Automated menu planning for pregnancy based on nutrition and budget using population-based optimization method

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ABSTRACT

Nutritional fulfilment during pregnancy depends on the budget. Meanwhile, nutrition is needed during pregnancy to keep the mother and fetus healthy. Therefore, this study aims to assist maternal nutrition planning by using population-based optimization methods such as genetic algorithm (GA), particle swarm optimization (PSO), duck swarm algorithm (DSA), and whale optimization (WO) according to their nutritional needs at minimum cost. Additionally, this study compares the method performance to find the best method. There are 55 foods obtained from previous studies divided into five groups: staple food (SF), vegetables (VG), plant-source food (PS), animal-source food (AS), and complementary (CP). The model evaluation results show that GA's performance differed significantly from other models because it obtained the highest fitness by 439.73 and more variation in fitness results. Three models other than GA have no significant difference, but DSA performance obtained a superior fitness of 367.18. Furthermore, optimization methods must be combined with other artificial intelligence methods to develop innovative technology to support maternal nutrition and prevent stunting.

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1. INTRODUCTION

During pregnancy, pregnant women require significant nutritional needs, so an optimal diet is essential. Adequate nutrition is necessary for both the mother and the growing fetus [1], [2]. In addition, unbalanced nutrition results in several disorders, such as gestational diabetes, hypertension, and developmental problems in the fetus. In fact, maintaining a balanced diet can help effectively reduce these disorders [3], [4]. Additionally, it can improve the health and well-being of both mother and fetus [5].

Pregnant women's nutrition fulfilment process will have implications for the budget owned [6]. When expecting mothers to have limited budgets, they prioritize using them for other purposes rather than fulfilling their nutritional needs. However, the food type and amount of nutrients consumed during pregnancy can significantly impact on the health of the mother and fetus. A healthy meal pattern has a positive effect on reducing the level of stress in the pregnant woman [2]. Therefore, it is necessary to educate pregnant women to implement a cost-effective nutrition plan when encountering uncertain economic conditions [7], [8]. Pregnant women can implement menu planning to be more effective and efficient.

Metaheuristic methods are advanced computational methods used to solve complex optimization problems. Metaheuristic methods provide efficient solutions to large-scale non-linear issues in various domains [9]–[11]. Population-based optimization methods are a subset of metaheuristic approaches [12]–[14].

These methods are often implemented in menu planning problems. In the last five years of research, menu planning has been done for stroke patients [15], school lunches [16], and diet programs [17] as shown in Table 1. No researcher has planned food menus for pregnant women, even though this is very much needed. In addition, the methods used are still mathematical. So, this study is a novelty that other researchers have not done, namely, food menu planning for pregnant women with population-based optimization methods.

Based on the previous explanation, designing food menus during pregnancy is very important to balance nutritional intake with appropriate costs. The purpose of this study is to automatically plan food menus for pregnant women based on their dietary needs and budget. The population-based optimization method will be implemented to help find automatic food menu planning with optimal results. The results obtained are expected to help reduce health risks related to nutrition and oxidative stress. In addition, it is hoped that regardless of financial conditions, all pregnant women have equal access to the best food to support a healthy pregnancy and prevent stunting.

Table 1. Previous research about menu planning problem

Researchers	Method	Object
[15]	Linear programming, Integer programming, delete-reshuffle algorithm	Stroke patient
[16]	Multi-objective optimization	Children in school
[17]	Linear programming	Diet program

2. METHOD
2.1. Problem definition

Adequate nutrition is critical during pregnancy to prevent stunting. Pregnant women need to fulfill five main components in every daily meal: staple food (SF), vegetables (VG), plant-source food (PS), animal-source food (AS), and complementary (CP). Based on previous studies [18], the factors calculated to determine maternal nutritional needs are total energy expenditure (TEE), basal energy expenditure (BEE), physical activity rate, and stress rate. However, pregnant women often neglect to consider this due to cost constraints [19], [20]. This study extends the work of Kurnianingtyas *et al.* [18] by considering the cost function to find recommendations for a daily menu to fulfill nutrition. Model of this study can be seen in Figure 1.

