Journal of Food Composition and Analysis 145 (2025) 107850

Contents lists available at ScienceDirect

Journal of Food Composition and Analysis

journal homepage: www.elsevier.com/locate/jfca

Nutritional analysis of AI-generated diet plans based on popular online diet trends

Hatice Merve Bayram [a,1], Sedat Arslan [b,*,2]

[a] Istanbul Gelisim University, Faculty of Health Sciences, Department of Nutrition and Dietetics, Istanbul, Turkey

[b] Department of Nutrition and Dietetics, Bandirma Onyedi Eylul University, Balikesir, Turkey

ARTICLE INFO

Keywords:
Artificial intelligence
Diet analysis
Popular diets
The Mediterranean diet
Raw diet
Vegetarian diet
Low sodium diet
High protein diet

ABSTRACT

This study aimed to evaluate the nutritional composition and consistency of 1500 kcal daily diet plans generated by four generative Artificial Intelligence (AI) tools (ChatGPT-4, ChatGPT-4o, Mistral, and Claude) based on five popular diet types identified via Google Trends (keto, paleo, Mediterranean, intermittent fasting, and raw). Each AI model was prompted with standardized requests, and the resulting menus were analyzed using Nutrition Information System (BeBIS) (version 9.0) to determine energy, macronutrient, and micronutrient content. Nutrient composition differences across AI tools were statistically assessed using SPSS 24.0 (ANOVA, $p < 0.05$). Results showed significant variations between AI outputs, with energy values ranging from 1357 kcal to 2273 kcal and protein intake varying by up to 65 g across models. Notable inconsistencies were also found in micronutrients such as calcium, iron, and vitamin D. AI models often failed to meet targeted caloric levels and showed inconsistent adherence to diet-specific nutrient profiles. These discrepancies suggest limitations not only in the AI tools' capabilities but also in their interpretation of user prompts. The findings highlight the need for improved prompt design, database integration, and AI training for safe and reliable use in personalized nutrition.

1. Introduction

In the digital age, interest in health and nutrition has surged rapidly, fueled by the proliferation of online information sources. Reflecting this growing interest, popular diets have had a significant impact both individually and socially, spreading quickly among people seeking a healthy lifestyle. Google Trends has emerged as a powerful tool for tracking these changes in interest over time (Nuti et al., 2014). Since 2004, Google Trends has been analyzing the relative volume of specific search terms, revealing the periods when popular diets garnered more attention and how this interest has evolved (Nuti et al., 2014; Bayram and Ozturkcan, 2023).

Popular diets, often disseminated widely through media and social media, directly influence people's eating habits. However, important questions arise regarding the scientific validity and long-term health effects of these diets (Gardner et al., 2023). Recent research, particularly over the past few years, has indicated that while popular diets may provide short-term weight loss benefits, they could also have negative long-term health consequences, including nutrient deficiencies (such as vitamins, minerals, and essential fatty acids), hormonal imbalances, increased cardiovascular risk due to unfavorable lipid profiles, impaired bone health from inadequate calcium and vitamin D intake, gastrointestinal disturbances, and potential adverse impacts on mental health, including increased anxiety or eating disorders (Herreman et al., 2020; Rutherfurd et al., 2015). The integration of artificial intelligence (AI) into healthcare and nutrition is progressing rapidly. Recent reviews have highlighted AI's growing role in clinical nutrition practices, particularly in managing conditions such as diabetes and obesity, as well as in monitoring dietary intake and health metrics via digital technologies and mobile applications (Bayram and Ozturkcan, 2023; Salinari et al., 2023).

Machine Learning and Large Language Models (LLMs) are both subsets of AI, but they differ in scope and application and require different approaches to understanding and applying AI. Machine learning involves algorithms that allow computers to learn from data and make predictions or decisions without being explicitly programmed. These algorithms can be trained on various tasks such as image recognition, natural language processing, and predictive analytics (Hao and

* Corresponding author.
E-mail addresses: merve.bayrm@gmail.com (H.M. Bayram), sarslan@bandirma.edu.tr, sedatarslan89@gmail.com (S. Arslan).
[1] https://orcid.org/0000–0002-7073–2907
[2] 0000–0002-3356–7332

https://doi.org/10.1016/j.jfca.2025.107850
Received 7 December 2024; Received in revised form 25 March 2025; Accepted 26 May 2025
Available online 27 May 2025
0889-1575/

Li, 2022). On the other hand, large language models like ChatGPT-4, Claude 3.5 Somet, Mistral Large 2, and Llama 3.1 405B are a specific type of machine learning model that focuses on understanding and generating human-like text. These models are trained on vast amounts of text data to learn the nuances of language, enabling them to generate responses that are coherent and relevant to the context (Hamaniuk, 2021). Beyond mere algorithms, these AI models represent the pinnacle of human creativity and technological advancement (Tai, 2020). These models are capable of analyzing large amounts of data, learning complex patterns, and producing consistent outcomes (Tai, 2020). While AI's integration into diverse sectors like finance and transportation is well documented, its potential in healthcare is arguably the most revolutionary (Aung et al., 2021; Quarajeh et al., 2023).

AI can create customized diet plans by considering various factors such as an individual's eating habits, genetic makeup, and health goals (Salinari et al., 2023; Arslan, 2024). However, the accuracy and scientific foundation of AI-generated diet recommendations remain underexplored (Arslan, 2023). As AI tools become increasingly accessible to the public for health-related queries, concerns have emerged regarding the scientific accuracy and nutritional appropriateness of their outputs. Therefore, our study aims to examine how popular diets identified through Google Trends data are addressed by five different AI models (ChatGPT-4o, ChatGPT-4, Claude 3.5 Somet, Mistral Large 2, and Llama 3.1 405B) and to analyze the macro- and micronutrients of three-day sample menus provided by these models. The primary purpose of this study was to evaluate how accurately popular AI assistants generate standardized diet plans when prompted by users without professional training. The study was designed to simulate a layperson or general consumer interacting with AI to receive nutrition advice, particularly in the absence of professional dietary guidance. Therefore, the menus were not intended for direct implementation in clinical or institutional settings, but rather to assess the reliability of AI tools as general-purpose, consumer-facing sources of dietary information. Understanding the consistency and scientific adequacy of these outputs is essential for determining whether AI systems can be considered dependable aids in public nutrition literacy. A practical level of reliability was assumed to involve alignment with known macronutrient ranges and energy targets as outlined in dietary guidelines.

2. Materials and methods

2.1. Study design

In this content analysis and comparative study, we analyzed the effectiveness of AI models in accurately aggregating information about the sample menus in selected diet models according to Google Trends. The AI models analyzed include ChatGPT-4o, Claude 3.5 Somet, ChatGPT-4, Mistral Large 2, and Llama 3.1 405B.

2.2. Google trends tool

Google Trends (https://trends.google.com/trends/) is a freely available online tool that allows the analysis of a selected expression, in a chosen region and period since January 2004. Google Trends enabled the comparison of up to five terms at once.

The tool provides an estimate of the relative search volume (RSV) of queries that are made using the Google search engine. RSV is an index of search volume in relation to the number of Google users in a particular geographic area and time interval. RSV ranges from 0 to 100, with 100 representing peak popularity (100 % of popularity in a given time and place) and 0 representing total disinterest (0 % of popularity in a given time and place) [1, 2 14].

Google Trends may qualify analyzed phrases as "search term" or "topic." Search terms are literal typed words, whereas Google Trends may suggest topics when it recognizes phrases linked to popular queries. Topics allow for easy comparison of the provided term across countries. For example, Google Trends will analyze the search term "diet" literally; thus, RSV will be highest in English-speaking countries, whereas the topic "diet" will include all queries linked with the query in all available languages (Bayram and Ozturkcan, 2023; Kamiński et al., 2020).

2.2.1. Google trends data

We used Google Trends to collect data from 01 January 2004–26 August 2024. Searches were conducted independently for each selected country using the filters "Country," "All Categories," and "Web Searches." Searches were selected "Worldwide" in the "Country" section. Popular dietary terms in English were searched individually using the "All Categories" and "Web Searches" filters.

The selection of specific diet terms analyzed through Google Trends was made considering both their popularity and scientific validity. To support this process, current literature was reviewed to identify diets that have been widely studied and associated with both health outcomes and media attention. Studies examining the nutritional composition, sustainability, clinical applications, and health impacts of these diets informed the final selection (Kamiński et al., 2020; Alphan, 2016; Shukla et al., 2019; Freire, 2020; American Heart Association Council on Lifestyle and Cardiometabolic Health, 2023). These references guided the inclusion of terms that are not only popular in public interest but also grounded in scientific evidence. The search terms are as follows: "Mediterranean diet", "Japanese diet", "Nordic diet", "DASH diet", "Pesketarian diet", "Vegetarian diet", "Frutarian diet", "Vegan diet", "FODMAP diet", "Low glycaemic index diet", "Low sodium diet", "Intermittent fasting", "Atkins diet", "GAPS diet", "Paleolithic diet", "Gluten-free diet", "Alkaline diet", "Swedish diet", "Kushan diet", "Low-fat diet", 'South beach diet', "Pritikin diet", "Egg diet", "Cabbage diet", "Yogurt cure diet", "Apple cider vinegar diet", "Leptin diet", "Rice diet", "Raw diet", "Raw food diet", "Low carb diet", "Ketogenic diet, "Low protein diet", "High protein diet", "Zone diet", "Liquid diet", "Blood group diet", "Low fiber diet", "Detox diet", "Water diet", and "Elimination diet". We excluded "Nordic diet" because there was no RSV associated with it. The mean RSVs of diet terms according to Google Trends were given in Table 1.

