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When healthier eating emits more: Socioeconomic divergence in U.S. diet sustainability

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ABSTRACT

Efforts to improve the sustainability of diets require a joint understanding of how nutritional quality and environmental impact vary across social and economic groups, and how they respond to policy levers, going beyond the now-standard “eat less meat” recommendation, too often repeated without asking who is actually able to change and how. Using nationally representative dietary data from the United States, we introduce a Data Envelopment Analysis framework that jointly scores how close each observed diet is to the best nutrition–emissions combinations already achievable in the population; we then combine this with regression and generalized additive models to identify how income, price, and education shape this nutrition–environment trade-off. We find that improvements in diet quality do not uniformly reduce environmental impact: among middle-income groups, income increase is associated with healthier diets but substantially higher emissions, whereas among high-income groups, further income gains reinforce both better nutritional profiles and lower emissions. Education exhibits a strongly nonlinear effect, with substantial gains in diet quality and large reductions in emissions emerging only at the highest educational levels. These findings show that sustainable diet policy cannot rely on a single dietary prescription. Targeted, equity-oriented food policies are needed to advance nutrition and climate goals jointly while accounting for differences in socioeconomic constraints, dietary baselines, and capacity to adopt low-emission, high-quality diets.

1. Introduction

Dietary choices are central to both human health and environmental sustainability. More than 5 billion people lack adequate intake of at least one essential micronutrient, with deficiencies in iodine, vitamin E, calcium, and iron common worldwide (Passarelli et al., 2024). In the United States, poor diet is a leading contributor to preventable mortality, including heart disease and type 2 diabetes (Murray et al., 2020). At the same time, food systems account for nearly one-third of global greenhouse gas (GHG) emissions and contribute substantially to environmental degradation (Vermeulen et al., 2012; Springmann et al., 2018; Willett et al., 2019; Rockström et al., 2025). Dietary change therefore sits at the intersection of two policy objectives: improving population health and reducing environmental pressure.

These objectives are connected, but they are not always aligned. Plant-forward dietary patterns can reduce environmental footprints and are often associated with better health outcomes (Poore and Nemecek, 2018; Springmann et al., 2020; Willett et al., 2019). However, health and environmental gains do not always move together. Some nutritionally desirable shifts, including higher intake of certain fruits, vegetables, or other resource-intensive foods, may increase specific environmental pressures, while some low-emission diets may fail to meet nutritional requirements (Godfray et al., 2010; Willett et al., 2019; Conrad et al., 2023). Moreover, dietary change is not applied to a uniform baseline. Individuals differ substantially in their existing food choices, nutritional adequacy, emissions profiles, and feasible substitutions (Heller et al., 2018; Rose et al., 2019; FAO and WHO, 2019; Biesbroek et al., 2023). For high consumers of beef or other high-impact animal products, reducing those foods may yield large environmental gains; for individuals who already consume little meat, the relevant health–environment improvement may lie elsewhere. The policy-relevant question is therefore not only whether diets are healthier or lower-emitting in isolation, but which diets combine nutritional quality and environmental performance more effectively, and which socioeconomic conditions make such combinations more or less attainable.

Socioeconomic disparities further complicate this challenge. In the United States, higher income and education are associated with healthier dietary patterns, including greater fruit, vegetable, and whole-grain intake and lower red-meat and processed-food consumption (Darmon and Drewnowski, 2015; Rehm et al., 2016). Lower-income populations

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often face financial and physical barriers to fresh and healthy foods, leading to greater reliance on calorie-dense but nutrient-poor diets (Mason-D'Croz et al., 2020). Education can support adherence to dietary guidance (Hiza et al., 2013), while dietary patterns also vary by demographic characteristics such as gender (Baker and Friel, 2017). Similar inequalities are observed globally (Dekker et al., 2015; He et al., 2021; Popkin et al., 2020; Swinburn et al., 2019). Yet relatively few studies examine how income, prices, education, and demographic characteristics jointly shape the health–environment performance of diets.

