-2
Baichuan2-7B [102]	23.19	10.24	6.58	3.36	14.64	29.78	7.84	23.31	50.79	81.32
CLLaMA2-7B [110]	12.59	5.50	2.38	0.97	0.97	27.18	8.15	21.55	67.99	90.83
InternLM2-7B [51]	16.29	5.91	3.22	1.08	8.73	24.90	3.79	19.57	33.41	64.37
Qwen-7B [111]	19.18	9.01	2.37	1.83	12.33	25.73	5.25	20.71	60.64	87.11
ChatGPT-3.5 [52]	23.54	10.66	4.44	1.43	13.12	28.67	6.53	22.93	46.46	76.36
FoodSky-7B (Ours)	22.95	13.53	9.72	7.34	16.18	28.79	8.00	22.44	60.83	87.32
FoodSky-13B (Ours)	24.84	15.27	11.01	8.89	18.26	34.50	14.08	28.78	57.81	82.54

and Answer (FoodQA) benchmark, respectively. In the CDE benchmark, we use the standard choice questions in the Chinese Chef Examination and the Dietetic Examination as our benchmarks to evaluate the performance of different LLMs in the food and nutrition domain. Specifically, we collect 628 choice questions from the Chinese Chef Examination and 111 choice questions from the Chinese Dietetic Examination to challenge LLMs in the setting of standard chef and dietetic exams⁶. The accuracy of the CDE benchmark is also the main metric for evaluating LLMs since it is the most objective indicator that determines whether the answer of LLMs is correct or not.

To evaluate the conversation and question-answering capabilities of the LLMs, we build FoodLongConv benchmark and FoodQA benchmark. The FoodLongConv contains 22 essay questions that require long answers, extracted from the Chinese Chef Examination and the Chinese Dietetic Examination. We use the metrics mentioned above to evaluate the quality of LLMs answers on FoodLongConv. The FoodQA is a benchmark focusing on comparing different performances of the model's answers and contains 25 short answer questions and essay questions extracted from the Chinese Chef Examination and the Chinese Dietetic Examination. Some examples are shown in the Fig. 7. We use GPT-4 as the judge to score LLMs' answers with respect to fluency, logic correctness, professionalism and information density on FoodQA.

B. Comparison with Baseline Methods

1) *Comparison on the CDE benchmark:* Table III presents the zero-shot and few-shot (5-shot) performance of differ-

ent LLMs on the CDE benchmarks, where the accuracy on questions from the Chef Exam and Dietetic Exam and mean accuracy are reported respectively.

In the zero-shot setting, FoodSky-7B and FoodSky-13B models achieve the highest accuracy on both Chef and Dietetic exams, outperforming all other baseline models. Specifically, FoodSky-7B achieves 62.0% accuracy on the Chef Exam and 60.1% accuracy on the Dietetic Exam, resulting in a total accuracy of 60.2%. FoodSky-13B further improves the performance, achieving 67.2% accuracy on the Chef Exam and 66.4% accuracy on the Dietetic Exam, with a total accuracy of 67.1%. Among the baseline models, InternLM2-7B and ChatGPT-3.5 perform the best, with 57.6% and 54.8% accuracy respectively, followed by Baichuan2-7B (51.8%) and CLLaMA2-13B (52.7%).

In the few-shot setting, all models show improved performance compared to the zero-shot setting, benefiting from the additional context provided by few-shot examples. FoodSky-13B maintains its lead, achieving a total accuracy of 69.7%, with 69.5% on the Chef Exam and 70.9% on the Dietetic Exam. FoodSky-7B closely follows with a total accuracy of 61.8%. InternLM2-7B and ChatGPT-3.5 also perform well, with total accuracy rates of 64.8% and 54.5%, respectively. Baichuan2-7B achieves a total accuracy of 60.6%, while CLLaMA2-13B obtains total accuracy of 48.2%, respectively.

The superior performance of FoodSky models can be attributed to their specialized training on a large-scale food and nutrition corpus, which enables them to better understand and reason about the domain-specific concepts and principles covered in the Chef and Dietetic Examinations. The results demonstrate that proposed FoodSky has the ability to pass the

⁶http://www.zyzgks.net/index_15.html

TABLE VI

ABALATION STUDIES ON MODEL STRUCTURES (%). THE BASELINE MODEL IS THE FOODSKY-7B TRAINED ON THE FOODEARTH-680K DATASET.

Model	Methods		CDE				FoodLongConv					FoodQA		
	TS3M	HTRAG	Chef	Dietetic	Total	BLEU-1	BLEU-4	GLEU	ROUGE-1	ROUGE-L	Fluent	Logic	Professional	Informative
FoodSky-7B	✓	53.4	53.6	53.5	16.41	6.62	13.51	26.07	20.30	86.25	73.80	72.20	74.00	
		56.8	60.0	57.2	18.40	6.09	14.09	26.57	21.09	89.00	77.20	77.20	81.80	
	✓	55.8	59.1	56.3	18.89	7.18	14.42	26.21	21.16	85.23	75.68	75.00	74.77	
	✓	✓	60.5	60.7	60.5	19.78	6.63	14.50	27.42	21.15	89.32	82.27	81.82	84.55

both Chinese Chef Examination and the Dietetic Examination, providing an available domain-specific LLM for the food and nutrition domain.

2) *Comparison on Different Topic Categories*: We use the CDE, which contains choice questions from Chef and the Dietetic examinations to evaluate the performance of different methods on different topic categories. Specifically, we divide the topics in the CDE benchmark into five main categories: Dietary Science, Food Flavor Profiles, Food Safety Measures, Food Recipes, and Healthy Eating Principles.

As shown in Table IV, FoodSky-13B achieves the highest scores in every topic subcategory with significant results. Specifically, FoodSky-13B achieves an accuracy of 68.3% in “Dietary Science” and an accuracy of 68.2% in “Food Flavor Profiles”, demonstrating a capable understanding of nutritional queries, which is fundamental to the dietetic examinations. FoodSky-7B also shows strong performance with an accuracy of 70.1% and 62.6%, respectively. The second best model, ChatGPT-3.5, follows with an accuracy of 66.9% in the “Dietary Science” and an accuracy of 59.1% in “Healthy Eating Principles”.

With respect to other topic categories, FoodSky-13B also outperforms all other models with an accuracy of 67.0% in “Food Safety Measures”, 65.6% in “Food Recipes” and 73.1% in “Healthy Eating Principles”. Its overall average accuracy is 67.1%. FoodSky-7B achieves notable performance with 62.8% in “Food Safety Measures”, 56.3% in “Food Recipes” and 62.1% in “Healthy Eating Principles”, averaging 61.7%.

Overall, the average performance across all categories for FoodSky-13B stands at 62.9%. The comparative analysis of different topic subcategories shows that FoodSky can generate more precise responses across diverse topics within the food and nutrition domain, compared other general models which show varied performance across these topic categories.

3) *Comparison on the Question Answering Task*: We use the FoodQA benchmark to evaluate different models on a question-answering task related to the food and nutrition domain. Experimental results are detailed in Table V and analyzed using NLP metrics such as BLEU, GLEU, ROUGE, and Distinct.

FoodSky-13B outperforms all models across most metrics, showing its robustness in generating detailed and relevant responses. It achieves the best in BLEU-1 (24.84%), BLEU-2 (15.27%), BLEU-3 (11.01%), BLEU-4 (8.89%), GLEU (18.26%), ROUGE-1 (34.50%) and ROUGE-2 (14.08%), and

ROUGE-L (28.78%), indicating the accuracy and linguistic richness in its responses. FoodSky-7B also shows capable performance, especially in BLEU-4 (7.34%) and GLEU (16.18%), showing its effectiveness in producing varied and precise language.

As for Distinct-1 and Distinct-2, compared with FoodSky, the baseline CLLaMA2-7B with lower accuracy achieves the highest Distinct scores since it does not have the knowledge to actually answer several questions and outputs more uncontrolled responses. With the improvement of professionalism and answer rigor, the answers tend to follow a certain correct logic, therefore influencing the output diversity of answers. Compared with the strong baseline InternLM2-7B and Qwen-7B, our FoodSky maintains a better balance between high-quality responses and diversity of responses. Baichuan2-7B displays strong performance in ROUGE metrics, with the significant ROUGE-1 score (29.78%) and ROUGE-L score (23.31%), highlighting its effectiveness in capturing key content from the context.

Overall, the results from the FoodQA benchmark confirm the superiority of FoodSky in understanding and responding to complex questions in the food and nutrition domain, still setting it apart from other general models that show varied performance across these metrics.

4) *Evaluation with GPT-4 Score*: In addition to the objective evaluation metrics, we also conducted a subjective evaluation using GPT-4 as the judge to assess the quality of the generated responses from different models. We used questions from the FoodQA benchmark and asked each model to generate responses. GPT-4 then evaluated the responses based on four criteria: fluent score, logic score, professional score and informative score.

Fig. 8 illustrates the performance comparison of different models based on GPT-4 assessment. FoodSky-7B achieves the highest score in fluency with a fluent score of 40. Among the baseline models, InternLM2-7B (Intern2) and Qwen-7B (Qwen) demonstrate strong performance, with scores ranging from 20% to 35% across the three criteria of logic score, professional score and informative score. ChatGPT-3.5 (ChatGPT) and Baichuan2-7B (Baichuan) also show competitive results in these three criteria, with scores between 20% and 30%. The baseline CLLaMA2-7B (CLLaMA), achieves lower scores, ranging from 0% to 20% in the four criteria.