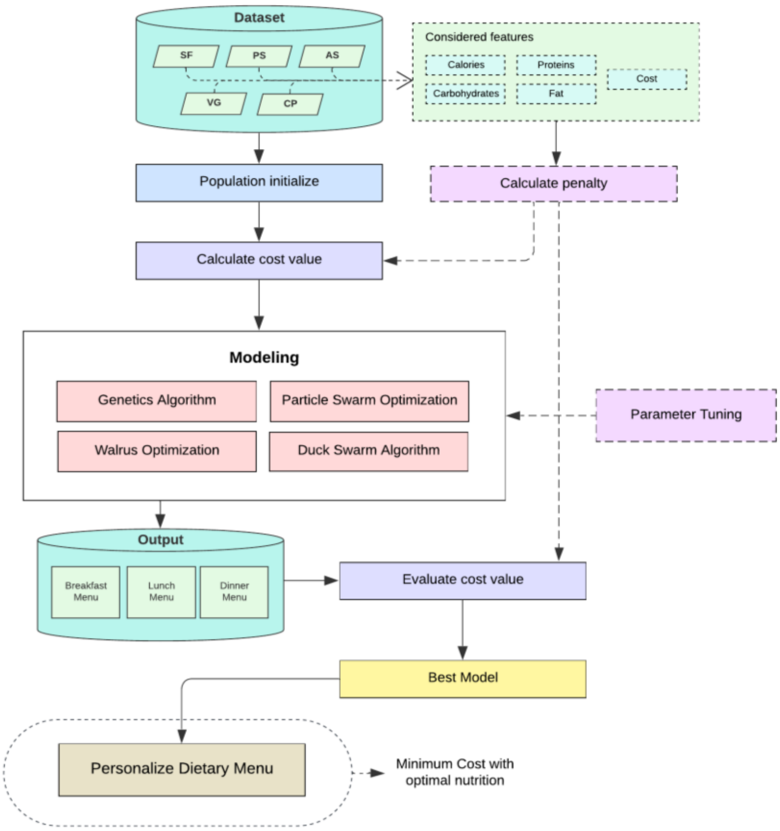


Figure 1. Model construction in this study

2.2. Data collection

The data used was obtained from study [18]. There were 55 food items divided into five groups: SF, PS, AS, VG, and CP, with each category consisting of 11 items. The characteristics of the dataset used in this study are shown in Table 2.

Table 2. Dataset characteristics

Type	Nutrient	Min-max	Mean	Var	Std
SF	Energy	124.0-916.0	493.3	65189.0	255.3
	Carbo	27.0-170.0	105.2	3103.7	55.7
	Protein	0.6-17.4	7.9	22.6	4.8
	Fat	0.0-28.8	3.3	72.2	8.5
	Cost	3,000-15,000	6090.9	15290909.1	3910.4
PS	Energy	45.0-299.0	124.9	8181.4	90.5
	Carbo	1.25-20.85	6.9	34.6	5.9
	Protein	4.35-21.9	7.8	25.7	5.1
	Fat	0.25-21.3	7.4	59.5	7.7
	Cost	1,250-5,000	2613.6	1967045.5	1402.5
AS	Energy	21.6-333.6	163.1	8523.2	92.3
	Carbo	0.0-26.72	9.5	81.9	9.0
	Protein	0.64-38.8	16.6	124.5	11.2
	Fat	0.4-18.72	8.3	32.5	5.7
	Cost	6,400-12,000	9236.4	4398545.5	2097.3
VG	Energy	16.0-424.0	174.5	17902.5	133.8
	Carbo	2.0-58.2	18.7	264.1	16.3
	Protein	0.4-30.6	9.1	94.2	9.7
	Fat	0.4-20.0	7.4	50.2	7.1
	Cost	4,000-9,000	6090.9	2490909.1	1578.3
CP	Energy	45.0-127.5	81.4	595.8	24.4
	Carbo	6.0-30.0	17.1	47.1	6.9
	Protein	0.45-4.95	1.4	1.5	1.2
	Fat	0.0-9.75	1.5	8.5	2.9
	Cost	3,000-18,000	6920.5	30975852.3	5565.6

2.3. Modeling

Four optimization models, genetic algorithm (GA), particle swarm optimization (PSO), duck swarm algorithm (DSA), and whale optimization (WO), are used to recommend the daily diet of pregnant women. All four models are population-based algorithms that use a population to simultaneously explore the solution space. Furthermore, each individual in the population is considered a potential solution to the problem. In this study, solution i can be expressed in (1).

$$\mathrm{x}_i = \left[x_{i_{breakfast,SF}}, x_{i_{breakfast,PS}}, \dots, x_{i_{dinner,CP}}\right] \tag{1}$$

Meanwhile, the initial population consist of P randomly initialized solution expressed in (2).

$$\mathrm{P} = \{\mathrm{x}_1, \mathrm{x}_2, \dots, \mathrm{x}_\mathrm{P}\} \tag{2}$$

Each solution needs to be evaluated with a fitness function f(x), which evaluates its quality. In this study, f(x) uses a cost function that considers the nutritional penalty value and the price of each food ingredient. The calculation of the nutritional penalty value is defined by the sum of the difference between the nutritional need (nn) and the nutritional gain (ng), as in (3).

$$f(\text{penalty}) = \sum(nn_\mathrm{x} - ng_\mathrm{x}) \tag{3}$$

Meanwhile, in (4) shows the fitness function used in this study, where C is the price of each food ingredient.

$$f(\mathrm{x}) = 0.997 \times f(\text{penalty}) + 0.003 \times \sum \mathrm{C}_{\mathrm{x}_i} \tag{4}$$

The weight values on the penalty value and the cost of each food are not comparable. However, the previous study made a proportional effort by assigning weights to the penalty value and cost of 0.997 and 0.003, respectively.

