FinNutriAgent (FNA): An Agentic AI for Nutrition Planning Considering Budget Constraints

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ABSTRACT

This paper presents an agentic Artificial Intelligence (AI) model that is price responsive and combines household budget constraints and dietary optimization. Based on income, fixed financial commitments, health-related requirements, and dynamically revised food expenses, the system produces meal plans that are nutritionally balanced, cost-effective, and respond automatically to market shifts. The proposed design is an implemented modular multi-agent system, which consists of specialized agents, budget planning, nutritional evaluation, price surveillance, and health-based personalization. These agents align themselves

with a common body of knowledge and use food substitution graphs to maintain nutritional adequacy and to reduce spending. The assessment based on a representative household in Saudi Arabia shows 13-18% savings in food expenses in comparison to the fixed weekly menus, nutrient adequacy greater than 95%, and stability in response to simulated price shocks of ±20 - ±30%. These findings indicate that the framework is valuable to match the affordability with nutritional sufficiency and offers a scalable solution to robust household diet planning in line with the Sustainable Development Goals associated with Zero Hunger and Good Health.

Keywords-agentic AI; household budgeting; diet optimization; nutritional adequacy; multi-agent systems; price-aware meal planning; sustainable development goals

I. INTRODUCTION

The developments in Artificial Intelligence (AI) have greatly impacted the fields of finance, medical care, and the provision of tailored digital services. Specifically, Large Language Models (LLMs) have been very effective in content generation, complex reasoning, and natural human-machine interaction through generative AI systems [1, 2]. However, the implementations applied until now are reactive in nature and run more or less in response to user initiations over time, without any long-term planning or execution. To overcome this weakness, agentic AI has emerged, which involves the employment of planning, state monitoring, memory retention, and action execution mechanisms, which makes it possible to have autonomous and goal-oriented behavior [3, 4]. These systems can perceive their surroundings, have contextual awareness, and invoke tools or simulations to perform tasks. Enterprise deployment is happening at an increasingly rapid pace, and Gartner estimates that by 2029, agentic AI will have autonomously resolved 80% of common customer service issues [5].

Although these changes have taken place, there is still minor support when it comes to everyday household decision-making, especially in terms of financial constraints and nutrition. Households often face the dilemma of having limited budgets and the necessity of nutritionally sufficient diets. These pressures increase due to growing living costs, unstable food prices, and dissimilar health needs, necessitating challenging trade-offs. The available solutions are usually based on expense monitoring or meal suggestions individually and do not, in any case, combine budget constraints, health customization, and real-time price data in the same decision model [6].

This issue has significant social consequences. Ineffective dietary habits and food insecurity have a close relation to long-term health problems, high healthcare costs, and low economic efficiency [7]. This is because many households are constrained in their budgets and tend to use cheap and energy-dense foods, which do not provide the necessary nutrients. A flexible system that combines financial planning and nutritional optimization can thus contribute to healthier consumption behaviors and further overall policy goals, such as the Sustainable Development Goals of zero hunger (SDG-2) and good health and well-being (SDG-3). This gap encourages the creation of a dietary planning agent driven by personal finance. In this study, an integrated agentic-AI model is proposed, integrating budgeting of the household, diet planning, real-time price tracking, and health condition personalization into a single decision-making system. The framework uses a multi-agent coordinated design to control financial constraints, nutrient demands, market unpredictability, cultural demands, and individualized health constraints by sharing a knowledge base. An optimization model that is price-conscious and a substitution graph are employed in order to maintain nutritional adequacy and respond to changes in costs. The system also delivers the closed-loop process by incorporating data absorption, volatility of price identification, renewed re-planning, and clear explanation generation.

The main contribution of this work is the architectural design of an integrated agentic-AI system, especially the coordination of the budgeting, nutrition planning, and dynamic price adaptation. The evaluation demonstrates the functionality of the proposed multi-agent elements and optimization mechanisms in the context of real-world situations at the household level. The proposed system provides a generalizable method with respect to integrating financial and nutritional decisions in a context where both affordability and diet quality have to be considered simultaneously.

II. BACKGROUND

A. Healthy Diet Fundamentals

A healthy diet is the key to well-being and preventing the occurrence of chronic diseases. According to the recommendations provided by the World Health Organization (WHO), balanced diets should provide adequate energy and the required amount of the main macronutrients, such as carbohydrates, proteins, and fats, as well as guaranteeing the sufficient intake of vitamins and minerals, avoiding excessive intake of added sugar, saturated fats, and sodium [8, 9]. Simultaneously, the Food and Agriculture Organization (FAO) emphasizes dietary diversity, suggesting that each person should eat fruits, vegetables, whole grains, legumes, sources of lean protein, and dairy products on a regular basis to ensure adequate intake of micronutrients [10]. A number of micronutrients are considered nutrients of concern, especially to children and women of reproductive age [11]. Cultural, religious, and lifestyle factors also influence dietary needs. For instance, in Muslim-majority settings, one must follow the halal dietary norms, whereas during Ramadan, a shift in the timing and the structure of meals implies the need to plan the diet flexibly [12]. These factors support the requirement to have meal-planning systems that can be customized and flexible.

