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SYSTEM ANALYSIS AND DECISION-MAKING THEORY

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AN INTELLIGENT SYSTEM FOR DISH-LEVEL DIET PLANNING BASED ON AN OPTIMIZATION MODEL

The paper addresses the problem of developing intelligent systems for personalized nutrition planning. Modern research in this field demonstrates a transition from classical formal diet models to hybrid architectures that combine two methodological paradigms: knowledge-driven and data-driven approaches. However, there is some methodological gap between them. Knowledge-driven models provide mathematical rigor and guarantee the satisfaction of nutritional and resource constraints, but they are usually limited in adaptability and personalization. In contrast, data-driven approaches, including modern generative models, demonstrate high flexibility and the ability to incorporate behavioral data, yet they do not provide formal guarantees of optimality and constraint satisfaction. This contradiction motivates the development of an integrated intelligent nutrition planning system that combines the advantages of both approaches. The objective of this study is to develop an intelligent dish-level nutrition planning system whose core is a formalized multicriteria diet optimization model. Unlike the classical diet problem, where optimization is performed over individual food products, the proposed approach models nutrition at the level of complete dishes, which improves the practical feasibility, interpretability, and usability of the resulting dietary plans. The mathematical model is formulated as a multicriteria optimization problem in which the decision variables represent the number of dish portions, while constraints reflect nutritional, energetic, logical, and temporal requirements. The proposed model is implemented within a multi-layer system architecture consisting of a data layer, an optimization core, an intelligent decision-support layer, and a user interaction layer. The optimization core ensures mathematical correctness and computes optimal solutions, whereas the intelligent layer provides adaptation, personalization, and interpretation of results. The model is further extended to a dynamic form using a rolling planning horizon, allowing the diet plan to be updated as new data and user preferences become available. Computational experiments have demonstrated that changes in criterion weights lead to transitions between several stable optimal meal structures, reflecting the discrete nature of the considered multicriteria optimization problem.

Keywords: Nutrition planning, diet, dish-level model, decision support system, multicriteria optimization, hybrid AI systems, recommendation systems.

Introduction. Nutrition planning is an important task in the field of dietetics, as dietary intake directly affects human health, disease prevention, and the maintenance of an adequate level of energy and physical activity. Modern approaches to diet formation require consideration of multiple factors, including individual physiological needs, taste preferences, cultural characteristics, food availability, and economic constraints. Due to the need to account for a high degree of personalization, the development of personalized decision support systems based on the use of modeling and optimization methods has become increasingly relevant, enabling the formation of balanced dietary recommendations adapted to individual conditions.

The classical diet problem is one of the first mathematical tools that was applied for rational nutrition planning. It allows one to minimize the total cost of a diet while maintaining nutrient intake standards. Despite its mathematical rigor and widespread application in optimization theory, the classical model has limitations: it does not account for taste preferences, meal structure, dietary diversity over time, or the dynamics of user needs. These limitations create a gap between the formal solutions of the optimization model and the practical realities of nutrition.

Modern intelligent systems and artificial intelligence methods open up new possibilities for the automation and personalization of meal planning. They enable the integration of expert knowledge, product and recipe data, and the application of machine learning methods to predict nutrient needs and dynamically optimize menus. One promising area is nutrition modeling at the dish level, rather than individual products, ensuring the practical feasibility of recommendations, taking into account taste preferences, and ensuring dietary diversity.

Literature review. The development of automated nutrition planning systems demonstrates a clear evolution from isolated formal models to hybrid intelligent architecttures, namely those that are a combination of two methodological approaches: knowledge-driven and data-driven. While early solutions were based primarily on formal optimization models and expert rules, modern systems increasingly integrate decision support methods, machine learning, and generative models [1–9].

The data-driven approach is based on the analysis of large data sets about users, their dietary preferences, health status, weight dynamics, physical activity, and other parameters. Unlike expert systems, decisions are made not based on predefined rules, but on identified statistical relationships. In the context of meal planning, a data-driven approach typically involves the use of machine learning algorithms for classifying users by diet type, regression models for predicting nutrient requirements, clustering methods for segmenting eating habits, gradient boosting and ensemble methods for optimizing calorie intake and balance, neural networks for modeling complex nonlinear relationships, and large language models (LLM) for generating recipes and text recommendations. Among main advantages of the approach are high adaptability to individual data, scalability, ability to account for complex nonlinear relationships, model updates for new data. However, the standalone use of the data-driven approach also has limitations. You may face such problems such the lack of strict constraint guarantees, low explainability of model decisions, dependence on the training sample quality, risk of generating incorrect or unbalanced menus. Thus, the data-driven approach ensures adaptability, but does not always guarantee the formal correctness of the diet.