GA is a heuristic search technique inspired by the process of biological evolution. There are six steps to implement GA: chromosome representation, initial population, fitness function, selection, crossover, and mutation. The selection process is carried out to select chromosomes that will be used to produce offspring. This selection is based on fitness value using the Elitism selection method shown in (5).

$$\mathrm{P}\ (t+1) = \{\mathrm{x}_1, \dots, \mathrm{x}_\mathrm{P}\} \cup \{\mathrm{x}_{\mathrm{P}+1}, \mathrm{x}_{\mathrm{P}+2}, \dots, \mathrm{x}_\mathrm{N}\} \quad (5)$$

Afterward, a single-point crossover process is performed to produce offspring from the two parent chromosomes by combining parts of the two chromosomes, as shown in (6) and (7).

$$\mathrm{x}_c = \left[x_{i_{breakfast,SF}}, x_{i_{breakfast,PS}}, \dots, x_{i_{dinner,CP}}\right] \quad (6)$$

$$\mathrm{x}_d = \left[x_{i_{breakfast,SF}}, x_{i_{breakfast,PS}}, \dots, x_{i_{dinner,CP}}\right] \quad (7)$$

Meanwhile, the mutation process is carried out to maintain genetic diversity in the population by randomly changing the values of some variables in the chromosomes shown in (8).

$$\mathrm{x}_i' = \left[x_{breakfast,SF}, \dots, x_{lunch,SF}', x_{dinner,CP}\right] \quad (8)$$

PSO is a population-based optimization algorithm inspired by the social behavior of birds or fish searching for food. Each particle in PSO represents a potential solution by updating the i-th particle at the t -th iteration. In (9) and (10) calculate particle position and velocity.

$$\mathrm{x}_i(t) = \left[x_{i_{breakfast,SF}}(t), \dots, x_{i_{dinner,CP}}(t)\right] \quad (9)$$

$$\mathrm{v}_i(t) = \left[v_{i_{breakfast,SF}}(t), \dots, v_{i_{dinner,CP}}(t)\right] \quad (10)$$

Furthermore, for velocity and position updates, in (11) and (12) are shown where ω is the inertia factor, c_1 and c_2 are the acceleration coefficients for cognitive and social influences, r_1 and r_2 respectively.

$$\mathrm{v}_i(t+1) = \omega \mathrm{v}_i(t) + c_1 r_1\big(\mathrm{p}_i - \mathrm{x}_i(t)\big) + c_2 r_2 (\mathrm{g} - \mathrm{x}_i(t)) \quad (11)$$

$$\mathrm{x}_i(t+1) = \mathrm{x}_i(t) + \mathrm{v}_i(t+1) \quad (12)$$

Additionally, WO [21] and DSA [22] are algorithms that incorporate elements from PSO. WO adds the social behavior and feeding behavior of walruses [23]. Meanwhile, DSA modifies some aspects that reflect the unique behavior of ducks. Therefore, the mathematical calculations are similar to PSO, as shown by (9) to (12).

2.4. Parameter input

To execute the method, initialize the input parameters. The input parameters help control the algorithm's behavior and determine the resulting solution's quality [24], [25]. All four methods are population-based. Thus, all methods use the same population size and number of iterations, 100. This condition strives for each method to operate under the same conditions. This standardization is essential for a fair comparison of the method's performance in finding daily menus for pregnant women based on nutritional needs and cost constraints. In addition, some parameters were chosen based on their effectiveness in previous studies [18], [26], [27] that have found optimal solutions. These parameters were chosen to balance exploration and exploitation to facilitate efficient convergence to the optimal solution [28], [29]. The initialization of input parameters used by GA, PSO, DSA, and WO are shown in Table 3.

2.5. Evaluation

The performance of the four methods was evaluated to recommend the best method for solving similar problems. The evaluation used a one-way analysis of variance (ANOVA) and Tukey's honestly significant difference (HSD) test in this study. ANOVA is used to see if there is a significant difference in [30] the fitness results produced by GA, PSO, DSA, and WO. Meanwhile, Tukey's HSD test to determine which methods are different from each other [31]. This calculation assumes (H_0) that there is no difference in average performance between GA, PSO, DSA, and WO. The Tukey's HSD test stage can be done if the p-value < ∝.