B. Personal Finance for Households

Another important determinant of well-being is household financial management. The traditional heuristics of budgeting, such as the 50/30/20 rule, which divides the revenues into the needs, discretionary expenses, and savings, provide a general framework, but these budgets are frequently not feasible in low- and middle-income households due to the fact that the basic needs are higher than the proposed limits [13]. Empirical studies indicate that food expenditure as a proportion of household income is generally 15%-25% in the middle-income environment and may rise significantly during times of inflation or unstable prices [14].

Dietary planning combined with household financial planning enables the amount of income that is left over after meeting the set fixed commitments to be more efficiently allocated to nutritionally sufficient food options with reduced inefficiencies and trade-offs between cost and diet quality.

C. Agentic AI Concepts

The concept of agentic AI is the development of classical AI systems, including functions of memory, planning, perception of the environment, and self-directed execution in the cycles of continuous and goal-oriented operation [15]. An agentic system is capable of functioning independently over a long duration of time without the need for a user to continually prompt it. It has already been utilized in other fields like retail and travel, product price comparison agents, automatic flight tracking, and re-booking agents.

Nevertheless, the majority of current consumer-facing solutions focus on convenience and operational efficiency; consequently, health and financial outcomes remain under-researched [15]. The combination of nutritional science, household economics, and instant price adjustment in a single agentic model can further assist the everyday decision-making of households.

III. RELATED WORK

The field of personal finance management and the study of dietary optimization are still at an early stage. Despite the independent evolution of both domains, research regarding the joint issue of matching the household financial planning and the nutritional sufficiency in changing market circumstances is rather limited. In the present study, the related work is surveyed in three strands, including budgeting and Financial Technologies (FinTech), diet optimization methods, and consumer-oriented agentic AI systems, and the research gap covered in this study is identified.

A. Budgeting and Financial Technologies

Recent FinTech has offered households digital methods of monitoring income, categorizing spending, and visualizing spending habits. Popular programs like Mint, You Need A Budget (YNAB), and PocketGuard allow tracking financial performance in real-time and enhancing user awareness regarding budget spending [16]. These platforms are, however, mostly reactive; for instance, they alert their users when budget limits are surpassed but do not propose any reallocation of funds. Besides, most available tools are only applicable in the financial field and do not consider external limitations like dietary needs or health-related necessities, which restrict their usage in the context of households where dietary habits and budgeting have to be handled together. Limited research investigating the integration of health-related information into financial planning systems remains relatively static, without proposing mechanisms to deal with changes in prices or the supply side upheaval [17-19]. The proposed system builds upon prior research by integrating a dynamic and price-sensitive agentic model that maximizes both financial spending and dietary performance.

B. Diet Planners and Nutritional Optimization

The history of diet optimization is extensive, originating with the work of Stigler, who developed the least-cost diet problem [20]. Modern methods are based on this principle and employ detailed databases on nutrients and diets to produce individualized meal plans that meet caloric and micronutrient needs [21-23]. Regardless of this progress, most models concentrate on individual users without considering the household level, such as common budgets, diverse age groupings, and cultural or religious inclinations [24].

Although some of them seek to reduce the food cost, they usually rely on the constant price assumption and fail to respond to the dynamic market and the changing health status. The current study addresses these limitations by incorporating continuous price tracking, health-based personalization, and adaptive optimization, thereby maintaining affordability and nutritional adequacy.

C. Agentic AI Systems in Consumer Domains

The agentic AI systems combine autonomous decision making, planning, reasoning, and self-monitoring. Intelligent shopping agents have been widely applied in consumer contexts to compare prices among vendors [25], while travel assistants independently monitor changes in itineraries and rebook them [26]. In [27], agentic architecture was enhanced by LLMs by interacting and making context-dependent decisions.

Nevertheless, applications dedicated to household finance or nutrition are limited. Current diet-like assistants are largely conversational-based systems offering general guidance or advice [28], without including built-in financial constraints as well as adaptive re-planning features. The proposed work overcomes this limitation by introducing agentic-AI functionality with financial and nutritional optimization, allowing constant adaptation to the changing prices and health conditions.

In the existing literature, financial tools focus on budget management, diet planners prioritize nutrient optimization, and agentic systems automate activities in fields such as retail or travel. These solutions remain periodic and mostly reactive, since they do not provide a single mechanism that can be used to combine real-time price changes, individual nutritional goals, cultural restrictions, and household budget constraints into one decision-making model. None of the previous systems combines dynamic pricing, personalized nutrition needs, health-condition modifications, and autonomous multi-agent re-planning into a single architecture. This disparity motivates the creation of FinNutriAgent (FNA), a price-conscious and health-sensitive agentic AI model designed to help household affordability and nutritional sufficiency in changing market environments. Table I provides a comparison with the representative categories of the related work.