Knowledge-driven approaches rely on modeling the knowledge of experts, the use of "if-then" rules, product databases, and nutritional guidelines. Classic expert systems can automatically select menus based on the user's parameters [10–13]. Another important tool is constrained optimization methods, which make it possible to construct a diet that simultaneously satisfies several requirements [14–16]. The main advantage of mentioned approach is the transparency of decisions, allowing specialists to trace the rules that led to the formation of a specific menu. However, they have a number of disadvantages, such as: limited adaptability – systems respond poorly to new or non-standard conditions, such as unexpected user dietary preferences; dependence on a knowledge base – outdated or incomplete data can lead to incorrect recommendations; scaling difficulty– maintaining rules and restrictions up-to-date for a large number of users is difficult.

One of the classic problems illustrating the application of this approach is the diet problem, which originally arose as an applied economic model for determining the cheapest diet that satisfies human physiological needs [17]. In such formulation, it is assumed that there is a finite set of foods, each characterized by its cost and nutrient content. The objective of the model is to minimize the total cost of the diet while satisfying the minimum nutritional intake requirements. Even in its basic form, the mentioned model solves a number of practically important problems: rational nutrition planning, economic evaluation of diets, and basic automation of calculations. In this sense, it remains a correct and mathematically rigorous model [18–19]. However, the classical formulation has several significant limitations when considered from the perspective of real-life tasks: ignoring taste preferences, habits, and cultural characteristics; foods are considered in isolation rather than as dishes consisting of multiple ingredients; the linear model may suggest fractional or excessive quantities of foods; dietary diversity and repetition over time are not taken into account; rigid and deterministic parameters (prices, food composition, consumption norms), which rarely correspond to real-life conditions.

To overcome these limitations, it's necessary to move from individual products to dishes. In everyday practice, people operate with dishes, not individual grams of ingredients: a diet is formed as a sequence of prepared meals with their own structure, taste, and context (breakfast, lunch, dinner). Shifting to dish-level modeling allows for the integration of recipes as fixed or parameterized combinations of products, taking into account technological constraints, repetition frequency, ingredient compatibility, and user preferences. This increases the interpretability of results and improves the practical applicability of models.

Thus, the conducted analysis has shown a number of remaining methodological limitations and underdeveloped aspects. Firstly, integrated dietary optimization models at the dish level are underrepresented, while actual meal planning is typically carried out in terms of ready-made dishes. Secondly, the multi-criteria nature of the problem is often formalized in a simplified manner and does not reflect all real economic, nutritional, behavioral and technological factors. Third, a significant limitation of many solutions is their static nature. The optimization problem is formulated for a fixed time horizon without a mechanism for revising the solution as conditions change. User preferences, changes in health, product seasonality, price fluctuations, and other factors remain outside the dynamic model. Thus, there is no mechanism for a rolling planning horizon, whereby the diet is adjusted as new data becomes available. Fourth, adaptive learning of user preferences is rarely built directly into the optimization problem formulation. Fifth, modern generative models demonstrate high flexibility in menu generation, but their decisions are not backed by strict optimization guarantees. They can generate diverse and personalized recommendations, but they do not guarantee global optimality and do not provide a formal structure for explaining the decision. This leads to a contradiction between adaptability and formal rigor.

Taken together, this means that existing research predominantly either provides formal rigor without sufficient adaptivity or provides adaptivity without strict constraint guarantees. An architecture that integrates these advantages into a single system is lacking.

Given the identified limitations, developing an integrated intelligent meal planning system based on a formalized, dish-level optimization model with a multi-criteria objective function seems a viable option. This model should operate in a dynamic, rolling-horizon mode, provide adaptive learning of user preferences, and maintain the explainability of decisions through a transparent optimization core. This architecture combines the rigor of classical models with the flexibility of modern artificial intelligence methods, bridging the identified methodological gap and providing a coherent foundation for further research.

The objective of this work is to develop an intelligent meal planning system at the dish level, where the core is a formalized diet optimization model, and the intelligent and user levels provide adaptation, personalization, and explainability of decisions.

The proposed information system is designed to formulate diet plans based on a formalized multi-criteria dynamic diet optimization model, expanded to the dish level. A key feature of the system is that the appropriate mathematical model serves as the computational core, defining the feasible and optimal solution space, while the intelligent and user components operate on top of this core. The design is based on the principle of strict separation of responsibilities between system components, which ensures the correctness of decisions, scalability, and explainability of results. The system is implemented as a multi-level architecture and includes the following logical layers:

- data layer,
- optimization core layer,
- intelligent decision support layer,
- user presentation and interaction layer.

The presence of layers allows us to separate the storage and preparation of data from decision-making, numerical solution of optimization problems, and interpretation of results. Fig. 1 shows a conceptual UML class diagram that clearly demonstrates the key entities of the system, their functions, and their relationships. Let's briefly review the contents of each layer.

The data layer is represented by two classes: UserProfile and Dish. The UserProfile class represents the system's personalization parameters. It contains user goals, individual preferences, constraints (medical, ethical, and taste-related), and a vector of criteria weights for the multi-criteria objective function. This class is associated with DietModel and performs the function of parameterizing the model: it is the user profile that determines the structure of the constraints and the relative importance of the criteria. The Dish class describes dishes as alternatives in an optimization problem. It includes nutrient profile, cost, and category characteristics.