The existing literature has two main limitations. First, prior studies have often examined diet quality and environmental pressure separately (He et al., 2018; Stylianou et al., 2021), or have documented their association across pre-defined dietary patterns without an integrated, individual-level optimization framework (Conrad et al., 2023). This makes it difficult to identify diets, or policy levers, that improve nutrition and emissions simultaneously rather than improving one at the expense of the other. Second, although socioeconomic disparities in diet quality are well documented, less is known about how income, prices, education, and demographic characteristics shape individuals' position within the nutrition–emissions trade-off.

This study addresses these gaps using dietary data from the National Health and Nutrition Examination Survey (NHANES) 2015–2016 in the United States. We make three contributions. First, we introduce a joint dietary efficiency score, derived from Data Envelopment Analysis (DEA), that benchmarks each individual's diet against the best observed combinations of nutritional quality, measured using the Healthy Eating Index (HEI), and diet-related GHG emissions. Second, we apply t-distributed stochastic neighbor embedding (t-SNE), a nonlinear dimensionality reduction technique, to examine whether diets cluster by similarity in food composition and whether these clusters align with socioeconomic and demographic characteristics. Third, we use regression models and generalized additive models (GAMs) to assess how income, prices, education, and demographic factors are associated with dietary efficiency and with health–environment synergies or trade-offs across income groups. Together, these analyses provide a framework for identifying dietary patterns and policy levers that can improve nutritional quality and environmental performance while accounting for socioeconomic disparities.

2. Analytical framework

2.1. Diets as a coupled health–environment system

The premise of this study is that a diet should not be evaluated as two separate assessment domains, one nutritional and one environmental, but as a single bundle of food choices with simultaneous implications for health-relevant dietary quality and environmental burden. On the health side, dietary patterns are a leading modifiable determinant of chronic disease risk (Murray et al., 2020; Passarelli et al., 2024); on the environmental side, the same choices contribute substantially to global greenhouse-gas emissions and other environmental pressures (Vermeulen et al., 2012; Springmann et al., 2018; Willett et al., 2019; Rockström et al., 2025). Crucially, these two dimensions are neither independent nor uniformly aligned. Plant-forward substitutions often lower both diet-related disease risk and environmental burden (Poore and Nemecek, 2018; Springmann et al., 2020), generating synergies; yet some health-promoting shifts, such as greater fruit and vegetable intake, may increase specific resource demands, generating *trade-offs* (Godfray et al., 2010; Willett et al., 2019). This combination of synergy and tension is the joint performance this paper seeks to assess. A framework that scores diets on only one axis cannot, by construction, distinguish a joint improvement from an improvement in one dimension purchased at the expense of the other.

2.2. Dietary efficiency and the best-practice frontier

To evaluate these two dimensions jointly, we treat each individual diet as a decision-making unit whose nutritional quality is assessed relative to its environmental cost. This individual-level framing is important because dietary change begins from heterogeneous baselines: people differ in their existing food choices, nutritional adequacy, emissions profiles, and feasible substitutions. A general recommendation, such as shifting toward more plant-forward diets, may identify an important direction of change, but it does not by itself indicate where the greatest joint health–environment improvement is possible for each observed diet.

The core innovation is therefore to move from separate impact measurement to joint performance scoring. Prior work can report diet quality and environmental burden as parallel indicators: a diet has a nutritional score and a greenhouse-gas footprint. Such measures are informative and can be examined together, but they do not provide a formal benchmark of joint performance. They do not tell us how close each diet is to the best observed nutrition–emissions combinations in the population, nor do they produce an individual-level efficiency score that ranks diets by how well they achieve nutritional quality relative to environmental burden.

The relevant benchmark is not a prespecified ideal dietary pattern, such as the EAT–Lancet planetary health diet (Willett et al., 2019), but the best observed nutrition–emissions combinations in the population: an empirical efficiency frontier. A diet is efficient if no other observed diet delivers at least as much nutritional quality with lower greenhouse-gas emissions, and it is inefficient to the extent that such dominating diets exist. This frontier logic, formalized in Data Envelopment Analysis (Charnes et al., 1978; Banker et al., 1984), provides a principled way to benchmark each diet's joint health–environment performance without imposing fixed external prices or ex ante weights on nutrition and emissions. It also marks the conceptual departure from prior work, which has typically assessed diet quality and environmental pressure in isolation, evaluated adherence to pre-defined dietary patterns, or documented associations between nutrition and emissions without an integrated, individual-level optimization framework.

