Prompting Session-based Context for Personalized Meal Recommendations: A Generative Model Perspective with Insights from Chain-of-Recommendations

Shubhanshi Singhal[1] and Vikram Singh[2]

[1] Department of Computer Science and Information Technology, Central University of Haryana, Mahendergarh `shubhanshi17@gmail.com`

[2] Deptartment of Computer Engineering, National Institute of Technology Kurukshetra `viks@nitkkr.ac.in`

Abstract. In information-seeking perspectives, users' intermediate interactions reflect rapidly changing intents, as seen in session-based recommender systems (SBRS). These systems adapt to intermediate recommendations but exceptionally result in context misalignments. This paper leverages the reasoning of generative models, with *Chain-of-Thought (CoT)*, in *Chain-of-Recommendations (CoR) Prompts* with the goal to understand and synthesize sequential user interactions, contextual data, and cross-session dependencies to generate coherent and personalized meal recommendation sequences. Further, we evaluate the efficacy of generative models, *Llama* and *Gemini*, in contextual SBRS under the '*CoR*' framework. It focuses on integrating nutritional assessment, context awareness (e.g., weekly meal synthesis for users with specific *diseases*), and alternative food suggestions that meet mineral thresholds. Using metrics like RMSE, MAE, and MSE, the study assesses model performance across contexts, *Prompts*, session complexities, and chaining scenarios. Results demonstrate that *Gemini* outperforms *Llama*, achieving higher compliance in meal plan personalization.

Keywords: Contextual Behavior · Generative AI · Prompt Learning.

1 Introduction

Recommendation systems (RSs) are crucial for guiding user information-seeking tasks, with a user-in-loop approach to adapt to dynamic preferences during browsing. However, traditional way of content-based and collaborative browsing on, primarily generate long-term personalized recommendations based on user profiles and historical data, overlooking short-term preferences [7]. The need to model short-term preferences, especially in intent modeling (at both user and item levels), arises from the importance of contextual behavior in predicting relevant next items [2]. This drives the development of *session-based recommendation systems* (SBRS) [11], where a session consists of user-item interactions within a specific temporal instance or theme is leveraged to predict the next items, enabling personalized recommendations tailored to short-term user behavior or moulded preferences. The notion of session-based preference modeling is significant in computational scenarios requiring alignment toward intermediate contextual suggestions, dynamically adapting to factors such as thematic, sentiment, location, and temporal aspects. In this context, sequential behavior and structural dependency of users' actions (*e.g., clicks, views, purchases*) are two driving factors [6] while the complex patterns of relationships during *Chain-of-Recommendations* (COR) data are modeled in session graphs.

The *Chain of Thought* (CoT) prompting represents a paradigm shift in contextual learning, designed to improve prediction model performance by explicitly guiding the model to generate step-by-step explanations before arriving at a final result [13] . Conceptually analogous to COR in session-based contextual learning, CoT emphasizes breaking down problems without skipping intermediate steps, thereby reducing reasoning failures. This effectiveness stems from the fundamental attention mechanism of *large language models* (LLMs). Similarly, within a session-based RS, short-term preference dynamic cues are captured and progressively encapsulated into subsequent reasoning/suggestions; the model focuses its attention on one part of the problem at a time. The chain-of-recommendations *Prompts* minimize the risk of errors that might arise from handling too much information simultaneously.

This paper demonstrates the capabilities of generative models in adapting to nutritional assessment and context awareness, considering factors such as location, time, and dietary requirements. The models, *Gemini* and *LLaMA*, generate comprehensive nutritional analyses (e.g.,*calorie count, protein, fibre, sugar, and carbohydrates*) to ensure dietary needs are met, in response to contextual *Prompts* leveraging real-time data, including geographical location, dietary preferences, and cuisines. The learning framework functions as a context-aware system, offering meal suggestions that balance nutrition with personal preferences. Model performance is evaluated using *Root Mean Square Error (RMSE)* , *Mean Square Error (MSE)*, and *Mean Absolute Error (MAE)* metrics.