Although energy-restricted or weight-loss diets are common in clinical and lifestyle contexts, they were excluded as search terms in this study because they do not refer to a specific, well-defined dietary pattern. Instead, our focus was on named diets that have distinct compositions and dietary guidelines, enabling standardized comparison across AI-generated menus. This approach ensured terminological specificity and methodological consistency.

2.3. Assessment of AI model performance

In scientific research, the accuracy, reliability, and depth of the model's responses are crucial. Quality-focused models are more likely to provide nuanced and accurate information, which is essential for rigorous analysis and valid results in scientific contexts. Therefore, we used the "Artificial Analysis Quality Index" for selecting the top 5 AI models. According to this index, ChatGPT-4o was in the first rank. This was followed by Claude 2.5 Somet, ChatGPT-4, Mistra Large 2, and Llama 3.1 405B (Artifical Analysis, 2024). We initially selected the top five most searched diet terms in Google Trends to create diet plans by AI. The "Liquid diet" had the second highest mean RSV; we excluded it because it is a very low-calorie diet. Similarly, we excluded "Raw food diet" due to the same term as "Raw diet." Although the Mediterranean diet was not among the top five in terms of average RSV, it was included due to its well-established evidence base supporting long-term health benefits and sustainability. It is frequently endorsed by global health authorities such as the FAO and WHO (FAO and WHO, 2019), making it a representative example of a scientifically validated and globally recommended dietary pattern. In contrast, although other diets like DASH also meet clinical criteria, their Google Trends popularity was significantly lower at the time of analysis, justifying their exclusion based on

Table 1
Mean RSV of diet terms according to Google Trends.

Diet terms	Mean RSV
Raw diet	62.48
Liquid diet	55.36
Vegetarian diet	53.86
Low-sodium diet	51.09
High protein diet	49.00
Raw food diet	42.30
Low fibre diet	41.96
Low-protein diet	40.87
Elimination diet	39.22
FODMAP diet	38.95
Low-carb diet	34.27
Detox diet	33.51
Japanese diet	33.02
Low-fat diet	32.53
Vegan diet	30.54
Mediterranean diet	30.28
GAPS diet	28.72
Paleolithic diet	27.15
Gluten-free diet	26.97
Alkaline diet	25.41
Intermittent fasting	23.23
Cabbage diet	22.67
Blood group diet	20.92
DASH diet	20.77
Egg diet	17.81
Ketogenic diet	17.22
Pritikin diet	16.05
Leptin diet	15.27
Swedish diet	11.66
Zone diet	11.05
Rice diet	7.96
South beach diet	7.20
Apple cider vinegar diet	5.68
Atkins diet	5.57
Frutarian diet	0.65
Yogurt cure diet	0.44
Pesketarianism	0.40
Low glycaemic index diet	0.40
Kushan diet	0.40

the dual criteria of popularity and scientific validity.

According to the characteristics of these diets, we planned sample menus of 1500 kcal per day. The energy level of 1500 kcal was selected as it is a commonly used caloric target in dietary planning for adults, particularly in weight management contexts. This energy level allows for meaningful comparison of macronutrient and micronutrient distribution across various diet types, while remaining within a safe and realistic range for adult individuals. It also facilitates the identification of nutrient inadequacies or excesses that may result from AI-generated recommendations. ChatGPT-4o, ChatGPT-4, Claude 3.5, Somet, and Mistral Large 2 were used to generate AI-based diet plans on August 26, 2024. We refreshed the model before the first input and provided two key sentences consecutively, without any refreshing between the inputs. The outputs were converted into plain text. To standardize the interaction with AI models, we used a two-step prompting method. First, the model was refreshed. Then, two consecutive prompt sentences were entered without further refresh. The base sentence used was: 'Create a 1500 kcal [diet type] sample menu for three days.' (Supplementary Tables 1, and 2). However, this sentence did not explicitly include considerations of seasonality, food accessibility, or cultural eating patterns. This was a deliberate decision to evaluate the default outputs of AI models based on minimal prompts, simulating a typical consumer or non-specialist usage scenario.

2.3.1. Evaluation of outputs

To enhance the transparency of our findings, the full 3-day sample menus generated by each AI model for the five selected diets are provided in Supplementary Tables 1 and 2. These tables include detailed food items, portion sizes, and meal distributions, enabling comparison not only at the nutrient level but also regarding food variety and dietary appropriateness.

The diet plans generated by the AI models were evaluated in a more comprehensive manner to ensure a thorough assessment. Specifically, the analysis focused on comparing the nutritional composition, caloric values, and the balance of macro and micronutrients across the diet plans produced by different models. This comparison was essential to determine the quality of the AI-generated diet plans. The diet plans were not retrieved from pre-existing databases but were directly created by AI models in response to standardized prompts. The nutrient analysis of AI-generated menus was conducted using the Turkish version of the Nutrition Information System (BeBİS, EBISpro for Windows, Willstaett, Germany; Turkish Version, BeBiS 9), a validated software widely used in nutritional studies in our country. All menus were entered manually by two trained dietitians without modifications. BeBiS includes a comprehensive Turkish nutrient database and calculates the macro- and micronutrient content based on standard food composition tables. The same protocol was applied to all AI-generated menus to ensure consistency.

2.4. Statistical analyses

Data was analysed using SPSS 24.0. We used descriptive statistical techniques to summarize how the AI models performed in defining the diet models. The difference between AI models in the macronutrient content of the 3-day sample menu of each diet model was tested using the Kruskal-Wallis test. A p-value ≤ 0.05 was considered statistically significant for the statistical test.

3. Results

Table 2 shows the mean energy and macronutrients of diets according to different AI models' analysis. Mistral Large 2 is the AI assistant that gives the highest energy value in all diet models except the Mediterranean diet. There were differences in energy and fat values between the 5 AIs on the raw diet (p: 0.012, p: 0.005, respectively). The groups with differences for energy and fat were ChatGPT-4o and ChatGPT-4, Mistral Large 2; ChatGPT-4o and ChatGPT-4, Mistral Large 2, and Claude 3.5 Somet; ChatGPT-4 and Mistral Large 2, Llama 3.1 405B, and Mistral Large 2 and Llama 3.1 405B. Statistical difference was found for energy, carbohydrate, and fiber for the vegetarian diet (p: 0.025, p: 0.003, p: 0.023, respectively). There was a significant difference between Mistral Large 2 and ChatGPT-4o and ChatGPT-4 for energy and carbohydrate. The 5 AIs for the low sodium diet showed statistical differences in energy, and the difference was between ChatGPT4 and Mistral Large 2 (p: 0.022). A high-protein diet showed statistical differences in terms of energy, protein, and fiber (p: 0.017, p: 0.019, p: 0.027, respectively). The groups with statistical differences were Mistral Large 2 and Claude 3.5 Somet and ChatGPT4 for energy; Mistral Large 2 and ChatGPT4o and Claude 3.5 Somet for protein; Claude 3.5 Somet and ChatGPT4 for fiber. Energy, protein, and fat showed statistical differences in the low-fiber diet (p: 0.017, p: 0.035, p: 0.008, respectively). The statistical difference for energy was between Mistral Large 2 and Claude 3.5 Somet and ChatGPT-4; for protein between ChatGPT-4 and Mistral Large 2, Llama 3.1 405B and ChatGPT-4 and Mistral Large 2; for fibre between Claude 3.5 Somet and ChatGPT-4. Energy, fat, carbohydrate, and fiber for the Mediterranean diet showed a statistical difference between the 5 AIs (p: 0.031, p: 0.018, p: 0.002, p: 0.019, respectively). For energy and carbohydrate, the differences were between Claude 3.5 Somet and ChatGPT-4 and Mistral Large 2; for fat between Claude 3.5 Somet and ChatGPT-4 and Mistral Large 2; between ChatGPT-4 and Mistral Large 2; for fiber between Claude 3.5 Somet and ChatGPT-4, Mistral Large 2 and Llama 3.1 405B. Notably, in the case of the raw diet, Mistral Large 2 generated a sample menu with a total energy content exceeding 2200 kcal, despite the explicit instruction

Table 2
The mean energy and macronutrients of diets according to different AI assistant analyses.