2.3. Socioeconomic structure as a determinant of dietary efficiency

If diets vary in their joint health–environment performance, the natural next question is what systematically moves an individual toward or away from the efficiency frontier. We argue that position on the frontier is not randomly distributed but socially structured, through three mechanisms that the framework treats as the channels linking socioeconomic conditions to dietary efficiency. The first is economic constraint: because price and income elasticities of food demand are steeper for lower-income households, changes in prices or disposable income translate more directly into changes in diet quality for those households (Darmon et al., 2014; McCullough et al., 2024; Santeramo and Shabnam, 2015). The second is human capital: education operates not as income but as the capacity to interpret dietary guidance and act on nutritional information (Hiza et al., 2013; Schoufour et al., 2018). The third is social differentiation: dietary patterns vary along demographic lines independent of resources, gender being the clearest case (Baker and Friel, 2017). Treating these as distinct channels, rather than a single "socioeconomic" effect, is what allows the analysis to ask not only whether these factors matter, but which lever moves which group toward better joint performance, and where the levers create synergies versus trade-offs.

3. Data and methods

3.1. Data

The dietary data for this study was sourced from the 2015–2016 National Health and Nutrition Examination Survey (NHANES), a biannual survey conducted by the National Center for Health Statistics. NHANES collects demographic, socioeconomic, dietary, and health-related information through interviews and employs a 24-hour dietary recall method over two nonconsecutive days. For this study, the average food intake across the two days was calculated for each individual (He et al., 2021). Following Claro et al. (2010), calorie intake was standardized to enable comparability across individuals, and samples with adjusted calorie intakes below 1500 kcal were excluded to ensure a robust sample for model development. Additional data from the Food and Nutrient Database for Dietary Studies (FNDDS) and the Food Patterns Equivalents Database (FPED) were used to categorize diets into 13 food ingredient groups and compile demographic and socio-economic profiles, providing a detailed basis for analysis.

The Healthy Eating Index (HEI), developed to measure diet quality, assesses the extent to which food consumption aligns with the recommendations outlined in the Dietary Guidelines for Americans. These guidelines, designed for nutrition and health professionals, provide strategies to help individuals and families maintain nutritionally balanced diets. For this study, we used the HEI-2015 version to calculate diet quality scores for each individual, with HEI serving as a key indicator of nutritional adequacy.

Environmental impacts were assessed using data from Stylianou et al. (2021), who conducted Life Cycle Assessments (LCAs) to quantify the "cradle-to-farm/processing gate" environmental footprints of various foods. Their study developed life cycle inventories (LCIs) to capture the resource usage and emissions associated with food production. Databases such as World+ v1.4, ecoinvent (Cut-off) v3.3, World Food LCA Database (WFLDB) v3.1, and ESU World food LCA were used to calculate these impacts. From their dataset, we extracted greenhouse gas (GHG) emissions as the primary environmental indicator for this study, reflecting the environmental burden associated with individual dietary patterns.

3.2. Methodology

The sustainability of individual diets, in terms of environmental impact and nutritional quality, was assessed using the Data Envelopment Analysis (DEA) method, a non-parametric, linear programming-based method for evaluating the relative efficiency of comparable decision-making units (DMUs) (Charnes et al., 1978; Lucas et al., 2021). In this study, each individual's daily diet is treated as a DMU. The analysis evaluates how efficiently each observed diet combines nutritional quality and environmental performance relative to the best-performing diets in the sample.