TABLE I. FNA COMPARED WITH EXISTING METHODS

Category	Prior work	Limitation	FNA (proposed)
FinTech tools	Budgeting apps (Mint, YNAB, PocketGuard) [16]	Focus on expense tracking; no nutrition or price adaptation	Integrates budgeting with nutrition-aware and price-sensitive optimization
Diet optimization models	Classical and modern diet optimization [20-24]	Static assumptions; no real-time pricing or health personalization	Dynamic optimization with substitution graph and health constraints
AI health assistants	Diet/health chatbots [28]	Advisory only; no autonomy, planning, or optimization	Multi-agent coordination with monitoring, memory, and adaptive re-planning
Consumer agentic systems	Shopping/travel agents [25-27]	Domain-specific; not connected to household finance or nutrition	Unified framework combining finance, nutrition, preferences, and market signals

IV. PROPOSED FRAMEWORK

The proposed framework is an integrated agentic AI implementation that can dynamically balance the household food budget and nutritional adequacy (Figure 1). It is developed on a multi-agent architecture whereby specialized agents are interconnected to produce meal plans that meet the financial and health limitations. The given structure allows reacting to the changes in prices in real-time, personalizing healthcare and cultural inclinations, and staying within the limits of financial capacity.

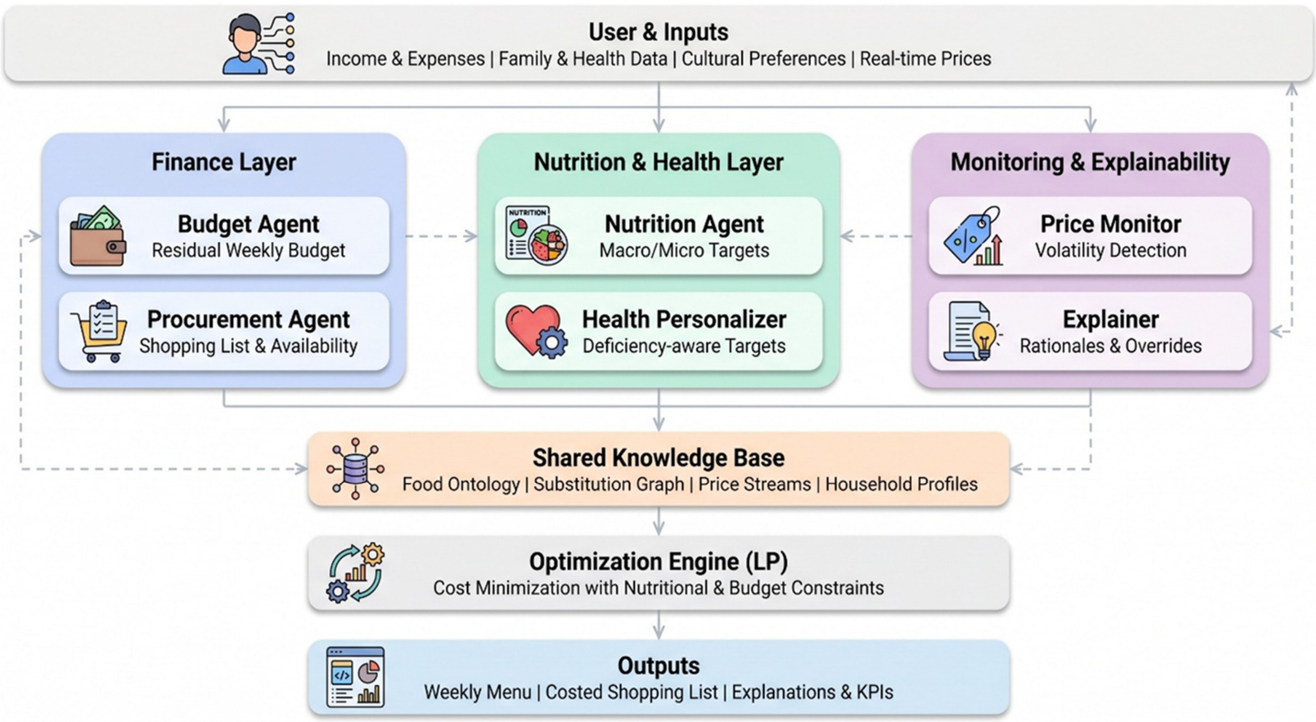

Fig. 1. Architecture of an agentic AI framework integrating budgeting, nutrition, and cultural preferences.

A. System Requirements and Assumptions

The model serves as a diet planner that works on the basis of personal finance, as it combines financial management of the household and individual nutrition planning. It operates on structured input data, as presented in Table II.

The system first determines the amount of food budget remaining after deducting the fixed expenses and savings from the total income, which is a weekly food budget B_w. These financial constraints are then matched with the nutritional goals, and this can be done through the proposed dietary allowance and the acceptability of the macronutrient distributions.

B. Multi-Agent System Architecture

The multi-agent design of the framework enables specialized agents to act autonomously while maintaining information sharing with a centralized knowledge base (Figure 2). This structure allows the system to optimize the cost, nutrition, health, and user preferences. Specifically:

- The Budget Agent: Calculates the remaining money that can be used to purchase food after attending to fixed demands and informs the Nutrition Agent about the budget per week.