	ChatGPT-4o	Claude 3.5 Somet	ChatGPT-4	Mistral Large 2	Llama 3.1 405B	p-value
Raw diet						
Energy (kcal)	1479.46[b,c]	1375.23[e,f]	1055.61[b,e, i,j]	2235.62[c,f, i,h]	1361.60[j,h]	**0.012***
Protein (g)	36.76	44.63	37.79	58.45	49.45	0.122
Fat (g)	95.13[b,c]	91.06[e,f]	48.01[b,e, i,j]	134.86[c,f,i,h]	67.37[j,h]	**0.005***
Carbohydrate (g)	117.65	92.28	113.60	197.75	138.88	0.117
Fiber (g)	41.88	45.00	31.54	61.35	60.07	0.410
Vegetarian diet						
Energy (kcal)	1383.47[c]	1657.56	1394.92[i]	1804.63[c,i]	1723.00	**0.025***
Protein (g)	69.1	70.06	62.60	77.47	67.87	0.051
Fat (g)	54.15	45.15	55.24	53.83	50.51	0.980
Carbohydrate (g)	151.62[c]	237.62	156.11[i]	243.55[c, i]	242.75	**0.003***
Fiber (g)	28.69[i,d]	43.14	35.57[i,j]	51.76[c,i]	59.25	**0.023***
Low-sodium diet						
Energy (kcal)	1543.3	1473.66	1300.29[i]	1624.68[i]	1266.06	**0.022***
Protein (g)	74.84	74.62	67.62	82.66	73.35	0.188
Fat (g)	72.97	59.24	51.96	72.76	47.52	0.225
Carbohydrate (g)	139.37	155.87	139.10	152.55	132.52	0.872
Fiber (g)	36.74	34.35	36.51	31.45	24.70	0.054
High-protein diet						
Energy (kcal)	1710.56	1318.1 [f]	1436.99[i]	1762.91 [f,i]	1261.70	**0.017***
Protein (g)	113.31[c]	98.75 [f]	83.84	117.00[c,f]	88.35	**0.019***
Fat (g)	65.7	55.51	54.21	77.59	52.34	0.0893
Carbohydrate (g)	160.98	100.35	145.86	139.29	107.13	0.666
Fiber (g)	61.53	19.98[e]	35.22[e]	29.84	17.68	**0.027***
Low-fiber diet						
Energy (kcal)	1456.03	1673.41	1749.35	2133.68	1588.46	0.598
Protein (g)	90.93[c]	88.44	86.31[c, i,j]	100.41[i]	92.04[j]	**0.035***
Fat (g)	35.91[a,c]	73.42[a]	45.70	71.87[c]	65.26	**0.008***
Carbohydrate (g)	185.53	160.22	239.75	261.11	153.40	0.203
Fiber (g)	9.6	12.51	13.32	14.16	6.41	1.000
Mediterranean diet						
Energy (kcal)	1459.36	1183.15[e,f]	1496.44[e]	1491.49 [f]	1189.17	**0.031***
Protein (g)	64.81	56.81	69.1	74.23	65.63	0.076
Fat (g)	65.02[c]	58.92[e,f]	68.58[e]	71.09[c,f]	54.52	**0.018***
Carbohydrate (g)	153.08	81.97[e,f]	147.23[e]	135.71 [f]	108.14	**0.002***
Fiber (g)	31.86	18.24[e,f,g]	31.96[e]	34.18 [f]	19.89 [g]	**0.019***

* p < 0.05, * *p < 0.001. [a] Differences between ChatGPT-4o and Claude 3.5 Somet, [b] Differences between ChatGPT-4o and ChatGPT-4, [c] Differences between ChatGPT-4o and Mistral Large 2, [d] Differences between ChatGPT-4o and Llama 3.1 405B, [e] Differences between Calude 3.5 Somet and ChatGPT-4, [f] Differences between Claude 3.5 Somet and Mistral Large 2, [g] Differences between Claude 3.5 Somet and Llama 3.1 405B, [h] Differences between Mistral Large 2 and Llama 3.1 405B, [i] Differences between Mmistral Large 2 and ChatGPT-4, [j] Differences between Llama 3.1 405B and ChatGTP 4

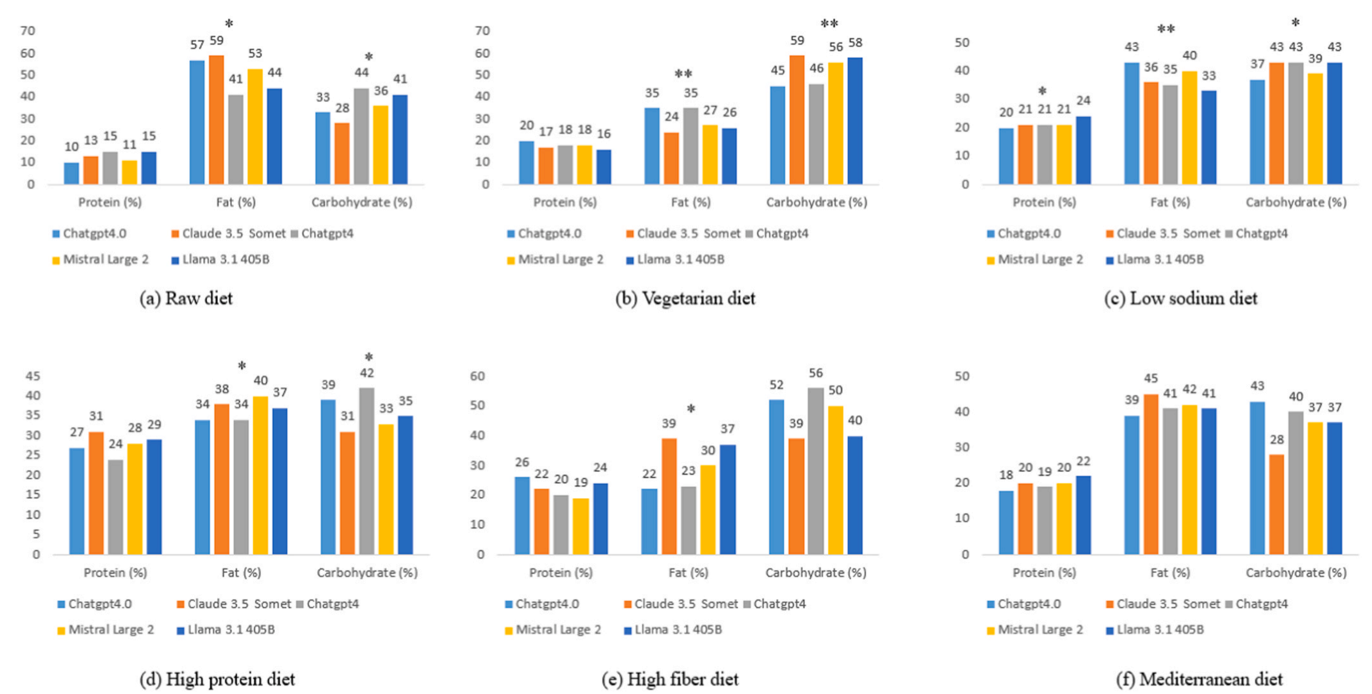

Fig. 1. Macronutrient percentage of the diets according to different AI assistant analyses (*p < 0.05, **p < 0.001).

for a 1500 kcal plan. This significant deviation illustrates a failure of the AI model to adhere to caloric constraints, which is a key practical limitation of current AI-driven dietary tools.

Fig. 1 shows the macronutrient percentage of the diets according to different AI assistant analyses. The protein percentages between AI models are generally close to each other, and there is a statistical difference between AI models only on the low sodium diet (p: 0.001). The Llama 3.1 405B model offered the highest percentage of protein overall (giving the highest values for the raw diet, low-sodium diet, and Mediterranean diet). In contrast, there were marked differences in fat percentage distribution among AI models. The Claude 3.5 Somet model showed the highest value for the raw diet, high fiber diet and Mediterranean diet (59 %, 39 % and 45 %), ChatGPT-4 and ChatGPT-4o for the vegetarian diet (35 %), ChatGPT-4o for the low sodium diet (43 %), Mistral Large 2 for the high protein diet (40 %). There was a statistical difference between the fat percentages of all diets except the Mediterranean diet (p: 0.003 for the raw diet, $p < 0.001$ for the vegetarian diet, $p < 0.001$ for the low-sodium diet, p: 0.003 for the high-protein diet, and p: 0.006 for the low-fiber diet). ChatGPT-4 had the highest percentage of carbohydrate on the raw diet (44 %), high-protein diet (42 %), and high fibre diet (56 %), Claude 3.5 Somet and ChatGPT-4o on the low-sodium diet (43 %), and ChatGPT-4o on the Mediterranean diet (43 %). There were statistical differences between AI models for carbohydrate percentages on the raw diet (p: 0.08), vegetarian diet ($p < 0.001$), low-sodium diet (p: 0.005), and high-protein diet (p: 0.006).