The model uses three types of variables. First, the 13 food ingredient groups derived from NHANES are used to characterize the composition of each diet: total vegetables, greens and beans, total fruit, whole fruit, unsaturated fats, seafood and plant protein, total protein, dairy, whole grains, refined grains, added sugar, and sodium. Second, the Healthy Eating Index (HEI) is specified as a desirable output, representing nutritional quality. Third, diet-related greenhouse gas (GHG) emissions are specified as an undesirable output, representing environmental burden. In the DEA implementation, the undesirable-output specification ensures that lower GHG emissions improve performance, while higher HEI improves performance.

DEA was then used to derive an efficiency score for each individual's diet. Diets on the efficient frontier represent the best observed combinations of nutritional quality and environmental performance in the sample. Diets below the frontier are relatively inefficient because other observed diets achieve a better combination of higher HEI and lower GHG emissions. The resulting score therefore captures relative joint health–environment performance, rather than diet quality or emissions alone.

Developed by Charnes et al. (1978), DEA is a non-parametric, linear programming-based technique designed to measure the relative efficiency of comparable units, referred to as decision-making units (DMUs). In this study, each individual's daily diet represents a DMU, characterized by its contributions to environmental impact and nutritional adequacy. For each individual, an efficiency score θ ranging from 0 to 1 was calculated. A score of 1 indicates a diet that is efficient relative to the best practices observed in the dataset achieving nutritional adequacy with the lowest environmental impact among peers. Scores below 1 reflect varying degrees of relative inefficiency, suggesting potential for improvement by moving closer to the performance of the most efficient diets.

The Non-Discretionary Variable Returns to Scale (VRS) model (Cooper et al., 2006), in its input-oriented envelopment form, serves as the framework in this study. The input variables are the 13 food ingredients, including: total vegetables, green beans, total fruit, whole fruit, unsaturated fats, seafood and plant protein, total protein, dairy, whole grains, refined grains, added sugar, and sodium. The output variables are HEI and GHG emissions. Considering a collection of n Decision-Making Units (DMUs) ($j = 1, \dots, n$) representing each individual's diet, each utilizing m inputs, $x_{i,j}$ ($i = 1, \dots, m$), where i belongs to discretionary inputs (D), representing environmental impacts, and i belongs to non-discretionary inputs (ND), representing dietary intake, to yield s outputs, $y_{r,j}$ ($r = 1, \dots, s$), the ensuing Linear Programming problem can be formulated to ascertain the efficiency score θ for each DMU:

$$\min_{\theta,\lambda,s_i^-,s_r^+} \quad \theta \tag{1}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} \lambda_j x_{i,j} + s_i^- = \theta x_{i,0}, \quad \forall i \in D \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j x_{i,j} + s_i^- = x_{i,0}, \quad \forall i \in ND \tag{3}$$

$$\sum_{j=1}^{n} \lambda_j y_{r,j} - s_r^+ = y_{r,0}, \quad \forall r \tag{4}$$

$$\sum_{j=1}^{n} \lambda_j = 1, \tag{5}$$

$$\lambda_j, s_i^-, s_r^+ \geq 0, \quad \forall j, i, r \tag{6}$$

$$\theta \text{ unrestricted.} \tag{7}$$

Here, s_i^- and s_r^+ are the slack variables for inputs and outputs, respectively, and λ_j represents the weights for the linear combination of efficient DMUs.

For each inefficient diet ($\theta < 1$), the DEA model projects it onto the efficient frontier by identifying a composite unit derived from the performances of efficient DMUs. This composite unit, constructed as a weighted linear combination of efficient diets, provides a benchmark for improvement. Efficient units with non-zero weights ($\lambda_j > 0$) constitute the reference set for inefficient diets, guiding their transition toward reduced environmental impact and improved efficiency.

3.3. Clustering of dietary patterns

To cluster the similar diets, we applied t-distributed stochastic neighbor embedding (t-SNE) (Van der Maaten and Hinton, 2008), a nonlinear dimensionality reduction technique. t-SNE projects each individual's 13-dimensional food intake vector into a two-dimensional space, positioning diets with similar food composition close together while placing dissimilar diets farther apart. The embedding was estimated with perplexity = 30, learning rate (eta) = 300, and angle parameter (theta) = 0.1, following standard practice for balancing the preservation of local neighborhood structure against global structure while ensuring stable convergence. Each point in the resulting two-dimensional map was subsequently colored by its DEA efficiency score and cross-tabulated against demographic attributes (age, gender, and race) to assess whether efficiency-based clusters coincide with socioeconomic groupings. This step is descriptive rather than inferential: *t*-SNE does not test for statistical association, but visualizes whether such association is plausible, motivating the regression analysis described below.

