Journal of Food and Nutrition Research (ISSN 1336-8672) Vol. *65*, 2026, No. 2, pp. 133–144

DOI: https://doi.org/10.64122/FWDF3373

Guideline-based evaluation of AI-generated vs dietitian-designed meal plans in cardiovascular disease

GUL AKDUMAN – AYBIKE CEBECI

Summary

Cardiovascular disease (CVD) remains a major global health burden, and diet quality is central to prevention and management. This simulation study compared artificial intelligence (AI)-generated and registered dietitian (RD)-designed one-day meal plans for 33 standardised cardiovascular risk profiles. RD plans were closer to predicted energy requirements than AI plans (median deviation –29.9 kJ vs –386.2 kJ; $p = 0.017$, $r = 0.41$). Macronutrient distribution differed. RD plans met the acceptable macronutrient distribution range for carbohydrates, protein, and fat, whereas AI plans were below the carbohydrate range and above the fat range; protein exceeded the range in 60.6 % of AI plans. AI plans also had lower plant-based protein (27.2 % vs 43.7 %) and higher saturated fat (12.4 % vs 9.5 %), along with higher n-3/n-6 fatty acids and dietary cholesterol ($p \leq 0.03$), while sodium did not differ ($p = 0.05$). Fibre was higher in RD plans ($p < 0.05$). Micronutrient adequacy was generally high, but AI plans more often fell short for calcium, zinc, iron, magnesium, folate, and vitamin C. AI-generated meal plans were insufficient for cardiovascular diet therapy when used alone and should be designed or revised under RD supervision.

Keywords

artificial intelligence; cardiovascular diseases; diet therapy; dietitians; medical nutrition therapy

Cardiovascular diseases (CVDs) are among the top causes of early death and cost burdens worldwide [1]. Modifiable risk factors such as hypertension, dyslipidaemia, obesity, and unhealthy dietary patterns are among the major risk factors for cardiovascular disease. This highlights the importance of promoting healthy eating in public health policies [2].

Dietary interventions aligned with mediterranean or dietary approaches to stop hypertension (DASH) nutritional patterns have demonstrated significant cardiovascular benefits [3, 4]. For example, adherence to the mediterranean diet correlates with improved vascular function, lipid-lowering, and decreased oxidative stress [3]; other studies report modest but clinically meaningful improvements in high-density lipoprotein cholesterol (HDL-C) and reductions in low-density lipoprotein cholesterol (LDL-C), triglycerides, and CVD outcomes [4, 5].

In clinical practice, registered dietitians (RDs) create personalised nutrition plans based on clinical data, lifestyle, and dietary needs [6]. Artificial intelligence (AI) systems are emerging as scalable and cost-efficient tools for nutrition planning, leveraging food recognition, nutrient analysis, and recommendation algorithms. However, their clinical applicability, contextual sensitivity (e.g., comorbidities, cultural diet patterns), and transparency remain under scrutiny [7].

While AI-powered platforms can rapidly generate nutritional recommendations and nutrient estimates by analysing images or using dietary databases [7], few articles in the literature have

Gul Akduman, Department of Nutrition and Dietetics, Faculty of Health Sciences, Burdur Mehmet Akif Ersoy University, Istiklal Campus, 15030 Burdur, Türkiye.
Aybike Cebeci, Department of Nutrition and Dietetics, Faculty of Health Sciences, Balıkesir University, Cagis Campus, 10145 Balıkesir, Türkiye.

Correspondence author:
Gul Akduman, e-mail: gakduman@mehmetakif.edu.tr

evaluated the accuracy or guideline adherence of AI-generated plans in disease-specific settings. Comparative studies, especially in the context of cardiovascular disease, are virtually nonexistent, creating a significant gap in the literature [8, 9].

The purpose of this study was to evaluate the nutritional adequacy and practical relevance of AI-generated diet plans for cardiovascular disease management by comparing them with meal plans designed by RDs. The analysis focused specifically on total energy, macronutrient distribution, micronutrient content, and adherence to established nutritional guidelines.

We hypothesised that AI-generated diet plans would differ significantly from RD-designed plans in terms of macronutrient and micronutrient composition and would exhibit lower adherence to clinical nutrition recommendations.

MATERIALS AND METHODS

Study design and participants

A simulation study was conducted using ChatGPT (Generative Pre-trained Transformer, version 4.0, OpenAI, San Francisco, California, USA) to evaluate the potential of AI in developing personalised nutrition plans for cardiovascular diseases. The simulated cases included 18 females and 15 males. The gender distribution was based on the cardiovascular disease prevalence reported by the Turkish Statistical Institute (5.8 % in males and 7.0 % in females, Turkey Health Survey 2022) [10]. The age-based prevalence of cardiovascular disease was distributed as follows: 25–34 years (n = 1), 35–44 years (n = 2), 45–54 years (n = 3), 55–64 years (n = 6), 65–74 years (n = 9), and ≥ 75 years (n = 12) according to Risk Factor in Turkish Adults (TEKHARF) [11].

Body mass index (*BMI*) was adjusted for simulated cases based on evidence of a higher risk of cardiovascular disease in those with a *BMI* > 24.9 kg·m^{-2} [12–14]. Accordingly, the 33 simulated participants were assigned to normal weight (n = 8), overweight (n = 15), and obese (n = 10). Because underweight individuals have a significantly lower rate of cardiovascular disease, this category was not included. For consistency, all individuals were defined as having a sedentary physical activity level.

This study was based entirely on simulated case profiles and did not involve human participants, patient data, or identifiable personal information. Therefore, according to institutional regulations, formal ethical approval was not required.

Clinical parameters for cardiovascular nutrition planning

Metabolic and cardiovascular risk markers frequently used in the literature were used for clinical data input related to cardiovascular diseases. Values assigned to simulated cases were determined based on the 2018 American Heart Association/American College of Cardiology (AHA/ACC) Cholesterol Management Guidelines [15]. All simulated cases were assigned an LDL-C value of 190 mg·dl^{-1} and a total cholesterol value of 250 mg·dl^{-1} to represent a high-risk lipid profile [14]. Blood pressure was set at 145/90 mmHg, above the diagnostic threshold for hypertension (≥ 130/80 mmHg in high-risk individuals) [16]. For glycaemic status, haemoglobin A1c (HbA1c) was set at 6.2 %, within the pre-diabetic range (5.7–6.4 %) [17]. These fixed clinical parameters were used as inputs in the AI model, and the resulting diet recommendations were compared with plans developed by expert dietitians.

Development of prompts for artificial intelligence

All commands were manually entered via the ChatGPT web interface using the paid version (ChatGPT Plus) and the GPT-4.0 model (March 2024 release). System prompts, external tools, or additional data sources (e.g., documentation, plugins, or browsing) were not provided, and commands were sent once without follow-up instructions. To minimise carryover effects, each case was created in a separate new chat session, and only the initial response generated for each command was stored for analysis. Because ChatGPT responses can vary across repeated runs of the same command and may change as the model is updated, we did not attempt repeated sampling, and this variability is addressed in the Limitations. A single output per case was used for analyses.