Table 3 shows the mean micronutrients of diets according to different AI model analyses. For the raw diet, SFA (p: 0.023), PUFA (p: 0.049), Vitamin K (p: 0.026), Vitamin C (p: 0.009), Vitamin B5 (p: 0.038), sodium (p: 0.013), calcium (p: 0.011), iron (p: 0.029) and zinc (p: 0.036) showed significant difference between the 5 AI models. SFA (p: 0.037), vitamin A (p: 0.007), vitamin C (p: 0.009), folic acid (p: 0.033), vitamin B5 (p: 0.015), biotin (p: 0.001), vitamin B12 (p: 0.022), sodium (p: 0.001), potassium (p: 0.005) for the vegetarian diet were statistically different between the 5 AIs. SFA (p: 0.031), vitamin A (p: 0.00), vitamin K (p: 0.024), vitamin C (p: 0.008), sodium (p: 0.012), calcium (p: 0.019), and iron (p: 0.005) showed statistical difference in the low-sodium diet. SFA (p: 0.019), PUFA (p: 0.034), MUFA (p: 0.029), vitamin A ($p < 0.001$), vitamin E (p: 0.011), vitamin K (p: 0.006), vitamin C (p: 0.027), folic acid (p: 0.047), niacin (p: 0.022), vitamin B5 (p: 0. 022), vitamin B12 (p: 0.004), sodium (p: 0.007), potassium (p: 0.012), calcium (p: 0.009), magnesium (p: 0.028), phosphorus (p: 0.034), iron (p: 0.018) and zinc (p: 0.024) were statistically different among the 5 AIs. SFA (p: 0.016), MUFA (p: 0.033), vitamin A (p: 0.007), vitamin E (p: 0.007), vitamin K (p: 0.008), vitamin C (p: 0.009), vitamin B12 (p: 0. 031), sodium (p: 0.009), potassium (p: 0.019), calcium (p: 0.018) and zinc (p: 0.017) were statistically different among the 5 AI models. For the Mediterranean diet, PUFA (p: 0.045), vitamin A (p: 0.009), vitamin E (p: 0.045), vitamin K (p: 0.002), vitamin C (p: 0.039), niacin (p: 0. 034), vitamin B5 (p: 0.033), sodium (p: 0.003), calcium (p: 0.043), phosphorus (p: 0.023), iron (p: 0.035) and zinc (p: 0.046) were statistically different.

4. Discussion

The use of AI assistants is growing rapidly, permeating many aspects of people's personal and professional lives (Makridakis, 2017; Olhede and Wolfe, 2018). The development of AI assistants also offers new opportunities for research on nutrients and nutrients that are important for individuals in terms of nutrition/health (Bayram and Ozturkcan, 2024). Nowadays, AI-supported assistants are becoming increasingly common, and understanding their ability to create dietary models according to diet types and the contents of these models is crucial for their integration into daily life as well as medical treatment. In this study, for the first time, the content of dietary models created by the five AI models with the highest analysis quality index was analyzed. Although the energy and macronutrient contents of the AI models varied after the command to create a 1500 kcal diet model, significant differences were observed for energy, protein, fat, and fiber values across various diet models. Mistral Large 2 was generally found to have a higher energy value in the diet models, particularly in high-protein and low-fiber diets. Llama 3.1 405B provided a higher protein percentage value in 3 of the diet models, while Claude 3.5 Somet had a higher fat percentage value than 3 of the diet models. In particular, ChatGPT-4 suggested higher carbohydrate percentages in most diet categories (raw diet, high protein diet, high fiber diet, and low sodium diet). The relatively small differences in macronutrient distribution observed across models suggest that some AI systems may be prioritizing a balanced dietary template rather than strictly targeting the requested energy level. This may reflect internal design preferences of the models, which favor conventional food group distributions over strict energy matching. Despite the 1500 kcal instruction, some AI models, such as Mistral Large 2, consistently produced higher energy values, possibly due to limited understanding of energy-density or underestimation of portion sizes. While some of these differences were statistically significant, they may not always be practically relevant. For instance, a difference of 3–5 g in protein or 20–30 kcal in energy is unlikely to have a meaningful impact in the context of a 1500 kcal diet. Therefore, we considered differences to be practically relevant when they exceeded $\pm$ 10 % of the total energy contribution from macronutrients or when essential micronutrients fell below recommended dietary reference values. This combined evaluation—statistical and practical—was critical for assessing the real-world applicability of the AI-generated menus.

The raw (food) diet is a growing phenomenon that not only challenges the daily practices of individuals. Neither a single practice nor a single philosophy, the raw food diet presents various forms of food exclusions and combinations that arise from different worldviews (Thircuir, 2020). A raw diet, often referred to as a raw food diet, is characterized by the consumption of unprocessed and uncooked foods, primarily consisting of fruits, vegetables, nuts, seeds, and sprouted grains (Abraham et al., 2022). Moreover, raw diets are often linked to enhanced intake of vitamins and antioxidants (Barad et al., 2020). For instance, our study found significantly higher values for vitamin C, vitamin K, and polyunsaturated fatty acids (PUFAs) in AI-generated raw diet menus ($p < 0.05$), particularly for Mistral Large 2 and Llama 3.1 405B. Raw diets are noted for their low-fat content and high fiber, which can help with weight management and overall health (Abraham et al., 2022; Barad et al., 2020). In this study, there were differences in the mean energy and macronutrients of raw diet menus written by AI models, and there were significant differences in the amounts and percentages of fat and carbohydrates. Fat percentages were also significantly higher. Additionally, key micronutrients like calcium and iron were inconsistently distributed across AI-generated menus, highlighting the variability in nutrient adequacy ($p < 0.05$). This underlines the need for continuous improvement and validation of dietary recommendations generated by AI. Despite the potential benefits, a raw food diet is not without its challenges. The lack of cooking can lead to reduced digestibility of some foods and may increase the risk of foodborne illness due to pathogens present in raw ingredients (Nüesch-Inderbinen et al., 2019). Furthermore, the restrictive nature of the diet may make it difficult for individuals to maintain a balanced nutrient intake in the long term (Cunningham, 2004). Importantly, one of the raw diet menus produced by Mistral Large 2 exceeded 2200 kcal, even though a 1500 kcal plan was requested. This clear deviation from the input highlights the model's inability to consistently follow user-specified constraints, which raises concerns regarding the reliability and safety of AI-generated dietary plans without expert supervision.

A vegetarian diet is defined by the exclusion of meat, poultry, and fish, while allowing for the consumption of plant-based foods and, depending on the specific type of vegetarianism, dairy products and eggs (Hargreaves et al., 2021). Research has shown that vegetarian diets can lead to numerous health benefits. For example, they are often associated with lower body mass index (BMI), lower cholesterol levels, better blood

Table 3
The mean of some micronutrients of diets according to different AI assistant analyses.