3.4. Regression and generalized additive models

We used regression analysis to evaluate how demographic and policy-relevant variables are associated with dietary outcomes. Three outcomes were modeled: log-transformed Healthy Eating Index (Log HEI), log-transformed greenhouse gas emissions per capita (Log MGHG), and log-transformed DEA efficiency score (Log Efficiency). Predictors common to all three models were ethnicity (indicators for White, Black, Asian, and Multi-Races, with Hispanic as the reference category), log household income, an energy conversion adjustment, log diet price, and gender (female indicator, with male as the reference category). The energy conversion variable follows Claro et al. (2010) and adjusts reported energy intake for under- and over-reporting bias in self-reported dietary recall data, ensuring that comparisons of HEI, GHG, and efficiency across individuals are not confounded by differential misreporting of total energy intake.

Because the relationship between education and dietary outcomes was not well captured by a linear specification, education was modeled as a Generalized Additive Model (GAM) penalized smooth (spline) function of log-transformed years of education, while all other covariates entered the model parametrically as described above. GAMs extend standard regression by allowing the marginal effect of a predictor to vary flexibly across its range rather than assuming a fixed linear (or polynomial) form, and were estimated separately for each of the three outcomes. Model fit was assessed using the effective degrees of freedom (EDF) of the smooth term, where EDF = 1 corresponds to a linear effect and higher values indicate increasing nonlinearity, alongside adjusted R^2 and the Un-Biased Risk Estimator (UBRE) criterion for model comparison.

4. Results

4.1. Balance

By assessing the overall efficiency of 13 major food categories, we identify how different food ingredients contribute to the balance between nutritional quality and environmental sustainability. Fig. 1 illustrates the relationship between food consumption and efficiency scores. Certain food groups, such as green beans, seafood and plant protein, whole grains, and whole fruit, exhibit a positive association with efficiency scores. These foods not only improve health outcomes by increasing HEI scores but also have relatively low environmental impacts (see Supplementary Fig. 1, 2). Conversely, food categories such as non-saturated fats and total protein demonstrate an inverse relationship with efficiency. Similarly, sodium and dairy have a relatively limited impact on diet quality but significantly contribute to environmental degradation, resulting in lower efficiency scores with increased consumption. Added sugars have a low environmental footprint but harm health, leading to lower efficiency scores. Dietary optimization follows distinct pathways, including a 'win-win' scenario where higher HEI scores coincide with lower GHG emissions (See Supplementary Fig. 3).

4.2. Demographics

Beyond food-category patterns, dietary efficiency also varies systematically across the population. Nutritional quality and environmental impacts of US diets vary significantly by socioeconomic factors. Age-related patterns are non-monotonic: HEI and efficiency scores decline from childhood through adolescence, reaching their lowest point among teenagers aged 10–20, before rising through adulthood and peaking among older adults around age 70 (Supplementary Fig. 4). Education shows a similar non-monotonic pattern: graduate-level education is associated with the highest HEI, while high-school and below-high-school education are associated with the lowest, and diet-related emissions rise before falling as education increases. By gender, females show higher median dietary efficiency than males (0.51 versus 0.46). By income, individuals earning above $100,000 annually show better nutritional quality than lower-income groups, though the second-lowest income group shows the highest efficiency scores, and efficiency scores are relatively stable above $50,000. By race and ethnicity, Asian shows the highest efficiency scores (0.57), while Asian individuals also show the largest environmental impact; Black individuals show the lowest HEI but slightly higher efficiency scores than White individuals.

