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Applications of Metaheuristic Algorithms in Nutritional Optimization and Personalized Diet Planning: A Review

Habibeh Karimi[1], Sapan Kumar Das[2], Bardia Khalilian[3,*]

[1] Department of Research Center, Shiroud Municipality, Mazandaran, Iran; sekarimimail@gmail.com.
[2] Department of Mathematics, National Institute of Technology Jamshedpur, 831014 Jharkhand, India; cool.sapankumar@gmail.com.
[3] Department of Management and International Business (MIB), University of Auckland, 1142 Auckland, New Zealand; bardiakhalilian82@gmail.com.

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Abstract

Nutritional optimization links food selection and meal scheduling to nutrient adequacy, affordability, preferences and environmental objectives. This narrative review examines where metaheuristic search can assist these decisions and where linear or mixed-integer programming offers a more informative baseline. It distinguishes the optimization of a dietary model from evidence that a recommended diet improves health. Genetic and multi-objective evolutionary methods are discussed alongside particle swarm and differential evolution as possible search architectures, with attention to encoding, feasibility repair and expensive preference models. Published diet-modeling work supports the importance of acceptability constraints, and a multi-level NSGA-II menu-planning study illustrates the joint treatment of meals, days and weekly menus. The review develops an evaluation framework covering constraint satisfaction, solution quality, computational budget, dietary diversity and independent validation. It does not estimate pooled algorithm effects or establish a universal optimizer ranking. Traceability limitations in the numerical compilations restrict quantitative synthesis. Priorities include transparent food databases, matched mathematical-programming comparisons, clinically appropriate constraints and prospective assessment of adoption and outcomes.

Keywords: Diet optimization, Menu planning, Nutritional constraints, Metaheuristics, Multi-objective optimization, Decision support.

1 | Introduction

Diet planning is an optimization problem only after its decision variables, nutritional requirements and measures of acceptability have been specified. A low-cost combination of foods can satisfy nutrient targets

Corresponding Author: bardiakhalilian82@gmail.com
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while remaining difficult to prepare, culturally unsuitable or unacceptable to the intended person. Diet-modeling reviews therefore treat nutrient, cost, environmental and acceptability constraints as distinct modeling requirements [1], [2]. This review examines the role of metaheuristics in nutritional optimization and personalized menu planning through that formulation-first perspective.

Linear programming provides an established starting point when food quantities, nutrient totals and cost are linear. Discrete food inclusion, portion alternatives, meal timing, repetition restrictions and nonlinear preference models can require integer or nonlinear formulations. Metaheuristics supply search procedures for such formulations, but their usefulness must be assessed against the strongest applicable exact or specialized methods rather than inferred from biological inspiration [3].

The No Free Lunch results concern averages over specified collections of objective functions [4]. They do not require continual invention of new metaphor-based algorithms and do not preclude useful performance differences on structured diet problems. For menu planning, the relevant questions are whether the representation preserves meal structure, whether feasibility is maintained, and whether search improves a decision-relevant objective within a defined budget.

The central comparison in this review is between the mathematical structure of a dietary decision and the mechanisms offered by an optimizer. Genetic algorithms can manipulate food and meal assignments; particle swarm optimization and differential evolution operate naturally on real-valued quantities or parameters [5], [6]. A multi-objective approach can retain trade-offs among cost, dietary change and other objectives, provided that hard nutritional requirements remain explicit.

The contribution is a critical organization of formulation choices, search mechanisms and validation requirements for diet planning. Sections 2 and 3 establish the modeling context and the narrative review boundary. Section 4 discusses search architectures, Section 5 connects them to meal and menu decisions, and Sections 6 and 7 examine evaluation and future research. The conclusions concern methodological choices rather than field-wide algorithm frequencies or pooled clinical effects.