The subjective evaluation shows that the baseline models lag behind in answering multiple-choice questions and can still

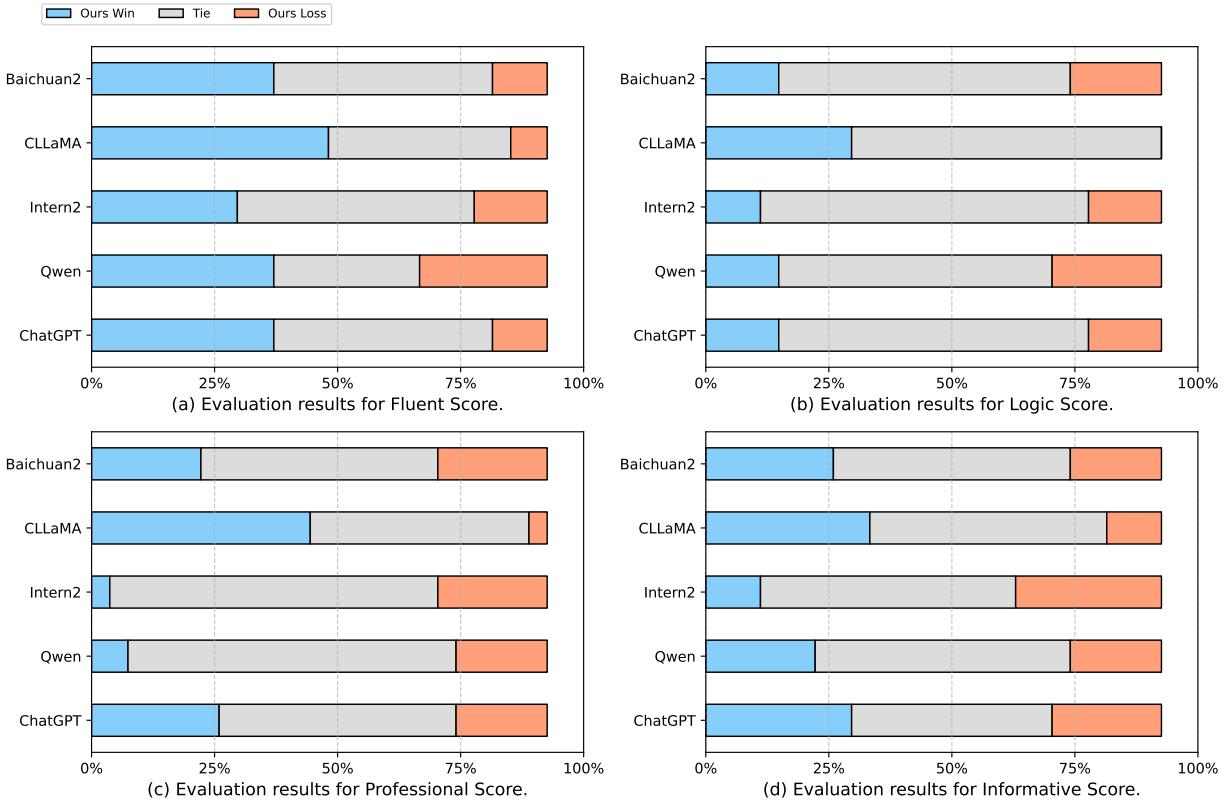


Fig. 8. Performance comparison of our FoodSky-7B with different baseline models on FoodQA benchmark evaluated by GPT-4. GPT-4 gives the Fluent Score, Logic Score, Professional Score and Informative Score based on the answers of the models, and judges which model wins on each score.

generate reasonable answers judged by GPT-4. It also confirms the reliable performance of FoodSky models in generating high-quality, professional, and informative responses in the food and nutrition domain. However, the Q&A ability of the proposed FoodSky can be further improved by reinforcement learning with human feedback.

C. Ablation Studies

To investigate the impact of different components in FoodSky, we conducted ablation studies by removing key components and evaluating the performance on the CDE, FoodLongConv and FoodQA benchmarks. In order to swiftly verify the validity of the proposed methods at the early stage of data construction, we use FoodEarth-680K, a high-quality version of FoodEarth with 680K instruction data to train our FoodSky. Table VI presents the results of ablation studies on model structure.

The baseline FoodSky-7B model, without any additional components, obtains an average accuracy of 53.5% in the CDE benchmark. Incorporating TS3M improved the average accuracy to 57.2%, an improvement of 3.7%, demonstrating its importance in enhancing topic understanding. Further, integrating HTRAG component resulted in a score of 56.3%, with an improvement of 2.8%, suggesting its effect in providing contextually relevant answers by leveraging external knowledge.

The most notable improvements were observed when both TS3M and RAG were simultaneously employed, pushing the

average score to 60.5%. This configuration also excelled in the FoodQA dataset, achieving the highest metrics across BLEU-1 (19.78%), BLEU-4 (6.63%), GLEU (14.50%), and ROUGE-L (21.15%). These scores confirm that the combination of TS3M and RAG can produce the most effective performance in generating accurate and relevant responses. The ablation study highlights the key role of TS3M and RAG in improving the performance of FoodSky-7B across different linguistic and semantic challenges, highlighting their synergies in improving model accuracy and response quality.

D. Evaluation on Different Numbers of Training Data

To assess the impact of training set size on the performance of FoodSky, we conducted ablation studies where both FoodSky-7B and FoodSky-13B were trained with varied numbers of instructions from the FoodEarth-680K dataset. The results in Fig. 9 demonstrate how changes in data volume influence model accuracy and linguistic metrics.

For FoodSky-7B, increasing the training set size lead to consistent improvements in performance on the CDE benchmark. Starting from 200K samples, the total accuracy on the CDE benchmark rose steadily from 28.8% to 61.7%. The FoodSky-13B model exhibits a more significant improvement with the expansion of the dataset. Notably, when trained with 600K samples, the model already achieves an accuracy of 48.67% on the chef exam in the CDE benchmark, which jumps to 67.2% by 811K samples. The total accuracy follows a similar trajectory, starting at 49.1% and reaching 67.1%.

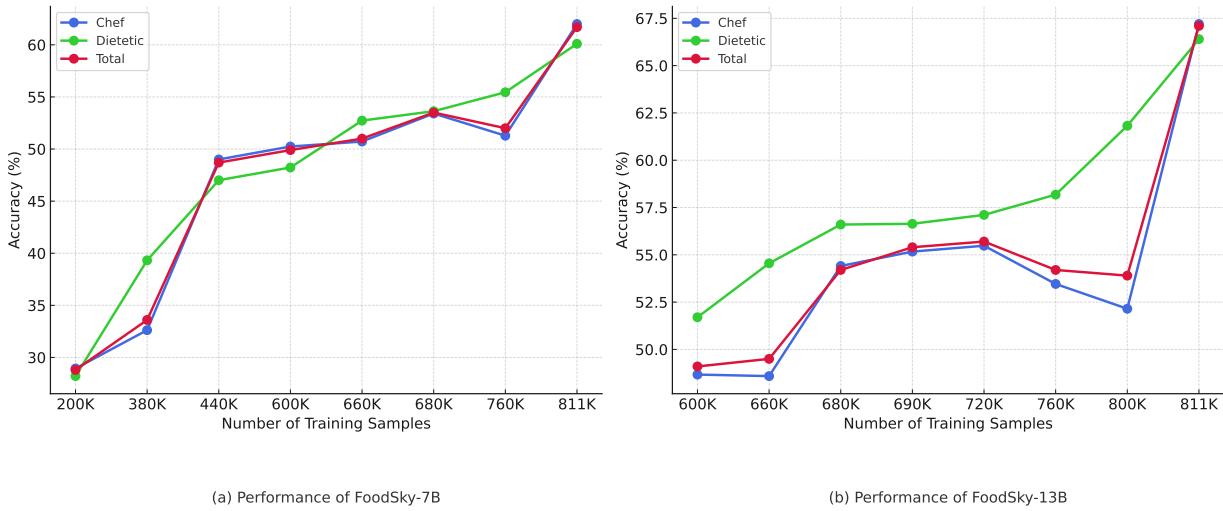


Fig. 9. Ablation study on instruction numbers in the training set. The results are the accuracy on the CDE benchmark.

It is worth noting that, when we increase the data sample to 780K, the accuracy of both FoodSky-7B and FoodSky-13B decreases in Fig. 9. This shows that simply increasing the amount of data does not necessarily improve the performance of the model. The amount of data we initially supplied from 680K to 800K, was provided by directly adding data extracted from public teaching datasets that were not double-checked for data quality. This suggests that data quality is also important for improving the accuracy of the model in chef and diet tests, even more important than pure data volume. We removed all the low-quality and duplicate data when we built the final version of FoodEarth, resulting in 811K high-quality samples.

The ablation study highlights the substantial benefits of scaling up the training data. FoodSky-13B, with its larger capacity, effectively leverages additional data to surpass the performance of FoodSky-7B. With the full training set of 811K instructions, FoodSky-13B achieves notable accuracy rates: 67.2% on the chef exam, 66.4% on the dietetic exam, and a total accuracy of 67.1% on the CDE benchmark. This demonstrates that the model can generate more accurate and informative responses as training data increases.

E. Qualitative Results

As illustrated in Fig. 11, the qualitative experimental results in the scenario of recipe recommendation highlight both strengths and weaknesses in the predictive capability of different LLMs. In the first example, FoodSky correctly recognizes the key information that describes ways to make chicken breast more delicious. This capability reflects a strong understanding of the fundamental principles of culinary arts. However, in Fig. 11, the baseline models Intern and ChatGPT demonstrate inaccuracies in capturing detailed culinary nuances. Specifically, they struggle with the richness of the cuisines. The Intern even overlooks the key requirement of saving time and effort. These mistakes suggest a gap in the model's ability to handle complex cooking instructions and ingredient interactions effectively.

Three more qualitative results in Fig. 10, which shows the examples of dietary education for adolescents, reveal the different focus and depth of analysis of different methods. FoodSky delivers the most in-depth exploration of the topic, focusing on the direct health impacts of fast food snacks, promoting moderation consumption for teenagers. The answers of Intern are lengthy as it offers too detailed health effects and extensive dietary advice. ChatGPT presents a balanced view that integrates moderate consumption of fast food with healthier dietary habits. Overall, FoodSky is capable of quickly identifying the immediate health risks associated with high-calorie and high-fat diets and providing actionable recommendations, which are critical to promoting healthier eating habits in teenagers.

VI. CONCLUSION

In summary, FoodSky stands as a robust food-specific LLM that provides new directions for future research and applications in the food field. To ensure the success of FoodSky, we first provided the basis for model training by building a large-scale, high-quality food corpus that contains various types of food-related instruction data. Second, we proposed the Topic-Based Selective State Space Model (TS3M) and Hierarchical Topic Retrieval-Enhanced Generation (HTRAG) to enhance FoodSky in processing and generating food-related content. Through extensive experiments, FoodSky has demonstrated significant capabilities in understanding and generating food-related content, surpassing existing general-purpose LLMs in both chef and nutrition exams. In the future, FoodSky will have broad prospects in several directions. First, by combining FoodSky with reinforcement learning enhanced by user feedback, the model can continually refine its understanding and generation capabilities. Second, FoodSky can also be extended as a Multimodal Large Language Model (MLLM). For example, recipe suggestions can be obtained through pictures of ingredients, and future weight changes can be predicted through nutritional analysis of dishes. We will also further introduce more data from the food industry, to create

TABLE VII
DETAILED DATA SOURCE INFORMATION OF AUTHORITATIVE PUBLIC ACCOUNT AND AUTHORITATIVE WEBSITE.