The optimization core layer consists of three classes: DietModel, Solver, and Solution. DietModel is the central entity of the system. It formalizes the mathematical model for multi-criteria dynamic diet optimization. This class aggregates the Dish set, obtains parameters from the UserProfile, generates a constraint system, and constructs an objective function. Thus, DietModel defines a feasible solution space but does not perform a numerical search for the optimum. The Solver class implements the computational procedure for solving the optimization problem, producing a Solution object as the result. It is important to emphasize that the Solver does not interpret the solutions or modify the model structure; it performs strictly a computational function. This ensures the autonomy of the optimization core. The Solution class represents the outcome of the optimization problem and contains the selected dishes, aggregated indicators (criterion values), and the final values of the objective function. This class serves as an intermediate object between the computational core and the intelligent layer.

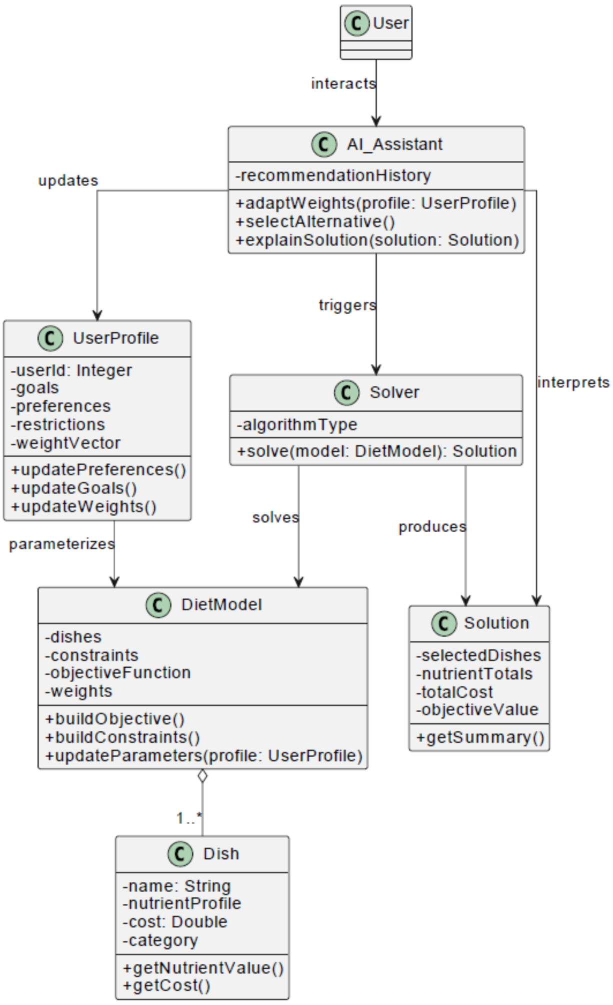

Fig. 1. Intelligent nutrition planning system conceptual UML class diagram

The decision support intelligent layer is represented by the AI_Assistant class, which implements the system's intelligent overlay. This class initiates the execution of the Solver, analyzes the Solution object, adapts criterion weights based on the user profile, interprets the results, and generates explanations. Class relationships: association with Solver (managing the solution process), association with Solution (interpreting the result), association with UserProfile (updating parameters). The intelligent layer does not interfere with the mathematical structure of DietModel, but operates within the feasible solution space.

At the presentation and interaction layer, the diagram has a User class, which represents the end user of the system and is associated with AI_Assistant.

The presented UML class diagram reflects the structural organization of the key entities of the system and the nature of their interactions. At the same time, for a more complete understanding of the logic of the intelligent system's functioning, we should consider its architecture in terms of logical layers.

The data layer serves as the basis for the formation and parameterization of the optimization model. It stores structured information necessary for creating nutrition plans and personalizing decisions. This layer does not contain decision-making logic: its purpose is to provide reliable and organized data to the upper layers of the system, including the optimization core and the intelligence layer. The layer includes the following databases: a product database, a dish database, a nutrient standards database, and a user profile database.

The product database contains nutritional information for each product, including calories, macronutrients, and micronutrients. It also stores product costs, information on potential allergens, and seasonal availability. This data allows for the appropriate planning of meals, taking into account nutritional value, economic factors, and seasonality.

The dish database includes the ingredients for each dish, creating a "food-dish" matrix. It specifies standard portion sizes, cooking restrictions, and categorization of dishes by mealtimes – breakfast, lunch, dinner, etc. It ensures the correct combination of ingredients in dishes and facilitates meal planning.

The nutrient database contains information on daily and weekly nutrient intake ranges, upper and lower limits for each nutrient, and energy balance targets. It serves as a guide for creating diets to ensure that nutrition meets the user's health standards and energy needs.