"Can you prepare a one-day healthy nutrition plan for a 27-year-old female patient with a history of cardiovascular disease, who is sedentary and has the following clinical characteristics: body weight: 76 kg, height: 168 cm, LDL cholesterol: 190 mg·dl^{-1}, total cholesterol: 250 mg·dl^{-1}, HbA1c: 6.2 %, blood pressure: 145/90 mmHg?"

All questions were written in Turkish and entered in a single step without follow-up or corrective input. The one-day menus created for each case were analysed for guideline compliance.

Standardisation of dietary guidelines

AI and dietitian-based nutritional approaches were compared in this study according to the American Heart Association's (AHA) 2021 "Dietary guidance to improve cardiovascular

Tab. 1. Lifestyle modification strategies in cardiovascular disease: evidence from American Heart Association guideline [18].

	Recommendation
Carbohydrate	Choose whole grains instead of refined grains. Consume fruits and vegetables whole instead of juice; they are rich in fibre and provide satiety. Minimise added sugars.
Protein	Choose protein sources from "healthy" ones: plant-based sources, regular fish/seafood consumption (2–3 serving per week), low-fat/fat-free dairy products, and if meat/chicken is desired, lean and unprocessed forms.
Fat	Choose liquid plant oils instead of tropical oils (coconut/palm/palm kernel), animal fats (butter/lard), and partially hydrogenated oils. Choose unsaturated fats (especially polyunsaturated and monounsaturated fatty acids) instead of saturated and trans fats. Get *n*-3 fatty acids by consuming oily fish.
Cholesterol (from dietary sources)	Cholesterol intake should not be increased.
Salt	Choose and prepare foods with little or no salt. Reducing sodium intake lowers blood pressure. The combined effect of the DASH diet and sodium reduction is greater than either approach alone. A practical alternative is replacing regular salt with potassium-enriched salts, especially in settings where added salt during food preparation is the main source of sodium intake.
Alcohol	If you don't drink alcohol, don't start; if you choose to drink, limit your intake. Limit for drinkers: ≤ 1 drink per day for women and ≤ 2 drinks per day for men.

DASH – dietary approaches to stop hypertension.

health" scientific statement [18], which served as the reference guideline (Tab. 1). This statement offers a framework based on dietary patterns rather than individual nutrient targets and emphasises the following components in the assessment: maintaining a healthy body weight by ensuring energy balance; consuming ample and varied fruits and vegetables; choosing predominantly whole grains instead of refined grains; preferring healthy protein sources (predominantly plant-based; regular intake of fish and seafood; low-fat or fat-free dairy products; and lean, unprocessed forms of meat or poultry if desired); using liquid plant oils instead of tropical oils, solid fats, and partially hydrogenated oils; choosing minimally processed foods instead of ultra-processed foods; minimising foods and beverages with added sugars; choosing and preparing foods with little or no salt; not starting alcohol consumption if you do not already drink and limiting intake if you do; and adhering to this guidance regardless of where food is prepared. These criteria were used to evaluate the alignment of meal plans generated by AI and a dietitian with the guideline. In addition, mineral adequacy was assessed using the estimated average requirement (*EAR*) cut-point method, and mineral intakes were classified as below versus at or above the *EAR* for each plan [19].

Basal metabolic rate (*BMR*) was calculated using the Harris-Benedict equation. Estimated energy requirements (*EER*) were determined by multiplying *BMR* by a sedentary physical activity level (*PAL*) factor of 1.2. Ideal body weight was used for participants with $BMI > 24.99\ \text{kg·m}^{-2}$, and adjusted body weight for those with $BMI > 30\ \text{kg·m}^{-2}$ in *BMR* and *EER* calculations. Percentage deviation in energy was calculated by determining how much the difference between total energy and estimated energy requirement corresponded to the estimated energy requirement, expressed as a percentage.

Dietitian-generated one-day menus were prepared by two RDs, each with more than 10 years of clinical experience. For each simulated case, the two RDs developed menus independently using the same clinical inputs provided to the AI, and they were blinded to the AI-generated outputs. A third RD subsequently reviewed all dietitian-generated menus for consistency and guideline adherence, without modifying the content unless an obvious error was identified. All one-day menus generated by the AI were subsequently analysed using the Nutrition Information System BeBiS 8.1 (Ebispro, Willstätt, Germany; Turkish version). This software was used to calculate the total energy and nutrient content of each menu, allowing for comparison with dietary guidelines and evaluation of nutrient adequacy.

Statistical analysis

Analyses were performed using IBM SPSS Statistics for Windows, Version 25.0 (IBM, Armonk, New York, USA) in a paired (within-subjects) design, as each participant received both RD-designed and AI-generated meal plans. Normality was tested using the Shapiro–Wilk test. As most variables deviated from normality, between-group differences were primarily analysed using the Wilcoxon signed-rank test and are reported as median (25th–75th percentile). Variables meeting normality assumptions were analysed using the paired-samples t-test and are presented as mean ± standard deviation. Statistical significance was set at $p < 0.05$ (two-tailed).

In addition to p-values, effect sizes were reported to reflect the practical importance of the observed differences. For Wilcoxon signed-rank tests, the effect size r was obtained by dividing the standardised test statistic (Z) by the square root of the number of paired observations [20], where Z is the standardised test statistic and N refers to the number of non-zero differences. This approach allows the interpretation of Wilcoxon outcomes on a comparable scale (small ≈ 0.10, medium ≈ 0.30, large ≥ 0.50).

A sensitivity analysis was conducted in G*Power (v3.1; Heinrich Heine University, Düsseldorf, Germany) using a matched-pairs framework ($\alpha = 0.05$, two-tailed). With 33 paired cases, the study had 80 % power to detect a minimum standardised effect size of $dz = 0.503$.

RESULTS AND DISCUSSION

The deviations between the dietitian- and AI-generated meal plans compared to the calculated energy requirements are shown in Tab. 2. Both absolute (in kilocalories or kilojoules) and percentage deviations by using the *EER* were calculated as described in the Methods section. The median deviation was –29.9 kJ for the dietitian-designed meals, compared to –386.2 kJ for the AI-generated plans. This statistically significant difference ($p = 0.017$, $r = 0.41$) suggests that dietitian-designed plans were closer to the calculated *EER* than AI-generated plans.

A significant difference was observed in macronutrient distribution between dietitian- and AI-generated meals (Tab. 2). When evaluated

Tab. 2. Comparison of energy and macronutrient distribution between dietitian-designed and AI-generated meal plans.

	Dietitian-designed menu			AI-generated menu			z	p	r
	Median	25th percentile	75th percentile	Median	25th percentile	75th percentile			
Energy [kcal]	–7.16	–28.56	11.12	–92.30	–274.72	40.57	–2.385	0.017*	0.41
Energy [kJ]	–29.9	–129.0	48.0	–386.2	–1 168.5	–281.9			
Carbohydrate [%]	52.0	49.4	53.5	32.4	30.9	34.6	–5.012	< 0.001**	0.87
Protein [%]	18.4	17.9	18.7	20.4	19.6	21.5	–4.762	< 0.001**	0.82
Plant-based protein [%]	43.7	41.9	46.0	27.2	22.9	31.2	–4.958	< 0.001**	0.86
Fat [%]	28.2	26.6	30.2	45.0	41.0	48.1	–5.012	< 0.001**	0.87
MUFA [%]	7.8	7.4	9.7	17.2	16.4	20.2	–5.012	< 0.001**	0.87
PUFA [%]	6.9	6.3	9.2	10.5	8.9	14.4	–4.226	< 0.001**	0.73
Saturated fat [%]	9.5	8.9	11.8	12.4	11.7	13.1	–4.083	< 0.001**	0.71

Values are expressed as the percentage of total energy intake except of plant-based protein, which is expressed as the percentage of total dietary protein. The Wilcoxon signed-rank test was used to assess the differences between paired samples.
MUFA – monounsaturated fatty acids, PUFA – polyunsaturated fatty acids, z – Wilcoxon test statistics, p – significance level (* – $p < 0.05$, statistically significant; ** – $p < 0.01$, highly significant), r – effect size (Cohen's r).