Name	Description	Source Citation
China Good Nutrition	It is a public account operated by the Chinese Nutrition Society or related nutrition professional organizations. It is dedicated to popularizing nutrition knowledge, providing scientific dietary guidance, and sharing healthy lifestyle information, and may involve The latest nutritional research results. This public account aims to help the public understand how to improve health, prevent disease, and enhance overall quality of life through proper diet. Over 2000 articles were collected from January to February 2024. [Accessed 28-2-2024]	Authoritative public account: China Good Nutrition
Clinical Nutrition Network	Co-founded by over 1500 nutritionists and physicians from over 700 public hospitals nationwide, it provides clinical nutrition services and includes several thousand posts from January to February 2024. [Accessed 28-2-2024]	Authoritative public account: Clinical Nutrition Network
Dr. Lilac	It is a popular health and medical information public account in China. it provides the public with medical and health knowledge, disease prevention, healthy lifestyle suggestions, and the latest medical information. Medical professionals usually run this public account which aims to increase public health awareness and help people better understand and manage their health. The dataset includes several thousand posts from January to February 2024. [Accessed 28-2-2024]	Authoritative public account: Dr. Lilac
Chestnut-eating Pie	It is a WeChat public account focusing on food, nutrition and food culture. It provides a variety of relevant content for lovers of healthy eating and cooking, including but not limited to recipe sharing, ingredient introduction, nutritional knowledge, dietary tips and cooking techniques. Public accounts may also involve food safety, diet trend analysis, and promotion of healthy eating and lifestyle. The dataset includes several thousand posts from January to February 2024. [Accessed 28-2-2024]	Authoritative public account: Chestnut-eating Pie
CNKI	CNKI (China National Knowledge Infrastructure) is one of the largest academic information resource providers in China. It provides a wide range of academic resources, including journal articles, theses, conference papers, standards, patents, books, etc. Through the keywords of disease and diet, more than 1,400 related papers were initially downloaded. [Accessed 31-4-2024]	Articles downloaded in April 2024, containing several thousand posts.

an LLM specifically for the food industry. This will enable intelligent transformation and upgrading in the food sector, with implications for key areas such as food design, food safety, and supply chain management.

APPENDIX

We list the data sources in detail in the appendix, including authoritative public accounts and websites, knowledge graph data, and public Chinese teaching datasets, and attach question-answering images of three different LLMs to demonstrate the question-answering comparison experiment between Foodsky and other models.

A. Data Sources Details

Table VII includes a detailed list of the data sources and descriptions of authoritative public accounts and websites used for this study. The table provides the name of each data source, a brief description of the specific content, and the corresponding citation source. These data sources cover public accounts related to nutrition, clinical nutrition services, medical health information, food culture, etc., as well as academic resources such as China National Knowledge Infrastructure (CNKI), providing rich data support for the study.

Table VIII provides the main sources of knowledge graph data and their descriptions. The knowledge graph data covers food nutrition data and nutrition knowledge data collected from multiple authoritative websites from 2021 to 2022.

Through multiple rounds of data cleaning and construction, a detailed knowledge graph was finally formed, providing solid data support for the research.

Table IX contains a table listing the main sources of public Chinese command datasets used for this study. These datasets were collected from multiple authoritative platforms, including GitHub, Hugging Face, and other open-source projects. A large amount of food-related conversation data was screened by keywords, providing important data support for the study.

B. More Qualitative Experimental Results

We provide more qualitative experimental results in this appendix, including 8 figures showing the responses of three different language models in different groups. The Fig 12, 13, 14, 15, 16, 17, 18 and 19 include questions and answers focus on issues for infants, fitness people, the elderly, nutrition and health workers, chronic disease patients, mental workers, manual workers, and pregnant women. Each figure records the performance of different language models when answering the same question. Our answers are concise and to the point, solving the core problems of the user groups.

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TABLE VIII
DETAILED DATA SOURCE INFORMATION OF KNOWLEDGE GRAPH DATA.

Name	Description	Source Citation
Food nutrition data	The knowledge graph collected data from multiple authoritative websites from 2021 to 2022. Through multiple rounds of data set cleaning and construction for three months by numerous people, it completed the construction of a knowledge graph with more than 283,000 relationship nodes and a total number of more than 80,000 nodes.	Institute of Nutrition and Health, Chinese Center for Disease Control and Prevention, Chinese Food Composition List, China Public Health Science Data Center, Chinese Nutrition Society, USDA Food Nutrition Facts Database
Nutrition knowledge data	The Nutrition Knowledge Graph collected data from multiple authoritative websites from 2021 to 2022. Through multiple rounds of cleaning and construction of the data set by multiple people, it completed the construction of 2,045 relationship nodes and a total number of more than 35,000 nodes, based on the Food Nutrition Knowledge Graph for additional connections.	U.S. Food and Drug Administration (FDA), European Food Safety Authority (EFSA), China State Food and Drug Administration (CFDA)

TABLE IX
DETAILED DATA SOURCE INFORMATION OF PUBLIC CHINESE INSTRUCTION DATASET.

Name	Description	Source Citation
ChatGPT Chinese corpus	The data set is a general scene Chinese conversation data set published in Git Hub, and 81,475 pairs of food-related data were filtered out through the tags set by the author.	Dataset downloaded in April 2024. [Online; accessed 30-4-2024], https://github.com/PlexPt/chatgpt-corpus
COIG	The COIG data set is an open-source general scene conversation data set released by the Beijing Academy of Artificial Intelligence on huggingface. There are 898 pairs of food-related data sets filtered by keywords.	Dataset downloaded in April 2024. [Online; accessed 30-4-2024], https://huggingface.co/datasets/BAAI/COIG
The Chinese dataset of Instruction Tuning with GPT-4	This data set is used in the paper published by Microsoft Research: INSTRUCTION TUNING WITH GPT-4. This data set is a Chinese and English conversation data set in a general scenario generated by ChatGPT-4. We use food keywords to find 8828 pairs of related datasets in the Chinese conversation data set	Dataset downloaded in April 2024, [Online; accessed 30-4-2024], https://github.com/Instruction-Tuning-with-GPT-4/GPT-4-LLM/tree/main/data
The Chinese dataset of RefGPT	RefGPT data set was jointly constructed by NLP practitioners from Shanghai Jiao Tong University, Hong Kong Polytechnic University and other institutions. Through fine-tuned GPT models, multiple rounds of dialogue data sets based on fact-based documents were generated. We filtered out more than 16,000 pieces of food-related conversation data from the Chinese data set.	Dataset downloaded in April 2024, [Online; accessed 30-4-2024], https://github.com/ziliwangnlp/RefGPT
The Chinese dataset of BELLE	This data set is a 3.5 million Chinese data set generated by ChatGPT3.5 provided by an open source project with more than 7,600 stars on GitHub. Through keyword search, we initially found more than 100,000 food-related data sets.	Dataset downloaded in April 2024. [Online; accessed 30-4-2024], https://github.com/LianjiaTech/BELLE
MOSS Chinese dataset	This data set is an open-source conversation data set of Fudan University used to train MOSS-002, with a total of more than 600,000 items. We initially screened out 70,000 food-related questions and answers through keywords.	Dataset downloaded in April 2024. [Online; accessed 30-4-2024], https://huggingface.co/datasets/fnlp/moss-002-sft-data

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吃快餐和零食对青少年的健康有什么影响?
What are the effects of eating fast food and snacks on the health of teenagers?

 foodsby

快餐和零食通常含有高热量、高脂肪、高糖分和高盐分的成分，长期摄入可能导致青少年肥胖、心血管疾病、糖尿病等健康问题。此外，快餐和零食中的添加剂和防腐剂也可能对青少年的健康产生负面影响。因此，建议青少年适量食用，并选择更健康的食品选项。

Fast food and snacks are often high in calories, fat, sugar and salt, and long-term intake can lead to adolescent obesity, cardiovascular disease, diabetes and other health problems. In addition, additives and preservatives in fast food and snacks may also have a negative impact on the health of adolescents. Therefore, teenagers are advised to eat in moderation and choose healthier food options.

吃快餐和零食对青少年的健康有什么影响?
What are the effects of eating fast food and snacks on the health of teenagers?

 intern

经常食用快餐和零食可能对青少年的健康产生一些负面影响。以下是一些可能的影响：1. **营养不均衡**：快餐和零食通常含有高热量、高脂肪、高糖分和高盐分，但缺乏足够的蛋白质、纤维、维生素和矿物质。长期食用可能导致营养不良和体重增加。2. **肥胖风险增加**：由于快餐和零食的高热量和高脂肪含量，经常食用会增加肥胖的风险。肥胖与多种慢性疾病，如心血管疾病、糖尿病和某些癌症有关。3. **心血管健康问题**：高盐分和高脂肪的饮食可能导致高血压和高胆固醇，这些都是心血管疾病的风险因素。4. **牙齿健康问题**：快餐和零食中的糖分可能导致龋齿和其他牙齿健康问题。5. **能量波动**：快餐和零食通常提供快速能量，但这些能量很快会被消耗，可能导致能量波动和疲劳。6. **消化问题**：快餐和零食可能含有添加剂和防腐剂，这些可能会影响消化系统的正常功能。7. **心理影响**：过度依赖快餐和零食可能导致对健康饮食的忽视，并可能与情绪和心理问题有关。为了保持健康，建议尽量减少快餐和零食的摄入，选择更健康的饮食选项，如全谷物、蔬菜、水果、瘦肉、鱼类和豆类。同时，保持适量的运动和规律的饮食作息也是维护健康的重要组成部分。如果您有特定的健康问题或饮食需求，请咨询专业医生或营养师的意见。

Regular consumption of fast food and snacks may have some negative effects on adolescents' health. Here are some possible effects: 1. **Nutritional imbalance** : Fast food and snacks are often high in calories, fat, sugar, and salt, but lack enough protein, fiber, vitamins, and minerals. Long-term consumption can lead to malnutrition and weight gain. 2. **Increased risk of obesity** : Due to the high calorie and fat content of fast food and snacks, regular consumption increases the risk of obesity. Obesity is associated with several chronic diseases, such as cardiovascular disease, diabetes, and certain cancers. 3. **Cardiovascular health issues** : Diets high in salt and fat can lead to high blood pressure and high cholesterol, which are risk factors for cardiovascular disease. 4. **Dental health problems** : Sugar in fast food and snacks can lead to tooth decay and other dental health problems. 5. **Energy fluctuations** : Fast food and snacks usually provide quick energy, but this energy is quickly used up, which can lead to energy fluctuations and fatigue. 6. **Digestive issues** : Fast food and snacks may contain additives and preservatives, which may affect the normal function of the digestive system. 7. **Psychological effects** : Over-reliance on fast food and snacks can lead to neglect of healthy eating and may be linked to emotional and psychological problems. To stay healthy, it is recommended to minimize your intake of fast food and snacks and choose healthier dietary options such as whole grains, vegetables, fruits, lean meats, fish, and legumes. At the same time, maintaining a moderate amount of exercise and regular diet and rest is also an important part of maintaining health. If you have specific health issues or dietary needs, consult a professional doctor or dietitian.

吃快餐和零食对青少年的健康有什么影响?
What are the effects of eating fast food and snacks on the health of teenagers?

 chatgpt

吃太多快餐和零食对青少年的健康有很多负面影响。快餐和零食通常含有高热量、高糖分、高盐分和高脂肪，但缺乏必要的营养素。长期摄入这些食物可能导致体重增加、肥胖、糖尿病、高血压和心血管疾病等问题。偶尔吃一些可以，但应尽量以健康的食品为主，如水果、蔬菜、全谷物和蛋白质。

Eating too much fast food and snacks has many negative effects on teenagers' health. Fast food and snacks are often high in calories, sugar, salt and fat, but lack essential nutrients. Long-term consumption of these foods can lead to problems such as weight gain, obesity, diabetes, high blood pressure and cardiovascular disease. It's okay to eat some occasionally, but try to focus on healthy foods such as fruits, vegetables, whole grains, and protein.

