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MULTIOBJECTIVE EVOLUTIONARY OPTIMIZATION OF OBSERVED BRAZILIAN MEALS ACROSS DIETARY REFERENCE PROFILES

OTIMIZAÇÃO EVOLUTIVA MULTIOBJETIVO DE REFEIÇÕES BRASILEIRAS OBSERVADAS EM DIFERENTES PERFIS DE REFERÊNCIA NUTRICIONAL

OPTIMIZACIÓN EVOLUTIVA MULTIOBJETIVO DE COMIDAS BRASILEÑAS OBSERVADAS EN DISTINTOS PERFILES DE REFERENCIA NUTRICIONAL

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ABSTRACT

This study examined whether menus assembled from observed Brazilian meals could improve nutritional and environmental outcomes while accounting for changes in food quantities. Four evolutionary algorithms were compared across six objective combinations using 2017–2018 Brazilian Household Budget Survey records for women and men aged 30 and 60 years, with weight-maintenance requirements. Adjusted hypervolume comparisons did not identify differences among the algorithms. However, choosing a menu from the resulting alternatives changed the dietary outcomes. Selection by distance to the ideal point of the searched objectives raised mean attainment of nutrient recommendations from 75.78% in observed diets to 97.98% and lowered carbon footprint, but increased water footprint. A retrospective rule requiring simultaneous improvements in nutrition, carbon, water and departure from observed quantities found an eligible menu in every run when it used the full candidate histories. Those choices averaged 95.67% attainment, with carbon and water 58.43% and 58.98% below observed profile means. Milk-based beverage and mate infusion quantities varied with the objectives and selection rule. Menu analysis showed that mean improvements coexisted with nutrient gaps, distinguishing front performance from the foods and quantities actually selected.

KEYWORDS: Multiobjective optimization. Observed meals. Diet planning. Evolutionary algorithms. Dietary profiles.

RESUMO

Este estudo examinou se cardápios formados por refeições brasileiras observadas poderiam melhorar os resultados nutricionais e ambientais, considerando também as mudanças nas quantidades de alimentos. Quatro algoritmos evolutivos foram comparados em seis combinações de objetivos, utilizando registros da Pesquisa de Orçamentos Familiares de 2017–2018 para

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mulheres e homens de 30 e 60 anos, com metas de manutenção de peso. As comparações de hipervolume com ajuste para múltiplos testes não identificaram diferenças entre os algoritmos. Entretanto, a escolha de um cardápio entre as alternativas produzidas alterou os resultados alimentares. A seleção por distância ao ponto ideal dos objetivos pesquisados elevou o atendimento médio das recomendações nutricionais de 75,78% nas dietas observadas para 97,98% e reduziu a pegada de carbono, mas aumentou a pegada hídrica. Uma regra retrospectiva que exigiu melhorias simultâneas em nutrição, carbono, água e distância das quantidades observadas encontrou uma opção em todas as execuções ao consultar o histórico completo de candidatos. Essas escolhas atingiram atendimento médio de 95,67%, com carbono e água 58,43% e 58,98% abaixo das médias observadas. As quantidades de bebidas lácteas e infusão de erva-mate variaram conforme os objetivos e a regra de seleção. A análise dos cardápios mostrou que as melhorias médias coexistiam com carências nutricionais, distinguindo o desempenho das fronteiras dos alimentos e quantidades efetivamente selecionados.

PALAVRAS-CHAVE: Otimização multiobjetivo. Refeições observadas. Planejamento de dietas. Algoritmos evolutivos. Perfis nutricionais.

RESUMEN

Este estudio examinó si los menús formados por comidas brasileñas observadas podían mejorar los resultados nutricionales y ambientales, considerando también los cambios en las cantidades de alimentos. Se compararon cuatro algoritmos evolutivos en seis combinaciones de objetivos mediante registros de la Encuesta de Presupuestos Familiares de Brasil de 2017–2018 para mujeres y hombres de 30 y 60 años, con metas de mantenimiento del peso. Las comparaciones de hipervolumen ajustadas por pruebas múltiples no identificaron diferencias entre los algoritmos. Sin embargo, elegir un menú entre las alternativas obtenidas modificó los resultados alimentarios. La selección por distancia al punto ideal de los objetivos de búsqueda elevó el cumplimiento medio de las recomendaciones nutricionales del 75,78% en las dietas observadas al 97,98% y redujo la huella de carbono, pero aumentó la huella hídrica. Una regla retrospectiva que exigió mejoras simultáneas en nutrición, carbono, agua y distancia respecto de las cantidades observadas encontró una opción en todas las ejecuciones al consultar el historial completo de candidatos. Estas elecciones alcanzaron un cumplimiento medio del 95,67%, con carbono y agua un 58,43% y 58,98% por debajo de las medias observadas. Las cantidades de bebidas lácteas e infusión de yerba mate variaron según los objetivos y la regla de selección. El análisis de menús mostró que las mejoras medias coexistían con carencias nutricionales, distinguiendo el desempeño de los frentes de los alimentos y cantidades seleccionados.

PALABRAS CLAVE: Optimización multiobjetivo. Comidas observadas. Planificación de dietas. Algoritmos evolutivos. Perfiles nutricionales.

INTRODUCTION

Diet optimization links nutrient requirements to choices about what people eat. In a Brazilian adult diet model, some nutritional recommendations could not be met together without relaxing the formulation, and meeting others required changes in food-group quantities (Dos Santos et al., 2018). Environmental objectives add another consideration: foods that supply nutrients also differ in their carbon and water footprints. Coefficients linked to Brazilian dietary records allow these outcomes to be evaluated for the same food choices (Garzillo et al., 2021, 2023).

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The decision unit determines which dietary changes an optimizer can make. Choosing foods and quantities independently allows changes within a meal. Choosing complete observed meals instead preserves their recorded combinations and portions, but restricts the alternatives available to meet nutrient targets. Here, each daily menu combines six meal positions drawn from the Brazilian Household Budget Survey (POF) 2017–2018. A meal can be exchanged for another observed meal at the same position; its individual foods cannot be resized.

We compare four evolutionary algorithms under this whole-meal representation for women and men aged 30 and 60 years. Nutritional attainment is considered together with carbon footprint, water footprint and departure from observed food quantities. The comparison addresses three questions:

1. How do the algorithms differ in front quality and execution time when they receive the same meals, initial menus and number of evaluations?
2. How do the objective combinations affect nutrient attainment, environmental outcomes and food quantities?
3. Can menu selection improve all measured outcomes relative to the corresponding observed diets, and which nutritional gaps remain?

The first two questions concern the original comparison of two- and three-objective searches. The third is examined retrospectively using the saved candidates. This distinction separates the alternatives retained by an algorithm from the subsequent choice of a daily menu. Food-level summaries and complete menu examples are used to interpret both analyses.

1 THEORETICAL FRAMEWORK

1.1 Nutrient requirements and changes in Brazilian diets

Brazilian diet models have examined whether nutrient recommendations can be met using foods from observed consumption. A linear-programming study minimized departure from adult intake and identified constraints that prevented simultaneous attainment of all recommendations (Dos Santos et al., 2018). A separate analysis compared current, healthy and sustainable scenarios in terms of cost and environmental impact (Caldeira et al., 2024). Together, these studies place nutritional goals within a choice of dietary changes and environmental outcomes, rather than treating nutrient totals as the only output.

The carbon footprint of Brazilian diets was estimated using 2008–2009 food records and food-specific coefficients (Garzillo et al., 2021). A later resource provides carbon and water coefficients for foods and culinary preparations linked to POF 2017–2018 (Garzillo et al., 2023).

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The present study uses the later survey and linkage. Estimates based on the earlier survey therefore serve as context rather than direct outcome comparisons.

Food-group reporting also appears in survey-based heuristic planning, which examined changes in fruit, vegetable and dairy consumption (Silva et al., 2025a), and in a multi-agent model for women and men aged 25 and 60 years (Silva et al., 2025b). These studies provide a basis for examining the foods selected by an optimizer alongside its nutrient and objective scores.

1.2 Multiobjective menu planning

Multiobjective diet formulations differ in what they allow the search to change. An early genetic-algorithm model considered menu cost and user ratings subject to nutritional requirements (Kaldirim; Kose, 2006). A Brazilian bilevel model combined nondominated sorting genetic algorithm II (NSGA-II) for food selection with mathematical programming for quantities across four daily meals (Pochmann; Von Zuben, 2022). In the bilevel representation, food selection and portion adjustment are separate decisions. The whole-meal representation used here instead fixes the foods and portions inside every alternative.

Algorithm comparisons have also been conducted for institutional menus. A school-lunch model minimized cost and repetition, with nutrient requirements imposed as constraints, and compared NSGA-II, strength Pareto evolutionary algorithm 2 (SPEA2) and an indicator-based method (Ramos-Pérez et al., 2021). A ten-day menu study compared a hybrid NSGA-II approach with nondominated sorting genetic algorithm III (NSGA-III) and swarm methods. Its formal scores favored the hybrid method, while an expert preferred human-designed menus for taste harmony (Alharan et al., 2026). This difference between an optimization score and the evaluation of a meal is relevant when interpreting computed diets.

Other formulations examine the trade-offs themselves. A Spanish study combined nutritional, environmental and economic targets through distance to target (Abejón et al., 2020). A French cohort model reported food changes along a health–environment Pareto trajectory under acceptability bounds (Kesse-Guyot et al., 2026). A Finnish model penalized departure from observed intake while evaluating nutrition and climate impact (Fu; Irz, 2025). Their food universes, constraints and reference diets differ from the Brazilian meal pools considered here, so their numerical outcomes are not ranked against ours.

1.3 Language-model dietary planning

Large language models (LLMs) offer a different route to menu generation. A Brazilian evaluation used ChatGPT, Gemini and DeepSeek with a combined one-shot and chain-of-thought

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prompt, then calculated the nutrients in the generated foods using the Brazilian Food Composition Table (TBCA) (Silva et al., 2026). Ten five-day requests per model produced 150 dietary days for one weight-loss reference profile.