Tab. 3. Classification of individual meal plans as below, within, or above the acceptable macronutrient distribution ranges for macronutrient intake in menus.

	Dietitian-designed menu						AI-generated menu					
	Below *AMDR*		Within *AMDR*		Above *AMDR*		Below *AMDR*		Within *AMDR*		Above *AMDR*	
	n	[%]	*n*	[%]	*n*	[%]	*n*	[%]	*n*	[%]	*n*	[%]
Carbohydrate	0	0.0	33	100.0	0	0.0	33	100.0	0	0.0	0	0.0
Protein	0	0.0	33	100.0	0	0.0	0	0.0	13	39.4	20	60.6
Fat	1	3.0	32	97.0	0	0.0	0	0.0	0	0.0	33	100.0

AMDR – acceptable macronutrient distribution range.

Tab. 4. Comparison of *n*-3 and *n*-6 fatty acid, dietary cholesterol and sodium intake between dietitian-designed and AI-generated meal plans.

	Dietitian-designed menu				AI-generated menu				*z*	*p*	*r*
	Median	*IQR*	Min.	Max.	Median	*IQR*	Min	Max			
n-3 fatty acid [g·d⁻¹]	3.1	1.0	1.8	4.2	5.0	1.8	3.2	8.0	–4.770	< 0.01*	0.84
n-6 fatty acid [g·d⁻¹]	10.3	3.7	5.9	14.9	12.6	8.2	5.4	30.2	–2.705	< 0.01*	0.48
Cholesterol [mg·d⁻¹]	287.0	52.0	265.4	395.8	354.7	46.1	96.8	450.8	–2.132	0.03*	0.38
Sodium [mg·d⁻¹]	2 256.4	51.4	2 139.0	2 495.0	2 336.5	2 590.2	1 500.6	5 954.2	–1.963	0.05	0.35

Values are expressed as the daily intake. The Wilcoxon signed-rank test was used to assess the differences between paired samples.
IQR – interquartile range, *z* – Wilcoxon test statistics, *p* – significance level (* – $p < 0.05$, statistically significant), *r* – effect size (Cohen's *r*).

according to the acceptable macronutrient distribution ranges (*AMDR*; carbohydrates 45–65 % of energy, protein 10–35 %, total fat 20–35 %), the dietitian-designed meals fell within the recommended ranges for all three macronutrients (carbohydrates 52.0 %, protein 18.4 %, total fat 28.2 %). In contrast, the AI-generated plans deviated from the *AMDR*; carbohydrates fell below the recommended range (32.4 %; 12.6 percentage points below the 45 % lower limit) and total fat was above the recommended range (45.0 %; 10.0 percentage points above the 35 % upper limit), while protein remained within the *AMDR* (20.4 %). These differences were statistically significant (all $p < 0.001$) and showed large effect sizes for macronutrient distribution ($r = 0.71–0.87$). Consistent with these median values, the *AMDR* classification of individual plans (Tab. 3) showed that all menus designed by the dietitian were within the *AMDR* for carbohydrates and protein (33/33, 100 %), and almost all were within the *AMDR* for total fat (32/33, 97 %). In contrast, all menus generated by AI were below the *AMDR* for carbohydrates (33/33, 100 %) and above the *AMDR* for total fat (33/33, 100 %); for protein, 20/33 (60.6 %) exceeded the *AMDR*, while 13/33 (39.4 %) remained within the *AMDR*. In meals designed by dietitians, plant-based protein constituted a larger proportion of total dietary protein compared to meals generated by AI (43.7 % vs. 27.2 %, $p < 0.001$). Furthermore, saturated fat was higher in AI-generated meals than in dietitian-designed meals (12.4 % vs. 9.5 %, $p < 0.001$), exceeding 10 % of energy.

Tab. 4 presents the comparison of *n*-3 and *n*-6 fatty acid intake, dietary cholesterol, and sodium intake between dietitian-designed and AI-generated meal plans. In AI-generated plans, *n*-3 fatty acid intake was higher than in dietitian plans (median 5.0 g·d⁻¹ vs 3.1 g·d⁻¹, *IQR* 1.8 g·d⁻¹ vs 1.0 g·d⁻¹; $p < 0.01$). *n*-6 fatty acid intake (median 12.6 g·d⁻¹ vs 10.3 g·d⁻¹, *IQR* 8.2 g·d⁻¹ vs 3.7 g·d⁻¹; $p < 0.01$) and dietary cholesterol intake (median 354.7 mg·d⁻¹ vs 287.0 mg·d⁻¹, *IQR* 46.1 mg·d⁻¹ vs 52.0 mg·d⁻¹; $p = 0.03$) were also higher in AI plans. There was no statistically significant difference in sodium intake, but a borderline trend was observed (median 2 336.5 mg·d⁻¹ vs 2 256.4 mg·d⁻¹, *IQR* 2 590.2 mg·d⁻¹ vs 51.4 mg·d⁻¹; $p = 0.05$).

Total, soluble, and insoluble fibre intakes were higher in meal plans generated by dietitians (respectively, 34.1 ± 3.10 g·d⁻¹, 8.61 ± 0.63 g·d⁻¹, 24.94 ± 2.5 g·d⁻¹) compared to those generated by AI (respectively, 31.1 ± 6.2 g·d⁻¹, 7.33 ± 2.0 g·d⁻¹, 19.71 ± 4.15 g·d⁻¹), $p < 0.05$) (Fig. 1).

In terms of micronutrient adequacy based on *EAR* cut-off method, both AI-generated and dietitian-designed meal plans demonstrated a generally high level of adequacy across most vitamins and minerals. For the dietitian-designed meal plans, all participants met or exceeded the *EAR* for vitamin A, vitamins B1, B2, B3, B6, total folate, vitamin B12, vitamin C, magnesium, phos-

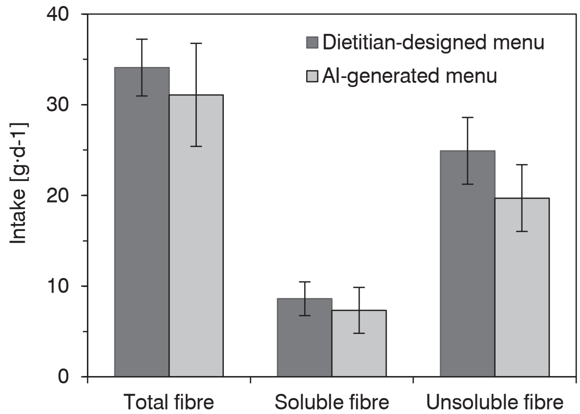

Fig. 1. Comparison of total, soluble, and insoluble fibre intake between dietitian- and AI-generated meal plans.