The user profile database stores personal data for each user: their goals (weight loss, weight maintenance, weight gain), dietary restrictions, including allergies and individual diets, food preferences, as well as their consumption history and previously created diets. This information allows the system to create personalized recommendations that best suit the user's needs and preferences.

Structured data at this level enables the dynamic generation of optimization models for each user and each scenario. It defines the parameters and constraints for the core of the system–the diet optimization model–forming the basis for accurate, personalized, and explainable decisions.

The central component of the architecture is the optimization core, represented by the diet model. The model formalizes the task of meal planning as an optimization problem, where the variables are the quantities of dish portions, and the constraints reflect nutrient, energy, logical, and time requirements. The optimization core does not contain user logic and does not interpret the results – it is solely responsible for the mathematical correctness of the solutions. The model can be formulated as a mixed-integer linear programming problem or its extension, depending on the complexity of the factors considered. The basic version of the model is described below.

Let's introduce the following notations:

$y_k \in Z, y_k \geq 0$ – number of portions of the k-th dish included in the diet, $k = 1, \ldots, K$;

K – total number of dishes;

r_{jk} – the amount of product j included in one portion of dish k, $j = 1, \ldots, n$;

n – total amount of food products;

c_j – unit cost of the j-th product;

a_{ij} – the content of nutrient i in one unit of product j, $i = 1, \ldots, m$;

m – total number of nutrients;

$b_i^{\min}, b_i^{\max}$ – minimum and maximum acceptable intake of the i-th nutrient.

It is suggested to apply the following aggregated parameters of dishes: amount of the i-th nutrient in the k-th dish: $A_{ik} = \sum_{j=1}^{n} a_{ij} r_{jk}$; total cost of the k-th dish: $C_k = \sum_{j=1}^{n} c_j r_{jk}$.

The basic single-criteria version of the model is the following.

Objective function: $\min \sum_{k=1}^{K} C_k y_k$; nutrient restrictions: $b_i^{\min} \leq \sum_{k=1}^{K} A_{ik} y_k \leq b_i^{\max}$; restrictions on the number of dishes: $0 \leq y_k \leq \bar{y}_k$; structural restrictions: $\sum_{k=1}^{K} y_k = M$, $\sum_{k \in G} y_k \leq 1$.

Let's consider possible extensions of the basic version of the model.

Below, we propose a multi-criteria model that simultaneously considers several, potentially conflicting, nutritional planning objectives. Unlike single-criteria models, this formulation allows us to formalize real trade-offs between economic, nutritional, behavioral, and consumer diet aspects.

Generally, the model can be presented as follows: $\min f(y) = (f_1(y), \ldots, f_G(y))$, where $f_g(y)$ – g-th optimality criterion, $g = 1, \ldots, G$.

Due to the inconsistency of the criteria, such a problem typically does not have a single optimal solution in the classical sense. Instead, a multitude of compromise alternatives is generated, between which a choice is made using specialized multi-criteria optimization methods (scalarization, ε-constraints, Pareto frontier) [20–23].

In the developed system we propose using a scalarization method to solve a multi-criteria dietary problem. This reduces the vector objective function to a single aggregated function of the form:

$$\min \sum_{g=1}^{G} w_g f_g(y), \; w_g \geq 0, \; \sum_{g=1}^{G} w_g = 1,$$

where w_g – weight of the g-th optimality criterion.

This approach significantly simplifies the computational implementation of the model and ensures its compatibility with MILP solvers. However, the key methodological challenge of scalarization is determining the weighting coefficients reflecting the relative importance of individual optimality criteria.

To solve this problem, we propose using expert methods of multicriteria analysis, particularly pairwise comparison methods. These methods allow us to formalize the subjective preferences of an expert or user and transform them into quantitative weights used in the model. It is assumed that the decision maker is able to express preferences between each pair of criteria in terms of relative importance. The pairwise comparison model is then defined by so cold square preference matrix:

$$\boldsymbol{H} = (h_{ij}),\ i, j = 1,...,G,\ h_{ij} \geq 0,\ h_{ii} = 1,\ h_{ij} = \frac{1}{h_{ji}}.$$

Matrix $\boldsymbol{H}$ is interpreted as a formalized representation of expert judgments regarding the importance of criteria. Based on this matrix, a weight vector is determined that reflects the aggregated relative importance of the criteria. Additionally, a measure of the preference matrix consistency can be considered, allowing one to assess the internal consistency of expert judgments and, if necessary, adjust the initial estimates. This ensures the stability and reliability of the resulting weighting coefficients. Thus, the pairwise comparison model serves as a link between the subjective preferences of the user or expert and the formalized optimization model, ensuring a correct and interpretable assignment of the parameters of the multi-criteria objective function [24–26].

The multi-criteria diet model discussed above describes the meal planning process in a static mode, where the diet is formed without explicitly considering the temporal structure of consumption. However, in practice, nutrition is distinctly dynamic: meals are distributed over time, nutrient and energy restrictions apply on both a daily and weekly basis, and the user's preferences and goals may change.