- Nutrition Agent: Examines the macronutrient and micronutrient targets of every household member and works with the Price and Health Personalizer Agents to identify the optimal nutrient quality and its cost.
- Price Monitor Agent: Tracks live prices of food, identifies any pronounced volatility, and causes re-planning through the Substitution Graph when the threshold τ is crossed.
- Health Personalizer Agent: Modifies nutrient goals to individual members according to health conditions, e.g., Vitamin D deficiency.
- Preference and Cultural Agent: Prepares cost-constrained shopping lists and finds substitutes for some of the ingredients in case they are not available.
- Procurement Agent: Prepares cost-constrained shopping lists and finds substitutes for some of the ingredients in case they are not available.
- Explainer Agent: Entails the clear explanation of the replacements or choices, e.g., spinach took the place of broccoli to maintain the iron intake at a lower cost, which helps in winning the trust of the user and optional human overrides.

TABLE II. CORE INPUT REQUIREMENTS AND DATA SOURCES

Categories	Examples/source
Income and expenses	Salary, rent, utilities, school fees (user input)
Family profile	Age, gender, activity level, household size (user input)
Health constraints	Deficiencies, allergies, low-sodium or diabetic diets (clinician or user input)
Price feeds	Supermarket APIs and web scrapers (Panda, Carrefour, Lulu)
Nutrition references	WHO, FAO, USDA nutrient tables (macros, micros)
Cultural preferences	Halal compliance, local cuisines, seasonal items (user input)

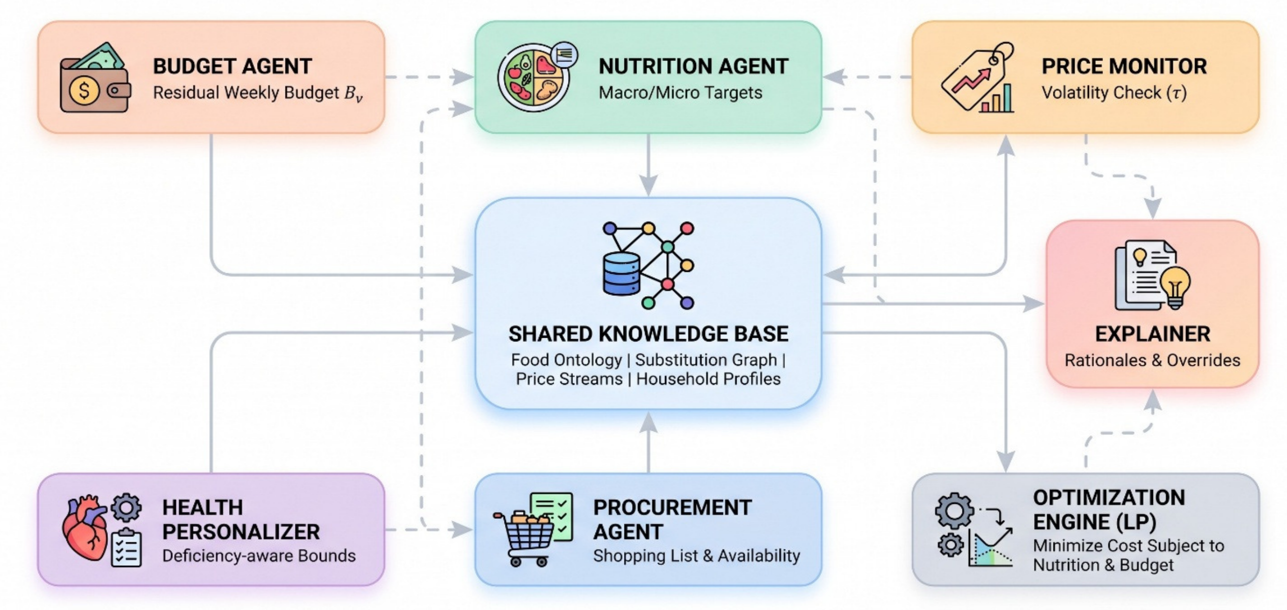

Fig. 2. Multi-agent workflow illustrating inter-agent collaboration through a shared knowledge base.

C. *Data and Optimization Model*

The shared knowledge base centralizes the data needed to coordinate and make decisions by the agents. It contains a Food Ontology with the mapping of items against nutrient composition and portion sizes, allowing an accurate calculation of nutrition. The Substitution Graph is the network of nutritionally similar foods, which provides an opportunity to make cost-saving substitutions in case of price fluctuations. Price Streams give price information of individual units in real-time feeds of supermarkets, whereas Household Profiles meet demographic and health data to personalized nutrient goals.