Fig. 10. Qualitative experimental results of question answering visualization by FoodSky, InternLM2 and ChatGPT-3.5. FoodSky. While the outputs from Intern and ChatGPT are relatively redundant and lack focus, the answers from our FoodSky are more accurate and concise.

鸡胸肉怎么做才不费时，又好吃？
How to cook chicken breast in a quick and delicious way?

 foodsy

鸡胸肉是一道美味的家常菜，也是营养丰富的食材。以下是一些制作鸡胸肉的方法，可以方便你快速做出美味又健康的菜肴：1. 烤鸡胸肉：将鸡胸肉切成均匀的大小，用盐、黑胡椒和橄榄油腌制一段时间，然后放在预热好的烤箱中烤制，直到鸡肉熟透并变得金黄色。2. 煎鸡胸肉：在平底锅中加入少量橄榄油，将鸡胸肉放入锅中煎至两面金黄，期间可以根据个人口味加入蒜末、姜末等调味料。3. 烹饪鸡胸肉：将鸡胸肉切成块状，加入开水中煮熟，然后捞出沥干水分，可以根据个人口味加入调料调味。4. 炒鸡胸肉：在锅中加入少量油，将切好的鸡胸肉放入锅中翻炒，加入适量的盐、酱油、糖等调味料，最后加入葱花、姜末等调味料即刻。无论哪种方法，都应该注意火候掌握，避免过熟或过生，以保证口感和营养价值。

Chicken breast is a delicious home cooked dish and a nutritious ingredient. Here are some ways to make chicken breasts into healthy dishes in a quick and delicious way: 1. Grilled chicken breasts: Cut the chicken breasts into even sizes, marinate them with salt, black pepper and olive oil for a while, then bake in a preheated oven until the chicken is cooked through and golden brown. 2. Fried chicken breast: Add a small amount of olive oil in the pan, fry the chicken breast in the pan until both sides are golden, during which you can add minced garlic, ginger and other seasonings according to personal taste. 3. Cook chicken breast: Cut chicken breast into chunks, add boiling water to cook, then remove and drain, you can add seasonings according to personal taste. 4. Fried chicken breast: Add a small amount of oil in the pot, put the cut chicken breast into the pot and stir fry, add an appropriate amount of salt, soy sauce, sugar and other seasonings, and finally add onion, ginger and other seasonings. Either way, we should pay attention to the heat to master, avoid overcooked or over-raw, to ensure taste and nutritional value.

鸡胸肉怎么做才不费时，又好吃？
How to cook chicken breast in a quick and delicious way?

 intern

制作鸡胸肉时，可以尝试以下方法来节省时间和提高口感：1. 提前腌制**： - 将鸡胸肉切成立方块，并用腌料（例如盐、黑胡椒、橄榄油、柠檬汁、大蒜等）腌制至少30分钟至过夜。这有助于增加鸡肉的味道和嫩度。2. **使用烤箱**： - 预热烤箱至200°C (392°F)。 - 在烤盘上铺上锡纸，防止汁液滴落。 - 将腌制好的鸡胸肉放在烤盘上，不要过度拥挤。 - 烤制大约20-25分钟，或直到鸡肉内部温度达到165°F (74°C)。3. **快速煎炒**： - 在平底锅中加热少量油，至中高温。 - 放入腌制好的鸡胸肉，每面煎约4-5分钟，或直到鸡肉变得非常嫩。4. **使用慢炖锅**： - 将腌制好的鸡胸肉放入慢炖锅中，加入一些蔬菜和调料。 - 慢炖约4-6小时，或直到鸡肉变得非常嫩。5. **使用压力锅**： - 将腌制好的鸡胸肉放入压力锅中，加入一些水或鸡汤。 - 按照压力锅的说明书设置压力和烹饪时间。6. **调味**： - 在烹饪过程中或完成后，根据个人口味加入额外的香料、香草或柠檬汁等来提升风味。7. **休息时间**： - 在完成烹饪后，让鸡胸肉在室温下休息5分钟，这样汁液可以重新分布，使鸡肉更加嫩滑。8. **切片或切丁**： - 在烹饪完成后，将鸡胸肉切成立方块，这样可以确保每一口都有相同的口感。通过上述方法，你可以快速制作出美味的鸡胸肉，同时节省时间并保持其嫩滑的口感。记得根据鸡胸肉的厚度和烹饪方法调整烹饪时间，以确保完全熟透且不过度干燥。

When making chicken breasts, try the following methods to save time and improve taste: 1. **Marinate ahead** : - Cut the chicken breasts into even cubes and marinate them with a marinade (e.g. salt, black pepper, olive oil, lemon juice, garlic, etc.) for at least 30 minutes until overnight. This helps to add flavor and tenderness to the chicken. 2. **Use the oven** : - Preheat the oven to 200°C (392°F). - Line a baking sheet with tinfoil to prevent the juices from dripping. - Place the marinated chicken breasts on a baking sheet without overcrowding. - Bake for approximately 20-25 minutes, or until the chicken reaches an internal temperature of 165°F (74°C). 3. **Quick saute** : - Heat a small amount of oil in a saucepan to medium-high heat. - Add the marinated chicken breasts and cook for about 4-5 minutes on each side, or until golden brown and cooked through. 4. **Using a slow cooker** : - Place the marinated chicken breast in a pressure cooker and add some water or chicken stock. - Set the pressure and cooking time according to the pressure cooker's instructions. 6. **Seasoning** : - During or after cooking, add additional spices, herbs or lemon juice according to personal taste to enhance the flavor. 7. **Rest time** : - After finishing cooking, let the chicken breasts rest at room temperature for 5 minutes so that the juices can be redistributed and the chicken is more tender and smooth. 8. **Sliced or diced** : - After cooking, cut the chicken breast into even slices or diced pieces, this will ensure that each bite has the same texture. With the above methods, you can quickly make a delicious chicken breast while saving time and maintaining its tender texture. Remember to adjust the cooking time according to the thickness and cooking method of the chicken breast to ensure that it is fully cooked and not over-dried.

鸡胸肉怎么做才不费时，又好吃？
How to cook chicken breast in a quick and delicious way?

 chatgpt

鸡胸肉是一种低脂肪高蛋白质的食材，以下是一些简单又美味的鸡胸肉烹饪方法：

1. 烤鸡胸肉：将鸡胸肉切成均匀的厚度，用盐、黑胡椒和其他喜欢的调味料腌制一段时间。然后，将鸡胸肉放在预热的烤箱中，以180°C烤10-15分钟，或直到鸡肉完全熟透。你可以在烤制过程中添加一些蔬菜或切成薄片的柠檬来增加风味。

2. 煎鸡胸肉：在平底锅中加热一些橄榄油，将腌制好的鸡胸肉放入锅中，煎至金黄色和完全熟透。翻转鸡肉时要小心，确保两面均匀受热。你可以在煎鸡胸肉之前将其切成薄片或拍扁，这样可以缩短烹饪时间。

3. 烹饪鸡胸肉：将鸡胸肉切成小块或薄片，放入煮开的热水中，煮熟约10-15分钟，或直到鸡肉完全熟透。你可以在煮鸡胸肉的过程中加入一些香料或蔬菜来提升味道。4. 鸡胸肉沙拉：将煮熟或烤好的鸡胸肉切成薄片或小块，与新鲜蔬菜、生菜、水果和喜欢的沙拉酱结合。这是一种快速简便的鸡胸肉食用方式，同时提供丰富的营养。5. 鸡胸肉卷：将鸡胸肉切成薄片，用调味料腌制一段时间。将腌制好的鸡胸肉片卷起来，可以添加蔬菜、奶酪或其他喜欢的配料。这是一种方便携带的高蛋白小吃。

无论你选择哪种烹饪方法，记得不要过度烹调鸡胸肉，以免使其变得干燥。根据鸡肉的厚度和大小，确保适当的烹饪时间，以保持鸡肉的嫩滑和美味。

Chicken breast is a low fat and high protein ingredient, here are some simple and delicious ways to cook chicken breast:

- Roast chicken breast: Cut the chicken breast into an even thickness and marinate for a while with salt, black pepper and other favorite seasonings. Then, roast the chicken breasts in a preheated oven at 180°C for 10-15 minutes, or until the chicken is cooked through. You can add some vegetables or thinly sliced lemons to the grilling process for added flavor.
- Saute chicken breasts: Heat some olive oil in a pan, add the marinated chicken breasts to the pan and fry until golden brown and cooked through. Be careful when turning the chicken to make sure both sides are evenly heated. You can slice or flatten chicken breasts before frying them to reduce cooking time.
- Cook chicken breasts: Cut chicken breasts into small pieces or thin slices, place in boiling hot water and cook for about 10-15 minutes, or until the chicken is cooked through. You can add some spices or vegetables during the cooking of the chicken breast to enhance the flavor. 4. Chicken breast salad: Cut the cooked or grilled chicken breast into thin slices or small pieces and mix with fresh vegetables, lettuce, fruit and favorite salad dressing. This is a quick and easy way to eat chicken breast meat while providing a lot of nutrients. 5. Chicken breast roll: Cut chicken breast into thin slices and marinate with seasoning for a while. Roll the chicken breast slices and add vegetables, cheese or other favorite toppings. This is an easy to carry high-protein snack.

Whatever cooking method you choose, remember not to overcook the chicken breast to avoid drying it out. Depending on the thickness and size of the chicken, ensure proper cooking time to keep the chicken tender and delicious.

Fig. 11. More qualitative experimental results of question answering visualization by FoodSky, InternLM2 and ChatGPT-3.5. The answers from our FoodSky are more informative than those from Intern and ChatGPT.

吃太多糖果和巧克力对我不好吗？
Is eating too much candy and chocolate bad for me?

 foodsky

是的，吃太多糖果和巧克力可能会导致体重增加、牙齿蛀坏、血糖波动、心血管疾病等健康问题。因此，建议适量食用，并注意均衡饮食。
Yes, eating too much candy and chocolate may cause health problems such as weight gain, tooth decay, blood sugar fluctuations, cardiovascular disease, etc. Therefore, it is recommended to eat in moderation and pay attention to a balanced diet.