phorus, iron, and zinc, with only a small proportion falling below the *EAR* for vitamin E (6.0 %) and calcium (3.0 %). In contrast, the AI-generated meal plans showed a higher prevalence of intakes below the *EAR* for several micronutrients. The proportion of meal plans falling below the *EAR* was higher for total folate (18.2 %), vitamin C (6.1 %), calcium (39.4 %), magnesium (18.2 %), iron (33.3 %), and zinc (78.8 %). However, no meal plans in the AI group fell below the *EAR* for vitamin A, vitamins B1, B2, B3, B6, vitamin B12, vitamin E, or phosphorus. Overall, while both meal planning approaches met or exceeded the *EAR* for many micronutrients, dietitian-designed meal plans demonstrated more consistent micronutrient adequacy, particularly for minerals such as calcium, iron, magnesium, and zinc (Fig. 2 and Fig. 3). Micronutrient adequacy was assessed using the *EAR* cut-point method; however, because the analysis is based on a single-day menu, these estimates should be interpreted cautiously. *EAR*-based classifications are intended for usual (ha-

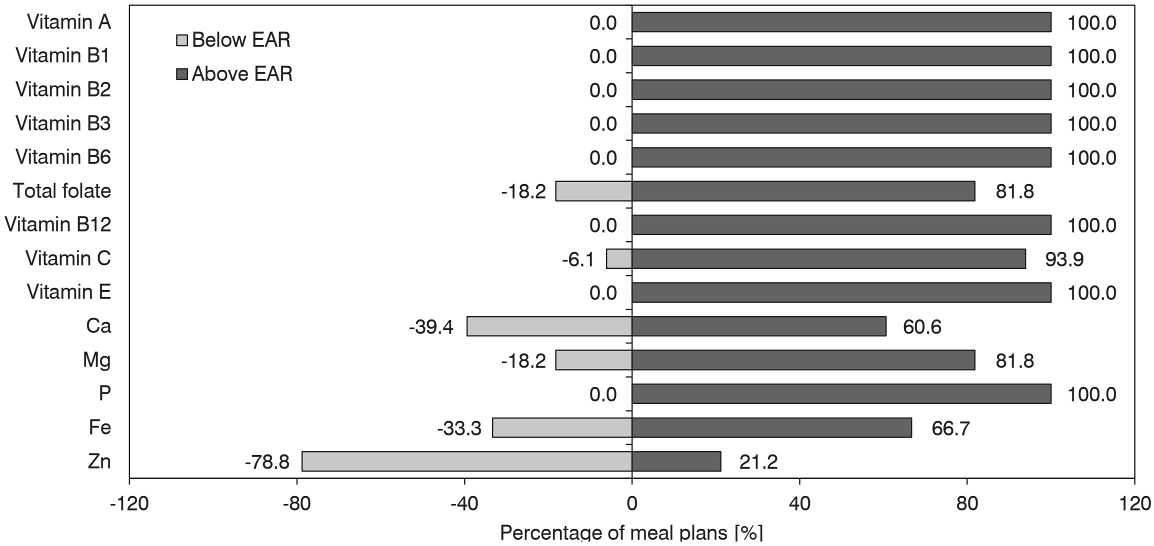

Fig. 2. Content of micronutrients below and above the estimated average requirement level in AI-generated meal plans.

EAR – estimated average requirement.

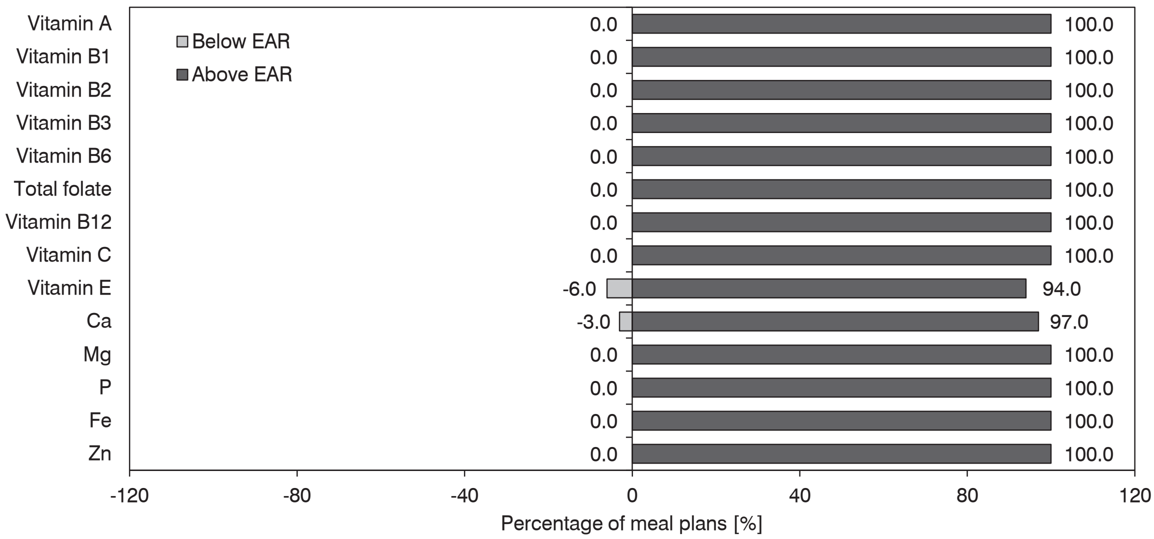

Fig. 3. Content of micronutrients below and above the estimated average requirement level in registered dietitian-designed meal plans.

EAR – estimated average requirement.

Tab. 5. Classification of individual meal plans as below or above the predefined limits for saturated fat intake, total dietary fibre intake, and sodium intake in menus.

	Limit		Dietitian-designed menu				AI-generated menu			
			Below limit		Above limit		Below limit		Above limit	
	Value	Ref.	*n*	[%]	*n*	[%]	*n*	[%]	*n*	[%]
Saturated fatty acid	< 10 %	[28]	19	57.6	14	42.4	3	9.1	30	90.9
Fibre	30–45 $g\cdot d^{-1}$	[18]	3	9.1	30	90.9	17	51.5	16	48.5
Sodium	< 2300 $mg\cdot d^{-1}$	[31]	33	100.0	0	0.0	14	42.4	19	57.6

bitual) intake, and a one-day plan may misclassify adequacy due to day-to-day variability.

A total of 33 pairs were analysed in this pairwise comparison. A sensitivity analysis performed in G*Power (two-sided, $\alpha = 0.05$) showed that the study with 33 pairs of cases had 80% power to detect a minimum standardised effect size $dz = 0.503$. The observed inter-approach differences were accompanied by effect sizes ranging from moderate (e.g., energy bias, $r = 0.41$) to large (e.g., macronutrient distribution, $r \geq 0.71$), supporting the robustness of the main findings.

Cardiovascular diseases remain a major global health burden, driven by lifestyle and environmental factors despite ongoing prevention efforts. Given the strong influence of nutrition on CVD management, this study explored the accuracy of ChatGPT-generated meal plans for simulated cardiovascular patient profiles.