In the dynamic model, a diet is considered as a sequence of decisions $y = \{y_t\}_{t \in T}$, where y_t describes the set of dishes consumed at time t. The set of feasible decisions is formed taking into account time constraints, such as: daily and weekly nutrient intake standards, restrictions on the frequency of meal repetitions, requirements for menu variety over time, cumulative effects (nutrient deficiencies or excesses).

Accordingly, the vector of objective functions also acquires a temporal structure and can be written in the following aggregated form:

$$\min F(y) = \left(\sum\nolimits_{t \in T} f_{1t}(y_t), ..., \sum\nolimits_{t \in T} f_{Gt}(y_t)\right).$$

Further, the problem can be represented as a problem of minimizing the weighted sum of aggregated criteria:

$$\min_{y \in Y} \sum\nolimits_{g=1}^{G} \sum\nolimits_{t \in T} w_g f_{gt}(y_t),$$

where $f_{gt}(y_t)$ – local indicator of diet quality at time t according to criterion g.

The dynamic multi-criteria model allows for consideration of trade-offs not only between various criteria but also between the user's short-term and long-term goals. For example, a temporary deviation from energy balance on a particular day can be compensated for within the weekly plan without compromising overall nutrient standards. The result is an adaptive nutrition plan that simultaneously considers the user's short-term needs and long-term goals.

From the perspective of the architecture of an intelligent meal planning system, dynamic formulation creates an expanded solution space within which the intelligent assistant performs:

- consistent adaptation of diets over time;
- recalculation of solutions when user data or external conditions change;
- support for "what if" scenarios and planning on a rolling horizon.

Using a sliding horizon mechanism means that optimization is performed over a limited time interval, after which the horizon is shifted forward, taking into account decisions already made and updated information.

Let the planning horizon be P days. At time t, the system solves a dynamic multicriteria problem over the interval $[t, t+P]$, generating a supply plan for several days in advance. After the solution for the first period is implemented, the horizon shifts, and the problem is solved again for the interval $[t+1, t+1+P]$.

This mechanism allows:

- to account for actual dishes consumed;
- to correct accumulated nutrient deviations;
- to adapt to changes in preferences or external conditions;
- to maintain flexibility without having to recalculate the entire long-term plan.

Additionally, a user preference learning mechanism can be integrated into the dynamic setup. User preferences are rarely explicitly and statically defined. In a real system, they are refined as the user interacts with the assistant. This requires the inclusion of an appropriate learning mechanism.

Let's say one of the model's criteria describes the discrepancy between the diet and individual preferences: $f_{\text{pref}}(y, \theta)$, where θ – user preference parameters. During system operation, these parameters are updated based on actual dish selections, rejections of proposed alternatives, satisfaction ratings, and the frequency of repeat selections for certain categories. Based on the history of accepted and rejected meal plans, the system adjusts the weighting coefficients of the multi-criteria objective function and the penalty parameters for deviations from preferences, ensuring gradual personalization of the model without changing its basic structure.

The described mechanisms of dynamic optimization, rolling horizon, and user preference learning are not implemented directly at the optimization core layer. Their use requires a separate control layer responsible for adapting model parameters, reinitializing optimization problems, and interpreting the resulting solutions in the context of user goals and behavior. In the architecture of an intelligent meal planning system, this function is performed by an intelligent decision support layer, described below.

The intelligent decision support layer adapts, personalizes, and explains the optimization model's results. It operates on top of the optimization core and uses the solutions provided by the solver to generate recommendations that can be directly understood and used by the user. Unlike the optimization layer, which is solely responsible for the formal correctness of solutions and the numerical solution of the optimization problem, this layer ensures interpretation, parameter management, and adaptation of solutions to the user's individual needs. The layer follows a hybrid approach that combines rule-based reasoning with lightweight data-driven adaptation mechanisms. Rule-based components ensure consistency with nutritional logic and model constraints, while data-driven elements enable personalization based on user preferences, feedback, and behavioral patterns. Let's consider the tasks at this layer.

Model parameter adaptation. The layer enables dynamic adjustment of multi-criteria model parameters, including weight adjustments in the multi-criteria objective function based on user preferences, activation or deactivation of constraints based on individual dietary requirements, consideration of the user's personal goals, such as weight loss, weight maintenance, or muscle gain. The update rule can be defined as:

$$w_g^{t+1} = w_g^t + \alpha u_g^t ,$$

where u_g^t – user feedback signal;

α – learning rate parameter.

In a rolling horizon context, adaptation is iterative: model parameters are adjusted as information about the user's behavior and preferences accumulates.

Solution space navigation. The dynamic model generates a set of feasible diets, including the Pareto frontier in multi-criteria settings. The intelligent layer evaluates and ranks these alternatives using a user-specific utility function constructed from the adapted weights: $U(y) = \sum_{g=1}^{G} w_g^t f_g(y)$. The preferred solution is selected from the Pareto set $P \subseteq Y$ as $y^* = \arg\min_{y \in P} U(y)$.