The formulation of meal planning is in the form of a Linear Programming (LP) model, minimizing the total food cost to meet nutritional specifications and weekly financial limitations:

$$Minimize{:}\ Z = \Sigma_{j\in J} p_j x_j \quad (1)$$

subject to:

$$\Sigma_{j\in J} n_{j,k} x_j \geq R_{k,i},\ \forall\, i \in I, \forall\, k \in K \quad (2)$$

$$\Sigma_{j\in J} p_j x_j \leq B_w \quad (3)$$

$$x_j \geq 0,\ \forall\, j \in J \quad (4)$$

where p_j is the price of item j, x_j is the purchased quantity, $n_(j,k)$ is the nutrient content of item j, and $R_(k,i)$ is the required intake of nutrient k for individual i. The budget B_w defines the weekly constraint.

This formulation is an interpretable, fast, and reproducible optimization that can be used to re-plan with changing conditions.

D. Price-Aware Adaptation

Affordability is ensured by real-time response to price fluctuations:

$$\frac{(|p_{j,t} - p_{j,t-1}|)}{p_{j,t-1}} > \tau$$

where τ is the volatility threshold (typically 10%).

Once it surpasses the limit, the Substitution Graph will be used to substitute items with nutritionally equivalent alternatives within one or two hops. An example of this would be an increase in the price of chicken, which would lead to partial replacement by lentils or sardines. Logging of all changes is done, and the Explainer Agent provides justification to the users and to manual intervention.

E. Health Personalization and Deficiency-Aware Planning

The system is dynamic in changing plans to personal health needs. In the case of Vitamin D deficiency, the target intake is raised with the help of foods such as oily fish, fortified milk, and egg yolks. The iron deficiencies will put high-sodium foods at a penalty, and red meat, spinach, or fortified cereals will be rewarded. These individualized constraints are updated in real-time to change (2) and enable the continuous recalibration of the equation with new health data provided by the user or clinician.

F. System Workflow and Integration

The framework functions on a ten-stage iterative workflow (Figure 3), which includes data intake, optimization, and feedback. B_w is calculated by the Budget Agent who has collected household, financial, health, and price data. Nutrient targets are established by the Nutrition Agent, and Market and health dynamics are managed by the Price Monitor and health personalizer Agents. The LP optimization engine produces a menu and cost shopping list on a weekly basis. Constant monitoring causes automatic re-optimization with the change in conditions. The Explainer Agent has provided explanations as well as override capabilities that are both transparent and controllable by the user. The procedure is repeated using new data to keep up with the current, cost-effective, and nutritionally sufficient recommendations.

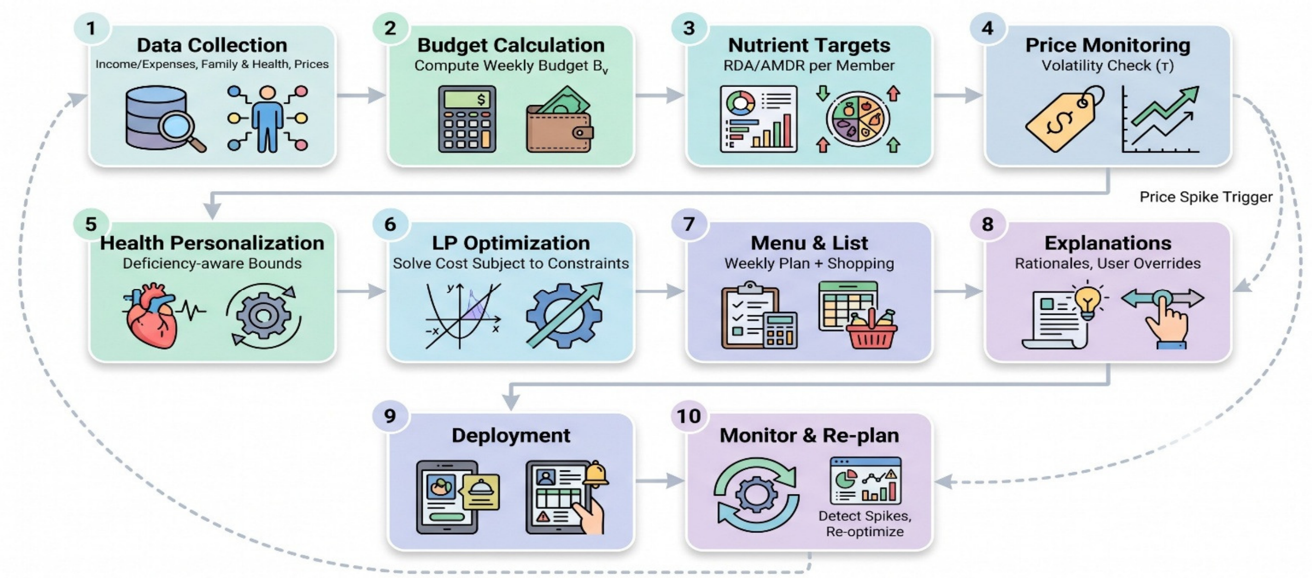

Fig. 3. End-to-end workflow of the agentic AI system from data collection to adaptive re-planning.