1.1 Motivation and Research Questions

Modern recommendation systems are pivotal in personalizing the *user experience* (UX) in the recent decade, spanning over a variety of applications areas. The level of personalization relies on the preferences across *short*, *mid*, and *long-term* periods using historical interaction data. While many state-of-the-art strategies focus on *long-term* preferences, *short-term* and contextual aspects are often overlooked. *Long-term* preferences are typically modeled using *matrix factorization, latent factor models, knowledge graphs,* and *pre-trained models. Mid-term* preferences are captured through *time-series models*, *hierarchical attention networks, and topic modeling*, while *short-term* preferences are effectively modeled using *attention mechanisms*, *temporal decay functions*, and *session-based models.*

Modeling *short-term* preferences involves capturing dynamic, evolving user behavior, but it is inherently complex due to high variability, sequential dependencies, contextual factors, limited data, and real-time processing needs. Session-based learning strategies address these challenges by predicting outcomes based on intermediate interactions or a chain of recommendations. The COR prompt enhances model performance, reduces risks like context misalignment, filter bubbles, algorithmic bias, and user disengagement. While effective in domains like e-commerce and entertainment, *short-term* modeling for personalized meal planning while incorporating implicit factors, e.g., time, location, mood, and nutritional thresholds, remains underexplored but holds significant potential for advancing health-focused recommendations.

Why Generative Models for Cross-Session Context Alignment in Meal Recommendations: Generative models [8] excel in session-based recommendation systems by dynamically adapting to user-specific contexts and preferences, enabling just-in-time optimized meal suggestions. For instance, models like Gemini and Llama [9] leverage real-time data—such as *location, time, and dietary behavior*, to synthesize personalized meal plans and integrate detailed nutritional metrics, including *calorie count, protein, fiber, sugar, and carbohydrates* via *Prompts* ensuring dietary alignment with health goals. Their context-aware design allows seamless adaptation to *short-term* variations in dietary behavior while maintaining personalization and nutritional relevance.

1.2 Contribution

In light of the aforementioned shortcomings, the primary contributions to the research can be outlined as follows:

- This article presents an alternative meal generation framework using advanced LLMs like Gemini and Llama to create personalized, adaptive meal plans. The CoR learning paradigm mirrors chain-of-thought reasoning, ensuring logical progression in recommendations. Generative models are benchmarked against medical standards, with each prompt evaluated for nutritional accuracy, guideline adherence, and suitability.
- The proposed framework integrates short-term meal compliance, geographic location, cuisine preferences, and dietary requirements (medical and personal) with nutritional analysis, including calorie count, protein, fiber, sugar, and carbohydrates, to deliver personalized and health-conscious meal suggestions.
- Discrepancy metrics assess deviations in AI-generated meal plans from real-world prescriptions, evaluating nutritional alignment, compliance, and personalization. This analysis highlights strengths and gaps in Gemini and Llama models, guiding AI-driven healthcare improvements.

The manuscript is organized as follows: Section 1 introduction outlines the motivation, research questions (RQs), and contributions. Related work summarizes relevant literature in Section 2. Section 3 details the proposed approach, while Section 4 covers the experimental setup, pre-trained generative models, and evaluation. Section 5 addresses RQs, and future directions. Finally, Section 6 concludes the proposed work.

2 Related Work

Contemporary research on session-based learning, e.g., session-based RSs, has evaluated and resolved the complex, contextual, and structural relationships within session data by employing deep learning, graph-based methods, and embedding techniques. More recently, generative models such as *Variational Autoencoder (VAE) [5]* and *Generative Adversarial Network (GAN) [1]* have been employed to capture sequential dependencies in session data. These models help to address data sparsity and cold-start problems by modeling complex user-item interaction patterns. In 2022, Wang et al. [12] presents a generative framework that uses adversarial networks to represent user behavior sequence for both rational and informative purposes. Deep learning methods like RNN, *Long short-term memory network* (LSTM) [4] and *Gated Recurrent Unit* (GRU) [14] are utilized to capture the sequential dependency of pattern of user interaction with item while attention-based mechanisms like *Self-Attention for Session-Aware Recommendation (SASREC) [3]* focus on the most relevant part of session data. Graph-based models represent the structural relationship between one item's interaction with other items by constructing a session graph where a node represents an item and an edge represents an interaction between these items. GNN-based SBRS captures item-item transition more effectively than sequential models.

3 Proposed Generative Approach to Meal Plan Synthesis

Session-based recommendation aims to capture historical user interaction cues within short-term preference behaviors of the current session while also considering contextual factors across a chain of sessions. *Chain-of-Recommendations* modeling enhances the usability of Session-Based Recommender Systems (SBRS) by structuring recommendations as a sequential reasoning process rather than independent suggestions. It builds upon intermediate user interactions to generate coherent, context-aware, and personalized recommendation sequences. A similar approach can be applied to meal synthesis, where nutritional needs (thresholds) are aligned with different temporal windows (e.g., weekly, daily, or time-specific) for individuals under medical supervision. In this context, compliance values—determined by medical experts—are interactively incorporated into the CoR framework for meal recommendations, ensuring optimized and personalized dietary plans. CoR and CoT reasoning structure complex decision-making into sequential steps for accuracy and coherence. Generative models like *Gemini* and *Llama* output weekly meal plans in JSON format, dynamically predicting alternative meals based on system timing while ensuring nutritional compliance.