The layer constructs a ranked subset of alternatives to support comparison, trade-off analysis, and "what-if" exploration. This enables informed decision-making in an expanded solution space that reflects both short-term preferences and long-term user goals.

The task of interpreting and explaining decisions. The explanation process consists of three sequential stages: feature extraction from the optimization solution, transformation into semantically meaningful indicators, and generation of user-oriented textual explanations. For each feasible diet plan, the system evaluates the contribution of individual dishes to objective criteria and constraint satisfaction. These contributions are directly derived from the parameters and structure of the optimization model and therefore remain fully consistent with the underlying mathematical formulation. Based on these evaluations, the relative importance of each dish within the solution is determined, allowing the identification of key elements responsible for achieving nutritional balance and satisfying user-defined goals. The interpretation mechanism is implemented using a set of deterministic rules that map quantitative indicators to predefined explanation templates. This enables the system to generate consistent justifications for dish selection, as well as to identify feasible substitutions that preserve nutritional and energetic properties of the diet.

Thus, the intelligent layer serves as a link between numerically determined optimal solutions and the end user, transforming the model's formal results into practical recommendations that are understandable and convenient for decision-making. This layer enables dynamic adaptation, supports "what-if" scenarios, and allows for real-time consideration of changing user preferences and conditions.

Let's consider the presentation and user interaction layer. It facilitates communication between the user and the intelligent meal planning system and serves as an interface layer over the system's analytical components. The layer does not contain its own data storage mechanisms or implement computational optimization logic, but rather handles query generation, result visualization, and interpretation of decisions received from the underlying architecture layers. Architecturally, this layer serves as an intermediary between the user, the intelligent decision support layer, and the centralized data layer. All access to recipe databases, nutrient tables, and user profiles is handled through the data layer's service interfaces, eliminating information duplication and ensuring system integrity. Let's consider it's main functions.

The user query generation and structuring function collects input parameters for the nutrition planning task. The user can specify target indicators (weight loss, fitness maintenance, weight gain), restrictions (allergies, medical contraindications, excluded foods), preferences (flavor categories, frequency of meal repetitions), planning time horizon, and acceptable deviations from target values. Input can be performed both in structured form (via parameters and filters) and in dialog mode. When using text input, the interpretation module transforms the natural language query into a formalized set of parameters passed to the intelligent layer. Thus, the presentation layer performs the function of parameterizing the multi-criteria optimization model without changing its mathematical structure.

Interaction with the intelligent layer. After the query is structured, the parameters are passed to the intelligent decision support layer, which refines criteria priorities, adjusts weighting factors, takes into account interaction history, and generates a problem statement for the optimization core.

The presentation layer does not make dietary decisions independently. It initiates the computational process and receives from the intelligent layer a pre-processed result corresponding to the feasible solution space generated by the optimization core.

Data layer access function. All operations related to obtaining information about dishes, recipes, nutritional composition, and user profiles are performed through a centralized data layer. The presentation layer requests the necessary data through service interfaces, displays the received information in a user-friendly format, and transmits updated parameters back to the system. Data storage, updating, and consistency are fully supported by the data layer and are not duplicated in the interface.

Decision visualization and explanation function. After receiving a decision from the intelligent layer, the user interface displays the diet plan by day and meal, displays the nutrient balance, visualizes deviations from target values, compares alternative options, and explains the reasons for choosing specific dishes. The explanation mechanism is based on the decomposition of the objective function and model constraints. The user can obtain information about the criteria and constraints that influenced the proposed diet. This ensures the transparency and explainability of decisions characteristic of intelligent decision support systems.

Feedback function. The presentation layer also collects feedback, including: acceptance or rejection of a proposed dish, request for alternatives, preference adjustments, and satisfaction ratings. The received information is passed to the intelligence layer, where it is used to adaptively adjust the model parameters (specifically, the criterion weights and preference function parameters).

Thus, the presentation layer closes the interaction loop: user data is fed to the intelligence layer, which manages the optimization model, and the decision results are returned to the interface for analysis and selection. This approach ensures the system's dynamic and personalization.

To illustrate the performance of the proposed multicriteria model, we consider the problem of creating a daily diet from a finite set of ten alternative dishes. Each dish is characterized by the following parameters: energy value, protein, fat, and carbohydrate content, cost per portion, and its functional group (breakfast, main meal, light meal). The goal is to create a daily diet from three dishes that satisfies established nutrient restrictions. The diet is created taking into account three optimality criteria: minimizing the total cost of the selected dishes, minimizing the deviation of the actual caloric content of the diet from the target value, and minimizing the penalty for not including representatives of functional groups in the diet. The numerical parameters of the problem are formed on the basis of generalized data contained in open tables of the chemical composition of food products.