	ChatGPT-4o	Claude 3.5 Somet	ChatGPT-4	Mistral Large 2	Llama 3.1 405B	p-value
Raw diet						
SFA (g)	13.57^{b}	13.27^{e}	6.74^{b,e,i}	16.87^{i}	9.07	**0.023***
PUFA (g)	23.79	26.03	13.35^{i}	64.3^{i}	31.85	**0.049***
MUFA (g)	50.29	44.56	23.3	48.53	22.87	0.119
Vitamin A (µg)	3125.73	2510.45	2057.4	2948.33	3794.75	0.089
Vitamin E (mg)	41.38	33.1	27.99	50.37	27.86	0.119
Vitamin K (µg)	958.88^{a,b}	454.77^{a,f}	384.67^{b,i}	939.05^{f,i}	766.35	**0.026***
Vitamin C (mg)	262.11	234.41	152.31^{i,j}	421.49^{i}	501.27^{j}	**0.009***
Tiamin (mg)	1,95	1,11	1,73	2,11	1,66	0.987
Riboflavin (mg)	1,07	1,69	0,78	1,57	1,19	0.568
Vitamin B6 (mg)	2,47	2,03	1,72	3,72	2,41	0.321
Folic acid (µg)	542.02	411.19	338.64	833.9	704.85	0.069
Niacin (mg)	14.74	27.52	13.46	21.89	16.69	-
Vitamin B5 (mg)	2.53	7.87^{e}	1.7^{e,i}	4.18^{i}	3.71	**0.038***
Biotin (µg)	55.35	79.42	41.24	93.05	53.45	0.071
Vitamin B12 (µg)	0	0	0	0	0	-
Sodium (mg)	279.02^{a,c,d}	295.46^{a}	260.64	341.68^{c}	287.85^{d}	**0.013***
Potassium (mg)	4113.83	4673.44	3195.69	6613.7	4893.65	0.182
Calcium (mg)	798.68^{a}	606.27^{a,g}	626.93	781.64	851.35^{g}	**0.011***
Magnesium (mg)	451.35	455.29	445.99	684.47	593.5	0.721
Phosphorus (mg)	842.24	1118.87	856.55	1133.25	1209.2	0.219
Iron (mg)	13.37^{c,d}	13.45^{f,g}	14.87	19.73^{c,f}	20.14^{d,g}	**0.029***
Zinc (mg)	6.6^{c,d}	7.77	6.51^{i,j}	9.51^{c,i}	9.24^{d,j}	**0.036***
Vegetarian diet						
SFA (g)	9.13	6.4^{g}	8.4	7.7	9.44^{g}	**0.037***
PUFA (g)	15.35	11.14	17.76	19.41	13.3	0.731
MUFA (g)	26.36	22.49	21.99	20.74	19.69	0.638
Vitamin A (µg)	702.45^{a,b,c,d}	2204.1^{a,e,f,g}	2019.95^{b,e,i,j}	1673.6^{c,f,i,h}	1801.7^{d,g,j,h}	**0.007***
Vitamin E (mg)	32.49	31.9	40.98	24.04	27.72	0.111
Vitamin K (µg)	267.5	194.35	141.75	287.8	215.65	0.121
Vitamin C (mg)	165.32^{b}	110.96	84.12^{b,i,j}	328.75^{j}	302.04^{j}	**0.009***
Tiamin (mg)	1.11	1.53	1.15	1.84	1.98	0.988
Riboflavin (mg)	0.8	0.8	0.87	1.67	1.35	0.541
Vitamin B6 (mg)	1.32	2.11	1.44	2.08	2.17	0.438
Folic acid (µg)	372.35^{d}	446.2	509.0	486.85	587.65^{d}	**0.033***
Niacin (mg)	13.19	9.25	12.52	16.37	8.95	0.078
Vitamin B5 (mg)	19.93^{d}	23.65	11.83^{i,j}	30.31^{i}	32.94^{d,j}	**0.015***
Biotin (µg)	3.08^{c}	5.42^{f}	3.92^{i}	8.22^{cf,i,h}	6.57^{h}	**0.001***
Vitamin B12 (µg)	34.26^{c,d}	59.53	41.7^{j}	67.33^{c}	51.17^{d,j}	**0.022***
Sodium (mg)	225.12^{b,c}	465.05	737.54^{b}	733.38^{c}	602.65	**0.001***
Potassium (mg)	3226.86^{b,c,d}	3324.5^{e,f,g}	2319.9^{b,e,i,j}	4287.0^{c,f,i}	4178.35^{d,g,j}	**0.005***
Calcium (mg)	735.95^{a,b,c,d}	700.15^{a,e,f,g}	1046.18^{b,e,i,j}	868.06^{c,f,i,h}	940.65^{d,g,j,h}	**0.007***
Magnesium (mg)	547.43	566.6	469.15^{j}	603.25	653.1^{j}	**0.040***
Phosphorus (mg)	1485.62	1457.95	1309.69	1904.83	1812.35	0.051
Iron (mg)	16.73	21.32	16.4	21.62	21.83	0.136
Zinc (mg)	8.85	11.78	9.26	11.79	11.54	0.382
Low-sodium diet						
SFA (g)	13.69^{b,d}	11.01^{f}	9.7^{b,i}	15.38^{f,h,i}	9.25^{d,h}	**0.031***
PUFA (g)	17.11	16.4	13.97	17.36	10.91	0.089
MUFA (g)	33.97	26.23	24.34	33.85	23.36	0.060
Vitamin A (µg)	1600.65^{b}	2572.3^{e,g}	605.6^{b,e,i}	1936.3^{i}	1139.7^{g}	**0.009***
Vitamin E (mg)	37.17	22.78	16.04	23.3	16.78	0.117
Vitamin K (µg)	101.1^{a,b,c,d}	262.0^{a}	173.45^{b}	268.4^{c}	211.0^{d}	**0.024***
Vitamin C (mg)	179.08	158.07	130.35^{i}	217.28^{i}	176.02	**0.008***
Tiamin (mg)	1.21	1.4	1.38	1.31	1.09	0.798
Riboflavin (mg)	1.21	1.03	1.18	1.63	1.49	0.830
Vitamin B6 (mg)	2.4	2.51	2.17	2.25	1.82	0.196
Folic acid (µg)	492.25	341.9	413.15	421.8	286.1	0.317
Niacin (mg)	10.5	10.79	8.1	10.88	9.25	0.113
Vitamin B5 (mg)	18.99	19.09	20.77	15.42	15.94	0.585
Biotin (µg)	4.26	4.77	4.1	5.92	4,69	0.692
Vitamin B12 (µg)	31.36	38.86	28.38	43.96	38.2	0.168
Sodium (mg)	676.7^{d}	501.2^{g}	425.1^{j}	510.59^{h}	262.5^{d,g,h,j}	**0.012***
Potassium (mg)	3634.45	3325.8	3870.3	3272.85	2750.4	0.078
Calcium (mg)	809.2^{a,d}	466.7^{a}	515.05	753.53^{h}	396.3^{d,h}	**0.019***
Magnesium (mg)	413.85	432.5	485.4	384.45	354.7	0.057
Phosphorus (mg)	1430.1	1419.0	1514.15	1546.54	1226.9	0.912
Iron (mg)	11.29^{d}	11.31^{g}	13.56^{j}	11.24^{h}	8.66^{d,g,h,j}	**0.005***
Zinc (mg)	6.35	7.46	7.72	7.37	6.63	0.521
High-protein diet						
SFA (g)	11.76^{a,b,c,d}	15.23^{a,e}	12.06^{b,e,j}	22.04^{c}	22.14^{d,j}	**0.019***
PUFA (g)	28.23^{d}	13.8	16.19	15.1	9.91^{d}	**0.034***
MUFA (g)	21.44^{c}	22.79	19.37^{i}	32.43^{c,h,i}	17.67^{h}	**0.029***
Vitamin A (µg)	2379.45^{d}	2440.2^{g}	1414.0^{i,j}	2810.55^{i,h}	818.55^{d,g,h,j}	**< 0.001** * *

(*continued on next page*)

Table 3 (*continued*)

	ChatGPT-4o	Claude 3.5 Somet	ChatGPT-4	Mistral Large 2	Llama 3.1 405B	p-value
Vitamin E (mg)	37.28[d]	15.73[e,f]	43.6[e,j]	36.44[f,h]	13.86[d,j,h]	**0.011***
Vitamin K (µg)	768.5[a,b,d]	232.2[a,g]	195.5[b,i,j]	677.95[i,h]	212.9[d,g,h,j]	**0.006***
Vitamin C (mg)	363.31[a,d]	182.62[a]	219.86	234.59	168.63[d]	**0.027***
Tiamin (mg)	1.45	1.21	1.31	1.32	1.1	0.701
Riboflavin (mg)	1.44	2.01	1.6	3.02	1.82	0.111
Vitamin B6 (mg)	2.46	2.33	2.24	3.26	2.27	0.311
Folic acid (µg)	790.4[a,d]	368.8[a]	446.35	665.55	307.45[d]	**0.047***
Niacin (mg)	24.71[a,b,c,d]	8.88[a]	12.96[b]	9.96[c]	6.22[d]	**0.022***
Vitamin B5 (mg)	40.19[a,b,c,d]	12.24[a]	19.15[b]	18.88[c]	10.67[d]	**0.022***
Biotin (µg)	5.21	6.79	5.85	7.99	6.28	0.899
Vitamin B12 (µg)	100.58[a,b,c,d]	68.11[a]	46.21[b]	66.53[c]	40.9[d]	**0.004***
Sodium (mg)	354.8[c]	487.3[f]	923.3[i]	1649.05[c,f,h,i]	613.3[h]	**0.007***
Potassium (mg)	5176.1[a,b,c,d]	2873.15[a]	3037.65[b]	3790.4[c]	2635.8[d]	**0.012***
Calcium (mg)	1021.3	495.7[e,f]	1392.0[e]	1705.15[f,h]	623.35[h]	**0.009***
Magnesium (mg)	762.05[a,c,d]	265.35[a]	520.15	379.3[c]	261.4[d]	**0.028***
Phosphorus (mg)	1859.95	1501.05[f]	1578.95	2012.25[f,h]	1368.5[h]	**0.034***
Iron (mg)	27.36[a,b,c,d]	9.0[a,e]	22.87[b,e,j]	13.11[c]	9.76[d,j]	**0.018***
Zinc (mg)	14.86[a,b,c,d]	6.74[a]	11.3[b,j]	10.16[c]	6.29[d,j]	**0.024***
Low-fiber diet						
SFA (g)	14.44[a,c,d]	29.98[a,e]	19.34[e,j]	28.78[c]	30.59[d,j]	**0.016***
PUFA (g)	6.13	11.2	7.54	9.85	7.98	0.231
MUFA (g)	12.37[a,c,d]	27.6[a]	15.33	28.38[c]	21.06[d]	**0.033***
Vitamin A (µg)	423.8[a,b,c,d]	1213.22[a,e,f,g]	2808.5[b,e,i,j]	1400.5[c,f,i,h]	670.35[d,g,j,h]	**0.007***
Vitamin E (mg)	5.95[a,b,c,d]	8.53[a,e,f,g]	7.09[b,e,i,j]	10.76[c,f,i,h]	4.78[d,g,j,h]	**0.007***
Vitamin K (µg)	45.55[b,d,c]	48.9[e,f,g]	73.7[b,e,i,j]	36.2[c,f,i]	15.65[d,g,j]	**0.008***
Vitamin C (mg)	49.34[c,d]	42.66[f,g]	114.64[j]	163.23[c,f,h]	9.68[d,g,j,h]	**0.009***
Tiamin (mg)	0.66	0.78	0.85	0.98	0.76	0.111
Riboflavin (mg)	2.38	1.62	2.06	2.56	2.15	0.200
Vitamin B6 (mg)	1.93	2.07	2.38	2.77	1.44	0.183
Folic acid (µg)	277.5	219.55	257.6	406.75	195.95	0.051
Niacin (mg)	4.61	7.49	5.37	6.73	6.73	0.092
Vitamin B5 (mg)	6.43	9.22	7.71	8.66	3.82	0.182
Biotin (µg)	5.92	4.99	6.33	6.97	6.31	0.311
Vitamin B12 (µg)	59.78	41.53	70.0	69.95	53.25	**0.031***
Sodium (mg)	1460.3[d]	1317.2[g]	2144.0[h]	1262.55[j]	11775.45[d,g,h,j]	**0.009***
Potassium (mg)	2443.7[d]	2663.55[g]	3433.2[j]	3540.15[h]	1821.85[d,g,h,j]	**0.019***
Calcium (mg)	982.95	609.91[f,g]	703.9	1267.95[f]	1282.05[g]	**0.018***
Magnesium (mg)	209.9	198.56	253.0	303.9	208.3	0.328
Phosphorus (mg)	1358.9	1227.4	1244.7	1642.45	1747.25	0.165
Iron (mg)	6.39	7.35	7.56	8.03	6.94	0.357
Zinc (mg)	7.6	7.08[g]	6.73[j]	10.42	11.75[g,j]	**0.017***
Mediterranean diet						
SFA (g)	16.18	13.98	14.82	15.41	17.22	0.357
PUFA (g)	16.04	11.04[e,g]	25.85[e,i]	14.2[i]	19.82[g]	**0.045***
MUFA (g)	29.51	30.76	25.38	36.08	15.84	0.101
Vitamin A (µg)	1358.8[a,b,d]	294.2[a,f,g]	171.3[b,i,j]	973.65[f,h,i]	2877.4[d,g,h,j]	**0.009***
Vitamin E (mg)	19.24	12.52[e]	19.84[e]	16.21	13.9	**0.045***
Vitamin K (µg)	232.0[a,b]	48,05[a,f]	58.1[b,i]	277.1[f,i]	174.8	**0.002***
Vitamin C (mg)	169.25	176.0	99.06[i]	202.09[i]	150.04	**0.039***
Tiamin (mg)	0.99	0.71	0.92	1.05	1.04	0.942
Riboflavin (mg)	1.29	1.03	1.34	1.42	1.1	0.999
Vitamin B6 (mg)	1.93	1.68	1.7	2.17	2.06	0.143
Folic acid (µg)	436.45	306.3	425.2	448.5	381.2	0.111
Niacin (mg)	10.89	6.98[e,g]	18.44[e]	9.83	13.83[g]	**0.034***
Vitamin B5 (mg)	15.4	8.78[e,g]	17.17[e]	20.49	10.56[g]	**0.033***
Biotin (µg)	4.31	3.05	3.28	5.17	4.23	0.211
Vitamin B12 (µg)	27.26	25.61	39.05	30.88	36.44	0.182
Sodium (mg)	877.0	334.75[e,f]	1689.5[e,j]	1343.15[f]	425.6[j]	**0.003***
Potassium (mg)	3192.5	2160.85	2711.4	3372.7	2483.0	0.357
Calcium (mg)	635.15	412.15[e]	743.1[e,j]	589.15	370.8[j]	**0.043***
Magnesium (mg)	383.2	196.15	366.2	375.25	266.9	0.342
Phosphorus (mg)	1455.25[a]	854.8[a,e,f]	1543.0[e]	1384.5[f]	1129.2	**0.023***
Iron (mg)	12.97[a,d]	7.13[a,e,f]	12.95[e,j]	12.14[f]	7.59[d,j]	**0.035***
Zinc (mg)	7.57	4.07[f]	7.71	7.64[f]	5.91	**0.046***