V. IMPLEMENTATION

This section outlines the application of the proposed agentic AI model, which focuses on modularity, real-time flexibility, and privacy. All of the elements, such as optimization to multi-agent orchestration, collaborate in creating dynamic and personalized meal plans to meet nutritional needs and financial limitations. The system is more concerned with computational efficiency, scalability, and transparency, guaranteeing sound performance in various household situations.

The framework incorporates the LP optimization engine, multi-agent orchestration, and cloud-based infrastructure with a modern technology stack, as presented in Table III. This architecture is scalable in deployment, fast data retrieval, and adaptive decision making. The optimization engine is an LP problem utilized to minimize food cost and meet all nutritional and budget constraints in real-time. LP has been chosen due to its interpretability, reproducibility, and computational efficiency when compared to metaheuristic methods like the genetic algorithm or simulated annealing.

TABLE III. IMPLEMENTATION SUMMARY OF MAJOR SYSTEM COMPONENTS

Categories	Examples/source
Optimization engine	Python (PuLP, Google OR-Tools) for LP formulation
Agent orchestration	Age, gender, activity level, household size (user input)
Database layer	Deficiencies, allergies, low-sodium or diabetic diets (clinician or user input)
Frontend interface	Supermarket APIs and web scrapers (Panda, Carrefour, Lulu)
Price integration	WHO, FAO, USDA nutrient tables (macros, micros)
Cloud infrastructure	Halal compliance, local cuisines, seasonal items (user input)

The multi-agent orchestration layer synchronizes the specialized agents described above. This layer employs LLM-based reasoning to generate contextual decisions and explanations. Persistent storage is a combination of relational databases and in-memory caching, and is effective in managing live and historical data. Lightweight user interface enables data entry and visualization, but the in-depth design of the user interface is beyond the concerns of this study, as it is restricted to the agentic framework and optimization logic.

A. *Data Sources*

The framework utilizes a combination of real and synthetic datasets to ensure system reliability and reproducibility. Real-time pricing data are collected through supermarket APIs (e.g., Panda, Carrefour, Lulu) and validated by web-scrapers of regularly bought products in Saudi markets. Nutritional specifications are obtained from USDA Food Data Central [29] and FAO/WHO databases, adjusted with the GCC dietary standards and national guidelines provided by the Saudi Ministry of Health. Household financial parameters are modeled using income-expenditure distribution sourced from the World Bank and CEIC data [30].

In order to test robustness, synthetic household profiles were created, with income ranging between 5,000 and 15,000 SAR, household size ranging between 2 and 6 members, prevalent health conditions (including nutrient deficiencies and allergies), and dietary habits (halal, vegetarian, and low-sodium). All these profiles were also tested in terms of market volatility of ±10, ±20, and ±30 price shocks to determine the system's capacity to retain cost efficiency and nutritional adequacy. The stratified random sampling and fixed seeds made it reproducible and did not reveal the actual user data.

B. *Evaluation Protocol*

System performance was evaluated by synthetic simulation and a case study of a Saudi household over a period of 4 weeks. Synthetic experiments tested 100 family profiles that were employed to assess scalability and adaptability when using income levels, household size, and health conditions. It was measured using three major metrics:

- Cost efficiency: Percentage savings relative to a baseline static meal plan.
- Nutritional adequacy: Average proportion of Recommended Daily Allowances (RDA) achieved across key macro- and micronutrients.
- Adaptability: Success rate of re-planning under simulated price shocks.

By quantifying the real-time cost savings and nutrient coverage of a case study, a comparison of static and adaptive planning was conducted, providing methodological rigor and ecological validity.

VI. EVALUATION AND PERFORMANCE METRICS

The performance of the proposed framework was evaluated through synthetic simulations, controlled ablation experiments, and a household case study. Three major indicators were utilized to measure the effectiveness, robustness, and practical applicability of the system under dynamic economic and dietary conditions: cost efficiency, nutritional adequacy, and responsiveness to price changes.

A. *Cost Efficiency*

A significant goal of the system is to reduce household food expenses without degrading its quality. To assess cost efficiency, the agentic AI system was compared with three baselines:

- A non-adaptive menu scheme that runs the same weekly menu without adjusting to price fluctuations.
- A cost-minimizing static optimization model that does not monitor and substitute prices in real-time.
- Planning of the household manually based on self-reported meal logs and budgets.

Table IV presents the average weekly expenditures and nutrient adequacy across all categories, while Figure 4 illustrates the comparative trends. In all conditions, the FinAgent system was able to reduce the weekly food costs by 13-18% of the baseline fixed menu. These savings were achieved with price-sensitive substitutions and re-optimization. These findings demonstrate that the proposed system generates significant savings while maintaining, or in some cases improving, nutritional adequacy.