The mathematical formulation of the problem is presented below:

$$\min_{y,d,z}(w_1\sum_{k=1}^{K} s_k y_k + w_2 d + w_3 \sum_{g\in G} Z_g),$$

$$w_1 + w_2 + w_3 = 1,\ w_1, w_2, w_3 \ge 0,$$

$$d = \left|\sum_{k=1}^{K} e_k y_k - e^*\right|,$$

$$z_g \ge 1 - \sum_{k: g_k = g} y_k,\ z_g \ge 0,$$

where $y_k \in \{0,1\}$ – the number of portions of the k-th dish included in the diet, $k = 1,\dots,K$;

d – deviation of the caloric content of the diet from the standard value;

z_g – penalty for absence of functional groups of dishes;

K – total number of dishes;

s_k – unit cost of the k-th dish;

e_k – unit calorific value of the k-th dish;

e^* – standard caloric value.

In this case, the following restrictions must be met.

Structural restrictions:

$$\sum_{k=1}^{K} y_k = 3.$$

Nutrient restrictions:

$$b_i^{\min} \le \sum_{k=1}^{K} A_{ik} y_k \le b_i^{\max},$$

where A_{ik} – the amount of nutrient i in dish k;

$i = 1,\dots,m$, $m = 3$ – total number of nutrients;

$b_i^{\min}$, $b_i^{\max}$ – minimum and maximum acceptable intake of nutrient i.

Calorie restrictions:

$$e^{\min} \le \sum_{k=1}^{K} e_k y_k \le e^{\max}.$$

To study the influence of the decision maker's preferences on the structure of the optimal diet, a computational experiment was conducted in the Python environment using the PuLP library.

During the experiment, the weight coefficient w_1 was sequentially varied within the range [0;1]. The remaining weight was distributed equally between w_2 and w_3. For each value of w_1 an optimization problem was solved, and the values of the key indicators were recorded: the total cost of the diet, the deviation from the target caloric level, and the diversity indicator. Based on the obtained results, graphs were constructed showing the dependence of these characteristics on the weight w_1 (see Fig. 2 – Fig. 3).

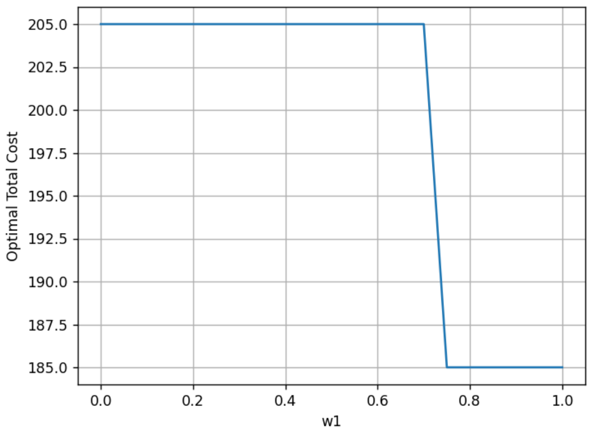

Fig. 2. Optimal total cost vs w_1

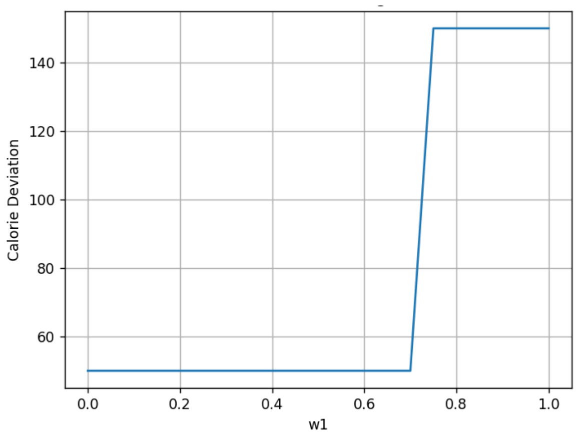

Fig. 3. Calorie deviation vs w_1

The cost graph demonstrates two stable solution regimes. For relatively small values of w_1, the optimal diet is the one that more closely matches the target caloric intake, but has a higher total cost. As w_1 increases, a transition to an alternative diet with a lower cost occurs. This transition occurs abruptly upon reaching a certain threshold.

The graph of deviation from the target calorie value shows the opposite trend. A decrease in the cost is accompanied by an increase in deviation from the target calorie value. This indicates a conflict between the criteria and confirms the need for a multi-criteria approach.

We do not present here the dependence of diet diversity on w_1, as in the current experiment, this diversity indicator remains constant. This means that both found optimal diets have the same structure across meal groups. Consequently, the diversity criterion in this set of alternatives does not significantly influence the choice of the optimal solution, although its inclusion in the model allows for control over the structural characteristics of the diet and may play a more significant role when expanding the set of feasible alternatives. Overall, the analysis shows that changing preferences between criteria leads to a transition between several stable structures of the optimal diet, reflecting the discrete nature of the current multi-criteria optimization problem.

Conclusions and future research directions. This paper develops the concept of an integrated intelligent meal planning system at the dish level, based on a formalized multi-criteria dynamic optimization model. Unlike the classic diet problem, where individual products are the object of optimization, the proposed approach implements modeling at the level of finished dishes, improving the practical feasibility, interpretability, and applicability of the resulting diets.