3.1 Proposed Architecture

Figure 1 illustrates the proposed scheme for this research, which demonstrates the adaptation of generative models for session-based learning, such as modeling short-term preferences to achieve extensive personalization. The proposed scheme begins by interacting with a generative model to submit user information,

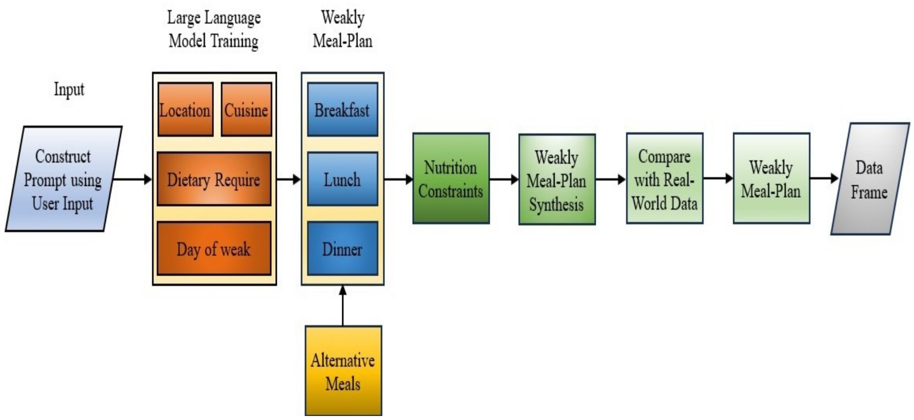

Fig. 1. Chain-of-Recommendations for Meals Generation

including *user dietary preferences*, enabling the model to generate recommendations (e.g., comprehensive meal plans and alternate meal plans). This interaction is referred to as the input prompt, executed via an API connected to an underlying generative model, such as *Gemini* or *Llama*. Subsequently, the *Compliance* function applies real-world thresholds for dietary values (e.g., nutritional needs) to the extracted meal plans, ensuring weekly plans meet the required standards.

– **Dataset**:The proposed framework relies on prompt-based learning to generate the extensive data instances of meal recommendations without requiring model training on a structured dataset. Instead of learning representations from historical representations, an instruction-based prompt is designed to allow the generative models to suggest meal plans based on the pre-existing knowledge. Next, the data is preprocessed and stored in a *DataFrame* and the dictionary specifies the acceptable range of all nutrients. User inputs such as location, preferred cuisine, and dietary requirements are incorporated through the prompt to guide meal generation.

– **Generative AI Models**: Gemini leverages session context and user behavior to deliver tailored recommendations [10]. By dynamically adapting suggestions using contextual features like time and location, it excels in uncovering insights even in less-explored domains. Its capability to process real-world data makes it highly effective for applications such as e-commerce. Llama developed by *MetaAI*, is a transformer-based architecture designed for natural language processing tasks. It excels in understanding user interaction patterns and generating tailored recommendations by incorporating contextual behaviours within and across sessions [15]. It effectively analyzes relationships among session events, managing complex contextual factors like prompts, and multi-turn interactions.

3.2 Chained Meals Recommendations via Contextual Prompting

Prompt learning is a trending topic, and pre-trained models are utilized for preference-based learning and subsequently handling data sparsity issues, specifically for short-terms based recommendation generation. It allows the user to incorporate input queries to generate task-relevant output. Prompt learning plays a vital role in SBRS in encoding the session attribute and predicting the response using pre-trained models. In the proposed work, a detailed and structured prompt is constructed to submit user-centric (*Patient, Dietician, and Doctor*) contextual semantics to personalized responses via prompts, *initial and intermediate*, from the adapted generative models:

Initial Prompt: *Generate a weekly meal plan for someone in {location} who prefers {cuisine} cuisine. The person has the following dietary requirements:{dietary_requirements}. Please provide breakfast, lunch, and dinner for each day of the week, ensuring that no meal is repeated throughout the week. Include alternative options for each meal, in case and provide the nutrient content per 100 grams. Provide me a response in a formatted JSON easy to parse. I want these columns:day, meal_type, meal_name, description, calories, protein, carbohydrates, fiber, fat, sugar, is_alternative. Don't add any extra information, not even a disclaimer.*

The *Initial prompt* extracts a generic and detailed weekly meal plan, including *breakfast, lunch, and dinner* for each day, with unique combinations (with no redundant meal). To ensure variety and flexibility, alternative meal options should also be included. *Nutritional information* for each meal per 100 grams should be provided to encourage healthy eating habits. The final plan needs to be presented in a JSON format with clearly defined sections for meal details.