Table 3. Parameter input

Methods	Parameter	
GA	Population size	100
	Iteration number	100
	Crossover rate	0.8
	Mutation rate	0.01
PSO	Swarm size	100
	Iteration number	100
	Inertia weight	0.5
	Cognitive coefficient	1.5
	Social coefficient	1.5
DSA	Swarm size	100
	Iteration number	100
	Attraction factor	0.7
	Cognitive coefficient	0.3
WO	Swarm size	100
	Iteration number	100

3. RESULTS AND DISCUSSION

3.1. Best model parameters

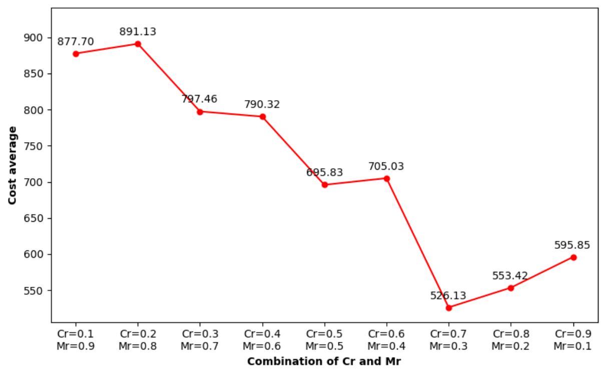
Parameter tuning is important to ensure the optimization algorithm works effectively and efficiently. Parameter tuning influences the solution generated by the optimization method [32], [33]. With the best parameters, the algorithm can find better solutions, converge faster, and adapt to optimization problems. In this study, parameter tuning is conducted on parameters besides population size and number of iterations. Hence, parameter tuning is only executed using three methods, namely GA, PSO, and DSA as shown in Figure 2. By using the population size and iteration size according to Table 3, GA obtained the best crossover and mutation values as 0.7 and 0.3, PSO had the best ω, c_1, and c_2 values equal to 0.5, 1.6, and 1.6, and DSA obtained the best P and FP values at 0.5 and 0.5. Therefore, a summary of the best parameters to be used to compare the performance of the four methods is addressed in Table 4.

Table 4. Best input parameters of the tuning process

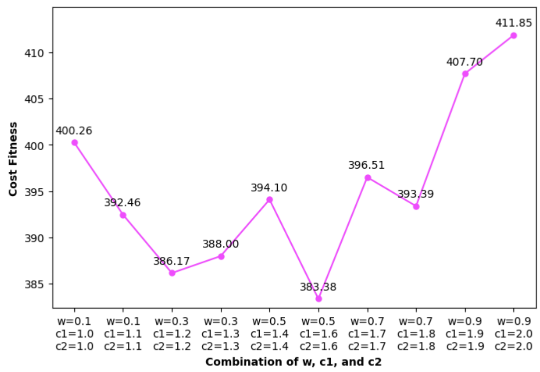
Methods	Parameter	
GA	Population size	100
	Iteration number	100
	Crossover rate	0.7
	Mutation rate	0.3
PSO	Swarm size	100
	Iteration number	100
	Inertia weight	0.5
	Cognitive coefficient	1.6
	Social coefficient	1.6
DSA	Swarm size	100
	Iteration number	100
	Attraction factor	0.5
	Cognitive coefficient	0.5
WO	Swarm size	100
	Iteration number	100