Mean energy matching did not ensure nutrient coverage. ChatGPT averaged 1446.0 kcal/day against a 1440.8 kcal target, with a daily standard deviation of 147.0 kcal. Across the three models, mean iron reached about 55–61% of the 18 mg/day target, and mean calcium remained below its recommendation (Silva et al., 2026). These findings concern the evaluated configurations and prompt, rather than every model version. They show why generated menu text requires nutrient-level assessment even when average calories are close to the requested value. The weight-loss profile and post-generation assessment also differ from the maintenance profiles and whole-meal search used here.

1.4 Algorithm selection mechanisms

The four methods compared here use different survival rules. NSGA-II combines nondominated sorting with crowding-based survival (Deb et al., 2002). SPEA2 uses strength-based fitness, density and a bounded archive (Zitzler; Laumanns; Thiele, 2001). NSGA-III distributes solutions using reference directions (Deb; Jain, 2014). The S-metric selection evolutionary multiobjective algorithm (SMS-EMOA) uses hypervolume contribution (Beume; Naujoks; Emmerich, 2007). The experiment holds meal representation, variation operators, initialization, constraints and evaluation counts constant to compare these mechanisms on the same dietary problems.

1.5 Positioning of the present study

Table 1 summarizes the differences in data, decisions, objectives and evaluation scope. The present design brings together a comparison of evolutionary methods and an analysis of dietary composition, using complete observed meals for four Brazilian reference profiles. Its six objective combinations all include nutrition, while the remaining coordinates describe environmental footprints and departure from observed quantities. Cost is not modeled because compatible prices are unavailable.

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Table 1. Diet-optimization studies by data source, decision representation, objective treatment and evaluation scope. NSGA-II denotes nondominated sorting genetic algorithm II and SPEA2 strength Pareto evolutionary algorithm 2.

Representative work	Input and method	Objectives / nutritional treatment	Evaluation scope
Brazilian nutrient-constrained diets (Dos Santos et al., 2018)	Brazilian adult survey; 68 aggregated foods; linear programming.	Minimum departure from observed mean intake; nutrient goals with relaxation of limiting constraints.	Population dietary changes and nutrient gaps; no evolutionary-method comparison.
Evolutionary school lunches (Ramos-Pérez et al., 2021)	School-lunch dishes; NSGA-II, SPEA2 and adaptive indicator-based evolution.	Cost and course/food-group repetition; nutritional constraints.	Algorithm and hypervolume comparisons across menu instances; school-age requirements.
Bilevel daily menus (Pochmann; Von Zuben, 2022)	Four daily meals; NSGA-II selects foods and mathematical programming sets quantities.	Cost and concentration across foods/meals; nutritional constraints.	Pareto menu examples with fictitious costs; a bilevel recommender rather than four matched optimizer families.
Health/environment compromises (Kesse-Guyot et al., 2026)	French cohort; 96 food groups; multicriteria compromise optimization.	Health and environmental-pressure indices; alternative acceptability bounds.	Pareto trajectory and food changes; health-risk and environmental scores differ from nutrient deviation.
Finnish diets with mycoprotein (Fu; Irz, 2025)	Finnish reference diets; quadratic optimization compared with a piecewise linear model.	Weighted departure from observed consumption; nutritional constraints and progressive emissions reductions.	Male/female food-group changes and sensitivity; ingredient and acceptability scenarios.
Observed-diet heuristic refinement (Silva et al., 2025a)	Brazilian observed individual diets; mutation, crossover and fitness-based selection.	Nutrient deviations with observed-food restrictions.	Nutrient and food-group outcomes across demographic groups; no matched four-algorithm Pareto comparison.
Multi-agent dietary refinement (Silva et al., 2025b)	Brazilian individual diets; multi-agent interaction and evolutionary refinement.	Nutritional scores and dietary changes.	Demographic and food-group comparisons; the younger reference age is 25, rather than 30.

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Representative work	Input and method	Objectives / nutritional treatment	Evaluation scope
LLM-generated dietary plans (Silva et al., 2026)	ChatGPT, Gemini and DeepSeek; combined one-shot and chain-of-thought prompting; one Brazilian weight-loss profile.	Generated menus assessed afterwards using TBCA-based energy and nutrient calculations.	150 dietary days from 30 five-day plans; mean calorie matching coexisted with iron and calcium shortfalls.
Present profile study	POF 2017–2018; women and men aged 30 and 60; six categorical whole-meal positions; four evolutionary algorithms.	Six pairs/triples containing capped attainment of 23 nutrient criteria with calibrated shortage penalties; carbon, water and departure from profile consumption.	Matched comparison: 20 replicates per profile/scenario/algorithm; nutritional gaps, food-group changes and actual fronts are reported from complete runs.

Source: Synthesis of the cited studies.

For each chosen menu, the analysis reports foods, portions and unmet nutrient targets. It then compares those quantities across objective sets, algorithms and profiles.

2 METHODOLOGY

2.1 Dietary Profile Definition and Nutritional Requirements

We define four reference scenarios for women and men aged 30 and 60 years, with weight maintenance as the energy goal. Exact recorded age and sex identify the corresponding food-consumption groups in POF 2017–2018 (Instituto Brasileiro de Geografia e Estatística, 2020). The reference anthropometry determines the scenario requirements and is not assigned as a measured characteristic of the survey respondents.

Sex and life stage are relevant because the nutrient references distinguish their requirements (Health Canada, 2025a, 2025c). The selected ages represent an adult and an older-adult scenario under the Brazilian age classification (Ministério da Saúde, 2004). These four study choices permit demographic contrasts while holding the reference body mass index and activity category constant; they are not nationally representative strata.

Height is the national sex-specific median in POF 2008–2009, using the 30–34-year and 55–64-year bands containing the reference ages. Table 1.1 gives heights of 1.600 and 1.566 m for women and 1.716 and 1.682 m for men (IBGE, 2010). These historical estimates anchor the reference body sizes in Brazilian data.

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Reference weight is $24h^2$, where h is height in metres. The common body mass index (BMI) of 24 kg/m^2 lies within the SISVAN eutrophy intervals for both adults and older adults (Ministério da Saúde, 2004). Selecting this value is a modeling decision that provides maintenance scenarios without adding an age-specific weight-change goal. Physical activity is fixed to the low-active category for F30, F60, M30 and M60. This is an assumed reference condition, not activity measured in the POF respondents. The same category is retained across profiles, while sex, age and reference body size determine different maintenance estimates.

Estimated energy requirement follows the 2023 adult low-active equations, with age a in years, height H in centimetres and weight w in kilograms (National Academies of Sciences, Engineering, and Medicine, 2023):

$$E_F = 575.77 - 7.01a + 6.60H + 12.14w, \quad (1)$$

$$E_M = 581.47 - 10.83a + 8.30H + 14.94w. \quad (2)$$

Equations (1) and (2) estimate total daily energy expenditure for weight-stable women and men, respectively; no additional activity multiplier is applied (National Academies of Sciences, Engineering, and Medicine, 2023). For example, M30 uses age 30, height 171.6 cm and reference weight 70.671744 kg, yielding 2736.69 kcal/day and an allowed interval of 2599.85–2873.52 kcal/day. The resulting profiles are given in Table 2. Energy is constrained to within 5% of the corresponding estimate. This modeling tolerance limits the extent to which footprint reductions can be obtained by lowering total energy. It is not a confidence interval for predicted requirements.

Table 2. Reference maintenance profiles. F denotes women and M men. Activity is low active in every profile. Reference weights use BMI 24 kg/m^2; heights use historical Brazilian median estimates.

Panel A.

Profile	Age	Height (m)	Weight (kg)	BMI
F30	30	1.600	61.44	24.0
F60	60	1.566	58.86	24.0
M30	30	1.716	70.67	24.0
M60	60	1.682	67.90	24.0

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Panel B.

Profile	Activity	Energy (kcal/day)	Basis
F30	low active	2167.4	(IBGE, 2010; Ministério da Saúde, 2004; National Academies of Sciences, Engineering, and Medicine, 2023)
F60	low active	1903.2	(IBGE, 2010; Ministério da Saúde, 2004; National Academies of Sciences, Engineering, and Medicine, 2023)
M30	low active	2736.7	(IBGE, 2010; Ministério da Saúde, 2004; National Academies of Sciences, Engineering, and Medicine, 2023)
M60	low active	2342.1	(IBGE, 2010; Ministério da Saúde, 2004; National Academies of Sciences, Engineering, and Medicine, 2023)

Source: Study definitions and calculations based on the cited references.

The scenarios assume apparently healthy adults who do not smoke and are neither pregnant nor lactating. We distinguish Recommended Dietary Allowances, Adequate Intakes and applicable total-intake Tolerable Upper Intake Levels using the sex- and age-specific reference tables (Health Canada, 2025a, 2025c). We apply these references as scenario goals, without estimating the prevalence of nutrient inadequacy in Brazil. Table 3 summarizes the assumptions and their sources.

Table 3. Characteristics and assumptions defining the four dietary scenarios. Modeling choices are identified when a reference supports the context rather than prescribing the selected value.

Characteristic	Definition	Source or modeling rationale
Membership	Women and men at exactly 30 and 60 years; recorded sex and age select the food records.	Study scenarios; survey fields (Instituto Brasileiro de Geografia e Estatística, 2020).
Health and physiology	Apparently healthy, nonsmoking, nonpregnant and nonlactating reference adults.	Reference-intake scope (Health Canada, 2025a, 2025c); no respondent diagnosis.
Dietary pattern	Observed profile foods and preparations, with no imposed vegetarian or vegan exclusion.	Observed-consumption basis (Instituto Brasileiro de Geografia e Estatística, 2020); conditional on source linkage.
Height	Historical national median in sex-specific 30–34 and 55–64 age bands.	POF 2008–2009, Table 1.1 (IBGE, 2010).