The subsequent prompts are designed to carry user-centric informatics to refine the models and personalise meals, ideally by suggesting alternative or additional items. For example, in the *Follow-Up Prompt* below, maintaining an appropriate nutritional composition ensures that the meal provides *energy*, supports *health*, and meets *dietary needs.* These intermediate prompts reinforce numerous thresholds in the initially generated dataset and responses by the models.

Follow Up Prompt: *Ensure that the nutritional content per 100 grams for each meal falls within the range: Calories: 100-200 Kcal, Protein: 5-10 g, Carbohydrates: 10-15 g, Fat: 2-6 g (focus on unsaturated fat), Sugar:$<$ 5 g (Preferably natural Sugars.*

Algorithm 1 presents the implicit steps of the proposed framework e.g. the training of generative models like *Gemini*, *LLaMA*, which integrate session/daily meals data with contextual behavior, etc. Thus, begin with the initialization of GenAI models and interaction with configured prompts to acquire comprehensive meal instances. At *Step 2*, a user-specified Prompt, configured with parameters and actions, steers the GenAI model leveraging the current date and time to determine the week and filter meal options. The AI-generated output is then parsed into a structured format for a diverse meal plan. Next, collected data is cleaned and to be kept in a well-structured *Dataframe*, to enable a structured, flexible, and efficient way to manage and analyze meal data. Towards the end, the proposed framework is also able to generate alternate meals if required.

Algorithm 1: Meal-Plan Generation and Synthesizing Dietary Constraints

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1. Initialize the model with the configuration:

```
Model= genai.Generativemodel
(model_name = "Gemini/Llama", system_instruction = "
    default_system_prompt")
```

2. Construct the Prompt using user input: `"Generate weekly meal plan based on location, cuisine, and dietary requirements with no repeated meal throughout the week and including alternative options for each meal"`
3. Generate the meal plan:

```
ai_response = generate_response( location, cuisine,
    dietary_requirement)
```

4. Get the current date and time:

```
Current\_Date = \today \
Current\_time = \currenttime\\
```

5. Determine the day of the week:

```
day\_of\_week =  datetime.now().strftime("%A")
```

6. Filter the DataFrame for the current day and meal type:

```
meals\_for\_today = df[(df['day'].
  str.lower() ==  dayofweek)\&
  (df['meal\_type'] == meal\_type)]
```

7. Get the main meal and alternative meal:

```
main_meal = meals_for_today
[meals_for_today['is_alternative'] == False]
alt_meal = meals_for_today
[meals_for_today['is_alternative'] == True]
```

8. Parse the meal plan:

```
meal_plan = parse_meal_plan(ai_response)
```

9. Return the parsed meal plan:

```
  return meal_plan
```

---

4 Experimental Evaluation

In the experiments, contemporary generative models are adapted for a range of solutions, including a set of libraries. *Google generative AI* is used to generate content such as text and image. *Gradio* is imported to create the user interface. *IPython Display* is utilized to visualize objects in *jupyter* notebook. *BytesIO* handles binary data in memory. A generative model is initialized with the following configuration where model_name specifies the model version. Safety_settings ensures the generated content adheres to safety guidelines. System_instruction defines system-level instruction for the model's behavior. The function generate_response generates a meal plan in response to the *time, location and dietary requirements* that were supplied in *Prompts*. Response from the model contains a structured weekly plan in JSON format: *response, max_ output_ tokens, temperature, top_ k, top_ p*.

The weekly nutritional requirements, including daily intake of *calories, protein, carbohydrates, fiber, fat, and sugar*, generated by generative models like *Gemini* and *Llama*, are compared with the dietary guidelines provided by the Medical Practitioner. This comparison is based on the nutritional values per 100 grams of food consumed across three daily meals. Table 1 illustrates the recommended nutritional requirement per 100 grams of food for individuals with Type 2 Diabetes. To compare real-world data with generated data, the average of nutrition intake from the meal consumed throughout the week, as generated by the generative models, i.e., Gemini and Llama, are illustrated in Table 4 and Table 5.