TABLE IV. AGE WEEKLY FOOD COST COMPARISON (SAR, 4-PERSON HOUSEHOLD)

Method	Mean weekly cost	Savings versus fixed Menu	Nutrition adequacy (%)
Fixed menu (baseline)	480	-	85
Static optimization (no adaptation)	440	8%	92
Household manual planning	455	5%	88
Agentic AI (proposed)	415	13-18%	97

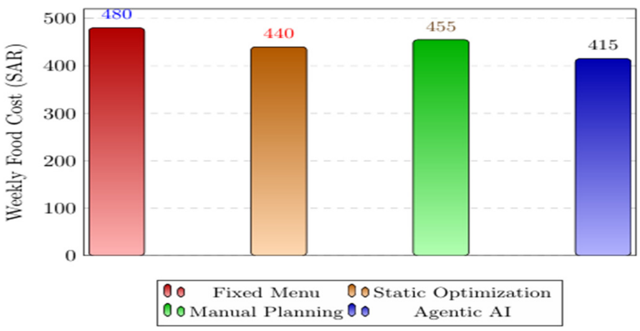

Fig. 4. Weekly food cost comparison across meal planning methods.

B. Nutritional Adequacy

Nutritional performance was evaluated based on the amount of the RDA for essential nutrients, including protein, Vitamin D, iron, and calcium. Four planning strategies were compared: the fixed-menu baseline, the non-adaptive cost minimization optimization, the manual household planning, and the proposed FinAgent system with dynamic price and health adaptation. As depicted in Figure 5, the agentic AI model consistently achieved 95% RDA compliance across all tracked nutrients, whereas the static and manual plans were deficient, particularly in Vitamin D and iron.

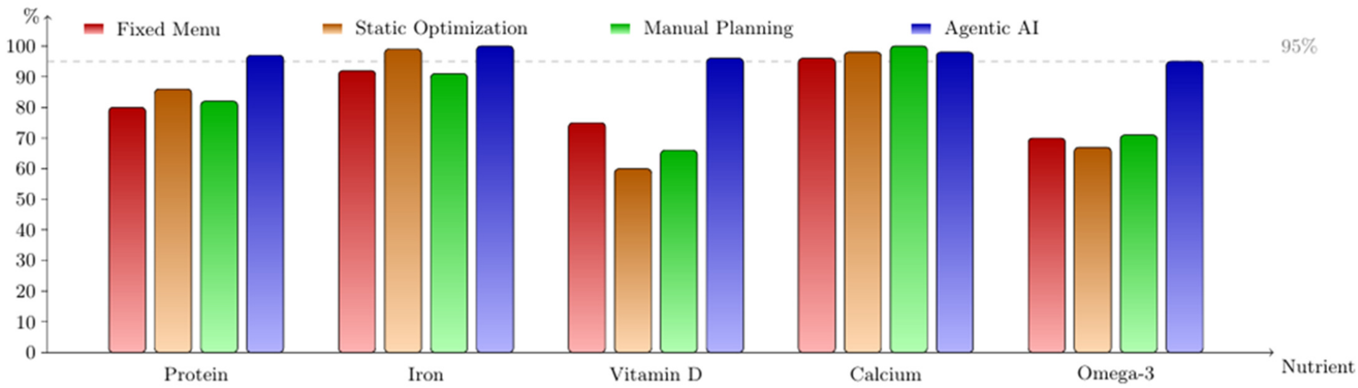

Fig. 5. Nutrient adequacy comparison across planning approaches.

C. Adaptivity under Price Shocks

The system robustness was assessed by simulating price volatility for essential food item prices of ±10, ±20, and ±30. The quantitative results are provided in Table V, while Figure 6 illustrates the adaptability of the framework to the different magnitudes of the shock. The results indicated that while the cost was 12% higher than the budget in the case of the static plans, the agentic AI system maintained the cost and balance of nutrients, as re-optimization and substitution were done in time.

TABLE V. ADAPTIVITY TO PRICE SHOCKS (B_w 4-PERSON HOUSEHOLD)

Scenario	Static plan (SAR)	Agentic AI (SAR)	Adequacy m,aintained?
Chicken +20%	495	425	Yes(substituted legumes/fish)
Fish -15%	465	410	Yes (increased fish allocation)
Rice +30%	510	445	Yes (shift to bread/whole wheat)
Mixed volatility (±20%)	500	430	Yes

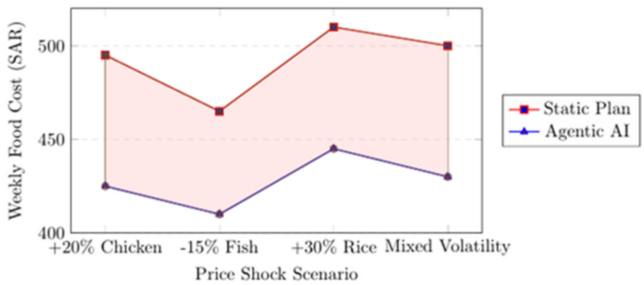

Fig. 6. System adaptability under simulated food price shocks.

D. Ablation Studies

In order to determine the role of individual agents, specific ablation experiments were performed. The removal of the Price Monitor Agent resulted in a 9% increase in total food expenditures during inflationary periods, which shows its sensitivity as far as finances are concerned. The Health Personalizer Agent was found to be beneficial in promoting the adequacy of Vitamin D among children since disabling it lowered the adequacy to approximately 70%, underlining the significance of customized nutrient limitations. The omission of the Preference Agent decreased the number of repetitive menus and reduced user satisfaction, which demonstrates its usefulness in keeping engagement and compliance. All these findings confirmed that system effectiveness in terms of cost, nutrition, and usability requires all agentic components.