* $p < 0.05$, * *$p < 0.001$. [a] Differences between ChatGPT-4o and Claude 3.5 Somet, [b] Differences between ChatGPT-4o and ChatGPT-4, [c] Differences between ChatGPT-4o and Mistral Large 2, [d] Differences between ChatGPT-4o and Llama 3.1 405B, [e] Differences between Calude 3.5 Somet and ChatGPT-4, [f] Differences between Claude 3.5 Somet and Mistral Large 2, [g] Differences between Claude 3.5 Somet and Llama 3.1 405B, [h] Differences between Mistral Large 2 and Llama 3.1 405B, [i] Differences between Mmistral Large 2 and ChatGPT-4, [j] Differences between Llama 3.1 405B and ChatGTP 4. SFA: saturated fatty acids, PUFA: polyunsaturated fatty acids, MUFA: monounsaturated fatty acids.

pressure, and lower risk of developing type 2 diabetes (Kim et al., 2012; Lee and Park, 2017). The macronutrient ratio of a vegetarian diet can vary significantly depending on the specific type of vegetarianism practiced (e.g., lacto-vegetarian, ovo-vegetarian, lacto-ovo-vegetarian, or vegan). Vegetarian diets are generally rich in carbohydrates, which can account for approximately 55–75 % of total caloric intake (Sobiecki et al., 2016). Protein is 15–25 % of total energy and fat 20–35 % (Orlich et al., 2014). In our analysis, AI-generated vegetarian menus contained statistically higher levels of vitamin A and folate compared to other diet models ($p < 0.05$). These nutrients are essential for maintaining immune function and supporting cellular growth, highlighting the potential of AI tools to align with some nutritional benefits of vegetarian diets. According to our findings, the AI models planned sample menus with the recommended carbohydrate, protein, and fat percentages (except the average carbohydrate percentage of the sample menus of ChatGPT-4o). This discrepancy suggests that while most AI models demonstrate a strong capability in creating balanced meal plans, there can still be variations in accuracy depending on the specific AI used. Additionally, differences in dietary fiber content were noted across AI-generated vegetarian menus, with ChatGPT-4o menus providing significantly lower fiber values compared to other models ($p < 0.05$). Despite these differences, fiber content across the AI models was generally consistent with dietary recommendations for vegetarian diets. Furthermore, vegetarian diets are typically rich in dietary fiber, vitamins, and phytochemicals, which contribute to their protective effects against chronic diseases such as cardiovascular diseases and some cancers (Craig, 2010). Although fiber values differed according to the diet menu contents of AI models, no statistical difference was found. Despite marked differences in fiber values, AI-generated menus are relatively consistent in providing similar fiber content, suggesting that this may indicate a level of reliability regarding this aspect of vegetarian diet planning across different AI models.

A low-sodium diet is characterized by the restriction of sodium intake to help manage various health conditions, particularly hypertension (high blood pressure) and heart disease (Mahan et al., 2020). Adopting a low-sodium diet has been linked to numerous health benefits. Research indicates that such dietary changes can lead to improved blood pressure control, reduced risk of stroke, and lower rates of heart failure (Derkach et al., 2017; Gupta et al., 2023). The percentage of macronutrients in the diet is 50–60 % for carbohydrates, 15–25 % for protein, and 20–35 % for fat (Gupta et al., 2023). AI models generally recommended sample menus with lower carbohydrate content and higher fat and protein content. For example, Mistral Large 2 menus had significantly higher fat content ($p < 0.05$), while Llama 3.1 405B provided menus with a protein percentage at the upper end of the recommended range ($p < 0.05$). The findings revealed that AI models tend to recommend sample menus for a low-sodium diet with lower carbohydrate content alongside higher fat and protein levels, with ChatGPT-4o producing menus with significantly lower carbohydrate percentages compared to other models ($p < 0.05$). This pattern can be interpreted as AI models do not have enough information for low-sodium diet recommendations. Additionally, the sodium content across AI-generated menus varied significantly, with Claude 3.5 Somet menus exceeding the recommended sodium levels in 2 out of 5 test cases ($p < 0.05$). This inconsistency highlights the need for improving AI models to align with the sodium restriction requirements essential for individuals managing hypertension and heart disease. Furthermore, micronutrients like potassium, which are critical for counteracting sodium's effects on blood pressure, were inconsistently included across AI-generated menus, suggesting potential gaps in their datasets or training parameters. These findings underscore the need for AI algorithms to integrate dietary guidelines more comprehensively and improve the contextual relevance of their recommendations.

High-protein diets are widely recognized for their potential benefits in weight loss, muscle preservation, and metabolic health (Moon and Koh, 2020). The recommended macronutrient distribution for a high-protein diet generally includes protein making up more than 25–30 % of total daily caloric intake (Hruby and Jacques, 2021). In our study, AI-generated high-protein menus varied significantly in protein quality and distribution, with Mistral Large 2 menus providing higher-than-recommended fat percentages ($p < 0.05$). This imbalance in macronutrient composition raises concerns about the long-term sustainability of these diets for health purposes. While the AI-generated menus generally adhered to these guidelines, there were notable differences in the macronutrient composition, particularly in fat and carbohydrate content. For instance, ChatGPT-4o produced menus with significantly lower carbohydrate percentages than other AI models, which may compromise energy balance for individuals following a high protein diet ($p < 0.05$). Furthermore, the micronutrient profile of high-protein diets generated by AI models showed variability. Key nutrients such as magnesium and phosphorus—critical for muscle health and metabolism—were inconsistently distributed among AI-generated menus ($p < 0.05$). Mistral Large 2 menus contained higher phosphorus levels, whereas Claude 3.5 Somet menus were deficient in magnesium compared to other models. These disparities suggest that while AI models are capable of generating high-protein diets, they may not consistently achieve the optimal macronutrient balance, potentially impacting the effectiveness of the diet. Additionally, some menus failed to account for fiber, which is often overlooked in high-protein diets but is essential for digestive health. ChatGPT-4o menus, for example, provided significantly lower fiber values ($p < 0.05$), which could contribute to gastrointestinal issues in long-term adherence to high-protein diets. The observed differences indicate a need for further refinement in the algorithms used by AI models to ensure they provide accurate and balanced dietary recommendations within the framework of high-protein diets.