Personalization requires more than replacing a demographic average with an individual record. The model must identify which requirements are established nutritional constraints, which preferences are elicited, and which response estimates come from predictive models. The optimization layer cannot confer clinical validity on an unvalidated response model. Recommendations intended for a medical condition require independently justified, condition-specific constraints and appropriate professional assessment.

2 | Background and Context

The modeling background connects dietary quantities and schedules to feasibility, objectives and the distinction between a computational optimum and a usable menu.

2.1 | Definitions and Fundamental Concepts

A metaheuristic is a high-level search strategy that guides lower-level solution transformations [3]. Population-based methods maintain several candidates, while trajectory-based methods modify one candidate over time. Neither family automatically guarantees a globally optimal result within a finite budget. Dietary constraints should be checked on the decoded menu, including quantities, units and all applicable daily or weekly bounds.

A candidate menu can be encoded by food identity, portion quantity and assigned meal or day. The same numerical vector may represent a feasible diet under one food database and an infeasible diet under another. Constraint repair and penalization therefore belong to the method definition. A low penalized objective is insufficient when a remaining violation concerns a required nutrient bound or an exclusion such as an allergy.

2.2 | Historical Evolution

The development of evolutionary and swarm methods provides a repertoire of search mechanisms rather than a hierarchy of diet-planning effectiveness. Particle swarm optimization uses individual and neighborhood

search information [5]; differential evolution builds trial vectors from population differences [6]; ant-system methods construct combinatorial solutions through learned pheromone information [7]. Their dietary application requires domain-specific decoding and constraint handling.

Multi-objective evolutionary methods such as NSGA-II maintain non-dominated candidate solutions [8]. These are approximations to a trade-off set, not certificates that the entire Pareto frontier has been recovered. Feasibility, coverage of the trade-off surface and the stability of selected menus under reasonable preference changes matter more than the name or metaphor of the search method.

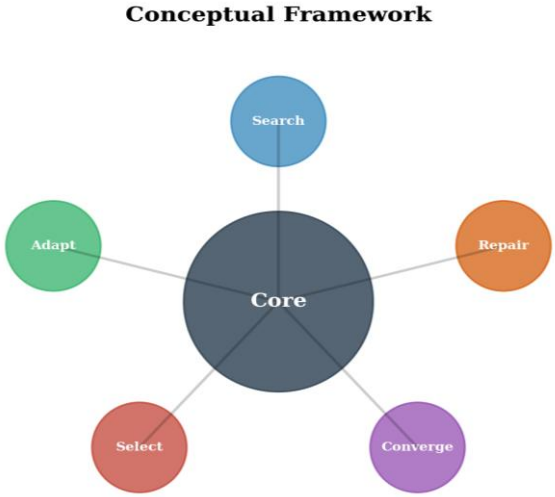


Fig. 1. General search components.

The schematic organizes search, repair, selection and adaptation; it does not establish a convergence guarantee or a validated dietary workflow (*Fig. 1*).

3 | Review Scope and Evidence Boundary

This article is a narrative methodological review of nutritional optimization and personalized menu planning. The literature is used to connect established dietary formulations to search and validation choices. No reproducible search log, deduplicated inclusion list or study-level extraction database is available for the numerical search compilation in *Table 1*. Its reported counts are therefore not used to define a systematic-review population or to estimate algorithm prevalence.

Table 1. Unverified search-count compilation.

Database	Results	Final Selection
IEEE Xplore	850	180
ScienceDirect	620	130
SpringerLink	450	95
Wiley Online	280	60
ACM Digital Library	180	35
Google Scholar	120	25
Total	2,500	541

Note: Entries are retained as reported; neither the selected-study total nor the selection process is established by these numbers.

The analytic synthesis is based on identifiable source connections rather than the counts in *Table 1*. In particular, van Dooren examines nutritional, economic, environmental and acceptability constraints [1], Donkor and colleagues review linear-programming formulations [2], and Koroušić Seljak [9] describes multi-level evolutionary menu planning. Their differing questions and evaluation settings preclude a pooled comparison of optimizer performance.