3.2. Model comparison

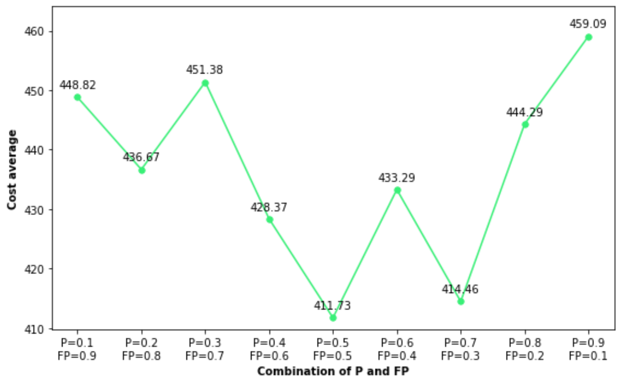
GA, PSO, DSA, and WO models have been successfully implemented in pregnant women's diet planning. However, the four methods have different performance results. Based on the ANOVA test results in Table 5(a), there is a significant difference between the models. It is indicated by the p-value equal to 0, implying a statistically significant difference between the models. Based on these results, H_0 is rejected. There is a significant difference between GA and PSO, DSA, and WO models. The t-test as, shown in Table 5(b), shows that the GA presented the most crucial average difference and the highest test value. In addition, GA has a broader confidence interval value, indicating a more substantial variation in the solution results. Also, based on the Tukey test shown in Table 5(c), GA showed a significant difference from the other models as having statistically different performance results, while the others showed no significant difference. As seen in Figure 3, the solutions reaching the global optimum in GA, PSO, DSA, and WO are 439.73, 382.76, 367.18, and 385.97, respectively. GA differs from PSO, DSA, and WO because GA is part of the evolutionary algorithm (EA) approach, and the three others are included in swarm intelligence (SI) [34], [35]. The two approaches have different characteristics. EA is often used in optimization problems involving global search and extensive exploration. Meanwhile, SI is suitable for problems requiring dynamic adaptation and agent collaboration [36], [37]. Therefore, a significant difference in model performance occurs with GA. The detailed parameters for the best solutions obtained by each model are presented in Figure 2. Figure 2(a) illustrates the optimal parameter configuration for GA, which produced the highest global optimum value of 439.73. Figure 2(b) presents the optimal parameters obtained by PSO, achieving a global optimum of 382.76. Meanwhile, Figure 2(c) shows the optimal parameters for DSA, resulting in a global optimum of 367.18. These parameter settings highlight the differences in search strategies and solution quality achieved by each optimization method.



(a)



(b)



(c)

Figure 2. Model comparison result: (a) GA's best parameter, (b) PSO's best parameter, and (c) DSA's best parameter

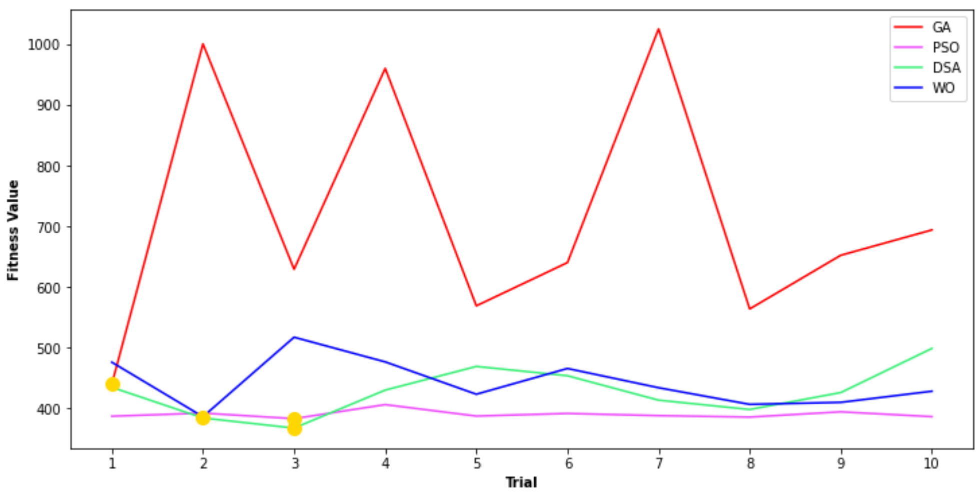


Figure 3. Model comparison result

Table 5. Evaluation model result: (a) ANOVA result, (b) One sample t-test, and (c) Tukey's HSD analysis

(a)

Source	Sum of squares	Degrees of freedom	Mean square	F-statistic	p-value
Between groups	724.782428	3	20.132845	20.132845	0
Within groups	N/A	36	N/A	N/A	N/A
Total	N/A	39	N/A	N/A	N/A

(b)

Model	Test value	t	df	Sig. (2-tailed)	Mean difference	95% confidence interval of the difference	
						Lower	Upper
GA	439.73	4.299	9	0.002	277.61200	131.5187	423.7053
PSO	382.76	3.435	9	0.007	7.13600	2.4364	11.8356
DSA	367.18	4.803	9	0.001	60.13400	31.8093	88.4587
WO	385.97	4.412	9	0.002	56.16400	27.3672	84.9608

(c)

Group 1	Group 2	Mean difference	p-adj	Lower bound	Upper bound	Reject
DSA	GA	290.028	0	162.3636	417.6924	TRUE
DSA	PSO	-37.418	0.8588	-165.0824	90.2464	FALSE
DSA	WO	14.82	0.9892	-112.8444	142.4844	FALSE
GA	PSO	-327.446	0	-455.1104	-199.7816	TRUE
GA	WO	-275.208	0	-402.8724	-147.5436	TRUE
PSO	WO	52.238	0.6906	-75.4264	179.9024	FALSE

3.3. Model recommendation result

Based on the comparison results of the four models, DSA achieved the lowest fitness value, approximately 367.18. This indicates that DSA has superior performance among the tested models. Table 6 presents the daily recommended menu based on these results.