Although AI tools like ChatGPT show promise in energy estimation, studies report ongoing limitations. Kaya Kaçar et al. [21] noted that ChatGPT outperformed other chatbots in energy accuracy but still lacked balance in macronutrients. Similarly, Phalle and Gokhale [7] and Kolla [22] highlighted that while AI systems are fast and user-friendly, they may produce inaccurate results in estimating energy and nutrient values. Kalivaraprasad et al. [23] found that even image-based models could miscalculate energy despite correctly identifying foods. In a diabetes-focused study, macronutrient mismatches were observed despite energy values being in line with targets [24]. In our study, AI-generated menus deviated more from energy targets than plans created by dietitians ($p = 0.017$). However, the absolute magnitude of this difference was small and may have limited clinical significance, as it corresponds to a relatively small daily energy amount when considered within a general dietary framework. Therefore, statistical significance should be interpreted cautiously, and a more applicable inference is that AI tools still need improvement in portion sizing, preparation assumptions, and personalisation to better align with individualised goals and nutrient distribution.

Following the finding of energy accuracy, differences in macronutrient distribution are also noteworthy. While there is positive evidence in the literature that AI-based meal planning systems can meet *AMDR*, some studies suggest that this balance can be disrupted. Plotnikova and Bocharov [25] reported that generative and hybrid models using *AMDR* as strict constraints can keep macro deviation below 5.0 % in 7-day menus. In contrast, Özlü Karahan et al. [26] and Khalifa and Albadawy [24] demonstrated that carbohydrate percentages in AI diets were below the recommended ranges, whereas protein and fat percentages were above the recommended levels [24, 26]. Similarly, in Kenger and Özlü Karahan's [27] AI-generated diet reviews for dyslipidaemia and hypertension, it was reported that fat rates were high and saturated fat rates exceeded guideline limits. In line with these reports, the current results suggest that AI-generated meal plans allocate less energy to carbohydrates and more to total fat, whereas dietitian-designed plans generally meet *AMDR* goals; Tab. 3 and Tab. 5 indicate that these departures are common across meal plans. This pattern is clinically relevant because shifting energy toward fat, particularly when saturated fat is not adequately constrained, may undermine cardiovascular-focused dietary goals.

At the nutritional level, this was reflected in AI menus that reduced or completely eliminated portions of whole grains/legumes or bread-like products, while the dietitian's menu, in line with the AHA guidelines, maintained structured whole-grain/legume portions and emphasised whole fruits and vegetables while limiting added sugar. Consistent with this, the plant-protein proportion was lower in AI menus than in dietitian menus (27.2 % vs 43.7 %), suggesting greater reliance on animal-derived protein sources, which may contribute to higher saturated fat and cholesterol exposure. This is also consistent with

AHA guidelines that emphasise healthier protein sources (e.g., plant-based sources and regular fish/seafood consumption). When fat subgroups were examined, saturated fat was higher in AI plans (12.4 %) than in dietitian plans (9.5 %), exceeding the commonly recommended 10 % of energy limit [28]. Given that most AI-generated menus exceeded the < 10 % energy threshold, this deviation is not only statistical but also clinically meaningful, as saturated fat is a modifiable dietary factor targeted in cardiovascular risk reduction. Monounsaturated fatty acids (17.2 % vs 7.8 %) and polyunsaturated fatty acids (10.5 % vs. 6.9 %) proportions were also higher in AI plans; however, this increase appears to track the substantially higher total fat content (45.0 %) in AI-generated plans. Overall, these results suggest that AI plans tend to reduce carbohydrate content below *AMDR* targets while increasing total fat, and particularly saturated fat, above guideline targets.

To illustrate these patterns at the food level, sample menus (samples of the same menu, designed by a registered dietitian and generated by AI; Tab. 6) show that the AI outputs generally reduce portions of key carbohydrate sources (e.g., whole grains/legumes or bread substitutes) while increasing energy from added fat-rich foods throughout the day (e.g., nuts, nut butters, added oils, and higher-fat animal foods). As a result, total fat and, in many cases, saturated fat can increase, even when menus include heart-healthy elements like fish. In contrast, the dietitian-designed sample preserves carbohydrate sources through structured whole-grain/legume portions and balances protein sources with a higher plant-based contribution; this can help maintain both *AMDR* compliance and fat quality targets more consistently.

Macronutrient differences were also seen in fat profile and cholesterol. Compared with dietitian-designed plans, AI-generated plans provided higher intakes of both n-3 and n-6 fatty acids but also substantially higher dietary cholesterol. These results indicate the need to improve fat quality and cholesterol control in AI plans. While a high n-3 intake can potentially be seen as a positive trait, the simultaneous increase in cholesterol is

Tab. 6. Comparison of sample menus designed by a registered dietitian and generated by artificial intelligence.

Dietitian-designed menu	AI-generated menu
Breakfast	**Breakfast**
1 glass of milk 1 boiled egg (medium) White cheese (2 finger-sized portion) Tomato and cucumber 2 thin slices of whole wheat bread	4 tablespoons rolled oats cooked in water (1 teaspoon ground cinnamon, 1 tablespoon ground flaxseed, 1 small banana or 1/2 large banana, 4 walnut halves, 1 glass unsweetened plant-based milk, e.g. oat milk) 1 cup unsweetened green tea or hibiscus tea
Snack	**Snack**
1 small banana 1 bowl of yoghurt	1 small apple 10 raw almonds
Lunch	**Lunch**
1 bowl of soup Oily fish (equivalent to 2 meatballs) 3 thin slices of whole wheat bread Large mixed salad (no oil)	6 tablespoons olive oil-based vegetable dish 3 tablespoons cooked quinoa or bulgur Mixed green salad with lemon and a small amount of olive oil 1 glass of ayran
Snack	**Snack**
30 g mixed berries 2 walnuts	1 small slice of avocado (1/4 fruit) 1–2 whole wheat crackers 1 cup hibiscus or linden tea
Dinner	**Dinner**
8 tablespoons vegetable dish 3 tablespoons pasta 1 bowl of yoghurt 2 thin slices of whole wheat bread	Grilled salmon (100–120 g) Steamed vegetables (broccoli, carrot, zucchini, cauliflower) 2 tablespoons olive oil lentil salad 1 slice whole wheat bread
Snack	**Snack**
1/8 of a small melon 5 almonds 4 hazelnuts	1 small pear or 1 kiwi 1 glass of kefir

undesirable from a cardiovascular risk management perspective. These findings suggest that AI-generated meal plans need to be better optimised in terms of fat source selection and cholesterol control.