吃太多糖果和巧克力对我不好吗？
Is eating too much candy and chocolate bad for me?

 intern

是的，吃太多糖果和巧克力对婴幼儿确实不好。以下是一些可能的原因：1. **牙齿健康问题**：糖果和巧克力中的糖分容易被细菌分解，产生酸性物质，长期接触可能导致龋齿（蛀牙）。婴幼儿的牙齿还未完全发育，抵抗力较弱，更容易受到糖分侵害。2. **肥胖风险**：过多的糖分摄入可能导致能量过剩，增加婴幼儿肥胖的风险。肥胖与多种慢性疾病相关，如2型糖尿病、心血管疾病等。3. **营养不均衡**：糖分往往缺乏其他必需营养素，如蛋白质、维生素、矿物质等，长期食用可能导致营养不良。婴幼儿期是建立健康饮食习惯的关键时期，过早摄入过多的糖分可能影响其后续的饮食选择。4. **能量过剩与行为问题**：摄入过多糖分可能导致婴幼儿能量过剩，表现出过度活跃、注意力不集中等问题。这些行为问题可能会影响其日后的学习和社交能力。5. **健康习惯养成**：婴幼儿期是形成健康生活习惯的关键时期，如果过多摄入糖分，可能会对其未来的饮食习惯产生负面影响。6. **睡眠质量**：糖分摄入过多可能导致血糖波动，影响睡眠质量。婴幼儿期充足的睡眠对生长发育至关重要。为了婴幼儿的健康，建议家长控制其糖果和巧克力的摄入量，并鼓励多样化、均衡的饮食。同时，家长应积极引导婴幼儿建立健康的饮食习惯，例如提供丰富的水果、蔬菜、全谷物、低脂乳制品和瘦肉等。如果婴幼儿出现明显的糖分摄入过多问题，应咨询儿科医生或营养师的意见。

Yes, eating too much candy and chocolate is bad for babies and toddlers. Here are some possible reasons: 1. **Dental health issues** :- Sugar in candy and chocolate is easily consumed
Bacteria break down producing acidic substances, and prolonged exposure may lead to dental caries (tooth decay). Infants' teeth are not fully developed, their resistance is weak, and they are more vulnerable to sugar attack
Uh-oh. 2. **Obesity risk** :- Too much sugar intake may lead to an energy surplus, increasing the risk of obesity in infants and young children. Obesity is associated with several chronic diseases, such as type 2 diabetes
Diseases, cardiovascular diseases, etc. 3. **Unbalanced nutrition** :- Sugar is often lacking in other essential nutrients, such as protein, vitamins, minerals, etc., and long term consumption may lead to camp
Poor rearing. Early childhood is a critical time to establish healthy eating habits, and too much sugar early in life may affect their dietary choices later on. 4. **Energy excess and behavior questions**
- Eating too much sugar can lead to excess energy in infants and young children, showing hyperactivity, inattention and other problems.
- These behavioral problems may affect their later life
Academic and social skills. 5. **Healthy habit formation** :- Infancy is a key period to form healthy lifestyle habits. If too much sugar intake, it may affect its future drink
Eating habits have a negative effect. 6. **Sleep quality** :- Excessive sugar intake may cause blood sugar fluctuations, affecting sleep quality.- Adequate sleep in infancy for growth and development
It's crucial. For the health of infants and young children, parents are advised to limit their intake of sweets and chocolate and to encourage a varied and balanced diet. At the same time, parents should actively guide the baby
Establish healthy eating habits for young children, such as providing plenty of fruits, vegetables, whole grains, low-fat dairy products, and lean meats. If a baby has a significant sugar intake, ask
You should consult a pediatrician or dietitian.

吃太多糖果和巧克力对我不好吗？
Is eating too much candy and chocolate bad for me?

 chatgpt

是的，吃太多糖果和巧克力对健康是不好的。以下是一些原因：

1. 蛀牙：糖分是导致蛀牙的主要原因之一。细菌在口腔中分解糖类时会产生酸，这些酸会腐蚀牙齿的釉质，导致蛀牙。
2. 体重增加：糖果和巧克力含有高热量，过多摄入会导致体重增加，增加肥胖风险。
3. 血糖波动：过多的糖分会导致血糖迅速升高，然后又迅速下降，容易引起疲劳和饥饿感。
4. 营养不均衡：过多摄入糖果和巧克力可能会占据正常饮食中的健康食品的空间，导致营养摄入不均衡。
5. 影响心血管健康：长期摄入过多的糖分可能增加心血管疾病的风险。

为了保持健康，建议适是食用糖果和巧克力，并多选择健康的食物，如水果、蔬菜、全谷类和蛋白质。

1. Tooth decay: Sugar is one of the main causes of tooth decay. When bacteria break down sugars in the mouth, they produce acids, which corrode the enamel of the teeth and cause tooth decay.
2. Weight gain: Candy and chocolate are high in calories, and excessive intake can lead to weight gain and increase the risk of obesity.
3. Blood sugar fluctuations: Too much sugar can cause blood sugar to rise rapidly and then fall rapidly, which can easily cause fatigue and hunger.
4. Unbalanced nutrition: Excessive intake of candy and chocolate may take up space for healthy foods in a normal diet, leading to unbalanced nutrition intake.
5. Impact on cardiovascular health: Long term intake of too much sugar may increase the risk of cardiovascular disease.
To stay healthy, it is recommended to eat candy and chocolate in moderation and choose more healthy foods such as fruits, vegetables, whole grains and protein.

Fig. 12. Visualization of dietary education question-answering for the children user group by different models. Our FoodSky gives the most concise and precise answers.

可以提供充足蛋白质的菜品有哪些
What dishes can provide sufficient protein

 foodsky

接下来，我会为您介绍几道采用充足蛋白質方法制作的菜品。黑椒三文魚,烤鸡胸肉是几种菜品的做法。
黑椒三文魚的做法如下：
 1. 准备食材。
 2. 将三文魚切成薄均匀的片。
 3. 将切好的三文魚片放入黑椒汁、盐和胡椒腌制十五分钟。
 4. 将洋葱切丝，蒜切末。
 5. 锅中倒入橄榄油烧热。
 6. 下入洋葱和蒜末爆香。
 7. 将腌好的三文魚片一片片放入锅中大火煎。
 8. 煎至两面金黄即可关火盛出。
 9. 最后淋上黑椒酱即可。
接下来是烤鸡胸肉的做法：
 1. 将鸡胸肉洗净，用厨房纸巾擦干水分。
 2. 在鸡胸肉上均匀地撒上盐、黑胡椒粉和任何其他喜欢的香料。
 3. 将鸡胸肉放入预热至180°C的烤箱中，烤约20-25分钟，或直到鸡肉熟透且表面呈金黄色。这两种菜品都是富含了丰富蛋白質的菜品。

Next, I will introduce you to several dishes made with sufficient protein. Black pepper salmon, grilled chicken breast, the above are several dishes. The method of making black pepper salmon is as follows: 1: Prepare the ingredients. 2: Cut the salmon into slices of uniform thickness. 3: Marinate the sliced salmon slices with black pepper sauce, salt and pepper for fifteen minutes. 4: Dice the onion and mince the garlic. 5: Heat the olive oil in the pan. 6: Add the onion and minced garlic to sauté. 7: Put the marinated salmon slices into the pan one by one and fry over high heat. 8: Fry until both sides are golden brown and turn off the heat. 9: Finally, pour the black pepper sauce on it. Next is the method of grilled chicken breast. 1. Wash the chicken breast and wipe it dry with kitchen paper. 2. Sprinkle salt, black pepper and any other spices you like evenly on the chicken breast. 3. Bake the chicken breasts in a preheated oven at 180°C for approx. 20-25 min., or until cooked through and golden brown. Both are great sources of protein.

 intern

以下是一些可以提供补充蛋白質的菜品：
 1. 煮鸡蛋：每个鸡蛋大约含有6克蛋白質。
 2. 烤鸡胸肉：每100克鸡胸肉含有约30克蛋白質。
 3. 三文魚：每100克三文魚含有约20克蛋白質。
 4. 煮豆腐：每100克豆腐含有约18克蛋白質。
 5. 瘦肉汉堡：每100克瘦肉汉堡含有约20克蛋白質。
 6. 烤虾：每100克烤虾含有约20克蛋白質。
 7. 煮豆奶：每杯豆奶含有约18克蛋白質。
 8. 炒虾仁炒蛋：这道菜同时提供蛋白質和脂肪，每份大约含有20克蛋白質。
 9. 煮牛肉面：每碗牛肉面含有约20克蛋白質。
 10. 烤鲑鱼沙拉：每份鲑鱼沙拉含有约20克蛋白質。
 这些菜品都是高蛋白低脂肪的选择，适合想要补充蛋白質的食客。

Here are some dishes that can provide a protein supplement: 1. Boiled eggs - Each egg contains about 6 grams of protein. 2. Grilled chicken breast - contains about 30 grams per 100 grams of chicken breast.
Protein 3. Salmon: Every 100 grams of salmon contains about 20 grams of protein. 4. Boiled tofu - Every 100 grams of tofu contains about 5 grams of protein. 5. Lean burger - per 100g
 The lean burger contains about 30 grams of protein. 6. Grilled shrimp - Grilled shrimp contains about 20 grams of protein per 100 grams. Seven. Boiled soy milk - Soy milk contains about 5 grams of protein per cup. 8. Stir-fried shrimps - Scrambled eggs - This dish can provide both protein and fat, with about 20 grams of protein per serving. 9. Boiled beef noodles - Each bowl of beef noodles contains about 20 grams of protein. 10. Grilled salmon - Salmon salad contains about 20 grams of protein per serving. These dishes are high protein and low fat options for diners who want to supplement their protein.

 chatgpt

当你需要增加蛋白質摄入时，以下是一些富含蛋白質的食物和菜品的例子：

- 1. 鸡胸肉: 鸡胸肉是低脂肪高蛋白質的理想选择，可以烤、煮或炒来制作各种菜品
- 2. 鱼类: 鱼类如鳕鱼、三文鱼、鲭鱼等是优质蛋白質的来源，同时富含健康的Omega-3脂肪酸。可以蒸、烤或煎来制作。
- 3. 瘦肉: 瘦牛肉、猪肉瘦肉等也是富含蛋白質的选择，可以炒、煮或烤来制作。
- 4. 蛋类: 蛋黄和蛋白都是蛋白質的良好来源，可以煮熟、煎或制作蛋白饼来摄入。
- 5. 豆类和豆制品: 豆类如黑豆、鹰嘴豆、红豆等含有丰富的植物蛋白質，可以煮汤、炒菜或制作豆腐、豆浆等。
- 6. 坚果和种子: 杏仁、核桃、腰果、花生等坚果，以及亚麻籽、葵花籽等种子富含蛋白質和健康脂肪。可以作为零食食用或加入到饮食中。
- 7. 奶制品和乳制品替代品: 牛奶、酸奶、希腊酸奶、乳清蛋白粉等都是富含蛋白質的选择。
- 8. 蔬菜: 虽然蔬菜的蛋白質含量相对较低，但一些蔬菜如菠菜、花椰菜、豌豆等含有一定量的蛋白質，可以作为蛋白質摄入的补充。

这些只是一些例子，你可以根据个人口味和偏好选择适合自己的食物。同时，结合不同的食材来制作丰富多样的菜品，可以提供更多蛋白質和营养。记得根据自己的饮食需求和目标，合理分配各类食物。

When you need to increase your protein intake, here are some examples of protein-rich foods and dishes:

- 1. Chicken breast: Chicken breast is an ideal choice for low fat and high protein. It can be grilled, boiled or fried to make a variety of dishes.
- 2. Fish: Fish such as cod, salmon, mackerel, etc. are a source of high-quality protein and are rich in healthy omega-3 fatty acids. They can be steamed, grilled or fried.
- 3. Lean meat: Lean beef, lean pork, etc. are also protein-rich choices. They can be fried, boiled or grilled.
- 4. Eggs: Both egg yolks and egg whites are good sources of protein. They can be boiled, fried or made into protein cakes.
- 5. Beans and soy products: Beans such as black beans, chickpeas, and red beans are rich in plant protein. They can be used to make soups, stir-fry vegetables, or make tofu, soy milk, etc.
- 6. Nuts and seeds: Nuts such as almonds, walnuts, cashews, peanuts, and seeds such as flax seeds and sunflower seeds are rich in protein and healthy fats. Can be eaten as a snack or added to the diet.
- 7. Dairy products and dairy alternatives: Milk, yogurt, Greek yogurt, whey protein powder, etc. are all protein-rich options.
- 8. Vegetables: Although vegetables are relatively low in protein, some vegetables such as spinach, broccoli, peas, etc. contain a certain amount of protein and can be used as a supplement to protein intake.