Table 6. Recommendation menu of the best model outputs

Mealtime	Code	Meal code	Meal name	Meal weight (gr)	Calories (kcal)	Carbohydrates (gr)	Proteins (gr)	Fat (gr)	Cost (Rp)
Breakfast	4	SF	White sticky rice	200	326	52	6	1	5,000
	7	PS	Oncom	50	93.5	11	7	3	1,500
	8	AS	Yellow pickled tilapia	80	264	10	14	19	6,400
	10	VG	Cucumber	200	16	3	0	0	4,000
	7	CP	Guava	150	73.5	18	1	0	3,000
Lunch	4	SF	White sticky rice	200	326	52	6	1	5,000
	7	PS	Oncom	50	93.5	11	7	3	1,500
	9	AS	Steamed carp	80	167.2	9	12	9	8,000
	10	VG	Cucumber	200	16	3	0	0	4,000
	9	CP	Sweet orange	150	67.5	17	1	0	4,875
Dinner	6	SF	Rice vermicelli	200	696	164	9	0	3,000
	4	PS	Fried tempeh	50	168	4	10	14	1,500
	9	AS	Steamed carp	80	167.2	9	12	9	8,000
	10	VG	Cucumber	200	16	3	0	0	4,000
	7	CP	Guava	150	73.5	18	1	0	3,000
			Total		2563.9	384	87	61	62,775

4. CONCLUSION

Nutritional needs are essential to maintain maternal and fetal health during pregnancy. However, the fulfilment of nutritional intake will be constrained by the budget owned. This study aims to help pregnant women plan a daily food menu by considering the required nutritional intake with a minimum budget divided into five food item categories: SF, PS, AS, VG, and CP. In addition, this study also tries to find the best method from four proposed methods: GA, PSO, DSA, and WO. The four methods were evaluated using the ANOVA and Tukey's HSD tests and comparing the fitness values obtained. The evaluation results show that GA significantly differs from other models with a fitness value equal to 439.73. GA tends to have more varied fitness results. Other than GA, the other three models do not have significant differences, but DSA is the most superior method compared to others, with a fitness value calculated at 367.18. This study has successfully provided daily menu recommendations to pregnant women, considering nutritional needs and budget. However, it is still necessary to explore various optimization methods and combine them with other artificial intelligence methods to provide more significant benefits and increase innovation in menu planning technology for pregnant women to prevent stunting. Recent advances show that learning- or hybrid-based metaheuristics can enhance population-based search for practical decision-making problems, indicating a promising direction for integrating evolutionary/swarm methods with AI-driven components.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Marji		✓				✓				✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
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I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

This study does not involve individual personal data or identifiable human subjects. Therefore, informed consent was not required.

ETHICAL APPROVAL

This study did not involve human participants or animals, and therefore did not require ethical approval. All procedures were conducted in accordance with relevant institutional and national guidelines.

DATA AVAILABILITY

The data that support the findings of this study were obtained from the first author. These data were used with permission and are not publicly available due to licensing restrictions. Requests for access may be directed to the corresponding author, [DK], subject to approval from the original authors.

REFERENCES

[1] B. M. Pepito, J. Dawes, D. Hildebrand, and J. Joyce, “Analysis of a state police academy menu cycle for dietary quality and performance nutrition adequacy,” *International Journal of Environmental Research and Public Health*, vol. 19, no. 19, 2022, doi: 10.3390/ijerph191912642.

[2] Q. Suriya, T. Razzak, N. Abid, and Q. Zia, “Maternal nutrition and fetal development: exploring dietary interventions, micronutrient deficiencies, and long-term health outcomes,” *Insights-Journal of Health and Rehabilitation*, vol. 3, no. 2, pp. 92–100, 2025, doi: 10.71000/x5sf5562.

[3] M. P. Singh and S. K. Dubey, “Recommendation of diet to anaemia patient on the basis of nutrients using AHP and fuzzy TOPSIS approach,” *International Journal of Intelligent Engineering and Systems*, vol. 10, no. 4, pp. 100–108, 2017, doi: 10.22266/ijies2017.0831.11.

[4] S. Saini and S. K. Dubey, “Recommendation of diet to jaundice patient on the basis of nutrients using AHP and fuzzy AHP technique,” *International Journal of Intelligent Engineering and Systems*, vol. 10, no. 4, pp. 91–99, 2017, doi: 10.22266/ijies2017.0831.10.

[5] A. Kwarteng, “The impact of budgetary planning on resource allocation: evidence from a developing country,” *African Journal of Economic and Management Studies*, vol. 9, no. 1, pp. 88–100, 2018, doi: 10.1108/AJEMS-03-2017-0056.