The FAO/WHO expert consultation report on fats and fatty acids emphasises the importance of absolute intake levels and the quality of fat sources for *n*-3 and *n*-6 fatty acids. Specifically, while the cardiovascular protective effects of *n*-3 fatty acids are strongly supported by evidence, there is insufficient evidence to suggest that *n*-6 fatty acids have an inflammatory effect within the recommended intake ranges [28]. Djuricic and Calder's studies [29] also demonstrated that *n*-3 fatty acids, particularly eicosapentaenoic acid (EPA) and docosahexaenoic acid (DHA), have cardiovascular protective effects by lowering triglyceride levels, modulating inflammation, and supporting atherosclerotic plaque stability. In contrast, it was noted that *n*-6 fatty acids cannot be reduced solely to pro-inflammatory effects; they may be precursors to biologically active lipid mediators that play a role in resolving inflammation via arachidonic acid derivatives. These findings suggest that the absolute intakes and biological effects of *n*-3 and *n*-6 fatty acids are more meaningful in cardiovascular risk assessment than simple ratio approaches. Perez-Martinez et al. [30] summarised in their study that *n*-3 fatty acids (EPA and DHA) can be used in clinical practice, especially for lowering triglyceride (TG) levels, at doses of 2–4 g per day. They also noted that in patients using statins and with high TG levels, the use of 4 g of EPA per day resulted in a 25 % reduction in the risk of major cardiovascular events. In this study, the calculated *n*-3 fatty acid intakes included EPA, DHA, and α-linolenic acid (ALA), and both dietitian-generated and AI-generated plans showed high levels of *n*-3 intake. However, the higher *n*-6 fatty acid intake observed in AI-generated plans warrants careful clinical consideration, particularly when accompanied by elevated dietary cholesterol and suboptimal fat sources, which together may complicate cardiovascular risk management.

These findings indicate that high *n*-3 intake alone is not sufficient; rather, cardiovascular risk management requires optimisation of overall dietary fat quality and cholesterol content, alongside consideration of absolute fatty acid intakes.

Additionally, sodium intake in AI-generated plans showed a markedly wider range (1 500.6–5 954.2 $mg \cdot d^{-1}$), and the median sodium intake in AI plans (2 336.5 $mg \cdot d^{-1}$) was slightly above the recommended < 2 300 $mg \cdot d^{-1}$ limit [31]. This wide variability is clinically relevant because sodium reduction is reported to lower blood pressure and, in some studies, is associated with a lower risk of cardiovascular disease [18].

Furthermore, recent genetic evidence supports sodium restriction as a preventive target by showing a positive causal association between sodium intake and multiple cardiovascular disease outcomes [32]. Fibre intake was also higher in dietitian plans, likely due to greater use of whole grains, legumes, and vegetables. Even so, AI-generated plans generally met daily fibre goals (30-45 g per day [33]). This is clinically relevant because higher fibre intake is associated with improved satiety and more favourable cardiometabolic outcomes, and increasing fibre via whole grains, legumes, fruits, and vegetables is a common target in cardiovascular nutrition therapy.

Notable differences were observed in micronutrient adequacy relative to *EAR* between AI-generated and dietitian-designed meal plans. Dietitian-designed plans demonstrated consistently high micronutrient adequacy, with the vast majority of participants meeting or exceeding the *EAR* for most assessed vitamins and minerals, and only minimal inadequacies observed for vitamin E and calcium.

In contrast, AI-generated meal plans were associated with a higher proportion of intakes below the *EAR* for several micronutrients, particularly folate, vitamin C, calcium, magnesium, iron, and zinc. These results align with Hieronimus et al. [34] who found that most AI-generated omnivorous, vegetarian, and vegan diets met dietary reference intakes, though B12 deficiency remained common in vegan plans, requiring supplementation. Similarly, Naja et al. [35] also noted that AI-based plans fell short of meeting recommended dietary allowances, particularly for calcium. These findings indicate that, although AI-based meal planning can generate structured meal plans, it may insufficiently account for certain micronutrient requirements, resulting in potential imbalances in vitamin and mineral adequacy. This pattern, observed in the current study, may be partly explained by the underlying menu composition of AI-generated plans, which frequently included fish, eggs, vegetables, and healthy fat sources but provided limited portions of mineral-dense foods. In particular, dairy products were typically offered in small quantities and milk was rarely included, potentially contributing to lower calcium adequacy. Similarly, the limited inclusion of heme iron- and zinc-rich foods, such as red meat, together with modest portions of legumes, may explain the higher prevalence of iron and zinc intakes below the *EAR*. When evaluated in terms of nutritional composition, the higher prevalence of intakes below the *EAR* for calcium, magnesium, folate, iron, and zinc in AI-generated plans is consistent with a more limited presence of micronutrient-rich essential food groups in the menus. Specifically, the smaller portion sizes or less frequent inclusion of dairy products and dairy-fortified alternatives are associated with lower calcium intake, while reduced structured portions of whole grains and legumes are linked to decreased magnesium and folate intake and may also limit key dietary sources of iron and zinc. Additionally, the lower vitamin C intake observed in AI-generated plans may negatively affect iron bioavailability, further increasing the risk of iron deficiency. When interpreted in the context of the AHA dietary guidelines, these patterns suggest that, even when cardioprotective components such as fish are included, recommendations emphasising whole grains, plant-based protein sources, and low-fat or fat-free dairy products are not adequately implemented in AI-based meal plans.

The statistical tests used in the study were selected in accordance with the distribution characteristics of the data set and the sample size, and reporting these selections together with their effect sizes strengthened the clinical significance of the results. However, alternative modelling approaches (e.g., multivariate regression analyses) may provide additional value in future studies. The post hoc power analysis highlights two aspects relevant for the interpretation of the findings. First, the power for small-to-moderate effects was limited: for example, in the comparison of energy intake, the observed effect size was $r = 0.41$, yielding a power of 72.7 %, which suggests that smaller effects may have been missed. Second, the power for medium-to-large effects was high: for saturated fat and other macronutrients, the power exceeded 98.0 % for $r \geq 0.71$, and for paired t-tests, the power was ≥ 0.994 for $dz \geq 0.74$. These results support the statistical reliability of the differences observed in these parameters. Furthermore, very high power levels (e.g., 0.999) suggest that additional sample size may not contribute significantly and that even clinically insignificant small differences may become statistically significant; therefore, findings should be interpreted within a clinical/guideline context. Finally, it is important to note that post hoc power values are conditional on observed effect sizes and are not a substitute for a priori sampling planning.

CONCLUSIONS

While AI-generated plans aligned well with some reference values, dietitian plans offered a better balance of saturated fat, cholesterol, and fibre-suggesting a more sustainable option for long-term cardiometabolic health. A combined approach that blends the speed and convenience of AI with professional dietitian guidance may offer the best results.

AI-based nutrition systems have made progress in energy estimation and nutrient recommendations, but they still fall short in accurately meeting energy and macronutrient needs. Key limitations of this study include: (1) the case profiles used in this study are simulation-based and do not reflect the heterogeneity that may be observed in real-life clinical parameters (such as blood pressure, lipid profile, HbA1c, and body composition) across age groups. Cardiometabolic risk profiles generally vary across different age groups; specific clinical values were kept constant in this study. This may limit the generalisability of how AI and dietitian performance might change in more realistic, age-specific clinical scenarios. (2) Only a single output was collected for each instruction, and no repeated sampling was performed. Therefore, response variability across repeated runs of the same instruction and potential changes in outputs over time as the model is updated were not assessed. (3) Evaluation of one-day menus only, which may not reflect habitual intake or week-to-week variability. (4) This simulation-based design did not account for factors that determine real-world dietary behaviours and outcomes, such as patient behaviour, adherence to prescribed diets, and socioeconomic constraints. Therefore, the findings should be interpreted as a controlled comparison of menu-generation performance rather than as evidence of effectiveness in real-world clinical practice. (5) Nutrient analysis was conducted using the Turkish BeBiS food composition database, which may limit generalisability to other populations and food environments. The BeBiS program cannot calculate trans fat and free sugar levels; therefore, analyses related to these parameters could not be performed.