These are just some examples, you can choose the food that suits you according to your personal taste and preference. At the same time, combining different ingredients to make rich and diverse dishes can provide more protein and nutrition. Remember to distribute various types of food reasonably according to your dietary needs and goals.

Fig. 13. Visualization of nutritional supplement question-answering for the sportspeople user group by different models. Our FoodSky gives the most concise and precise answers.

为什么我需要控制盐的摄入量？
Why do I need to control my salt intake?

 foodsky

老年人需要控制盐的摄入量是因为随着年龄的增长，肾脏功能逐渐下降，导致体内钠和水的平衡失调。过多的盐分会导致高血压、水肿等问题，对心血管健康造成影响。此外，高盐饮食还可能增加骨质疏松的风险。因此，老年人应该限制盐的摄入，保持健康的生活方式。

The need to control salt intake in the elderly is due to the gradual decline in kidney function as we age, resulting in an imbalance in the balance of sodium and water in the body. Too much salt can lead to high blood levels. Problems such as pressure and edema can affect cardiovascular health. In addition, a high-salt diet may also increase the risk of osteoporosis. Therefore, the elderly should limit salt intake to maintain A healthy lifestyle.

为什么我需要控制盐的摄入量？
Why do I need to control my salt intake?

 intern

您好，盐是人们日常饮食中必不可少的调味品，但过量的盐摄入会对健康产生不利影响。以下是一些关于控制盐摄入量的原因：1. **高血压**：摄入过多的盐会增加体内钠的积累，导致血容量增加，进而升高血压。高血压是心脑血管疾病的主要风险因素之一。2. **心血管疾病**：高盐饮食与心脏病和中风等心血管疾病的风险增加有关。3. **肾脏负担**：过多的盐需要肾脏排出，长期高盐饮食可能加重肾脏负担，尤其是对于已有肾脏疾病的人群。4. **骨质疏松**：过量的盐摄入可能导致钙的流失，增加骨质疏松的风险。5. **水肿**：高盐饮食可能导致水分滞留，引起水肿。6. **胃肠道问题**：过量的盐可能导致胃肠道不适，如胃痛、腹泻等。为了维护健康，世界卫生组织建议成人每日盐摄入量不超过克。您可以通过减少加工食品和餐馆食品的摄入，选择新鲜的食材，并自己控制盐的使用量来控制盐的摄入。同时，您还可以尝试使用其他调味品，如酸味、甜味和香料，来增加食物的味道。希望这些信息能对您有所帮助。如果您有任何其他问题，我会很乐意为您提供帮助。让我们一起关注健康，享受美味又健康的饮食。

Hello, salt is an essential condiment in People's Daily diet, but excessive salt intake will have adverse effects on health. Here are some tips for controlling your salt intake
Cause: ** Hypertension **: Consuming too much salt increases the accumulation of sodium in the body, leading to an increase in blood volume, which in turn raises blood pressure. Hypertension is a major risk factor for cardiovascular and cerebrovascular diseases
One of them, 2. ** Cardiovascular disease **: Diets high in salt are associated with an increased risk of cardiovascular disease such as heart attack and stroke, 3. ** Kidney burden **: Too much salt needs to be excreted by the kidneys.
Long term high-salt diets may increase the burden on the kidneys, especially in people with pre-existing kidney disease. 4. ** Osteoporosis **: Excessive salt intake may cause calcium loss and increase bone
The risk of loose quality. 5. ** Edema **: A diet high in salt may lead to water retention, causing edema. 6. ** Gastrointestinal problems **: Excess salt may cause gastrointestinal discomfort, such as in the stomach
Pain, diarrhea, etc. To maintain health, the World Health Organization recommends that adults consume no more than 5 grams of salt a day. You can choose by reducing your intake of processed foods and restaurant foods
Choose fresh ingredients and limit your salt intake by controlling the amount of salt you use. At the same time, you can also try using other condiments, such as sour, sweet and spices, to enhance the flavor
The flavor of things, I hope you find this information helpful. If you have any other questions, I will be happy to help you. Let's focus on health and enjoy delicious food
And a healthy diet.

为什么我需要控制盐的摄入量？
Why do I need to control my salt intake?

 chatgpt

随着年龄的增长，高盐饮食会对我的健康造成更大的影响。盐中含有的钠会导致血压升高，增加心脏病和中风的风险。控制盐的摄入量有助于保持血压在健康范围内，减少心血管疾病的风险。为了减少盐的摄入，可以使用香草和香料来增加食物的味道，选择低钠食品，并尽量避免加工食品和快餐。

As I get older, a high-salt diet will take a bigger toll on my health. The sodium contained in salt can raise blood pressure and increase the risk of heart disease and stroke. haloccontrol
Intake helps keep blood pressure within a healthy range and reduces the risk of cardiovascular disease. To reduce salt intake, herbs and spices can be used to enhance the flavor of food, choose
Choose low sodium foods and avoid processed foods and fast foods.

Fig. 14. Visualization of health maintenance question-answering for the elderly user group by different models. Our FoodSky gives the most concise and precise answers.



Fig. 15. Visualization of academic inspiration question-answering for the healthcare worker user group by different models. Our FoodSky gives the most concise and precise answers.

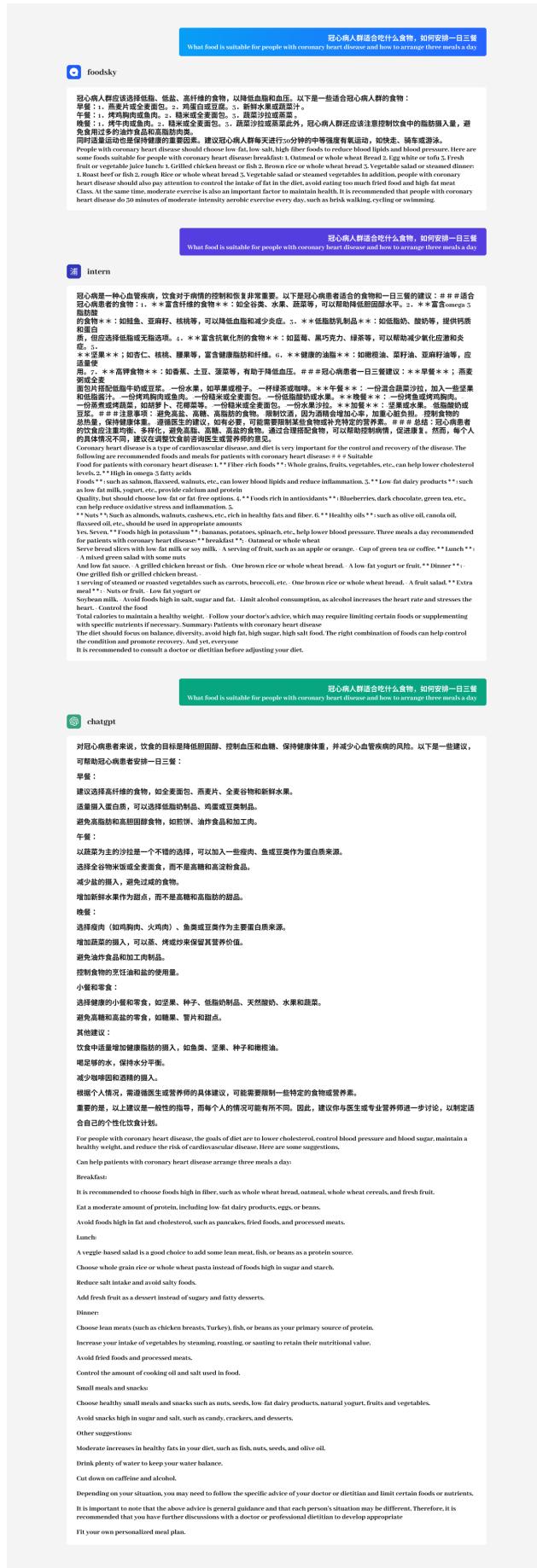


Fig. 16. Visualization of health diagnosis question-answering for the chronic patient user group by different models. Our FoodSky gives the most concise and precise answers.

FoodSky

我应该如何调整我的饮食，以应对长时间的工作，同时减少疲劳？
How should I adjust my diet to cope with long working hours while reducing fatigue?

食物摄入量会根据工作强度和营养需求而不同。为了应对应长时间的工作，建议尝试以下饮食调整：

- 1. 增加蛋白质摄入：蛋白质是身体维持肌肉功能的主要来源，有助于保持能量水平。过多的碳水化合物会导致胰岛素水平上升，从而抑制胰岛素敏感性。
- 2. 吃均衡的饮食：确保摄入足够的蔬菜、水果、全谷物、豆类和坚果。
- 3. 增加健康脂肪摄入：健康的脂肪有助于提供能量和改善心情。选择富含不饱和脂肪酸的食物，如鱼类、坚果、种子和橄榄油。
- 4. 均衡饮食：确保您的饮食包含足够的维生素、矿物质和纤维素，以帮助您保持身体健康和精力充沛。
- 5. 喝足够的水：水分摄入不足会导致脱水，从而降低能量水平。补充维生素和矿物质，如镁和钾，也有助于缓解疲劳。

长时间工作可能会影响您的饮食和营养摄入。为应对这种情况，您可以尝试以下饮食调整：

1. 均衡饮食 **：确保每餐都包含蛋白质、健康脂肪、维生素和矿物质。
2. * 定时进食 **：保持规律的进餐时间，避免长时间不吃饭，这可能导致血糖水平剧烈波动，引起疲劳。
3. * 饮食习惯：如果您的工作时间较长，可以考虑携带健康的零食，如坚果、水果或能量棒，以补充能量。
4. * 水分摄入 **：保持充足的水分摄入，有助于维持身体水平衡，提高工作效率和注意力。
5. * 营养摄入：多吃蔬菜水果，以获取必要的维生素和矿物质，帮助身体保持健康。
6. * 补充维生素和矿物质：如果感到疲惫或缺乏精力，可以考虑补充维生素和矿物质，如镁和钾。
7. * 延长用餐时间：尝试在一天中安排更多的用餐时间，以分散能量摄入。
8. * 咨询专业人士：如果您有特殊健康问题或需要更详细的建议，请咨询专业医生或营养师。