4 | Survey of Metaheuristic Algorithms

The following algorithm families are considered through their representations and constraint mechanisms. No claim is made that their relative popularity or performance has been measured across a complete diet-planning corpus.

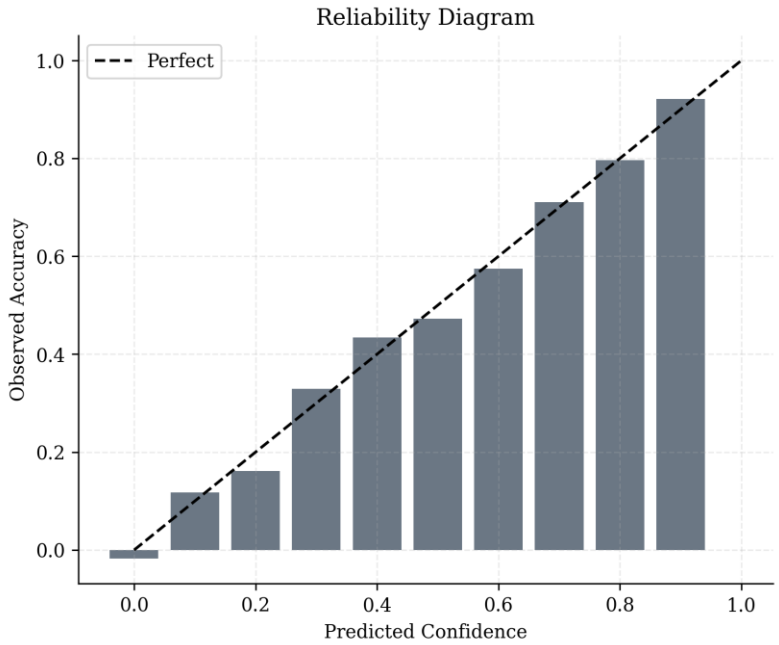


Fig. 2. Unverified calibration plot.

The underlying predictions, outcomes and bin counts are unspecified, so the plot supplies no evidence of calibration quality for a dietary prediction or recommendation system (*Fig. 2*).

4.1 | Evolutionary Algorithms

Evolutionary algorithms use selection and variation to update a population of candidate menus or parameter vectors. Genetic operators can exchange meals or food assignments, but unrestricted crossover may violate daily nutrient bounds or repetition limits. Differential evolution operates on continuous vectors [6], while CMA-ES adapts the covariance of a sampling distribution [10]. Their original mechanisms do not automatically solve mixed food-selection and portion-scheduling constraints.

Adaptive differential evolution changes search-control parameters during optimization; SHADE is a documented example [11]. Adaptation can reduce reliance on a fixed parameter choice but is not parameter-free and does not ensure superiority on dietary tasks. Hybrid local refinement may improve a candidate menu, and it must be compared with a matched search budget and a clearly specified feasibility rule.

4.2 | Swarm Intelligence

Particle swarm optimization updates a candidate using individual and social search information [5]. For diet planning, a particle can describe portion quantities or model parameters, whereas discrete food inclusion requires a specified discrete transformation. Ant-system methods build combinatorial candidates [7]; a meal sequence or food-assignment graph is a possible representation, but nutritional totals must still be checked separately.

Search simplicity is an implementation property, not evidence of nutritional suitability. Particle velocities, trial-vector differences and pheromone updates all require bounds, decoding conventions and stopping criteria. Changing these elements can have a larger practical effect than changing the algorithm label. Reported dietary benefits require evidence on the resulting feasible menus and their actual use.

4.3 | Physics- and Bio-Inspired Methods

Trajectory-based search can modify one meal or portion at a time, while population-based methods can retain several dietary alternatives. The essential distinction is the mechanism for proposing, evaluating and accepting feasible candidates. A new biological metaphor supplies no additional evidence unless it corresponds to a distinct operator or a testable architectural change [12].