[6] Z. B. S. Hamid, R. Rajikan, S. M. Elias, and N. A. Jamil, "Utilization of a diet optimization model in ensuring adequate intake among pregnant women in Selangor, Malaysia," *International Journal of Environmental Research and Public Health*, vol. 16, no. 23, 2019, doi: 10.3390/ijerph16234720.
[7] M. Shah, M. Hasan, and A. Afeworki, "Cost-efficient child vaccination project results from hard-to-reach rural communities in Kenya," *European Journal of Public Health*, vol. 33, 2023, doi: 10.1093/eurpub/ckad160.1375.
[8] Nikmawati *et al.*, "Analysis of household economic conditions and community habits on the incidence of anemia in pregnant women through household nutrition management in the working area of the Salugatta Health Center, Central Mamuju Regency," in *Proceedings of the International Conference on Industrial Engineering and Operations Management*, 2021, pp. 3324–3331. doi: 10.46254/SA02.20210904.
[9] M. J. Geiger, "MOOPPS: an optimization system for multi objective scheduling," *arXiv-Computer Science*, pp. 1–6, 2008.
[10] E. M. Porras, A. C. Fajardo, and R. P. Medina, "Solving dietary planning problem using particle swarm optimization with genetic operators," in *Proceedings of the 3rd International Conference on Machine Learning and Soft Computing*, 2019, pp. 55–59. doi: 10.1145/3310986.3311005.
[11] M. A. Megatama, W. F. Mahmudy, and E. Santoso, "Food menu recommendations based on recommended dietary allowances using genetic algorithm," *Bulletin of Culinary Art and Hospitality*, vol. 1, no. 2, pp. 70–77, 2021, doi: 10.17977/um069v1i22021p70-77.
[12] A. Fajar and R. Sarno, "Optimization of time and cost of multi organization business processes in a port container terminal," *International Journal of Intelligent Engineering and Systems*, vol. 12, no. 6, pp. 259–271, 2019, doi: 10.22266/ijies2019.1231.25.
[13] A. S. Chandrashekhar, N. M. Chandrashekarappa, P. B. Hanumanthagowda, and A. M. Bongale, "Multi objective prairie DoG optimization algorithm for task scheduling and load balancing," *International Journal of Intelligent Engineering and Systems*, vol. 17, no. 2, pp. 585–594, 2024, doi: 10.22266/ijies2024.0430.47.
[14] D. Suganthi and A. Geetha, "Predicting postpartum depression with aid of social media texts using optimized machine learning model," *International Journal of Intelligent Engineering and Systems*, vol. 17, no. 3, pp. 417–427, 2024, doi: 10.22266/ijies2024.0630.33.
[15] M. A. Jamaludin and S. F. Sufahani, "Nutritious menu and nutrient planning for avoiding stroke disease by using optimization technique," in *Proceedings of the Third International Conference on Trends in Computational and Cognitive Engineering*, 2022, pp. 45–56. doi: 10.1007/978-981-16-7597-3_4.
[16] E. Segredo, G. Miranda, J. M. Ramos, C. Leon, and C. Rodriguez-Leon, "SCHOOLTHY: automatic menu planner for healthy and balanced school meals," *IEEE Access*, vol. 8, pp. 113200–113218, 2020, doi: 10.1109/ACCESS.2020.3003067.
[17] A. B. Khoshaim, "A linear programming optimization model for a diet program," *Review of Business & Finance Studies*, vol. 12, no. 1, pp. 31–39, 2021.
[18] D. Kurnianingtyas, N. Daud, I. Indriati, and L. Muflikhah, "Comparison genetics algorithm and particle swarm optimization in dietary recommendations for maternal nutritional fulfillment," *Jurnal Sains dan Teknologi Industri*, vol. 21, no. 2, p. 216, 2024, doi: 10.24014/sitekin.v21i2.28937.
[19] D. Kurnianingtyas, Indriati, and L. Muflikhah, "Application of artificial intelligence for maternal and child disorders in Indonesia: a review," 2024, pp. 289–306. doi: 10.1007/978-981-99-7240-1_23.
[20] N. Daud and D. Kurnianingtyas, "Food image classification for maternal nutritional fulfillment using MobileNet," in *2024 IEEE International Conference on Communication, Networks and Satellite (COMNETSAT)*, Nov. 2024, pp. 529–535. doi: 10.1109/COMNETSAT63286.2024.10862862.
[21] M. Han, Z. Du, K. F. Yuen, H. Zhu, Y. Li, and Q. Yuan, "Walrus optimizer: A novel nature-inspired metaheuristic algorithm," *Expert Systems with Applications*, vol. 239, 2024, doi: 10.1016/j.eswa.2023.122413.