长时间工作可能让您感到疲劳和营养不良。为应对这种情况，您可以尝试以下饮食调整：

1. * 均衡饮食 **：确保每餐都包含蛋白质、健康脂肪、维生素和矿物质。
2. * 补充维生素和矿物质：如果感到疲惫或缺乏精力，可以考虑补充维生素和矿物质，如镁和钾。
3. * 增加蛋白质摄入：蛋白质有助于肌肉修复和生长，对于体力劳动者尤其重要。在工作中，确保每餐都有高质量的蛋白质来源，如肉、豆类、坚果和豆制品。
4. * 选择复合碳水化合物：复合碳水化合物（如全谷物、豆类和蔬菜）可以提供稳定的能量，并有助于维持血糖水平。
5. * 增加健康脂肪摄入 **：健康脂肪（如橄榄油、鱼油、坚果和种子）对提供能量和维持细胞功能非常最重要。适量摄入这些脂肪可以帮助减少疲劳。
6. * 定时进食 **：避免长时间不吃东西，因为这可能导致血糖下降和能量不足。尝试每隔5-6小时进食一次，以保持能量水平。
7. * 避免过多咖啡因和酒精 **：虽然咖啡因可以提供短暂的能量提升，但过量摄入可能导致能量崩溃和睡眠问题。酒精则可能影响睡眠质量和第二天的表现。
8. * 补充电解质 **：长时间工作可能导致大量出汗和电解质流失。通过饮用运动饮料或含有电解质的水来补充流失的钠、钾和其他电解质。
9. * 考虑补充营养素 **：如果你担心饮食中某些营养素的不足，可以考虑在医生或营养师的指导下补充维生素和矿物质。

通过这些饮食调整，你可以更好地应对长时间的工作，减少疲劳，并保持身体和精神的最佳状态。

To cope with long working hours and reduce fatigue, you can adjust your diet in the following ways:

1. * Eat a balanced diet **: Make sure your diet contains enough protein, complex carbohydrates, healthy fats, vitamins and minerals. These nutrients are essential for providing energy.
2. * Increase your protein intake **: Protein helps muscle repair and growth, and is especially important for manual workers. During the working day, make sure to include high quality protein at every meal.
3. * Choose complex carbohydrates **: Complex carbohydrates (such as whole grains, legumes, and vegetables) provide steady energy and help maintain blood sugar levels, avoid simple carbohydrates (such as sugar and white bread), as they may cause a rapid rise in energy followed by a rapid decline.
4. * Maintain water balance **: Dehydration can lead to fatigue and decreased energy. Make sure to drink water regularly during work, especially if working in a hot or dry environment.
5. * Eat healthy fats in moderation **: Healthy fats (such as olive oil, fish oil, nuts and seeds) are important for providing energy and maintaining cell function. Eat these fats in moderation.
6. * Eat regularly **: Avoid going without food for long periods of time, as this can lead to a drop in blood sugar and low energy levels. Try to eat every 3-4 hours to maintain energy levels.
7. * Avoid too much caffeine and alcohol **: While caffeine can provide a brief energy boost, excessive consumption can lead to energy crashes and sleep problems. Alcohol can be harmful.

Sound sleep quality and next day performance.

8. * Replace electrolytes **: Working long hours can lead to excessive sweating and electrolyte loss. Replace lost sodium, potassium, and other sodium by drinking sports drinks or water containing electrolytes.

9. * Consider nutrient supplements **: If you are concerned about the inadequacy of certain nutrients in your diet, consider taking vitamins and mineral supplements under the guidance of a doctor or dietitian.

With these dietary adjustments, you can better cope with long work hours, reduce fatigue, and stay in top physical and mental shape.

intern

我应该如何调整我的饮食，以应对长时间的工作，同时减少疲劳？
How should I adjust my diet to cope with long working hours while reducing fatigue?

应对应长时间工作并减少疲劳，您可以采取以下饮食调整建议：

1. * 均衡饮食 **：确保每餐都包含蛋白质、健康脂肪、维生素和矿物质。
2. * 定时进食 **：保持规律的进餐时间，避免长时间不吃饭，这可能导致血糖水平剧烈波动，引起疲劳。
3. * 增加蛋白质摄入：蛋白质有助于肌肉修复和生长，对于体力劳动者尤其重要。
4. * 增加健康脂肪摄入 **：健康脂肪（如橄榄油、鱼油、坚果和种子）对提供能量和维持细胞功能非常最重要。
5. * 增加碳水化合物摄入：复合碳水化合物（如全谷物、豆类和蔬菜）可以提供稳定的能量，并有助于维持血糖水平。
6. * 补充维生素和矿物质：如果感到疲惫或缺乏精力，可以考虑补充维生素和矿物质，如镁和钾。
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chatgpt

我应该如何调整我的饮食，以应对长时间的工作，同时减少疲劳？
How should I adjust my diet to cope with long working hours while reducing fatigue?

为了应对长时间的工作并减少疲劳，你可以通过以下方式调整饮食：

1. * 均衡饮食 **：确保你的饮食中包含足够的蛋白质、复合碳水化合物、健康脂肪、维生素和矿物质。这些营养素对于提高身体功能和减少疲劳至关重要。
2. * 增加蛋白质摄入 **：蛋白质有助于肌肉修复和生长，对于体力劳动者尤其重要。在工作中，确保每餐都有高质量的蛋白质来源，如肉、豆类、坚果和豆制品。
3. * 选择复合碳水化合物 **：复合碳水化合物（如全谷物、豆类和蔬菜）可以提供稳定的能量，并有助于维持血糖水平。
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8. * 补充电解质 **：长时间工作可能导致大量出汗和电解质流失。通过饮用运动饮料或含有电解质的水来补充流失的钠、钾和其他电解质。
9. * 考虑补充营养素 **：如果你担心饮食中某些营养素的不足，可以考虑在医生或营养师的指导下补充维生素和矿物质。

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With these dietary adjustments, you can better cope with long work hours, reduce fatigue, and stay in top physical and mental shape.

Fig. 17. Visualization of meal planning question-answering for the mental worker user group by different models. Our FoodSky gives the most concise and precise answers.

如何确保我的饮食提供足够的能量，以支持我的体力劳动？
How can I ensure that my diet provides enough energy to support my physical work?

 foodsky

体力劳动需要消耗能量，确保饮食提供足够的能量有助于维持体力劳动。建议多食用富含碳水化合物、蛋白质和健康脂肪的食物，如全谷类、肉类、鱼类、坚果和种子。此外，保持适当的水分摄入也很重要。
Physical work requires energy, and ensuring that the diet provides enough energy can help maintain physical work. It is recommended to eat more foods rich in carbohydrates, proteins and healthy fats, such as whole grains, lean meats, fish, nuts and seeds. In addition, it is also important to maintain proper water intake.

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要确保您的饮食能够提供足够的能量来支持体力劳动，您可以采取以下措施：1. **均衡饮食**：摄入来自五大食物类别的食物：谷物、蔬菜、水果、蛋白质来源（如肉类、鱼类、豆类和坚果）以及乳制品或替代品（如豆浆）。确保每餐都包含适量的碳水化合物、蛋白质和健康脂肪。2. **增加碳水化合物摄入**：碳水化合物是身体主要的能量来源。选择复杂的碳水化合物，如全谷物、燕麦、糙米和薯类，它们提供长效能量。避免高糖和高加工的食品，它们可能导致能量峰值和崩溃。3. **蛋白质摄入**：蛋白质对于肌肉修复和生长至关重要。选择瘦肉、鱼类、豆类、豆制品和坚果作为蛋白质来源。每餐摄入适量的蛋白质，以支持肌肉恢复和维持。4. **增加健康脂肪摄入**：摄入健康的脂肪，如橄榄油、鱼油、坚果和种子，它们有助于维持能量水平和支持心脏健康。避免饱和脂肪和反式脂肪，它们可能增加心脏病风险。5. **水分摄入**：确保充足水分摄入，以避免脱水，脱水会影响体力表现。在体力劳动前、中、后都应适量饮水。6. **定时进餐**：定时进餐可以帮助维持稳定的血糖水平，避免能量不足。在体力劳动前 2 小时的进餐，以确保有足够的时间消化。7. **补充电解质**：在长时间或高强度体力劳动后，补充电解质（如钠、钾和镁）可以帮助恢复体力。运动饮料或含有电解质的食物和饮品是一个不错的选择。8. **个性化调整**：根据个人的体力劳动强度、持续时间和目标，调整饮食计划。可能需要额外的能量补充，如能量棒或能量胶。9. **监测反应**：注意饮食变化对身体的影响，记录能量水平和体力表现。如果需要，调整饮食以优化能量供应。10. **咨询专业人士**：如果您有特殊的营养需求或限制，如食物过敏或特定的健康状况，咨询注册营养师或医生以获取个性化建议。通过遵循上述建议，您可以确保您的饮食能够提供足够的能量来支持体力劳动，并帮助您保持最佳的身体状态。记得在开始任何新的饮食或锻炼计划之前，先咨询专业人士以获得个性化建议。

To ensure that your diet provides enough energy to support physical exertion, you can take the following steps: 1. **Balanced diet** - Eat foods from the five food groups: grains, vegetables, fruits, protein sources (such as meat, fish, legumes and nuts), and dairy products or alternatives (such as soy milk). Make sure each meal contains the right amount of carbohydrates, protein and healthy fats. 2. **Carbohydrates** - Carbohydrates are the body's main source of energy. Choose complex carbohydrates, such as whole grains. Food: oats, brown rice and potatoes, which provide long-lasting energy. Avoid foods that are high in sugar and processed, which can cause energy spikes and crashes. 3. **Protein** - Eggs. White matter is essential for muscle repair and growth. Choose lean meats, fish, beans, soy products, and nuts as protein sources. Consume the right amount of protein at each meal to support muscle recovery and maintenance. 4. **Healthy fats** - Eat healthy fats such as olive oil, fish oil, nuts and seeds, which help maintain energy levels and support heart health. 5. **Water** - Avoid saturated and trans fats, which may increase the risk of heart disease. 6. **Regular meals** - Ensure adequate water intake to avoid dehydration, which can affect physical strength. 7. **Electrolytes** - Drink adequate amounts of water before, during and after physical work. 8. **Supplement electrolytes** - Regular meals can help maintain stable blood sugar levels and avoid energy loss. 9. **Monitor reaction** - Eat 1-2 hours before physical exertion to give your body adequate time for digestion. 10. **Consult professionals** - Supplement electrolytes after prolonged or high-intensity physical labor. Substances (such as sodium, potassium and magnesium) can help restore strength. Sports drinks or foods and drinks that contain electrolytes are a good choice. 11. **Personalized adjustment** - According to individual physical activity intensity, duration and goals, adjust diet plan. Additional energy supplements, such as energy bars or gel, may be needed. 12. **Adjust diet** - Pay attention to the effects of dietary changes on the body and record energy levels and physical performance. Adjust your diet to optimize energy supply if needed. 13. **Consult doctor** - If you have special nutritional needs or limitations, such as food allergies or specific health conditions, consult a registered dietitian or doctor for personalized advice. By following the above advice, you can make sure that your diet provides enough energy to support physical work and help you stay in top physical shape. Remember before starting any new diet or exercise program. Before doing so, consult a professional for personalized advice.