Table 1. Optimal Nutrient Composition per 100g for Type 2 Diabetes Management

Nutrient	**Recommended Range***
Calories	100–200 kcal
Protein	5–10 g
Carbohydrates	10–15 g (preferably low GI carbs)
Fiber	3–6 g
Fat	2–6 g (focus on unsaturated fats)
Sugar	$<$ 5 g (preferably natural sugars)

Table 2 and Table 3 show the performance metrics for comparison of generative data with real-world data is evaluated using RMSE, MSE, and MAE evaluation metrics. Error difference between the predicted minimum and maximum range of nutritional values is compared with the range prescribed by the doctor. LLaMA model achieved MSE, RMSE, and MAE values of 7395.65, 85.99, and 41.48, respectively. On the other hand, the Gemini model demonstrates better performance, with corresponding values of 3772.86, 61.42, and 28.92. As a result, LLaMA model exhibits higher errors, particularly in predicting calories and fats, with significantly higher percentage errors across all evaluation metrics compared to the Gemini model. In contrast, Gemini model demonstrates superior overall performance, showing notably low error for sugar and more reasonable values for other nutrients.

A *compliance function* is used to verify whether each predicted nutritional value falls within the prescribed range for each nutrient. It also counts the number of compliant predictions for each meal type. The *percentage compliance* is used to calculate the mean of these values. For threshold '2', if a meal has 2 compliant nutrients then it would return true otherwise, it returns false. For example: if meal 1 has '3' compliant nutrients (Calories, Protein, Fat) and meal 2 has '3' compliant nutrients (Calories, Protein, Fat). In response to this, all meals were marked as compliant because each meets the threshold of '2' compliant nutrients. When we compared the performance of *Gemini* and *Llama* on different thresholds and marginal differences with the range value of nutrients prescribed by the doctor, the *Gemini* model performed better then *Llama* model.

Table 2. Performance Metrics for LLaMA

Metric	Calories (kcal)	Protein (g)	Carbohydrates (g)	Fiber (g)	Fat (g)	Sugar (g)
Absolute Error	209.52	17.76	8.81	0.14	7.40	5.24
Percentage Error (%)	209.52	253.71	58.73	3.50	164.44	104.80

Table 3. Performance Metrics for Gemini

Metric	Calories (kcal)	Protein (g)	Carbohydrates (g)	Fiber (g)	Fat (g)	Sugar (g)
Absolute Error	149.76	12.33	6.24	1.00	4.14	0.07
Percentage Error (%)	149.76	176.14	41.60	25.00	92.00	1.40

Table 6 displays the compliance percentage for each nutrients (Calories, Protein, Carbohydrate, Fiber, Fat, Sugar) according to the Gemini model. Table 7 shows the compliance percentage for the same nutrients by *Llama* model. In Figure 2, X- axis represents the list of nutrients and Y- axis represents the compliance percentage. Gemini outperforms Llama for all nutrients, showing a higher compliance percentage, particularly for Fiber, Carbohydrate, and Sugar. Llama compliance percentages are either low or zero for most nutrients. Figure 3 compares the compliance of meal plan generated by two LLM models (Gemini and Llama) with doctor's recommendations within a range of $\pm 10\%$ margin. Full compliance in blue color shows that meal plan meets the doctor's recommendation within the allowed margin and partial compliance in red color predicts that meal plan meets atleast 5 out of 6 recommendations within 5 margin. As a result, Gemini outperforms Llama in partial compliance, scoring a higher percentage.

Table 4. Gemini's Nutritional values

Nutrient	Average Value
Calories	300.00
Protein	23.61
Carbohydrates	24.19
Fiber	6.19
Fat	10.76
Sugar	5.80

Table 5. LLaMA's Nutritional values

Nutrient	Average Value
Calories	229.52
Protein	22.71
Carbohydrates	19.00
Fiber	5.09
Fat	10.61
Sugar	6.61

Table 6. Gemini Compliance (%)

Nutrient	Compliance %
Calories	7.14
Protein	14.29
Carbohydrates	42.86
Fiber	80.95
Fat	50.00
Sugar	69.05

Table 7. LLaMA Compliance (%)

Nutrient	Compliance %
Calories	0.00
Protein	9.52
Carbohydrates	23.81
Fiber	85.71
Fat	9.52
Sugar	23.81