Low-fiber diets are typically prescribed for managing specific gastrointestinal conditions, such as irritable bowel syndrome, and generally include less than 10–15 g of fiber per day (Fritsch et al., 2021; Bailen et al., 2020). These diets are designed to minimize the mechanical and chemical irritation of the gastrointestinal tract, making them an essential intervention for individuals with inflammatory bowel diseases, diverticulitis, or post-surgical recovery. In this study, the AI-generated low-fiber diet menus demonstrated significant variability in protein and fat content across different models. For instance, Mistral Large 2 menus had significantly higher fat percentages ($p < 0.05$) compared to other models, potentially altering the energy balance and making these menus unsuitable for individuals requiring low-fat dietary plans. Similarly, Claude 3.5 Somet menus provided higher-than-recommended protein percentages in 3 out of 5 test cases, which may not align with clinical guidelines for individuals on restricted diets. While the fiber content was generally kept within the desired range, ChatGPT-4o menus produced fiber levels that were consistently at the lower limit of the recommended range, which could compromise dietary adequacy for some patients ($p < 0.05$). These findings suggest that AI models may need additional training or adjustments to better align with clinical guidelines for low-fiber diets, ensuring that the dietary recommendations they generate are both accurate and safe for users with specific health needs. Moreover, micronutrient deficiencies were observed in AI-generated low-fiber diet menus. For example, menus often lacked sufficient levels of potassium and magnesium, which are crucial for maintaining electrolyte balance and preventing muscle cramps, common concerns for patients on restrictive diets ($p < 0.05$). These gaps highlight the importance of enhancing AI datasets and algorithms to ensure they consider both macronutrient and micronutrient requirements comprehensively. Additionally, these menus frequently included processed and high-sodium food options, such as cured meats and packaged snacks, which may contradict the therapeutic goals of a low-fiber diet for managing gastrointestinal health. These inconsistencies indicate the need for AI models to integrate more robust nutritional logic and contextual awareness when designing specialized diets.

The Mediterranean Diet has become known for its associated health benefits and continues to attract interest, especially given the growing challenge of malnutrition in all its forms (undernutrition, micronutrient deficiencies, overweight, and obesity) (Artifical Analysis, 2024). The recommended macronutrient percentages for the Mediterranean diet are 40–65 % for carbohydrate, 28–40 % for fat, and 10–35 % for protein (Davis et al., 2015; Preston and Clayton, 2023). Our study revealed significant discrepancies in AI-generated menus for the Mediterranean

Diet, particularly with the Claude 3.5 Somet model exceeding the recommended ranges for macronutrient percentages ($p < 0.05$). This finding suggests that the Claude 3.5 Somet model may prioritize energy-dense food options, resulting in higher fat content and lower carbohydrate levels compared to the traditional Mediterranean guidelines. Although the other 4 AI models defined the macronutrient percentages within the required range, no difference was found between the mean macronutrient contents (excluding carbohydrate amount) and percentages of the menus recommended by the AIs. Additionally, the micronutrient composition of AI-generated menus showed variability. For instance, menus created by ChatGPT-4o contained significantly lower levels of vitamin E and magnesium—nutrients critical for the antioxidant and anti-inflammatory benefits associated with the Mediterranean Diet ($p < 0.05$). Conversely, Mistral Large 2 menus provided higher levels of polyunsaturated fatty acids (PUFA), which align more closely with Mediterranean dietary principles. This result suggests that although the health benefits of the Mediterranean Diet are widely recognized and have clear guidelines for macronutrient distribution, there is variability in how different AI models interpret and recommend macronutrient compositions within this dietary framework. In particular, the Claude 3.5 Somet model tends to suggest macronutrient percentages higher than the recommended ranges, highlighting a need for improved algorithmic alignment with evidence-based dietary guidelines. Another notable limitation in the AI-generated Mediterranean Diet menus is the lack of emphasis on seasonal and local ingredients, which are core principles of the Mediterranean dietary pattern. For example, menus frequently included out-of-season fruits and vegetables such as strawberries and asparagus during the summer months. This oversight not only challenges the practical implementation of these recommendations but also raises concerns about sustainability and food accessibility.

Additionally, when we asked AIs to write menus for the diets we asked for, they added many vegetables and fruits that were not in season to the lists of diet menus, although we asked these questions in the summer season. These results reveal a limitation in the dietary menus created by the AI, particularly in their ability to account for seasonality. Incorporating seasonality into dietary recommendations is crucial for both the practicality and sustainability of dietary recommendations as it ensures that the recommended foods are accessible, fresh, and often more affordable (FAO, 2010; James-Martin et al., 2022). The inclusion of out-of-season produce in AI-generated menus may reflect a gap in the contextual understanding of the models or the datasets on which they are based and indicates a need for further development in this area to increase the relevance and applicability of the dietary advice they provide.

While AI-generated diets can offer general guidance for healthy individuals seeking dietary advice at home, their use in clinical or therapeutic settings requires a higher level of precision. For medical purposes, such as hypertension or chronic kidney disease management, tolerances for nutrient deviations must be much narrower. In our study, the most searched diets according to Google Trends data were included. We observed that the generated menus often lacked the precision required for clinical application and underlined the importance of professional oversight and more advanced contextual training for AI applications in the field of nutrition in healthcare.

This study has several limitations. First, the internal data sources and food composition databases used by AI assistants are not publicly disclosed. As a result, it was not possible to determine whether the menus generated by each model were based on reliable, evidence-based nutritional information. This lack of transparency may limit the interpretability and reproducibility of AI-generated outputs. To mitigate this issue, all menus were re-analyzed using a validated and standardized national Nutrition Information System (BeBiS 9.0), which was used as the reference tool for nutritional calculations. Additionally, since the AI systems are frequently updated and improved, their responses may vary over time, making it difficult to replicate results in the long term. Second, the AI prompts did not include instructions related to cultural dietary patterns, local food preferences, or seasonality. As a result, some of the AI-generated menus included impractical or out-of-season food items, which may reduce the real-world applicability of the outputs. Future studies should consider incorporating culturally and seasonally relevant prompts to evaluate whether such guidance improves the practicality and accuracy of AI-generated dietary recommendations. These limitations should be considered when interpreting the generalizability and applicability of the findings.

5. Conclusion

Nowadays, AI-powered assistants are becoming increasingly common, and their potential in healthcare may be the most revolutionary. This study provides a novel evaluation of AI-generated dietary plans, highlighting their capabilities and limitations in adhering to established nutritional guidelines. Our results showed that the energy and macronutrient contents of the AI assistants varied after the command to create a 1500 kcal diet model. Mistral Large 2 was found to frequently generate menus with higher energy and fat values, whereas Llama 3.1 405B provided higher protein percentages, and ChatGPT-4 produced menus with elevated carbohydrate content. These variations indicate that while AI models show promise in dietary planning, inconsistencies remain in their ability to balance macronutrients effectively across different dietary frameworks.

Additionally, micronutrient distribution showed notable discrepancies, with certain AI models failing to meet recommended levels of key nutrients such as magnesium, vitamin E, and potassium. This variability highlights the need for ongoing refinement of AI algorithms to ensure their outputs align with clinical guidelines and nutritional adequacy standards. Furthermore, the lack of consideration for seasonality and regional dietary practices underscores the limitations of current AI-generated recommendations in providing contextually relevant and sustainable solutions.

This study may provide critical insights into the applications of AI in nutrition science and contribute to a better understanding of the use of these technologies in dietary guidance. The findings not only emphasize the potential for AI to revolutionize nutrition science but also underscore its limitations in creating dietary plans that are practical, personalized, and scientifically accurate. Furthermore, the findings provide valuable clues about the effectiveness of AI not only in the health sector but also in shaping societal dietary habits. Consequently, this research will contribute to more informed and scientifically based decision-making in the field of diet and nutrition, while paving the way for future studies to optimize the use of AI in personalized nutrition and public health initiatives.

Author Contributions

- **Hatice Merve Bayram:** Literature review, data collection and analysis, drafting of the manuscript.
- **Sedat Arslan:** Conceptualization, methodology design, supervision, statistical analysis, critical revision, and corresponding author responsibilities.

All authors agree to be accountable for all aspects of the work and ensure that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Author Statement

We, the undersigned authors, confirm that:

1. The manuscript titled *"Nutritional Analysis of AI-Generated Diet Plans Based on Popular Online Diet Trends"* is our original work and has not been published or submitted for publication elsewhere.

2. All authors have made substantial contributions to the conception, design, data acquisition, analysis, and interpretation of the study. All authors have participated in drafting or revising the manuscript and have approved the final version submitted.
3. There is no conflict of interest to declare. The study received no financial support from any organization.
4. All data generated or analyzed during this study are included in this published article and its supplementary files.
5. The corresponding author, Assoc. Prof. Sedat Arslan, takes responsibility for the integrity of the work as a whole, from inception to published article.