Hybridization can combine global search with mathematical programming or local repair. For example, discrete meal assignments can be proposed by a metaheuristic and quantities adjusted by a suitable programming subproblem. The subproblem must be stated precisely, and the cost of repair, tuning and final feasibility checks must be included in the comparison. A hybrid advantage is a question to test, not a default conclusion.

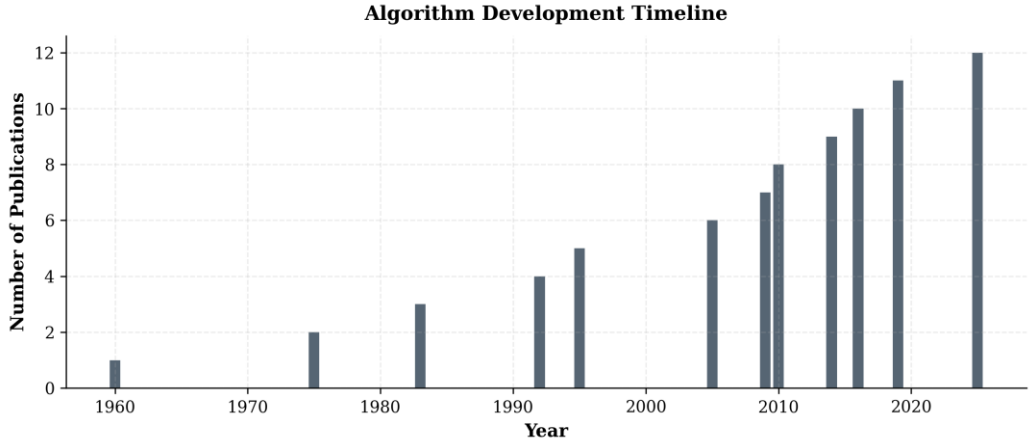


Fig. 3. Unverified publication-count graphic.

Its vertical axis reports publications, not the introduction dates of named algorithms; no historical or dietary publication trend is inferred from it (*Fig. 3*).

5 | Applications

Dietary applications differ in the decision they optimize: food quantities, multi-day menus, individual preference adaptation or the balance of nutritional and environmental objectives. This distinction determines what a useful search procedure must preserve.

5.1 | Primary Application Areas

Nutrient-constrained food composition remains an important mathematical-programming baseline [1], [2]. A diet model should identify food quantities and units, nutrient lower and upper bounds, budget restrictions and any excluded foods. When all relevant relationships are linear, a generic metaheuristic comparison should include a linear-programming solution and report the optimality gap where available. Integer menu choices should instead be compared with an appropriate mixed-integer or constraint-based baseline.

Koroušić Seljak provides a concrete evolutionary menu-planning architecture [9]. The method applies NSGA-II at meal, daily and weekly levels, with food identity and quantity represented within nested menu structures. Its significance for this review is the explicit coordination of constraints at different nutritional time scales. It is not evidence that the same architecture is clinically effective for every population or that it outperforms all modern exact solvers.

Personalized and sustainable diet design adds preference and environmental objectives without changing the need for nutritional feasibility. The reviewed diet-modeling literature identifies acceptability as a substantive modeling challenge [1]. Predicted preferences, observed adherence and clinical outcomes are different

quantities. Validation should therefore separate satisfaction of the mathematical model from acceptance by the user and subsequent health effects.

Table 2. Unvalidated qualitative ratings retained from the numerical compilation.

Algorithm	Convergence	Robustness	Scalability	Ease of Use
PSO	Fast	Medium	Good	High
GA	Medium	Good	Good	High
DE	Fast	Good	Good	Medium
GWO	Fast	Good	Medium	High
WOA	Medium	Medium	Medium	High
ACO	Medium	Good	Medium	Medium
CMA-ES	Slow	Excellent	Poor	Low
SHADE	Fast	Excellent	Good	Medium

Note: The ordinal labels have no documented task set, budget or scoring rubric and are not used as comparative evidence.