E. Case Study: Saudi Household

To determine a real-life feasibility and user experience, a longitudinal study was performed on a representative Saudi family (monthly income: 10,000 SAR) in four simulated weeks. The key outcomes included:

- Mean grocery spending: 1,660 SAR, which is a 17% decrease from the self-reported baseline (2,000 SAR).
- Adequacy of nutrients: ≥ 95% among all members of the family with Vitamin D supplementation in the youngest child.
- Price shocks: This was accepted without much disturbance, e.g., a 20% increase in the price of chicken was neutralized by replacing a quarter of portions with lentils and sardines.
- User satisfaction (Likert scale, 1-5): 4.5 for cost transparency, 4.2 for cultural relevance.

Figure 7 demonstrates how the meal plans can be adjusted every week according to the changing market conditions, reflecting the responsiveness of the framework to market and nutrition changes.

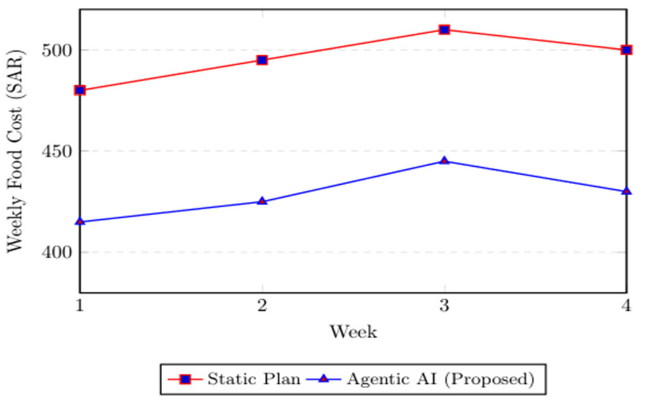

Fig. 7. Weekly adaptation of meal plans under varying market conditions, personal-finance.

VII. DISCUSSION AND CONCLUSION

The results indicated that the proposed agentic AI framework is effective in supporting household meal planning by ensuring nutritional adequacy and cost-efficiency simultaneously, as well as dynamically reacting to changes in the market. A four-member family in the Saudi household case study ensured nutrient coverage of above 95% in a limited budget. The meal plans were prepared according to cultural and religious needs, such as halal, traditional cuisine, and fasting times like Ramadan. This contextual adaptable flexibility can increase the acceptance of the user, and can encourage long-term compliance, demonstrating the feasibility of the practicality of financial optimization in combination with dietary personalization in daily life. The simulation research and empirical analysis further reported a steady cost reduction of 13-18% compared to baseline methods, with constant results in price shocks as great as ±30%. These findings highlight the framework's contribution to strengthening household resilience to inflation and nutrition-related problems.

However, there are still several constraints. Retailer real-time food price feeds can be incomplete or inconsistent, and the nutritional databases available might fail to capture regional food variations. Another factor is household compliance, whereby the actual consumption might not be the same as the optimized recommendations because of taste preference, social occasions, or lack of time. Moreover, the proposed framework requires proper implementation, which is determined by the availability of digital infrastructure, which differs between socioeconomic groups and geographic areas.

The framework has wider implications on public policy and health strategies, other than in technical contributions. Its combination with governmental food assistance programs, school lunch, or community health surveillance systems may improve nutritional results and enable specific interventions. On a global scale, agentic AI enhances fair access to healthy and affordable food, which is in line with Sustainable Development Goal 2 (zero hunger) and Goal 3 (good health and well-Being).

The framework presented how agentic AI can support the household decision-making process through coordinated multi-agent functionality by combining an integrated budget modeling system, nutritional optimization, real-time price adjustment, and personalization of the health solution to the constraints of real-life decisions. A decrease in cost, a high nutrient coverage, and resistance to price volatility were observed, meaning that this strategy can serve as a realistic and generalizable base when it comes to applications where affordability and dietary quality need to be considered at the same time.

Future research directions can focus on large-scale implementation and longitudinal studies to assess adherence levels, user satisfaction, and long-term health consequences. To make it even more personalized and cost-effective, additional improvements might include data from loyalty programs, subsidy systems, or school meal databases. Finally, this prototype will need to be scaled to a socially responsible household assistant by instituting all-encompassing ethical governance, such as transparency, accountability, and trust systems.

DECLARATION OF COMPETING INTERESTS

The authors declare no conflicts of interest.

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DATA AVAILABILITY

The datasets used in this study were synthetically generated to preserve household privacy and confidentiality. The synthetic data retain the statistical properties and distributions of real household income, expenditure, dietary preferences, and nutritional requirements, while containing no identifiable or real individual records. This approach ensures full reproducibility of the experiments without exposing sensitive personal information. The synthetic dataset and experimental configurations are publicly available at [31].

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