CRediT authorship contribution statement

Sedat Arslan: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Hatice Merve Bayram:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Financial disclosures

This study received no financial support.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jfca.2025.107850.

Data availability

Data will be made available on request.

References

Nuti, S.V., Wayda, B., Ranasinghe, I., Wang, S., Dreyer, R.P., Chen, S.I., Murugiah, K., 2014. The use of Google Trends in health care research: a systematic review. PloS One 9 (10), e109583.
Bayram, H.M., Ozturkcan, A., 2023. Public interest in weight loss and diet-related topics in Europe: An infodemiology study of Google trends data from 2004–2022. Int. J. Food Sci. Nutr. 74 (4), 568–579.
Gardner, C.D., Hartle, J.C., Garrett, R.D., Offringa, L.C., Wasserman, A.S., 2023. Popular dietary patterns: alignment with American Heart Association 2021 dietary guidance: a scientific statement from the American Heart Association. Circulation 147 (22), 1715–1730.
Herreman, L., Nommensen, P., Pennings, B., Laus, M.C., 2020. Comprehensive overview of the quality of dietary proteins: DIAAS as a preferred method. Nutr. Rev. 78 (11), 994–1008.
Rutherfurd, S.M., Fanning, A.C., Miller, B.J., Moughan, P.J., 2015. Protein Digestibility-Corrected Amino Acid Score (PDCAAS) versus Digestible Indispensable Amino Acid Score (DIAAS). Curr. Opin. Clin. Nutr. Metab. Care 18 (3), 217–221.
Salinari, A., Machì, M., Armas Diaz, Y., Cianciosi, D., Qi, Z., Yang, B., Giampieri, F., 2023. The application of digital technologies and artificial intelligence in healthcare: an overview on nutrition assessment. Diseases 11 (3), 97.
Hao, C., Li, Y., 2022. Simulation of english speech recognition based on improved extreme random forest classification. Comput. Intell. Neurosci. 2022, 1948159.
Hamaniuk, V.A., 2021. The potential of large language models in language education. Educ. Dimens. 5, 208–210.
Tai, M.C.T., 2020. The impact of artificial intelligence on human society and bioethics. Tzu-Chi Med. J. 32 (4), 339.
Aung, Y.Y., Wong, D.C., Ting, D.S., 2021. The promise of artificial intelligence: a review of the opportunities and challenges of artificial intelligence in healthcare. Br. Med. Bull. 139 (1), 4–15.
Quarajeh, A., Tangpanithandee, S., Thongprayoon, C., Suppadungsuk, S., Krisanapan, P., Aiumtrakul, N., Cheungpasitporn, W., 2023. AI-Powered Renal Diet Support: Performance of ChatGPT, Bard AI, and Bing Chat. Clin. Pract. 13 (5), 1160–1172.
Arslan, S., 2024. Decoding dietary myths: the role of ChatGPT in modern nutrition. Clin. Nutr. ESPEN 60, 285–288.
Arslan, S., 2023. Exploring the potential of Chat GPT in personalized obesity treatment. Ann. Biomed. Eng. 51 (9), 1887–1888.
Kamiński, M., Skonieczna-Żydecka, K., Nowak, J.K., Stachowska, E., 2020. Global and local diet popularity rankings, their secular trends, and seasonal variation in Google Trends data. Nutrition 79-80, 110759.
Alphan, E., 2016. *Diyetler ve Gerçekler* (1. Baskı). Ank.: Hatipoğlu Yayınları.
Shukla, P.R., Skea, J., Calvo Buendia, E., MassonDelmotte, V., Portner, H.O., Roberts, D. C., Malley, J., 2019. IPCC Special Report. IPCC: Clim. Change Land.
Freire, R., 2020. Scientific evidence of diets for weight loss: Different macronutrient composition, intermittent fasting, and popular diets. Nutrition 69, 110549.
American Heart Association Council on Lifestyle and Cardiometabolic Health, 2023. Popular dietary patterns: Alignment with American Heart Association 2021 dietary guidance. Circulation 147 (22), 1715–1730.
Artifical Analysis (2024). ⟨https://artificialanalysis.ai/models/gpt-4o⟩.
FAO and WHO (2019). Sustainable and healthy diets: Guiding principles.
Makridakis, S., 2017. The forthcoming Artificial Intelligence (AI) revolution: its impact on society and firms. Futures 90, 46–60.
Olhede, S.C., Wolfe, P.J., 2018. The growing ubiquity of algorithms in society: implications, impacts, and innovations. Philos. Trans. R. Soc. A 376 (2128), 20170364.
Bayram, H.M., Ozturkcan, A., 2024. AI showdown: Info accuracy on protein quality content in foods. Br. Food J. 126 (9), 3335–3346.
Thircuir, S., 2020. From culture to nature? The raw food diet and the ideal of natural eating. Food, Cult. Soc. 23 (4), 506–522.
Abraham, K., Trefflich, I., Gauch, F., Weikert, C., 2022. Nutritional intake and biomarker status in strict raw food eaters. Nutrients 14 (9), 1725.
Barad, A., Rivero-Mendoza, D., Dahl, W.J., 2020. Popular diets: Raw foods. Edis 2020 (5).
Nüesch-Inderbinen, M., Treier, A., Zurfluh, K., Stephan, R., 2019. Raw meat-based diets for companion animals: a potential source of transmission of pathogenic and antimicrobial-resistant Enterobacteriaceae. R. Soc. Open Sci. 6 (10), 191170.
Cunningham, E., 2004. What is a raw foods diet and are there any risks or benefits associated with it? J. Am. Diet. Assoc. 104 (10), 1623.
Hargreaves, S.M., Raposo, A., Saraiva, A., Zandonadi, R.P., 2021. Vegetarian diet: an overview through the perspective of quality of life domains. Int. J. Environ. Res. Public Health 18 (8), 4067.
Kim, M.K., Cho, S.W., Park, Y.K., 2012. Long-term vegetarians have low oxidative stress, body fat, and cholesterol levels. Nutr. Res. Pract. 6 (2), 155–161.
Lee, Y., Park, K., 2017. Adherence to a vegetarian diet and diabetes risk: a systematic review and meta-analysis of observational studies. Nutrients 9 (6), 603.
Sobiecki, J.G., Appleby, P.N., Bradbury, K.E., Key, T.J., 2016. High compliance with dietary recommendations in a cohort of meat eaters, fish eaters, vegetarians, and vegans: results from the European prospective investigation into cancer and nutrition–oxford study. Nutr. Res. 36 (5), 464–477.
Orlich, M.J., Jaceldo-Siegl, K., Sabaté, J., Fan, J., Singh, P.N., Fraser, G.E., 2014. Patterns of food consumption among vegetarians and non-vegetarians. Br. J. Nutr. 112 (10), 1644–1653.
Craig, W.J., 2010. Nutrition concerns and health effects of vegetarian diets. Nutr. Clin. Pract. 25 (6), 613–620.
Mahan, K., Escott-Stump, S., Raymond, J.L., 2020. Krause's Food & the Nutrition Care Process. Elsevier Saunders.
Derkach, A., Sampson, J., Joseph, J., Playdon, M.C., Stolzenberg-Solomon, R.Z., 2017. Effects of dietary sodium on metabolites: the dietary approaches to stop hypertension (DASH)–sodium feeding study. Am. J. Clin. Nutr. 106 (4), 1131–1141.
Gupta, D.K., Lewis, C.E., Varady, K.A., Su, Y.R., Madhur, M.S., Lackland, D.T., Allen, N. B., 2023. Effect of dietary sodium on blood pressure: A crossover trial. JAMA 330 (23), 2258–2266.
Moon, J., Koh, G., 2020. Clinical evidence and mechanisms of high-protein diet-induced weight loss. J. Obes. Metab. Syndr. 29 (3), 166.
Hruby, A., Jacques, P.F., 2021. Protein intake and human health: implications of units of protein intake. Adv. Nutr. 12 (1), 71–88.
Fritsch, J., Garces, L., Quintero, M.A., Pignac-Kobinger, J., Santander, A.M., Fernández, I., … & Abreu, M.T. (2021). Low-fat, high-fiber diet reduces markers of inflammation and dysbiosis and improves quality of life in patients with ulcerative colitis. *Clinical Gastroenterology and Hepatology*, 19(6), 1189-1199.
Bailen, E.S., et al., 2020. Irritable bowel syndrome: Management and dietary interventions. Springer.
Davis, C., Bryan, J., Hodgson, J., Murphy, K., 2015. Definition of the Mediterranean diet: a literature review. Nutrients 7 (11), 9139–9153.
Preston, A.M., Clayton, P.K., 2023. Macronutrient adequacy of a mediterranean-type meal examined at recommended and below recommended energy values. J. Food Sci. Nutr. Res. 6 (2), 51.
FAO, 2010. *Sustainable diets and biodiversity.* Directions and solutions for policy, research and action. FAO Headquarters, Rome.
James-Martin, G., et al., 2022. Environmental sustainability in national food-based dietary guidelines: a global review. Lancet Planet. Health 6, e977–e986.