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要确保你的饮食提供足够的能量以支持体力劳动，可以考虑以下几点：

1. **均衡饮食**：确保每天摄入足够的碳水化合物、蛋白质和健康脂肪。这些营养素是提供能量的关键。
2. **增加碳水化合物摄入**：碳水化合物是提供能量的主要来源，特别是复杂碳水化合物（如全谷类、蔬菜）能够提供持久的能量。
3. **适量摄入蛋白质**：蛋白质对于修复和建立肌肉至关重要。选择瘦肉、鸡蛋、豆类、坚果和鱼类等优质蛋白来源。
4. **增加健康脂肪摄入**：健康脂肪（如橄榄油、鱼油、坚果和种子）有助于提供额外的能量，并维持身体正常功能。
5. **多吃水果和蔬菜**：水果和蔬菜富含维生素、矿物质和纤维，有助于提供额外的能量和维持身体健康。
6. **保持水平衡**：保持良好的水分摄入，因为脱水会导致体力劳动时的疲劳和能量不足。
7. **避免空热量**：尽量避免高糖饮料、炸食和高加工食品，它们提供的能量往往不够稳定且缺乏营养价值。
8. **根据个人需求调整**：每个人的体力劳动量不同，可以根据自己的具体情况调整饮食，确保摄入足够的能量以支持工作或运动。

如果你需要更具体的饮食建议，建议咨询营养师或医生，以便根据个人情况制定适合的饮食计划。

To ensure that your diet provides enough energy to support physical work, you can consider the following points:

1. **Eat a balanced diet** - Make sure to consume enough carbohydrates, protein and healthy fats every day. These nutrients are key to providing energy.
2. **Increase carbohydrate intake** - Carbohydrates are the main source of energy, especially complex carbohydrates (such as whole grains, vegetables) can provide long-lasting energy.
3. **Ingest protein in moderation** - Protein is essential for repairing and building muscles. Choose high-quality protein sources such as lean meat, eggs, beans, nuts and fish.
4. **Increase healthy fat intake** - Healthy fats (such as olive oil, fish oil, nuts and seeds) help provide additional energy and maintain normal body functions.
5. **Eat more fruits and vegetables** - Fruits and vegetables are rich in vitamins, minerals and fiber, which help provide additional energy and maintain good health.
6. **Maintain water balance** - Maintain good water intake, because dehydration can lead to fatigue and lack of energy during physical work.
7. **Avoid empty calories** - Try to avoid high-sugar drinks, fried foods and highly processed foods, which often provide unstable energy and lack nutritional value.
8. **Adjust according to personal needs** - Everyone has different physical labor, so you can adjust your diet according to your specific situation to ensure that you consume enough energy to support work or exercise.

If you need more specific dietary advice, it is recommended to consult a nutritionist or doctor to develop a suitable diet plan based on your personal situation.

Fig. 18. Visualization of nutrition recommendation question-answering for the manual worker user group by different models. Our FoodSky gives the most concise and precise answers.

每餐应吃多少？孕妇每餐应摄入多少食物以保证摄取足够的营养而不过量？
How much should you eat at each meal?
How much food should pregnant women eat at each meal to ensure adequate nutrition without overeating?

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孕妇每餐应摄入适量的食物，以确保获得足够的营养而不会过度进食。一般来说，孕妇每天需要摄入约2500-3000卡路里的食物，这可以分为三餐和两个小食。具体来说，早餐应该包括一份蛋白质、一份碳水化合物和一份水果或蔬菜。午餐和晚餐应该包括一份蛋白质、一份碳水化合物、一份蔬菜和一份水果。两个小食可以是酸奶、坚果、水果或蔬菜。此外，孕妇还应该多喝水，保持身体水分平衡。

Pregnant women should eat the right amount of food at each meal to ensure adequate nutrition without overeating. Generally speaking, pregnant women need to consume about 2500-3000 calories of food per day, which can be divided into three meals and two snacks. Specifically, breakfast should include one protein, one carbohydrate and one fruit or vegetable; lunch and dinner should include one protein, one carbohydrate, one vegetable and one fruit; two snacks can be yogurt, nuts, fruit or vegetables. In addition, pregnant women should drink plenty of water to maintain the body's water balance.

每餐应吃多少？孕妇每餐应摄入多少食物以保证摄取足够的营养而不过量？
How much should you eat at each meal?
How much food should pregnant women eat at each meal to ensure adequate nutrition without overeating?

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孕妇在每餐中应该摄入多少食物，需要根据孕妇的个体差异、孕期阶段、身体状况以及医生的建议来确定。以下是一些一般的指导原则：1. **营养均衡**：确保每餐都包含五大类食物：谷类、蔬菜、水果、蛋白质来源（如肉类、鱼类、豆类、坚果和种子）以及乳制品或替代品。2. **适量控制**：每餐的食物分量应该适中，避免暴饮暴食，以免造成消化不良和体重过快增加。3. **定时进餐**：每天应规律地进食，包括三餐和可能的小吃。4. **个性化建议**：孕妇应该咨询医生或营养师，以获得根据个人情况量身定制的饮食建议。5. **水分摄入**：确保每天足够的水分摄入，以保持身体水平衡。6. **避免高糖和高脂肪食物**：减少加工食品、含糖饮料和高脂肪食物的摄入，这些食物可能导致体重增加和健康问题。7. **维生素和矿物质补充**：根据医生的建议，孕妇可能需要额外的维生素和矿物质补充剂，特别是叶酸、铁和钙。8. **控制热量**：孕期体重增加应控制在合理的范围内，通常建议孕妇在整个怀孕期间增重11-16公斤。9. **避免生食和生肉**：确保所有食物烹饪熟透，以避免食源性疾病。10. **适量运动**：适当的运动有助于控制体重和维持健康，但应在医生指导下进行。请注意，上述建议是普遍性的指导原则，而孕妇的具体饮食需求可能因个体差异而有所不同。因此，请务必咨询医生或营养师以获取针对个人情况的详细建议。

How much food a pregnant woman should eat at each meal depends on her individual differences, stage of pregnancy, physical condition, and doctor's advice. Here are some general guidelines: 1. **Balanced nutrition**: Make sure each meal contains five major food groups: cereals, vegetables, fruits, protein sources (such as meat, fish, beans, nuts and seeds), and dairy products or alternatives. 2. **Moderate control**: The portion of each meal should be moderate, and overeating should be avoided to avoid indigestion and excessive weight gain. 3. **Regular meals**: Eat regularly every day, including three meals and possible snacks. 4. **Personalized advice**: Pregnant women should consult a doctor or nutritionist for dietary advice tailored to their individual situation. 5. **Water intake**: Make sure to consume enough water every day to maintain body water balance. 6. **Avoid high-sugar and high-fat foods**: Reduce the intake of processed foods, sugary drinks and high-fat foods, which may lead to weight gain and health problems. 7. **Vitamin and mineral supplements**: Based on the doctor's advice, pregnant women may need additional vitamin and mineral supplements, especially folic acid, iron and calcium. 8. **Calorie control**: Weight gain during pregnancy should be kept within a reasonable range, and it is generally recommended that pregnant women gain 11-16 kg throughout pregnancy. 9. **Avoid raw food and raw meat**: Make sure all food is cooked thoroughly to avoid foodborne diseases. 10. **Moderate exercise**: Appropriate exercise can help control weight and maintain health, but it should be done under the guidance of a doctor. Please note that the above recommendations are general guidelines, and the specific dietary needs of pregnant women may vary depending on individual differences. Therefore, please be sure to consult a doctor or nutritionist for detailed advice for your individual situation.

每餐应吃多少？孕妇每餐应摄入多少食物以保证摄取足够的营养而不过量？
How much should you eat at each meal?
How much food should pregnant women eat at each meal to ensure adequate nutrition without overeating?

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孕妇在孕期每餐的食量应该是适量，即摄入足够的营养但不过量。以下是一些一般的建议，但实际的饮食需求会因个人体重、活动水平、怀孕阶段和健康状况而有所不同：

1. 分餐进食：孕妇应尽量分成多餐进食，每天保持规律进食，避免长时间空腹。
2. 控制食物种类：每餐尽可能包括多种食物类别，包括蛋白质、水果、蔬菜、全谷类食品和适量的健康脂肪。
3. 多样化食物选择：确保每餐中有来自各种食物类别的食物，以获得全面的营养。
4. 根据饥饿感调节食量：在进餐前了解自己的饥饿感，避免饥食。
5. 注意体重：注意清食的提示，尽量避免空腹路里的食物，如果和高糖饮料。
6. 饮食平衡：确保膳食中包含足够的蛋白质、健康碳水化合物和脂肪，以满足身体所需的各种营养。
7. 依据能量需求摄入：依据孕妇个人的能量需求酌情增减食量，不要过量摄入导致肥胖。

一般来讲，孕妇每日应保证三餐均衡，同时可适量添加两次零食，避免在短时间内食用过多食物。如果有关于怀孕饮食的具体问题，建议向医生或专业营养师咨询，以根据个人估况制定更个性化的饮食计划。

Pregnant women should eat moderate amounts of food at each meal during pregnancy, that is, adequate nutrition but not excessive intake. Here are some general recommendations, but actual dietary needs will vary depending on personal weight.

activity level, stage of pregnancy and health status:

1. Eat separately: Pregnant women should try to eat in multiple meals, eat regularly every day, and avoid long periods of fasting.
2. Control food types: Each meal should include as many food categories as possible, including protein, fruits, vegetables, whole grains and appropriate amounts of healthy fats.
3. Diverse food choices: Make sure that each meal has food from a variety of food categories to obtain comprehensive nutrition.
4. Adjust food intake according to hunger: Understand your hunger before eating and avoid eating too much.
5. Pay attention to the prestige: Pay attention to the reminder of clean eating, try to avoid empty calorie foods, if and high sugar drinks.
6. Balanced diet: Make sure that the meal contains enough protein, healthy carbohydrates and fats to meet the various nutrients needed by the body.
7. Intake according to energy needs: Increase or decrease food intake according to the individual energy needs of pregnant women, and do not consume excessively to cause obesity.

Generally speaking, pregnant women should ensure three balanced meals a day, and can add two snacks in moderation to avoid eating too much food in a short period of time. If you have specific questions about pregnancy diet, it is recommended to consult a doctor or professional nutritionist to develop a more personalized diet plan based on personal assessment.

Fig. 19. Visualization of dietetic contraindication question-answering for the pregnant woman user group by different models. Our FoodSky gives the most concise and precise answers.