This study has shown that AI-generated nutritional plans are not sufficiently clinically optimised in the context of cardiovascular disease. While n-3 and n-6 fatty acids were higher in AI-generated menus, total fat, the saturated fat percentage, and dietary cholesterol were found to be above recommended limits. Furthermore, deficiencies in some essential minerals were remarkably high. These findings indicate that current AI systems cannot provide the therapeutic accuracy required for cardiovascular risk management. Especially in individuals for whom strict control of cardiometabolic parameters such as saturated fat, cholesterol, and sodium is necessary, AI-generated menus are unsuitable for clinical use. Therefore, the use of AI outputs as a standalone medical nutrition therapy tool in individuals with cardiovascular disease is not recommended. Although AI systems have the potential to save time in the menu generation process, the results obtained in this study show that they do not constitute a reliable alternative in clinical practice due to the substantial deviation of diet quality from therapeutic goals.

Future studies should use age-stratified, realistic cardiometabolic profiles (e.g., age-specific ranges for blood pressure, lipid profile, HbA1c, and body composition) to improve clinical translatability. In particular, focusing on narrower age bands (e.g., 50–75 years) and varying risk profiles within each band may better reflect real-world heterogeneity.

REFERENCES

1. Luengo-Fernandez, R. – Little, M. – Gray, A. – Torbica, A. – Maggioni, A. P. – Huculeci, R. – Timmis, A. D. – Vardas, P. – Leal, J.: Cardiovascular disease burden due to productivity losses in European Society of Cardiology countries. European Heart Journal – Quality of Care and Clinical Outcomes, *10*, 2024, pp. 36–44. DOI: 10.1093/ehjqcco/qcad031.
2. Mazur, M. – Przytuła, A. – Szymańska, M. – Popiołek-Kalisz, J.: Dietary strategies for cardiovascular disease risk factors prevention. Current Problems in Cardiology, *49*, 2024, article 102746. DOI: 10.1016/j.cpcardiol.2024.102746.
3. Pant, A. – Chew, D. P. – Mamas, M. A. – Zaman, S.: Cardiovascular disease and the Mediterranean diet: insights into sex-specific responses. Nutrients, *16*, 2024, article 570. DOI: 10.3390/nu16040570.
4. Laffond, A. – Rivera-Picón, C. – Rodríguez-Muñoz, P. M. – Juárez-Vela, R. – Ruiz de Viñaspre-Hernández, R. – Navas-Echazarreta, N. – Sánchez-González, J. L.: Mediterranean diet for primary and secondary prevention of cardiovascular disease and mortality: an updated systematic review. Nutrients, *15*, 2023, article 3356. DOI: 10.3390/nu15153356.
5. Hareer, L. W. – Lau, Y. Y. – Mole, F. – Reidlinger, D. P. – O'Neill, H. M. – Mayr, H. L. – Greenwood, H. – Albarqouni, L.: The effectiveness of the Mediterranean diet for primary and secondary prevention of cardiovascular disease: An umbrella review. Nutrition & Dietetics, *82*, 2025, pp. 8–41. DOI: 10.1111/1747-0080.12891.
6. Rozga, M. – Latulippe, M. E. – Steiber, A.: Advancements in personalized nutrition technologies: guiding principles for registered dietitian nutritionists. Journal of the Academy of Nutrition and Dietetics, *120*, 2020, pp. 1074–1085. DOI: 10.1016/j.jand.2020.01.020.
7. Phalle, A. – Gokhale, D.: Navigating next-gen nutrition care using artificial intelligence-assisted dietary assessment tools – a scoping review of potential applications. Frontiers in Nutrition, *12*, 2025, article 1518466. DOI: 10.3389/fnut.2025.1518466.
8. Swamy, P.: Personalized nutrition prescription generated by AI platform improves cardiometabolic health. International Journal of Life Sciences Biotechnology and Pharma Research, *14*, 2025, pp. 1554–1558. ISSN: 2977-0122 (print), 2250-3137 (online). DOI: 10.69605/ijlbpr_14.7.2025.259.
9. Wang, X. – Sun, Z. – Xue, H. – An, R.: Artificial intelligence applications to personalized dietary recommendations: a systematic review. Healthcare (Basel), *13*, 2025, article 1417. DOI: 10.3390/healthcare13121417.
10. Türkiye Sağlık Araştırması, 2022. (Türkiye health survey.) In: TUIK [online]. Ankara : Turkish Statistical Institute, 2023 [accessed 20 August 2025]. <https://data.tuik.gov.tr/Bulten/Index?p=Turkiye-Saglik-Arastirmasi-2022-49747&utm> In Turkish.
11. Onat, A. (Ed.): TEKHARF 2017: Tıp Dünyasının Kronik Hastalıklara Yaklaşımına Öncülük. (TEKHARF 2017: Leading the medical community's approach to chronic diseases.) İstanbul : Turkish Society of Cardiology Publications, 2017. ISBN: 978-975-349-081-8. <https://file.tkd.org.tr/pdfs/tekharf-2017.pdf> In Turkish.
12. Yusuf, S. – Hawken, S. – Ôunpuu, S. – Dans, T. – Avezum, A. – Lanas, F. – McQueen, M. – Budaj, A. – Pais, P. – Varigos, J. – Lisheng, L.: Effect of potentially modifiable risk factors associated with myocardial infarction in 52 countries (the INTERHEART study): case-control study. The Lancet, *364*, 2004, pp. 937–952. DOI: 10.1016/S0140-6736(04)17018-9.
13. Dagenais, G. R. – Leong, D. P. – Rangarajan, S. – Lanas, F. – Lopez-Jaramillo, P. – Gupta, R. – Diaz, R. – Avezum, A. – Oliveira, G. B. F. – Wielgosz, A. – Parambath, S. R. – Mony, P. – Alhabib, K. F. – Temizhan, A. – Ismail, N. – Chifamba, J. – Yeates, K. – Khatib, R. – Rahman, O. – Zatonska, K. – Kazmi, K. – Wei, L. – Zhu, J. – Rosengren, A. – Vijayakumar, K. – Kaur, M. – Mohan, V. – Yusufali, A. – Kelishadi, R. – Teo, K. K. – Joseph, P. –Yusuf, S.: Variations in common diseases, hospital admissions, and deaths in middle-aged adults in 21 countries from five continents (PURE): a prospective cohort study. The Lancet, *395*, 2020, pp. 785–794. DOI: 10.1016/S0140-6736(19)32007-0.
14. Hubert, H. B. – Feinleib, M. – McNamara, P. M. – Castelli, W. P.: Obesity as an independent risk factor for cardiovascular disease: a 26-year follow-up of participants in the Framingham Heart Study. Circulation, *67*, 1983, pp. 968–977. DOI: 10.1161/01.CIR.67.5.968.
15. Grundy, S. M. – Stone, N. J. – Bailey, A. L. – Beam, C. – Birtcher, K. K. – Blumenthal, R. S. – Braun, L. T. – de Ferranti, S. – Faiella-Tommasino, J. – Forman, D. E. – Goldberg, R. – Heidenreich, P. A. –

Hlatky, M. A. – Jones, D. W. – Lloyd-Jones, D. – Lopez-Pajares, N. – Ndumele, C. E. – Orringer, C. E. – Peralta, C. A. – Saseen, J. J. – Smith Jr, S. C. – Sperling, L. – Virani, S. S. – Yeboah, J.: 2018 AHA/ACC/AACVPR/AAPA/ABC/ACPM/ADA/AGS/APhA/ASPC/NLA/PCNA guideline on the management of blood cholesterol: a report of the American College of Cardiology/American Heart Association Task Force on Clinical Practice Guidelines. Circulation, *139*, 2019, pp. e1082–e1143. DOI: 10.1161/CIR.0000000000000625.