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Characteristic	Definition	Source or modeling rationale
Weight and BMI	Weight = $24h^2$; body mass index (BMI) = 24 kg/m^2.	Study choice within adult/older-adult eutrophy intervals (Ministério da Saúde, 2004).
Physical activity	Low active, assumed for all four profiles.	Common scenario choice; the equation category is defined in (National Academies of Sciences, Engineering, and Medicine, 2023).
Energy goal	Weight maintenance; energy within 5% of the calculated requirement.	Maintenance equations (National Academies of Sciences, Engineering, and Medicine, 2023); the interval is a modeling tolerance.
Meal eligibility	Positive quantities and complete source linkage; six positions with absent meals empty.	Study inclusion rule, conditional on the available POF records (Instituto Brasileiro de Geografia e Estatística, 2020).

Source: Study definitions and calculations based on the cited references.

Carbohydrate uses the 45–65% energy distribution range (Health Canada, 2025b). Protein combines a minimum of 0.8 grams per kilogram per day with an Acceptable Macronutrient Distribution Range of 10–35% of candidate energy (Health Canada, 2025b). Total fat uses the intersection of the 20–35% reference range with the World Health Organization (WHO) maximum of 30% (Health Canada, 2025b; World Health Organization, 2023). Fiber uses the larger of the sex/age adequate intake and the WHO adult minimum of 25 g/day (Health Canada, 2025b; World Health Organization, 2023). Saturated and trans fatty acids have respective maxima of 10% and 1% of candidate energy (World Health Organization, 2023). Sodium has a 2000 mg/day maximum, identified as a WHO recommendation rather than a tolerable upper intake level (World Health Organization, 2012). Table 4 lists the 23 modeled criteria.

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Table 4. Daily energy and nutrient requirements. Energy is a hard constraint with a study-defined tolerance of 5%; its bounds are rounded to the nearest kcal here. The 23 nutrient criteria contribute capped attainment percentages and are evaluated individually after optimization. Energy-dependent nutrient bounds are displayed at the maintenance estimate and recomputed from candidate energy. RDA denotes Recommended Dietary Allowance, AI Adequate Intake, UL Tolerable Upper Intake Level, AMDR Acceptable Macronutrient Distribution Range and WHO World Health Organization. RAE means retinol activity equivalents and NE niacin equivalents. Vitamin E is alpha-tocopherol.

Panel A.

Nutrient	Unit	Type	F30	F60
Energy	kcal	Hard range	2059–2276	1808–1998
Protein	g	RDA/AMDR	54.18–189.64	47.58–166.53
Carbohydrate	g	AMDR	243.83–352.19	214.12–309.28
Total fat	g	AMDR/WHO	48.16–72.25	42.29–63.44
Fiber	g	AI/WHO	≥ 25	≥ 25
Saturated fat	g	WHO max	≤ 24.08	≤ 21.15
Trans fat	g	WHO max	≤ 2.41	≤ 2.11
Sodium	mg	WHO max	≤ 2000	≤ 2000
Calcium	mg	RDA/UL	1000–2500	1200–2000
Iron	mg	RDA/UL	18–45	8–45
Magnesium	mg	RDA	≥ 310	≥ 320
Phosphorus	mg	RDA/UL	700–4000	700–4000
Potassium	mg	AI	≥ 2600	≥ 2600
Copper	mg	RDA/UL	0.9–10	0.9–10
Zinc	mg	RDA/UL	8–40	8–40
Vitamin A (RAE)	μg RAE	RDA	≥ 700	≥ 700
Thiamin	mg	RDA	≥ 1.1	≥ 1.1
Riboflavin	mg	RDA	≥ 1.1	≥ 1.1
Niacin (NE)	mg NE	RDA	≥ 14	≥ 14
Vitamin B6	mg	RDA/UL	1.3–100	1.5–100
Vitamin B12	μg	RDA	≥ 2.4	≥ 2.4
Vitamin D	μg	RDA/UL	15–100	15–100
Vitamin E	mg	RDA	≥ 15	≥ 15
Vitamin C	mg	RDA/UL	75–2000	75–2000

Panel B.

Nutrient	Unit	Type	M30	M60	Source
Energy	kcal	Hard range	2600–2874	2225–2459	(National Academies of Sciences, Engineering, and Medicine, 2023)

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Nutrient	Unit	Type	M30	M60	Source
Protein	g	RDA/AMDR	68.42–239.46	58.55–204.94	(Health Canada, 2025b)
Carbohydrate	g	AMDR	307.88–444.71	263.49–380.6	(Health Canada, 2025b)
Total fat	g	AMDR/WHO	60.82–91.22	52.05–78.07	(Health Canada, 2025b; World Health Organization, 2023)
Fiber	g	AI/WHO	≥ 38	≥ 30	(Health Canada, 2025b; World Health Organization, 2023)
Saturated fat	g	WHO max	≤ 30.41	≤ 26.02	(World Health Organization, 2023)
Trans fat	g	WHO max	≤ 3.04	≤ 2.6	(World Health Organization, 2023)
Sodium	mg	WHO max	≤ 2000	≤ 2000	(World Health Organization, 2012)
Calcium	mg	RDA/UL	1000–2500	1000–2000	(Health Canada, 2025a)
Iron	mg	RDA/UL	8–45	8–45	(Health Canada, 2025a)
Magnesium	mg	RDA	≥ 400	≥ 420	(Health Canada, 2025a)
Phosphorus	mg	RDA/UL	700–4000	700–4000	(Health Canada, 2025a)
Potassium	mg	AI	≥ 3400	≥ 3400	(Health Canada, 2025a)
Copper	mg	RDA/UL	0.9–10	0.9–10	(Health Canada, 2025a)
Zinc	mg	RDA/UL	11–40	11–40	(Health Canada, 2025a)
Vitamin A (RAE)	μg RAE	RDA	≥ 900	≥ 900	(Health Canada, 2025c)
Thiamin	mg	RDA	≥ 1.2	≥ 1.2	(Health Canada, 2025c)
Riboflavin	mg	RDA	≥ 1.3	≥ 1.3	(Health Canada, 2025c)
Niacin (NE)	mg NE	RDA	≥ 16	≥ 16	(Health Canada, 2025c)
Vitamin B6	mg	RDA/UL	1.3–100	1.7–100	(Health Canada, 2025c)
Vitamin B12	μg	RDA	≥ 2.4	≥ 2.4	(Health Canada, 2025c)
Vitamin D	μg	RDA/UL	15–100	15–100	(Health Canada, 2025c)
Vitamin E	mg	RDA	≥ 15	≥ 15	(Health Canada, 2025c)
Vitamin C	mg	RDA/UL	90–2000	90–2000	(Health Canada, 2025c)

Source: Study definitions and calculations based on the cited references.

Energy and meal membership determine numerical feasibility. The nutrient requirements in Table 4 are scored separately, as defined in Section 2.3.

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Folate remains descriptive because the POF field is not verified as dietary folate equivalents. The carbohydrate criterion uses the POF total-carbohydrate field with a 45–65% energy interval (Health Canada, 2025b). This operational measure is not a separately measured digestible-carbohydrate fraction; no digestible-carbohydrate RDA is imposed. Supplemental-magnesium, synthetic-niacin, supplemental-vitamin-E and preformed-vitamin-A upper limits are not imposed on the corresponding total food fields because the restricted fractions cannot be identified (Health Canada, 2025a, 2025c).

2.2 POF Preparation into Observed Meals

The consumption records are joined to the resident file through the official household/respondent identifiers. Recorded sex and exact age select each reference group. The collection-day field identifies the two dietary days, the quantity field gives grams, and each consumption line contains 29 absolute nutrient/energy amounts (Instituto Brasileiro de Geografia e Estatística, 2020). We sum those reported amounts within a meal.

2.2.1 Six daily meal positions

The source dictionary defines eating occasion and nearest recorded hour. The occasions breakfast, lunch, dinner and supper map directly to their corresponding positions. A snack before 12:00 maps to the morning snack and a snack at or after 12:00 to the afternoon snack. Other or unspecified occasions use the time intervals in Table 5. The interval cutoffs define the study's six meal positions; they are not nutrient recommendations. A snack or unspecified occasion without a valid hour makes the day ineligible; it is never assigned a default lunch.

Table 5. Mapping of POF eating occasions to the six menu positions. Codes and recorded-hour meaning follow the source dictionary (Instituto Brasileiro de Geografia e Estatística, 2020); interval cutoffs for other/unspecified occasions are study choices.

Position	Explicit source occasion	Other/unspecified occasion by hour
Breakfast	Code 1	04:00–08:59
Morning snack	Code 3 before 12:00	09:00–10:59
Lunch	Code 2	11:00–13:59
Afternoon snack	Code 3 at/after 12:00	14:00–16:59
Dinner	Code 4	17:00–20:59
Supper	Code 5	21:00–03:59

Source: Study definitions and calculations based on the cited references.

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All lines assigned to the same respondent, day and position form one observed slot intake. Multiple consumption events mapped to a position are aggregated with their original amounts; this daily-position representation does not infer a single simultaneous eating event. Foods repeated in a position are summed. Every source day has exactly six entries. A position with no consumption has an empty food list, zero nutrient totals and zero footprint. Empty alternatives enter a profile/position pool only when that absence occurred in an eligible source day.

2.2.2 Eligibility, provenance and meal pools

A retained day has positive finite portions, finite nonnegative amounts in all 29 fields, positive energy and at least one non-water food. Each non-water food/preparation combination must have a positive carbon and water coefficient under the environmental linkage (Garzillo et al., 2023). Blank preparation on addition lines uses preparation 99 only when the addition crosswalk is unique. A failed line excludes its entire day, preventing a partial meal from being treated as observed complete intake. Reported nutritional zeros retain the source dictionary's uncertainty (Instituto Brasileiro de Geografia e Estatística, 2020).

One eligible day per distinct respondent is retained by a fixed hash ordering of the respondent/day key. This choice avoids weighting two-day respondents twice and does not select on nutrient quality. Each profile supplies six separate pools. A meal is deduplicated only when its foods, portions and reported nutrient amounts match; otherwise the alternatives remain distinct. Original days are stored as six pool indices and supply matched observed initial populations.