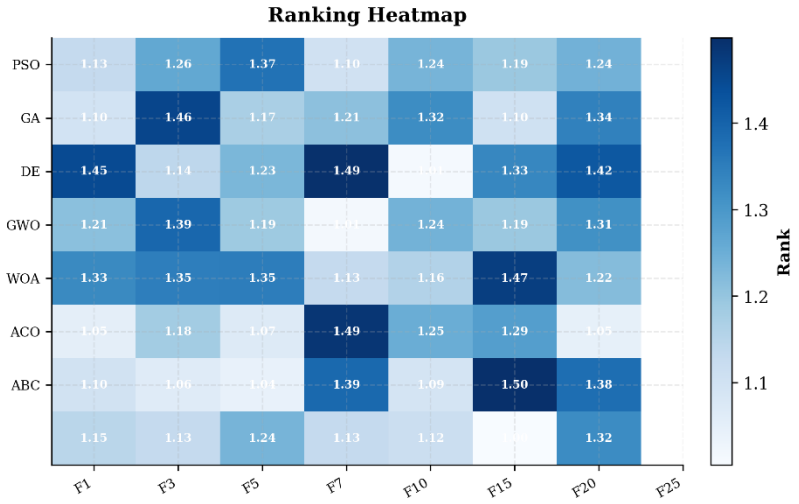


Fig. 4. Unverified rank graphic.

The functions, observations and ranking rule are unspecified, and the displayed values are not a valid complete within-function ranking of eight algorithms. It is excluded from the analytic synthesis (*Fig. 4*).

6 | Challenges and Limitations

The principal limitations concern the formulation, the evidence for numerical comparisons and the relationship between a feasible menu and a useful dietary intervention. The unverified tables and quantitative graphics cannot establish algorithm superiority, publication trends or clinical effectiveness.

6.1 | Parameter Tuning

Parameter settings should be selected using a tuning budget separate from final evaluation. Population size, stopping rules and repair frequency can change both computational cost and feasible-menu quality. Adaptive mechanisms such as CMA-ES and SHADE modify particular search components [10], [11]; they still require implementation choices, initial settings and an evaluation budget.

6.2 | Benchmark Fairness and Reproducibility

Fair comparisons require the same food database, nutritional constraints, user profile, objective definitions and computational resources. Exact or bounded solutions should be used where feasible. Stochastic methods require independent runs, but repeated seeds on the same menu instance do not create independent dietary populations. Comparative claims should report feasibility rates and decision-relevant gaps alongside run variability [13].

6.3 | Theoretical Analysis and Scalability

Theoretical convergence and practical usability are separate questions. A search process may have an asymptotic property under ideal conditions while returning infeasible or unacceptable menus within the operational time limit. Scaling analysis must include candidate evaluation, food-data access, repair and any predictive model used in the objective. The optimization model also inherits errors and omissions in its food composition and preference data.

When algorithms are evaluated on the same independent menu instances, paired tests preserve the matching. Wilcoxon signed-rank comparisons and a suitable multiple-comparison procedure can be considered, while rank-sum testing addresses independent samples. Friedman and Nemenyi methods require a complete matched algorithm-by-instance design and valid ranks [13], [14]. Confidence intervals and effect sizes should be reported for the defined independent unit rather than treating correlated runs as unrelated studies.