16. Cohen, J. B.: What is new in the ESC hypertension guideline? Hypertension, *82*, 2025, pp. 11–13. DOI: 10.1161/HYPERTENSIONAHA.124.23724.
17. 2. Diagnosis and classification of diabetes: standards of care in diabetes – 2024. Diabetes Care, *47*, 2024, Suppl. 1, pp. S20–S42. DOI: 10.2337/dc24-S002.
18. Lichtenstein, A. H. – Appel, L. J. – Vadiveloo, M. – Hu, F. B. – Kris-Etherton, P. M. – Rebholz, C. M. – Sacks, F. M. – Thorndike, A. N. – Van Horn, L. – Wylie-Rosett, J.: 2021 Dietary guidance to improve cardiovascular health: a scientific statement from the American Heart Association. Circulation, *144*, 2021, pp. e472–e487. DOI: 10.1161/CIR.0000000000001031.
19. Stallings, V. A. – Harrison, M. – Oria, M. (Eds.): Dietary reference intakes for sodium and potassium. Washington, D. C. : National Academies Press, 2019. ISBN: 9780309488341. DOI: 10.17226/25353.
20. Rosenthal, R.: Meta-analytic procedures for social research. Newbury Park : Sage Publications, 1991. ISBN: 9780803942462. DOI: 10.4135/9781412984997
21. Kaya Kaçar, H. – Kaçar, Ö. F. – Avery, A.: Diet quality and caloric accuracy in AI-generated diet plans: a comparative study across chatbots. Nutrients, *17*, 2025, article 206. DOI: 10.3390/nu17020206.
22. Kolla, V. R. K.: A novel machine learning approach to calorie estimation for diabetes and obesity management. International Journal of Innovations in Engineering Research and Technology, *11*, 2024, pp. 8–16. DOI: 10.26662/ijiert.v11i12.pp8-16.
23. Kalivaraprasad, B. – Prasad, M. V. D. – Vamsi, R. – Tejasri, U. – Santhoshi, M. N. – Pramod Kumar, A.: Analysis of food recognition and calorie estimation using AI. AIP Conference Proceedings, *2407*, 2021, article 020020. DOI: 10.1063/5.0074506.
24. Khalifa, M. – Albadawy, M.: Artificial intelligence for diabetes: enhancing prevention, diagnosis, and effective management. Computer Methods and Programs in Biomedicine Update, *5*, 2024, article 100141. DOI: 10.1016/j.cmpbup.2024.100141.
25. Plotnikova, N. – Bocharov, A.: Artificial intelligence and personalized nutrition: how algorithms facilitate balanced macro- and micronutrient intake. Endocrinology Nutrition ClinKey Now – EMC & Outils Cliniques, 2025, article hal-05069680f. ISSN: 1155-1941. <https://hal.science/hal-05069680>
26. Özlü Karahan, T. – Kenger, E. B.: ChatGPT-4o for weight management: comparison of different diet models. Food Science and Nutrition, *13*, 2025, article e70639. DOI: 10.1002/fsn3.70639.
27. Kenger, E. B. – Özlü Karahan, T.: Artificial intelligence-generated diet plans for hypertension and dyslipidemia: adherence and nutritional insights. Iranian Journal of Public Health, *54*, 2025, pp. 1243–1251. DOI: 10.18502/ijph.v54i6.18902.
28. Fats and fatty acids in human nutrition: Report of an expert consultation. FAO Food and Nutrition Papers *91*. Rome : Food and Agriculture Organization, 2010. ISSN: 0254-4725. ISBN: 9789251067338. <https://www.fao.org/fileadmin/user_upload/nutrition/docs/requirements/fatsandfattacidsreport.pdf>
29. Djuricic, I. – Calder, P. C.: Omega-3 (*n*-3) fatty acid–statin interaction: evidence for a novel therapeutic strategy for atherosclerotic cardiovascular disease. Nutrients, *16*, 2024, article 962. DOI: 10.3390/nu16070962.
30. Perez-Martinez, P. – Katsiki, N. – Mikhailidis, D. P.: The role of *n*-3 fatty acids in cardiovascular disease: back to the future. Angiology, *71*, 2020, pp. 10–16. DOI: 10.1177/0003319719842005.
31. Snetselaar, L. G. – de Jesus, J. M. – DeSilva, D. M. – Stoody, E. E.: Dietary guidelines for Americans, 2020–2025: Understanding the scientific process, guidelines, and key recommendations. Nutrition Today, *56*, 2021, pp. 287–295. DOI: 10.1097/NT.0000000000000512.
32. Fu, Q. – Chen, R. – Ding, Y. – Xu, S. – Huang, C. – He, B. – Li, S.: Sodium intake and the risk of various types of cardiovascular diseases: a Mendelian randomization study. Frontiers in Nutrition, *10*, 2023, article 1250509. DOI: 10.3389/fnut.2023.1250509.
33. Visseren, F. L. J. – Mach, F. – Smulders, Y. M. – Carballo, D. – Koskinas, K. C. – Bäck, M. – Benetos, A. – Biffi, A. – Boavida, J.-M. – Capodanno, D. – Cosyns, B. – Crawford, C. – Davos, C. H. – Desormais, I. – Di Angelantonio, E. – Wanner, C. – Williams, B. – ESC Scientific Document Group: 2021 ESC guidelines on cardiovascular disease prevention in clinical practice: Developed by the Task Force for cardiovascular disease prevention in clinical practice with representatives of the European Society of Cardiology and 12 medical societies with the special contribution of the European Association of Preventive Cardiology (EAPC). European Heart Journal, *42*, 2021, pp. 3227–3337. DOI: 10.1093/eurheartj/ehab484.
34. Hieronimus, B. – Hammann, S. – Podszun, M. C.: Can the AI tools ChatGPT and Bard generate energy, macro- and micro-nutrient sufficient meal plans for different dietary patterns? Nutrition Research, *128*, 2024, pp. 105–114. DOI: 10.1016/j.nutres.2024.07.002.
35. Naja, F. – Taktouk, M. – Matbouli, D. – Khaleel, S. – Maher, A. – Uzun, B. – Alameddine, M. – Nasreddine, L.: Artificial intelligence chatbots for the nutrition management of diabetes and the metabolic syndrome. European Journal of Clinical Nutrition, *78*, 2024, pp. 887–896. DOI: 10.1038/s41430-024-01476-y.

Received 24 October 2025; 1st revised 25 February 2026; accepted 1 April 2026; published online 14 April 2026.