Carbon and water are obtained from recorded quantities and the per-gram environmental coefficient over a meal's foods. Tap water remains inside its observed meal and contributes its reported nutrients; the workbook's zero footprint assignment is a modeling convention rather than a measured impact. Tap water is excluded from the food-mass departure calculation and food-group change denominators. Source nutrient coefficients and unselected meal pools remain local.

2.2.3 Observed comparator under shared energy intervals

A retrospective comparison uses unchanged recorded days from the same sex and exact-age groups, evaluated against the same 23 nutrient criteria and profile-specific energy intervals as the optimized menus. The original day retained for each respondent is kept; we then include it only if reported energy lies within $[0.95E_p, 1.05E_p]$. We neither substitute a second recorded day nor rescale portions or select on nutrient attainment or footprints. Re-extraction from the POF archive reproduces the original retained cohorts before this energy filter is applied.

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The energy filter retained 27 of 437 respondents for F30, 38 of 339 for F60, 24 of 347 for M30 and 19 of 248 for M60. Each comparator uses that profile's sex, exact age and energy interval. A day is not transferred to another profile because its energy happens to fit that interval. The optimized menus likewise use only their own profile's meals.

This matching makes the reference requirements comparable without making energy intakes identical or estimating each respondent's individual needs. The observed and optimized sides use the same nutrient conversions and environmental linkage. Their aggregation and menu-selection rules are defined in Section 2.4.3.

2.3 Whole-Meal Multiobjective Formulation

For profile p, let $T = \{1, \dots, 6\}$ denote the ordered meal positions and R_{pt} the pool of observed alternatives for position t. Alternative r has a fixed nutrient vector a_{ptrk}, carbon footprint c_{ptr}, water footprint w_{ptr} and food/position mass vector g_{ptri}. An empty alternative has zero values. The binary selection variables satisfy

$$y_{ptr} \in \{0,1\}, \tag{3}$$

$$\sum_{r \in R_{pt}} y_{ptr} = 1, \qquad t \in T. \tag{4}$$

Equation (3) defines binary choices, and Equation (4) selects one complete alternative per position. There is no independent food-quantity variable and no scaling of a selected meal. In the evolutionary implementation, the same selection is encoded by six categorical pool indices.

Daily nutrient totals and food masses are given by Equations (5) and (6), respectively:

$$q_k(y) = \sum_{t \in T} \sum_{r \in R_{pt}} a_{ptrk}\, y_{ptr}, \tag{5}$$

$$g_i(y) = \sum_{t \in T} \sum_{r \in R_{pt}} g_{ptri}\, y_{ptr}. \tag{6}$$

The energy constraint is $0.95E_p \le q_E(y) \le 1.05E_p$, where E_p is the reference maintenance requirement. Environmental comparisons therefore use menus within the same profile energy interval.

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2.3.1 Capped nutritional attainment

The nutritional objective maximizes mean attainment over the $K = 23$ criteria in Table 4. For a criterion with a lower requirement L_{pk}, define coverage $\ell_k(y) = \min\{q_k(y)/L_{pk}(q_E),1\}$; otherwise set $\ell_k = 1$. For a criterion with an upper limit U_{pk} and positive intake, define compliance $u_k(y) = \min\{U_{pk}(q_E)/q_k(y),1\}$; otherwise set $u_k = 1$. Then

$$A(y) = \frac{100}{K}\sum_k \min\{\ell_k(y), u_k(y)\}. \tag{7}$$

The capped attainment in Equation (7) neither rewards exceeding a recommended minimum beyond 100% nor penalizes it unless a separate upper bound is exceeded. Upper-only criteria such as sodium measure compliance with a maximum, rather than rewarding intake towards that maximum. The distinction between recommended intake and a documented upper limit follows the nutrient references (Health Canada, 2025a, 2025c; World Health Organization, 2012).

Macronutrient fractions are converted to grams using candidate energy and the declared kcal/g factors. Equal criterion weights are a modeling choice, without ranking clinical severity. The score is a computational percentage, not an estimate of physiological adequacy or a probability of good health. Energy and categorical membership determine numerical feasibility; each nutrient's attained status, deficit and excess are reported separately.

Carbon and water footprints are computed separately in Equations (8) and (9):

$$C(y) = \sum_{t,r} c_{ptr}\, y_{ptr}, \tag{8}$$

$$W(y) = \sum_{t,r} w_{ptr}\, y_{ptr}. \tag{9}$$

Let b_{pi} be the mean recorded grams for food, preparation and position i across retained respondents, excluding tap water. Quantity departure is

$$D(y) = \frac{\sum_i |\, g_i(y) - b_{pi}|}{\sum_i b_{pi}}. \tag{10}$$

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The reference b_p in Equation (10) describes mean food quantities in a profile, not a particular person's menu. Consequently, $D(y)$ measures departure from that aggregate. This ratio is dimensionless; values are multiplied by 100 when reported as percentages in tables and figures. It does not measure willingness to eat the assembled diet. Food-level summaries are also needed because daily totals can conceal changes in preparation and meal position.

2.3.2 Shortage penalties and search coordinates

N denotes the nutritional coordinate, with physical outcome A maximized. The scenarios are NC, NW and ND, then NCW, NCD and NWD. The pairs isolate nutrient–carbon, nutrient–water and nutrient–departure tensions; the triples add a second environmental measure or a quantity-change coordinate. For minimization, nutritional loss is $f_N = 1 - A/100$. The other coordinates are $f_j = j/B_{pj}$, $j \in \{C, W, D\}$, with fixed pool-derived upper bounds B_{pj} determined before search.

Let K_L be the criteria with a lower requirement. Their mean shortage is

$$P(y) = \frac{1}{|K_L|} \sum_{k \in K_L} (1 - \ell_k(y)). \tag{11}$$

Using the shortage term in Equation (11), the evolutionary algorithms minimize $\tilde{f}_N = f_N$ and $\tilde{f}_j = f_j + \lambda P$ for each included non-nutritional coordinate. Adding the shortage term after normalization makes its weight effective in the trade-off search. A reduced matched study selects λ using both nutritional outcomes and the included non-nutritional outcomes (Section 2.4.1). Upper-limit compliance remains in A and individual outcome reporting, while this additional penalty targets shortages specifically.

Physical outcomes, unpenalized normalized coordinates and penalized search coordinates are retained separately. The search archive contains energy-feasible points nondominated in $\tilde{f}$. Its unpenalized nondominated subset forms the reporting front. Indicators and displayed fronts use f, with higher A and lower C, W and D preferred. Thus penalty terms are not presented as environmental footprints, and a reporting front is a sampled subset rather than the unrestricted true Pareto front.

2.4 Algorithms and Experimental Design

All algorithms used a population of 66 menus and the six-index representation defined in Section 2.3. Within each profile, objective set and replication, they received the same 66 distinct

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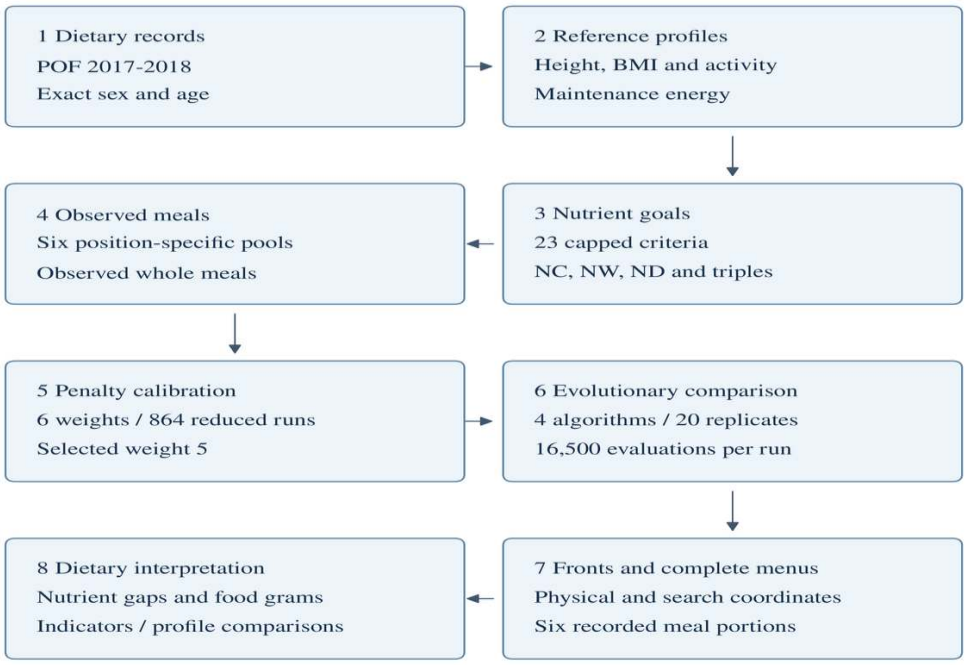
observed daily menus, sampled without replacement. This matched initialization makes the comparison conditional on the same starting diets.

Uniform crossover, with probability 0.9, exchanged complete meal positions between two parents. Mutation independently replaced each position with probability $1/6$, drawing an alternative from that profile's corresponding pool. An empty alternative could be drawn only where absence had been observed. The operators changed neither the foods nor the portions within a selected meal. SPEA2 used normalized objective-space density, with a unit divisor for a zero-span coordinate so that constant coordinates contributed zero distance without undefined fitness values.

The main experiment comprised four profiles, six objective sets, four algorithms and 20 matched replications, giving 1920 runs. Each run used 16500 objective-function evaluations, including initialization. A one-hour wall-time limit identified incomplete runs; all reported runs reached their evaluation count. Figure 1 summarizes the sequence from meal preparation to front and menu analysis.

Figure 1. Study workflow: preparation of observed meals, whole-meal search, front evaluation and analysis of the selected menus.



Source: Study workflow.

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The implementation used Python 3.14.4, pymoo 0.6.1.6 (Blank; Deb, 2020), NumPy 2.4.1 and SciPy 1.17.0. Runs executed on Windows 11 with an AMD Ryzen 5 8500G and 64 GiB RAM, using eight workers and one numerical-library thread per worker. Reported optimizer times describe this concurrent execution environment and exclude preparation and postprocessing.