An analysis of existing research revealed a methodological gap between knowledge-driven and data-driven approaches to personalized nutrition. The former provide mathematical rigor and constraint guarantees, but have limited adaptability. The latter are characterized by high flexibility and the ability to incorporate behavioral data, but do not provide formal guarantees of decision correctness. The proposed architecture bridges this gap by integrating a formal optimization core and an intelligent adaptation layer.

A multi-criteria diet model was developed using a scalarization method and an expert-based weighting mechanism based on pairwise comparisons of criteria. This ensures the formalization of user subjective preferences and their integration into a rigorous optimization formulation. Additionally, the model was expanded to a dynamic form, taking into account the time structure of nutrition, intertemporal constraints, and a sliding planning horizon mechanism.

A multi-layered system architecture is proposed, including a data layer, an optimization core, an intelligent decision support layer, and a user interaction layer. A clear division of responsibilities between the components ensures scalability, modifiability, and explainability of the system. The intelligent layer implements adaptation of model parameters, navigation in the solution space, and a preference learning mechanism without disrupting the mathematical structure of the problem.

Thus, the developed approach forms a holistic theoretical and methodological basis for the construction of intelligent personalized nutrition planning systems that combine the rigor of optimization methods with the adaptability of modern artificial intelligence technologies.

Promising areas for further research include experimental validation of the model on real user data; integration of stochastic factors; and the use of robust and stochastic optimization methods. In addition, the preference learning mechanism can be extended using data-driven approaches to improve the adaptation of criterion weights over time. Further development of the intelligent decision-support layer, particularly the explanation module, is also of interest, including the use of advanced natural language generation techniques to enhance the quality and interpretability of recommendations. Finally, future work may focus on the development of a prototype software implementation of the system and its comparative evaluation with existing solutions.

Declaration on the use of generative AI. During the preparation of this work, the authors used ChatGPT and Grammarly for grammar and spell checking, as well as for rephrasing and reformulating the text. After using these tools, the authors reviewed and edited the content as necessary and take full responsibility for the content of this publication.

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ІНТЕЛЕКТУАЛЬНА СИСТЕМА ПЛАНУВАННЯ ДІЄТИ НА РІВНІ СТРАВ НА ОСНОВІ ОПТИМІЗАЦІЙНОЇ МОДЕЛІ

У статті розглянуто проблеми створення та впровадження інтелектуальних систем персоналізованого планування харчування. Сучасні дослідження у цій галузі демонструють перехід від класичних формалізованих моделей дієти до гібридних архітектур, що поєднують дві методологічні парадигми: knowledge-driven та data-driven підходи. Проте між ними існує певний методологічний розрив. Моделі, орієнтовані на знання (knowledge-driven), забезпечують математичну строгість і гарантують дотримання нутріційних та ресурсних обмежень, однак зазвичай мають обмежену адаптивність і персоналізацію. Натомість підходи, орієнтовані на дані (data-driven), зокрема сучасні генеративні моделі, демонструють високу гнучкість і здатність враховувати поведінкові дані, але не забезпечують формальних гарантій оптимальності та виконання обмежень. Це протиріччя зумовлює необхідність розроблення інтегрованої інтелектуальної системи планування харчування, яка поєднує переваги обох підходів. Метою дослідження є створення інтелектуальної системи планування харчування на рівні страв, ядром якої є формалізована багатокритеріальна оптимізаційна модель дієти. На відміну від класичної задачі дієти, де оптимізація виконується щодо окремих харчових продуктів, запропонований підхід моделює харчування на рівні готових страв, що підвищує практичну реалізованість, інтерпретованість та зручність використання отриманих дієтичних планів. Математична модель формулюється як задача багатокритеріальної оптимізації, у якій змінні рішення представляють кількість порцій страв, тоді як обмеження відображають нутріційні, енергетичні, логічні та часові вимоги. Запропонована модель реалізована в межах багаторівневої архітектури системи, що складається з рівня даних, оптимізаційного ядра, інтелектуального рівня підтримки прийняття рішень та рівня взаємодії з користувачем. Оптимізаційне ядро забезпечує математичну коректність і обчислення оптимальних рішень, тоді як інтелектуальний рівень забезпечує адаптацію, персоналізацію та інтерпретацію результатів. Модель також розширено до динамічної форми із використанням ковзного горизонту планування, що дозволяє оновлювати план харчування у міру надходження нових даних та змін користувацьких уподобань. Обчислювальні експерименти продемонстрували, що зміна ваг критеріїв призводить до переходів між кількома стабільними оптимальними структурами раціону, що відображає дискретну природу розглянутої задачі багатокритеріальної оптимізації.

Ключові слова: планування харчування, дієта, модель на рівні страв, система підтримки прийняття рішень, багатокритеріальна оптимізація, гібридні системи штучного інтелекту, рекомендаційні системи.

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