[22] M. Zhang and G. Wen, "Duck swarm algorithm: theory, numerical optimization, and applications," *Cluster Computing*, vol. 27, no. 5, pp. 6441–6469, 2024, doi: 10.1007/s10586-024-04293-x.
[23] M. Said, E. H. Houssein, E. A. Aldakheel, D. S. Khafaga, and A. A. K. Ismaeel, "Performance of the Walrus optimizer for solving an economic load dispatch problem," *AIMS Mathematics*, vol. 9, no. 4, pp. 10095–10120, 2024, doi: 10.3934/math.2024494.
[24] W. Yi, R. Qu, L. Jiao, and B. Niu, "Automated design of metaheuristics using reinforcement learning within a novel general search framework," *IEEE Transactions on Evolutionary Computation*, vol. 27, no. 4, pp. 1072–1084, 2023, doi: 10.1109/TEVC.2022.3197298.
[25] L. Chen, T. Wu, Z. Wang, X. Lin, and Y. Cai, "A novel hybrid BPNN model based on adaptive evolutionary artificial bee colony algorithm for water quality index prediction," *Ecological Indicators*, vol. 146, 2023, doi: 10.1016/j.ecolind.2023.109882.
[26] Z. Halim *et al.*, "An effective genetic algorithm-based feature selection method for intrusion detection systems," *Computers and Security*, vol. 110, 2021, doi: 10.1016/j.cose.2021.102448.
[27] B. Wang, X. Cui, J. Sun, and Y. Gao, "Parameters optimization of central pattern generators for hexapod robot based on multi-objective genetic algorithm," *International Journal of Advanced Robotic Systems*, vol. 18, no. 5, 2021, doi: 10.1177/17298814211044934.
[28] S. Bahirje and V. Potdar, "Review paper on implementation of particle swarm optimization for multi-pass milling operation," *International Journal of Engineering Research and*, vol. 9, no. 9, pp. 237–239, 2020, doi: 10.17577/IJERTV9IS090153.
[29] J. Fang, W. Liu, L. Chen, S. Lauria, A. Miron, and X. Liu, "A survey of algorithms, applications and trends for particle swarm optimization," *International Journal of Network Dynamics and Intelligence*, vol. 2, no. 1, pp. 24–50, 2023, doi: 10.53941/ijndi0201002.
[30] P. Stoker, G. Tian, and J. Y. Kim, "Analysis of variance (ANOVA)," in *Basic Quantitative Research Methods for Urban Planners*, London, United Kingdom: Routledge, 2020, pp. 197–219. doi: 10.4324/9780429325021-11.
[31] A. Nanda, B. B. Mohapatra, A. P. K. Mahapatra, A. P. K. Mahapatra, and A. P. K. Mahapatra, "Multiple comparison test by Tukey's honestly significant difference (HSD): Do the confident level control type I error," *International Journal of Statistics and Applied Mathematics*, vol. 6, no. 1, pp. 59–65, 2021, doi: 10.22271/maths.2021.v6.i1a.636.
[32] I. Negrin, D. Roose, and E. Chagoyen, "Parameter tuning strategies for metaheuristic methods applied to discrete optimization of structural design," *Revista Investigación Operacional*, vol. 43, no. 2, pp. 241–258, 2022.
[33] J. Zheng, J. Ning, H. Ma, and Z. Liu, "A dynamic parameter tuning strategy for decomposition-based multi-objective evolutionary algorithms," *Applied Sciences*, vol. 14, no. 8, 2024, doi: 10.3390/app14083481.
[34] B. Alhijawi and A. Awajan, "Genetic algorithms: theory, genetic operators, solutions, and applications," *Evolutionary Intelligence*, vol. 17, no. 3, pp. 1245–1256, 2024, doi: 10.1007/s12065-023-00822-6.
[35] M. H. Nasir, S. A. Khan, M. M. Khan, and M. Fatima, "Swarm intelligence inspired intrusion detection systems — a systematic literature review," *Computer Networks*, vol. 205, 2022, doi: 10.1016/j.comnet.2021.108708.
[36] S. Cheng, L. Ma, H. Lu, X. Lei, and Y. Shi, "Evolutionary computation for solving search-based data analytics problems," *Artificial Intelligence Review*, vol. 54, no. 2, pp. 1321–1348, 2021, doi: 10.1007/s10462-020-09882-x.

[37] J. Tang, H. Duan, and S. Lao, “Swarm intelligence algorithms for multiple unmanned aerial vehicles collaboration: a comprehensive review,” *Artificial Intelligence Review*, vol. 56, no. 5, pp. 4295–4327, 2023, doi: 10.1007/s10462-022-10281-7.

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