2.4.1 Calibration of the shortage penalty

The penalty weight was selected before the main experiment because it controls the trade-off between nutrient shortages and the other objectives. A separate experiment compared $\lambda \in \{0,1,5,10,25,50\}$ across all profiles and algorithms in NC, NW and NCD. These settings include pairs and triples and cover all non-nutritional coordinates. Three matched replications with 3300 evaluations each produced 864 runs and 2851200 evaluations. Weights shared seeds and initial menus; the main experiment used different seeds. Weight zero provided the control under the same nutritional score.

For each calibration run, the menu nearest the unpenalized normalized origin supplied attainment, attained-criterion count and the mean included non-nutritional outcome. The selection rule first retained weights whose mean attainment was within 0.5 percentage point of the maximum and whose mean attained count was within 0.5 criterion of the maximum. Among those weights, it selected the lowest mean non-nutritional outcome, breaking a tie by smaller weight. These tolerances were fixed before inspecting the results.

2.4.2 Front quality and statistical comparisons

Hypervolume was calculated from normalized energy-feasible nondominated sets, using a reference value of 1.1 in each coordinate. Inverted generational distance plus (IGD+) measured distance to the pooled nondominated solutions from all methods and replications within a profile and objective set (Ishibuchi et al., 2015). This is an empirical reference, not the unknown true front. Convergence was recorded at ten evaluation checkpoints.

Algorithm comparisons used matched sign flips and bootstrap intervals. The 144 within-profile and 36 GLOBAL pairwise hypervolume contrasts formed one Holm-adjusted family (Holm, 1979). GLOBAL assigned equal weight to each profile within a replication. The resulting uncertainty concerns optimizer variation, not population differences between women and men.

2.4.3 Choosing a menu from the evaluated alternatives

A reporting front is a set of alternatives, whereas a daily-diet comparison requires a menu choice. Three rules were applied separately to each run's final reporting front:

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- Max N selected maximum nutrient attainment, breaking ties by lower normalized carbon, water and departure, in that order.
- Ideal selected the menu nearest the normalized origin using only the objectives searched in that run. Its nutrition coordinate was $1 - A/100$, where A is attainment, and the shortage penalty was excluded from the distance.
- Min D selected minimum quantity departure, including in NC, NW and NCW, where departure was not a search objective.

Equal distances or departures retained the first menu in saved front order. The rules could select the same menu. Ideal did not require improvement over observed diets, and water did not enter its distance in NC, ND or NCD.

A retrospective rule, Ref., addressed that additional requirement. It used the full pool H_{psar} of energy-feasible evaluated menus, including initialization, and retained $\mathcal{E}_{psar} \subseteq H_{psar}$ satisfying $A > \bar{A}_p$, $C < \bar{C}_p$, $W < \bar{W}_p$ and $D < \bar{D}_p$. The bars denote the corresponding profile's observed means. The departure reference was the mean distance of individual observed days from the aggregate profile vector, not the zero distance of that vector from itself.

Ref. minimized $\| \hat{\boldsymbol{f}}_p(x) \|_2$ over $x \in \mathcal{E}_{psar}$ using all four unpenalized coordinates and the fixed profile normalization. Ties preferred the smaller evaluation index, and a 10^{-12} relative-gain tolerance handled floating-point equality. An empty eligible set would yield no choice. Selected menus were rescored and checked for four-coordinate nondominance within the run's energy-feasible evaluations. This analysis changed both the candidate pool and the selection requirement, while leaving the searches and their reporting fronts unchanged. The supplementary selection analysis examines what could be achieved when choices were restricted to those final fronts.

2.4.4 Consolidating nutritional and food-quantity outcomes

Each rule contributed one menu from each run, hence $6 \times 4 \times 20 = 480$ records per profile and 1920 overall. These are run-level selections, not necessarily distinct diets. A run received the same weight regardless of its front size, and repeated menus from different runs

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retained their separate records. For menu-level outcome y, profile p and rule q, the mean was computed using Equation (12):

$$\bar{y}_{pq} = \frac{1}{6 \cdot 4 \cdot 20} \sum_{s=1}^{6} \sum_{a=1}^{4} \sum_{r=1}^{20} y\,(x_{psar}^{q}). \tag{12}$$

Thus all 24 algorithm–scenario cells had equal weight. Physical outcomes were included even when they were omitted from a run's search objectives. GLOBAL averaged the four profile means with weight $1/4$. Complete-attainment counts used denominators of 480 per profile and 1920 overall. The rules were summarized separately rather than pooled. The observed comparison likewise averaged the profile means equally, using the 27, 38, 24 and 19 energy-matched days described in Section 2.2.

Food-type mass summed daily grams across meal positions and preparations of the same POF code. Means and sample standard deviations used the 20 independently selected menus in each profile–objective–algorithm cell, including zero when a code was absent. Mean change subtracted the fixed observed baseline, so its standard deviation equaled that of the selected mass. Relative change used the observed mean where positive. Tap water remained a separate descriptive quantity and was excluded from D. These summaries describe optimizer selections; no food-specific significance tests were performed.

The main food displays ranked absolute NC mean gram changes, averaging algorithm means equally and excluding plain water from the ranking. They showed the leading code in each profile and the three leading F30 codes across all six objective sets. This retrospective display rule did not remove other foods from the complete summaries.

2.4.5 Front figures and menu examples

Figures used the run closest to each algorithm's median hypervolume. Lines in two dimensions and semitransparent triangulations in three dimensions were visual guides between evaluated points, not additional diets. Triangulation removed duplicate projections and masked edges longer than the greater of 0.90 in projected unit-range coordinates and twice the median nearest-neighbor spacing.

The online menu examples used NSGA-II throughout. Within each profile and objective set, the displayed menu was nearest the unpenalized origin in the representative run's reporting front. The 24 examples illustrated the selected foods and portions; the repeated-run summaries

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described their variation. Complete foods, portions and source identifiers were reconstructed from the saved meal indices.

3 RESULTS AND DISCUSSION

Every main-experiment run produced an energy-feasible reporting front. The saved fronts contained 15022 entries across runs, with one to 70 points per front and a median of five. Table 6 gives the meal alternatives available to each profile. Empty alternatives reflect absences in the source records.

Table 6. Meal alternatives by profile and position. B, AM, L, PM, D and S denote breakfast, morning snack, lunch, afternoon snack, dinner and supper. Counts include empty alternatives where absence was observed.

Panel A.

Profile	Respondents	B	AM	L
F30	437	355	98	425
F60	339	305	100	334
M30	347	286	75	345
M60	248	216	57	244

Panel B.

Profile	PM	D	S
F30	284	386	86
F60	236	305	70
M30	187	332	82
M60	148	230	62

Source: Study results.

3.1 Penalty calibration

The calibration selected $\lambda = 5$ under the rule defined in Section 2.4.1. Compared with weight zero, mean attainment increased from 94.24% to 95.92%, the mean number of attained criteria rose from 17.47 to 18.43, and relative lower-target shortage fell from 5.34% to 3.14% (Table 7).

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Table 7. Reduced matched penalty study: 144 runs per weight. Attainment is capped at 100%; count is the mean fully attained criteria. Other denotes the mean included non-nutritional normalized outcome (lower is better).

Weight	Attainment (%)	Count	Other
0	94.24	17.47	0.0340
1	95.52	17.94	0.0394
5	95.92	18.43	0.0569
10	96.12	18.65	0.0729
25	96.24	18.72	0.0824
50	96.37	18.80	0.0893

Source: Study results.

Increasing the weight further to 50 raised mean attainment to 96.37%, but the mean included non-nutritional outcome rose from 0.05694 at weight 5 to 0.08927, where lower values are preferred. Weight 5 was within the prespecified nutritional tolerances and retained a lower non-nutritional score. Supplementary Figure S1 shows the response curves.

The same priority also changed the retained alternatives. Median reporting-front size fell from 23 points at weight zero to two at weight 5 across the 144 runs per weight. One of the 144 weight-5 selections attained all 23 criteria. The main experiment therefore used a setting that reduced mean shortages without treating complete attainment as an established outcome.

3.2 Algorithm comparison and front geometry

None of the 180 Holm-adjusted hypervolume contrasts met the $p < 0.05$ threshold. Median ordering varied by profile and objective set (Table 8). For example, NSGA-II and SPEA2 had respective F30 NC medians of 1.148 and 1.141, while their NCW medians were 1.203 and 1.215. The tests did not identify a difference at the chosen threshold; they did not establish algorithm equivalence.

Table 8. Median unpenalized hypervolume over 20 runs. Comparisons are within each profile/objective column, with larger values preferred. GLOBAL averages profile values within a replication before taking the median. Normalization is fixed within each profile.

Panel A.

Profile	Algorithm	NC	NW	ND
F30	NSGA-II	1.148	1.155	1.172
F30	SPEA2	1.141	1.152	1.171
F30	NSGA-III	1.143	1.14	1.172

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Profile	Algorithm	NC	NW	ND
F30	SMS-EMOA	1.141	1.154	1.172
F60	NSGA-II	1.123	1.138	1.169
F60	SPEA2	1.126	1.137	1.17
F60	NSGA-III	1.13	1.137	1.173
F60	SMS-EMOA	1.12	1.14	1.168
M30	NSGA-II	1.17	1.167	1.19
M30	SPEA2	1.17	1.171	1.19
M30	NSGA-III	1.17	1.17	1.189
M30	SMS-EMOA	1.169	1.17	1.189
M60	NSGA-II	1.126	1.13	1.161
M60	SPEA2	1.133	1.141	1.164
M60	NSGA-III	1.133	1.145	1.161
M60	SMS-EMOA	1.112	1.127	1.165
GLOBAL	NSGA-II	1.137	1.146	1.171
GLOBAL	SPEA2	1.139	1.144	1.173
GLOBAL	NSGA-III	1.142	1.142	1.174
GLOBAL	SMS-EMOA	1.132	1.143	1.17

Panel B.