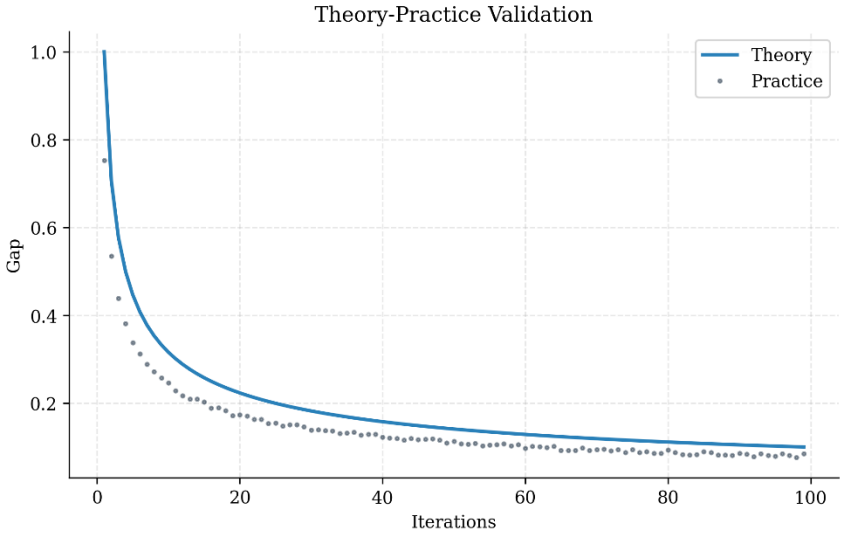


Fig. 5. Unverified theory–practice curves.

No mathematical prediction, experiment or dietary endpoint is specified, so the curves do not validate a theorem or an optimization method (*Fig. 5*).

7 | Future Research Directions

A useful research agenda begins with diet-specific benchmarks and transparent formulations. The main questions are feasibility, acceptability, uncertainty in food data and the practical value of additional optimization complexity.

Surrogate models can approximate expensive preference or response calculations, but optimizer evaluations should be periodically checked against the underlying model or observations. When machine learning predicts an individual response, predictive performance must be evaluated on information unavailable during model selection. Optimizing that prediction is a subsequent decision step and does not repair a biased predictor.

Multi-objective search should present feasible alternatives whose cost, nutritional adequacy, environmental footprint and departure from current habits can be interpreted by the intended decision-maker. Changes in these objectives or in elicited preferences should be examined for their effect on the chosen menu. A stable numerical ranking alone does not demonstrate that users accept the resulting choices.

Future comparative studies should release food-data versions, constraint definitions, menu instances, algorithm configurations, independent seeds and the scripts used to calculate results. Reporting should distinguish simulated user profiles from observed participants and distinguish computational feasibility from

adoption and health outcomes. Prospective deployment requires appropriate nutritional expertise and study design.

This review has a bounded narrative evidence base. It does not provide an exhaustive systematic search, a reproducible bibliometric survey or a new benchmark experiment. The numerical search counts, ordinal ratings and quantitative figures remain outside the validated conclusions until their source records and generating procedures are established.

8 | Conclusion

Metaheuristics can contribute to nutritional optimization when the dietary decision contains discrete, nonlinear or expensive components that justify the search architecture. The strongest methodological principle is to formulate and validate the decision before selecting an optimizer. Linear and mixed-integer programming remain essential baselines, while evolutionary menu planning illustrates how constraints at meal, daily and weekly levels can be coordinated.

The available source connections support careful treatment of nutritional feasibility, acceptability and trade-offs rather than a universal algorithm ranking. Computational comparisons should account for tuning and evaluation budgets, maintain matched instances and verify every final menu against its constraints. Clinical effectiveness and sustained adoption require evidence beyond optimization scores.

Progress depends on transparent dietary models and validation that follows the path from data to menu, from menu to use, and from use to outcomes. A reproducible, domain-specific comparison has greater scientific value than an unsupported claim of optimizer superiority.

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Data Availability

Sufficient data is available upon request.

Conflict of Interest

No potential conflict of interest was reported by the authors.

Consent for Publication

All authors have provided their consent for the publication of this manuscript.

Ethics Approval and Consent to Participate

This article does not involve studies with human participants or animals conducted by any authors.

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