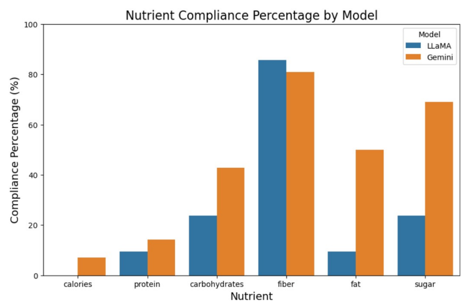

Fig. 2. Generative Models Nutrient Compliance Analysis

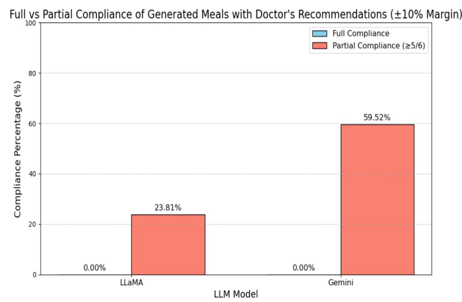

Fig. 3. Nutritional Compliance in AI-Generated Meals: Full vs. Partial Alignment with Medical Advice

5 Overall Analysis and Elaboration to RQs

The experimental evaluation asserts elaboration on the theme question *'How can generative models integrate contextual factors such as time, location, and dietary preferences to provide personalized meal recommendations that are both nutritionally balanced and aligned with user preferences?'*: Generative models analyze temporal patterns to suggest meals at specific times of day, e.g., breakfast, lunch, and dinner, and also the biological factors are taken into consideration. If location-based inputs like regional cuisine, ingredients, and seasonal produce are incorporated, then the recommendation performance may be enhanced. These systems provide a suitable choice of meal plan according to personalized dietary requirements. Further, it provides insights into the formalized RQs to confirm the overall objective of the work. The assertions of each RQs are discussed below:

RQ-I: *What is the impact of combining sequential modeling techniques (e.g., RNN) with structural dependency analysis (e.g., GNN) on the accuracy and adaptability of meal recommendations in the scenario of context-aware RSs?*: RNN is employed to capture the shift in user behaviour such as dynamic dietary preferences or seasonal eating habits whereas GNN models the structural relationship between user-item interaction (user dietary needs, different meals temporal) or incorporates the contextual factors, including time and location. Thus, by combining the strengths of GNN and RNN, context-aware systems can capture a high level of accuracy and adaptability that makes them well-suited for users' ever-changing preferences.

RQ-II: *How effectively do Gemini and Llama models predict personalized meal recommendations, as evaluated by evaluation metrics such as MAE, RMSE?* : Gemini performs or generates better predictions then Llama because it is trained on relevant data. On the other hand, Llama requires more fine-tuning to generate more accurate and relevant personalized recommendations. Evaluation metrics such as MAE and RMSE are employed to assess the performance and effectiveness of both models. As a result, the Gemini model scores lower on these metrics while Llama requires more fine-tuning to lower these scores.

RQ-III: *How does the 'Chain-of-Recommendations' prompt affect personalization and accuracy in recommendation systems?*: The 'CoR' system may improve the recommendation performance by incorporating the previous one. Recommendations may be improved by incorporating the ongoing context of user behavior. Chain-based recommendation systems enhance performance by filtering out irrelevant data from previous feedback sequences.

6 Conclusion

The computational capabilities of generative models are evident in a range of real-world use cases, such as generating data challenges to validate synthesized data against real-world thresholds. The experiential work conducted in this study asserts the feasibility of generative models to deliver personalized meal plan in response to *Prompts*, requiring the incorporation of numerous nutritional thresholds into intermediate recommendations and validates the final reasoning with the ground variables. The inherent contextual settings make it a complex task and require multiple *Prompts* of reasoning/learning over intermediate chain-of-recommendation (CoR) meal. The proposed work is assessed using metrics like RMSE, MAE, and MSE, the study assesses model performance across contexts, *Prompts*, session complexities, and chaining scenarios. Results demonstrate that *Gemini* outperforms *Llama*, achieving higher compliance in meal plan personalization. Integrating multi-modal data (e.g., user feedback, health metrics, meal images) can enhance personalization in generative models. Expanding *CoR* with adaptive learning can refine long-term user preferences and medical compliance, while reinforcement learning can further optimize meal plans through continuous feedback.

Long-term personalization such as adapting to user feedback or health outcome is essential for real-world impact cited as a key area of research in future development. The potential use cases of *chain-of-recommendation* are health-aware meal planning and dietary compliance tracking, clinical validation or real-time deployment.

Executable Codes can be downloaded by clicking here.

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