Profile	Algorithm	NCW	NCD	NWD
F30	NSGA-II	1.203	1.231	1.253
F30	SPEA2	1.215	1.231	1.254
F30	NSGA-III	1.194	1.237	1.235
F30	SMS-EMOA	1.196	1.238	1.246
F60	NSGA-II	1.167	1.213	1.211
F60	SPEA2	1.168	1.212	1.231
F60	NSGA-III	1.164	1.212	1.228
F60	SMS-EMOA	1.166	1.211	1.235
M30	NSGA-II	1.242	1.264	1.266
M30	SPEA2	1.24	1.264	1.265
M30	NSGA-III	1.243	1.26	1.262
M30	SMS-EMOA	1.241	1.266	1.264
M60	NSGA-II	1.191	1.217	1.224
M60	SPEA2	1.171	1.215	1.235
M60	NSGA-III	1.201	1.216	1.228
M60	SMS-EMOA	1.203	1.213	1.223
GLOBAL	NSGA-II	1.194	1.229	1.24

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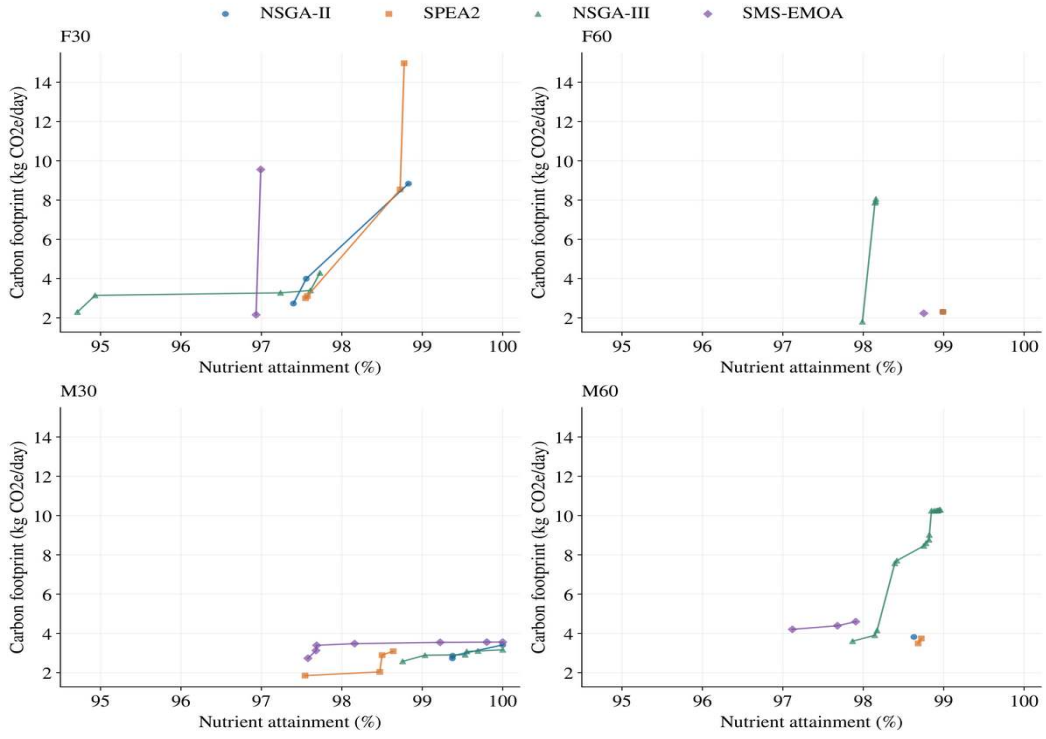
Profile	Algorithm	NCW	NCD	NWD
GLOBAL	SPEA2	1.195	1.225	1.242
GLOBAL	NSGA-III	1.195	1.232	1.238
GLOBAL	SMS-EMOA	1.198	1.232	1.238

Source: Study results.

Execution times differed under the same evaluation limit. GLOBAL scenario medians ranged from 41.53 to 42.61 seconds for SMS-EMOA and from 5.45 to 5.58 seconds for NSGA-II. The supplementary algorithm indicators report the runtime and IGD+ results.

Figure 2 shows the nutrient–carbon alternatives retained in the representative runs. The profiles differ in the attainment and carbon ranges covered by these fronts. These examples describe the available menu choices; the repeated-run comparisons in Table 8 provide the algorithm-level statistical assessment.

Figure 2. Nutrient attainment and carbon footprint in the representative NC fronts for all profiles. Each point is an evaluated menu. Shared axis limits support within-scenario comparisons; lines join points as visual guides.



Source: Study results.

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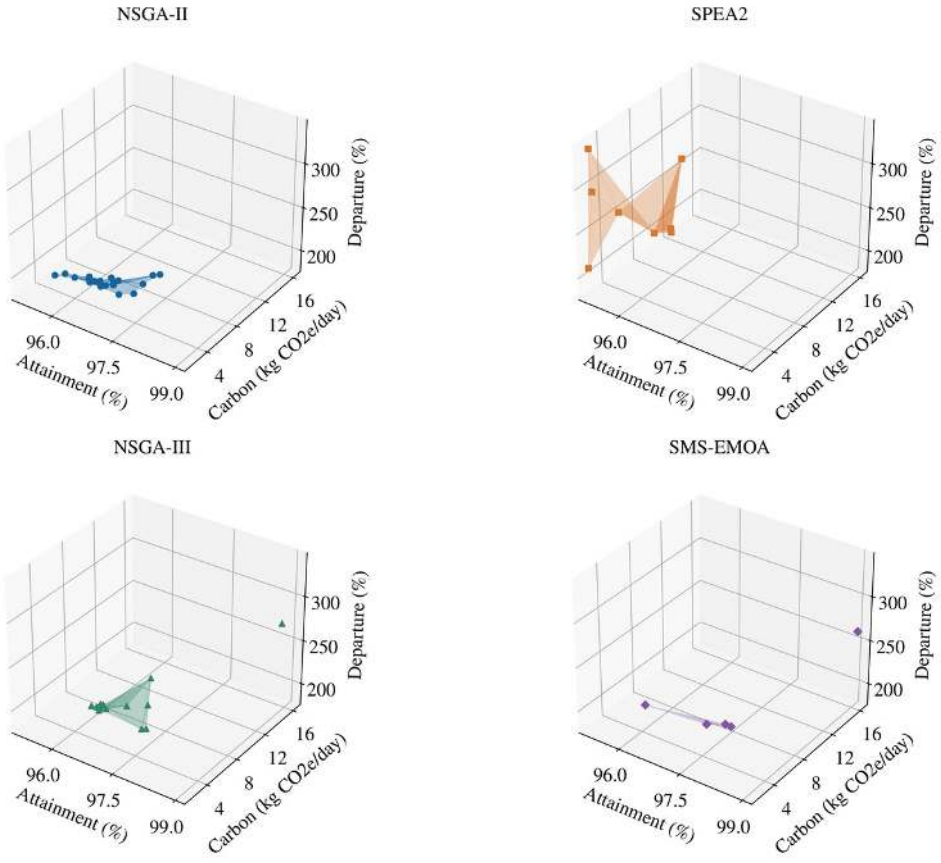
Adding quantity departure produces alternatives that a nutrient–carbon projection cannot distinguish. In the F30 NCD fronts, menus with similar attainment and carbon can have different departure values (Fig. 3). The additional front views give the corresponding water and departure comparisons.

Figure 3. F30 NCD fronts by algorithm. Attainment is maximized; carbon and quantity departure are minimized. Translucent faces connect evaluated points for depth interpretation and do not represent additional feasible menus.



Source: Study results.

3.3 Observed diets and the choice of an optimized menu

The original ideal-distance selections raised equal-profile mean nutrient attainment, computed using Equation (7), from 75.78% in the observed diets to 97.98% and reduced mean carbon footprint from 6.41 to 4.05 kg CO_2e/day. Mean water footprint, however, rose from 5933

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to 6152 L/day (Table 9). Thus proximity to the searched ideal point did not ensure improvement in outcomes omitted from that distance.

Table 9. Observed diets, original ideal-distance selections and reference-constrained compromises (Ref.). Each optimized profile row summarizes six objective sets × four algorithms × 20 runs. Ref. uses all energy-feasible evaluated menus and requires improvement in A, C, W and D over observed profile means. Original ideal selections use the final reporting fronts. All profiles assume low-active activity. E_{max} and mean energy E are kcal/day; A is capped nutrient attainment (%), C carbon (kg CO_2e/day), W water (L/day), D departure (%) and All 23 simultaneous attainment (%). D is a relative mass distance and can exceed 100%. GLOBAL gives profiles equal weight.

Panel A.

Profile	Diets	n	E_{max}	E	A
F30	Observed	27	2276	2160.3	74.99
F30	Ideal	480	2276	2216.4	97.23
F30	Ref.	480	2276	2151.2	94.41
F60	Observed	38	1998	1894.1	74.93
F60	Ideal	480	1998	1935.3	97.98
F60	Ref.	480	1998	1880.5	95.24
M30	Observed	24	2874	2695.2	76.24
M30	Ideal	480	2874	2676.3	99.09
M30	Ref.	480	2874	2664.6	97.80
M60	Observed	19	2459	2355.7	76.97
M60	Ideal	480	2459	2420.6	97.63
M60	Ref.	480	2459	2347.8	95.22
GLOBAL	Observed	108	–	2276.3	75.78
GLOBAL	Ideal	1920	–	2312.2	97.98
GLOBAL	Ref.	1920	–	2261.0	95.67

Panel B.

Profile	Diets	n	C	W	D	All 23
F30	Observed	27	5.53	5262	186.2	0.00
F30	Ideal	480	4.61	6379	222.1	0.00
F30	Ref.	480	2.77	2774	180.6	0.00
F60	Observed	38	5.18	5705	206.1	0.00
F60	Ideal	480	2.91	5921	213.3	0.00
F60	Ref.	480	1.87	2148	190.7	0.00
M30	Observed	24	6.52	6144	178.8	0.00
M30	Ideal	480	3.55	4561	187.7	6.67

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Profile	Diets	n	C	W	D	All 23
M30	Ref.	480	2.86	2633	171.8	0.00
M60	Observed	19	8.40	6623	200.3	0.00
M60	Ideal	480	5.15	7745	219.2	0.00
M60	Ref.	480	3.16	2178	181.3	0.00
GLOBAL	Observed	108	6.41	5933	192.9	0.00
GLOBAL	Ideal	1920	4.05	6152	210.6	1.67
GLOBAL	Ref.	1920	2.66	2434	181.1	0.00

Source: Study results.

The reference-constrained choices improved all four measured outcomes relative to the corresponding observed profile means in every run. They averaged 95.67% nutrient attainment, 2.66 kg CO_2e/day, 2434 L/day water and 181.11% quantity departure. Relative to observed means, carbon, water and departure decreased by 58.43%, 58.98% and 6.09%. Attainment remained 2.31 percentage points below the original ideal-distance result. These comparisons use one selected menu per run, with equal algorithm, objective-set and profile weights as defined in Section 2.4.3.

Access to the full candidate history mattered to this result: 1906 Ref. choices were outside the final reporting fronts. Even choosing the lowest-water member of every final front would leave mean water at 5487.5 L/day in F30 and 6675.0 L/day in M60, respectively 4.29% and 0.79% above their observed references. Supplementary Table S10 reports these front-restricted bounds. Changing selection within the retained fronts alone could not satisfy the same requirement in every run.

3.4 Remaining nutrient gaps

The mean attainment score and complete attainment describe different properties of the selected menus. Across the original ideal-distance choices, 32 of 1920 menus attained all 23 criteria, all in M30. Max N produced 291 such selections and Min D 30, also confined to M30. No Ref. selection attained every criterion (Table 10).

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Table 10. Mean nutrient attainment and complete-attainment counts under four decision rules. Each rule selects one menu from each of 480 runs per profile and 1920 for GLOBAL, with equal run and profile weights. Max N, Ideal and Min D use the original final reporting fronts; Ref. uses all energy-feasible evaluated menus with strict observed-reference improvement. E_{max} is the energy ceiling (kcal/day). A is mean capped attainment (%); All 23 counts selections attaining every criterion. All profiles assume low-active activity with different nutrient targets and meal pools.

Panel A.

Profile	E_{max}	Max N		Ideal	
		A	All 23	A	All 23
F30	2276	98.04	0/480	97.23	0/480
F60	1998	98.34	0/480	97.98	0/480
M30	2874	99.82	291/480	99.09	32/480
M60	2459	98.49	0/480	97.63	0/480
GLOBAL	–	98.67	291/1920	97.98	32/1920

Panel B.

Profile	E_{max}	Min D		Ref.	
		A	All 23	A	All 23
F30	2276	96.95	0/480	94.41	0/480
F60	1998	97.92	0/480	95.24	0/480
M30	2874	98.64	30/480	97.80	0/480
M60	2459	97.70	0/480	95.22	0/480
GLOBAL	–	97.80	30/1920	95.67	0/1920

Source: Study results.

The rules also produced different footprints. Max N averaged 6.00 kg CO_2e/day and 9364 L/day, compared with 4.05 kg and 6152 L under Ideal, for a mean attainment difference of 0.69 percentage point. Maximizing the nutritional score therefore did not identify the same menu as minimizing distance to the included objectives.

The nutrient-level results show where the remaining gaps occurred. Among F30 Ideal selections, 20.42% met the sodium maximum, 22.08% the vitamin D target and 41.46% the iron target (Fig. 4). Vitamin D attainment was 2.50% in F60 and 3.33% in M60. M30 reached that target in 82.92% of selections, but met the sodium maximum in 16.88%.

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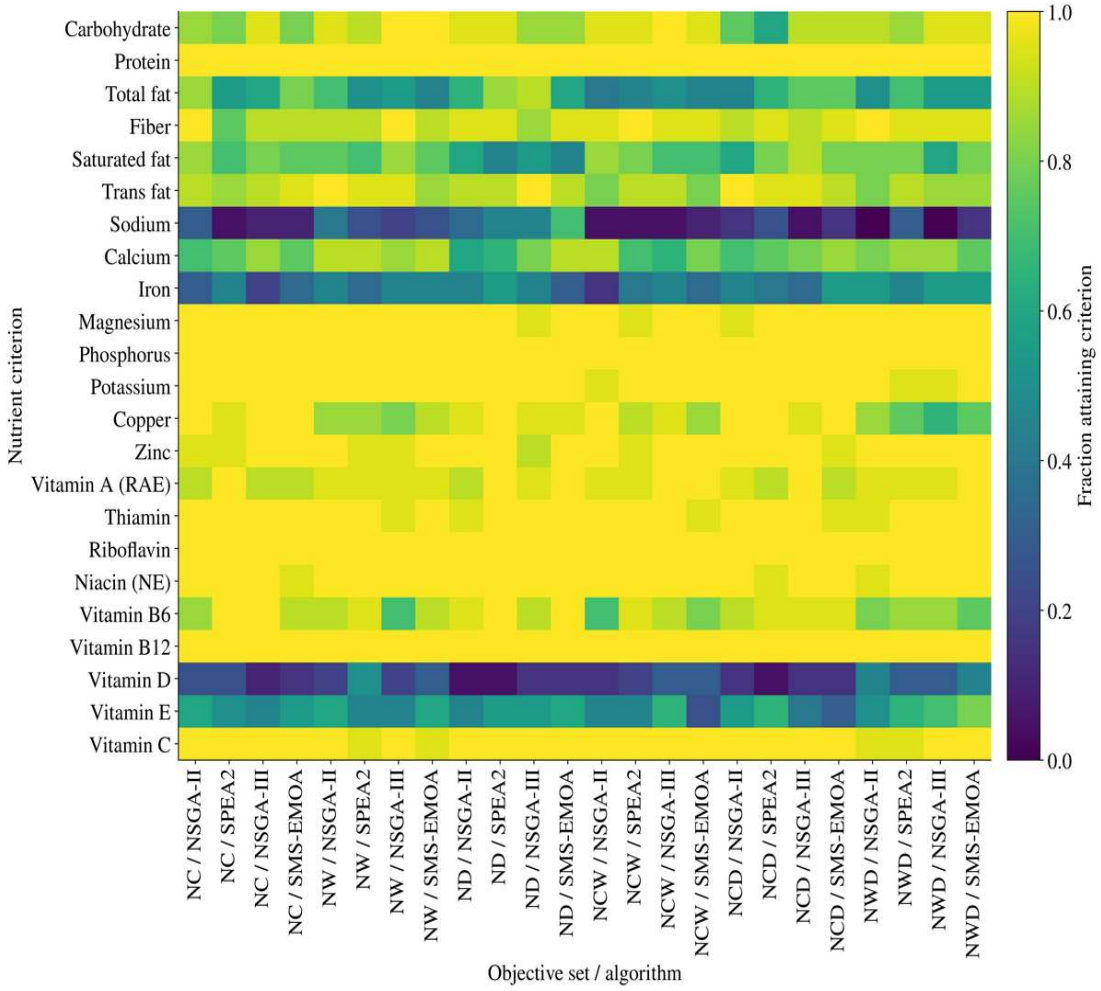
Figure 4. Frequency of attaining each nutrient criterion among the 20 F30 Ideal selections per algorithm and objective set. The colors describe criterion-level attainment, not the average nutritional score.



Source: Study results.

3.5 Changes in food quantities

The largest absolute NC mean change was chocolate milk drink in F30, F60 and M30, and hot mate infusion in M60. Table 11 compares these foods between NC and ND to show how including quantity departure changes the selected amounts.

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Table 11. Largest absolute NC food-type mean change in each profile, selected by the equal-algorithm mean and excluding plain water from this display selection. Baseline is the observed-day mean. NC and ND show daily grams as mean ± sample SD over 20 compromise menus per algorithm, including zeros for absence. Δ is optimized mean minus baseline; its SD equals the displayed mass SD because the baseline is fixed.

Algorithm	Baseline (g)	NC (g/day)	ND (g/day)	ΔNC (g)	ΔND (g)
F30: Chocolate milk drink (7903102)					
NSGA-II	7.3	270.0 ± 165.8	265.0 ± 184.3	+262.7	+257.7
SPEA2	7.3	325.0 ± 209.9	225.0 ± 165.0	+317.7	+217.7
NSGA-III	7.3	385.0 ± 192.7	295.0 ± 211.4	+377.7	+287.7
SMS-EMOA	7.3	315.0 ± 181.4	210.0 ± 171.4	+307.7	+202.7
F60: Chocolate milk drink (7903102)					
NSGA-II	6.3	495.0 ± 176.1	335.0 ± 189.9	+488.7	+328.7
SPEA2	6.3	480.0 ± 150.8	345.0 ± 201.2	+473.7	+338.7
NSGA-III	6.3	420.0 ± 150.8	405.0 ± 201.2	+413.7	+398.7
SMS-EMOA	6.3	465.0 ± 153.1	310.0 ± 183.2	+458.7	+303.7
M30: Chocolate milk drink (7903102)					
NSGA-II	7.9	240.0 ± 208.8	120.0 ± 150.8	+232.1	+112.1
SPEA2	7.9	345.0 ± 243.8	45.0 ± 109.9	+337.1	+37.1
NSGA-III	7.9	195.0 ± 146.8	120.0 ± 204.2	+187.1	+112.1
SMS-EMOA	7.9	270.0 ± 192.2	105.0 ± 146.8	+262.1	+97.1
M60: Hot mate infusion (8202804)					
NSGA-II	103.2	737.5 ± 561.0	377.5 ± 470.9	+634.3	+274.3
SPEA2	103.2	577.5 ± 455.8	352.5 ± 529.5	+474.3	+249.3
NSGA-III	103.2	614.0 ± 413.7	460.0 ± 550.7	+510.8	+356.8
SMS-EMOA	103.2	642.5 ± 465.5	310.0 ± 513.9	+539.3	+206.8

Source: Study results.

For F60 with NSGA-II, chocolate milk drink rose from a 6.3 g/day observed baseline to 495.0 ± 176.1 g/day under NC, compared with 335.0 ± 189.9 under ND. It appeared in 19 and 17 of the 20 selected menus, respectively. Across F60 algorithms, NC means ranged from 420.0 to 495.0 g/day and ND means from 310.0 to 405.0. In M30, SPEA2 selected 345.0 ± 243.8 g/day under NC and 45.0 ± 109.9 under ND, with presence falling from 16 to three menus.

Hot mate infusion followed the same direction in M60. NSGA-II selected 737.5 ± 561.0 g/day under NC and 377.5 ± 470.9 under ND, against an observed baseline of 103.2 g/day. Presence fell from 15 to nine menus, and the other algorithms also had lower ND means.

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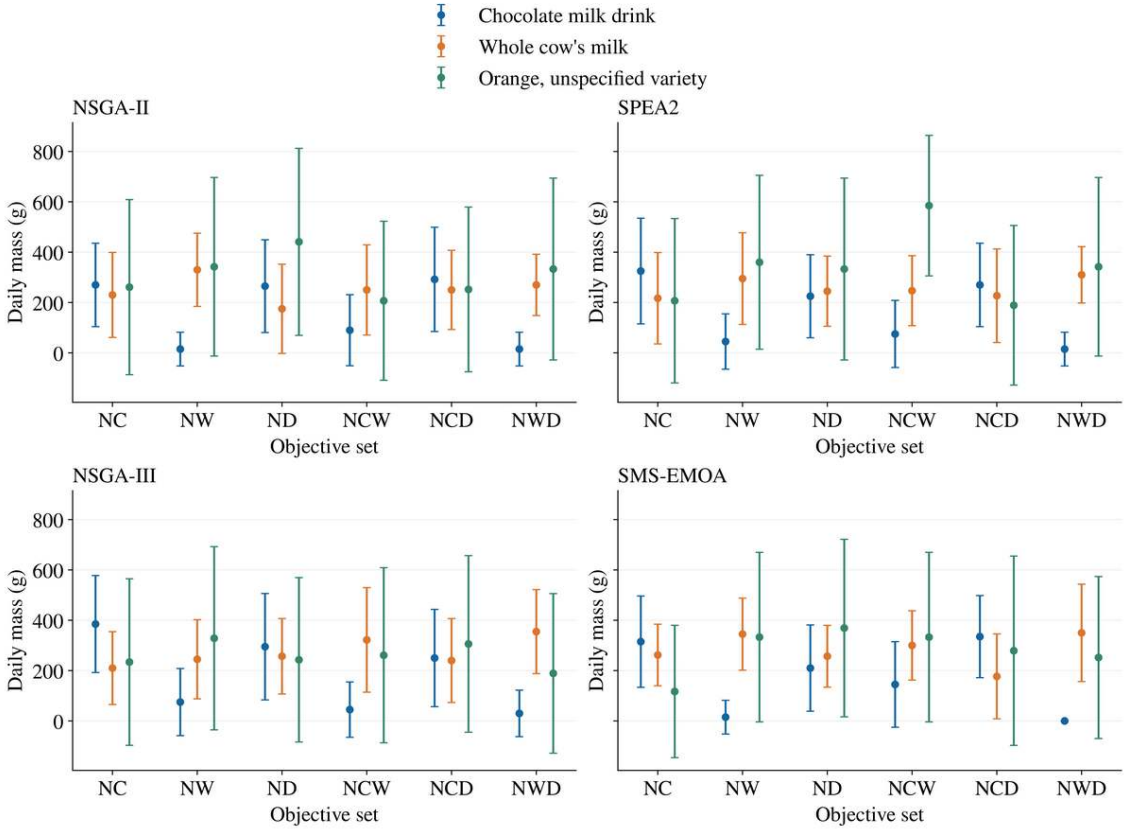
This moderation did not apply to every food. For F30 with NSGA-II, orange increased from 261.0 ± 347.8 g/day under NC to 441.0 ± 371.5 under ND, while whole cow's milk fell from 230.0 ± 168.9 to 175.0 ± 177.3. Figure 5 places these changes alongside all six objective sets. Because departure measures the joint food–preparation–position vector, reducing it does not require every individual food amount to decrease.

Figure 5. Daily quantities of the three leading F30 food types by absolute NC mean change. Points and bars are means and sample standard deviations over 20 Ideal selections, including zeros for absence. Each algorithm is shown across the six objective sets.



Source: Study results.

Selection rule and candidate pool changed the food-level result as well. For NSGA-II in NC, mean chocolate milk drink fell from 270.0 ± 165.8 g/day under Ideal to 15.0 ± 67.1 under Ref. in F30, and from 495.0 ± 176.1 to 15.0 ± 67.1 in F60. The profiles, algorithms, objective set and original runs were the same; Ref. used a different candidate pool and imposed improvement in

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all four outcomes. The beverage increases under Ideal were therefore not an inevitable consequence of the meal pools.

The additional food-type comparisons cover beans and white rice. The complete menu examples show the meal combinations behind individual front points. The repeated-run summaries, rather than those individual examples, describe how quantities varied across selections.

3.6 Interpretation and limitations

3.6.1 Nutritional scores and the meals that produce them

The results distinguish improvement in the average nutritional score of Equation (7) from simultaneous attainment of every nutrient target. The remaining vitamin D and sodium gaps explain why a mean close to 100% cannot be read as a fully adequate diet. With fixed within-meal portions, the search cannot adjust an individual nutrient amount without selecting a different meal. This restriction may contribute to the remaining gaps, although unsuccessful search alone does not prove that complete attainment is impossible.

Food quantities show a related limitation of the score. The original selections increased milk-based beverages in three profiles, while adding departure or changing to Ref. often reduced those amounts. Nutrient targets do not cover every dimension of a diet, including added sugars, processing and individual preferences. The selected combinations must therefore be assessed through their foods and unmet criteria, rather than ranked for personal use by the average score alone.

The need for nutrient-level checking also appears in LLM-based planning. The Brazilian evaluation of generated diets found iron and calcium shortfalls despite mean energy close to the requested target (Silva et al., 2026). In the present model, nutrient totals are computed from the selected meals rather than accepted from a generated description, yet unmet criteria still remain. The distinction is between producing a menu and verifying its nutritional properties, not a demonstrated performance ranking between LLMs and evolutionary search.

The quantity summaries also depend on how absence is represented. A mean over optimizer replications includes zero when a food is not selected, so its standard deviation reflects both presence and portion differences between observed meals. These are distributions of computed choices, not measurements of variation in population intake.

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3.6.2 Why the menu-selection rule changes the comparison

Improvement in water was not required by Ideal, and water was absent from some objective sets. Proximity to the searched ideal point could therefore select a menu whose water footprint exceeded the observed reference. Ref. imposed improvement in all four outcomes. Its results answer that additional requirement rather than showing that every ideal-distance compromise should improve every outcome.

The candidate pools also differ. Final reporting fronts retain a subset of the feasible menus encountered during search. Some evaluated alternatives satisfy the four reference conditions without surviving into those fronts. Recovering them made a Ref. choice possible in every run, but it did not change the algorithms' original front-quality results. The original penalty calibration likewise pertains to the original search and reporting procedure, not to an optimization of this later selection preference.

Joint improvement is defined against profile means, not the diet of a particular respondent. The observed comparison uses the same reference energy intervals and nutrient rules on each side, but its observed days come from the data used to form the meal pools. It is neither a paired intervention nor an independent validation sample. The observed-to-selected changes describe the choices available under this model.

3.6.3 Profile conditions and interpretation limits

M30 had both the largest energy ceiling and the highest mean attainment under Ideal and Ref. A larger energy allowance permits more food within the interval, but this experiment does not isolate its effect: sex, age, nutrient targets and available meals change together. M60, for example, had a higher ceiling than F60 but slightly lower Ref. attainment, 95.22% against 95.24%. Low-active physical activity is a shared reference assumption, not a measured characteristic of the respondents.

Environmental coefficients, self-reported portions, the mapping of eating occasions and uncertain nutrient zeros can affect the outcomes. The model also omits prices and individual health conditions. Preserving an observed meal does not establish acceptance of a daily menu assembled from different respondents' meals.

Future analysis can examine which nutrient constraints restrict whole-meal feasibility and how the findings respond to changes in meal pools and composition data. Dietary use would additionally require assessment of the assembled menus and their suitability for the intended people.

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4 FINAL CONSIDERATIONS

The four algorithms produced reporting fronts without a detected difference in the adjusted hypervolume comparisons, while execution times differed. At the menu level, the objective set and subsequent choice rule led to different nutrient outcomes, footprints and food quantities. Algorithm indicators alone did not describe those dietary differences.

The original ideal-distance selections improved mean nutrient attainment and carbon footprint relative to observed diets but increased mean water footprint. Requiring joint improvement and searching the full evaluated candidate histories recovered a menu in every run, at lower mean attainment than the original choices. Neither rule removed all nutrient gaps across the selected menus.

Food-level analysis identified which foods changed and how the direction varied by profile. Beverage amounts that increased under the original rule were reduced when departure or observed-reference conditions were imposed, while some foods, such as orange, increased even when total departure was minimized. Reporting these quantities and the remaining nutrient deficits explains what the computed trade-offs mean as meals. The findings concern the stated reference profiles and observed-meal pools, rather than clinical recommendations or population dietary effects.

DATA AND CODE AVAILABILITY

The study repository, https://github.com/thalyson004/sec-brazilian-diet-multiobjective, provides the code, configurations, reporting fronts and complete food/portion lists. It includes the observed comparison diets, the selected menus under the original and reference-constrained rules, and their nutrient and food-quantity summaries. These records link the reported results to the meals that produced them.

The supplementary results at https://github.com/thalyson004/sec-brazilian-diet-multiobjective/tree/main/supplementary-results provide additional algorithm indicators, front views, food-quantity comparisons, complete menu examples and selection sensitivity in Markdown, with downloadable tables and figures.

The POF archives and environmental workbook are obtained separately from their sources (Garzillo et al., 2023; Instituto Brasileiro de Geografia e Estatística, 2020). Source nutrient coefficients, unselected meal pools and full evaluation histories are reconstructed locally using the supplied commands.

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