Different efficiency groups and related socioeconomic clusterings can be identified based on dietary patterns. Building on these demographic patterns, Fig. 2 presents the *t*-SNE clustering of individual diets by 13 food components, colored by efficiency score (see Section 2.3 for method). The resulting clusters align closely with efficiency level and demographic composition. The highest-efficiency cluster (0.8–1.0) is composed predominantly of children and adolescents of both genders, with low energy and emissions intensity and reduced dairy, saturated fat, and sugar consumption, and a higher representation of Hispanic and White individuals (Supplementary Fig. 7). Conversely, the lowest-efficiency cluster (0.0–0.2) is composed predominantly of early- to middle-aged males with high energy, dairy, and saturated fat consumption, elevated GHG emissions, and a higher representation of White individuals. Between these extremes, the intermediate clusters (0.2–0.4 and 0.4–0.6) are composed of teenagers and young adults with elevated sugar consumption, and middle-aged males with moderate HEI and lower sugar and saturated fat intake, respectively. These patterns are further supported by Supplementary Figs. 6–8.

4.3. Projections

GHG emissions can be significantly reduced if all individuals adopt more efficient dietary patterns, but the magnitude of reduction varies notably across demographics. As shown in Fig. 3, the median per capita reduction in GHG emissions exceeds 50% across all groups. Within this overall pattern, the magnitude of reduction differs across demographic groups. By age, teenagers show the largest median reduction and children the smallest. By education, individuals with a high-school education show the largest reduction and those with graduate-level education the smallest. By gender, males show greater reductions than females. By income, mid-income groups show the lowest baseline efficiency and the greatest reduction potential, while the lowest-income group shows the highest baseline GHG emissions. By race, White and Hispanic groups show the greatest reduction potential, while Asian and Black individuals show smaller reductions. Across all groups, HEI remains stable or improves slightly even as GHG emissions decline.

4.4. Responsiveness of dietary outcomes to policy levers

Having shown that reduction potential varies by demographic group, we turn to the policy-relevant drivers such as income, price, and education that may explain and help close these gaps. Understanding how diet-related outcomes respond to policy-relevant variables such as income, price, and education is important for designing targeted

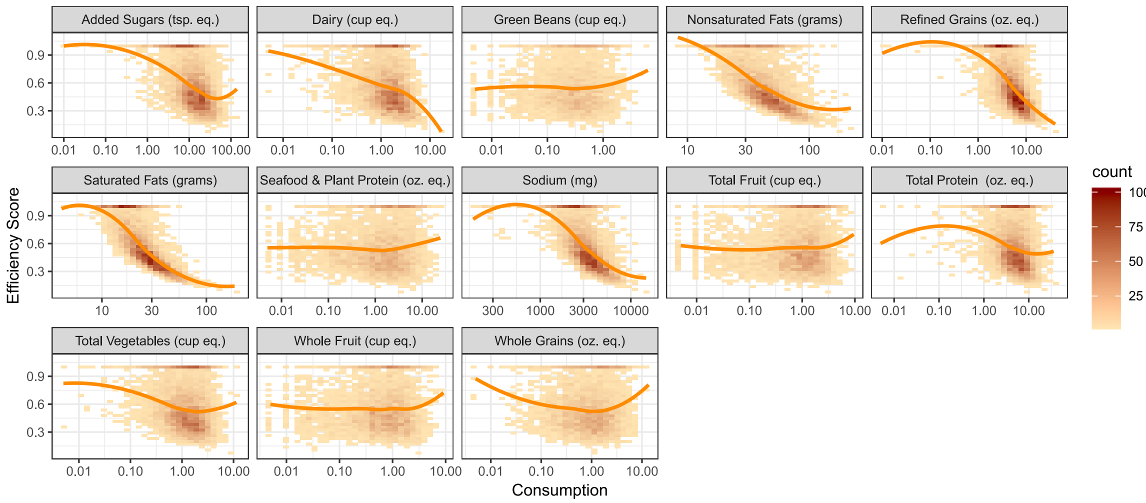

Fig. 1. The relationship between the consumption of 13 food categories and efficiency scores. The shading represents the density of observations, with darker areas indicating higher density. The orange line represents the trend line showing the overall relationship.

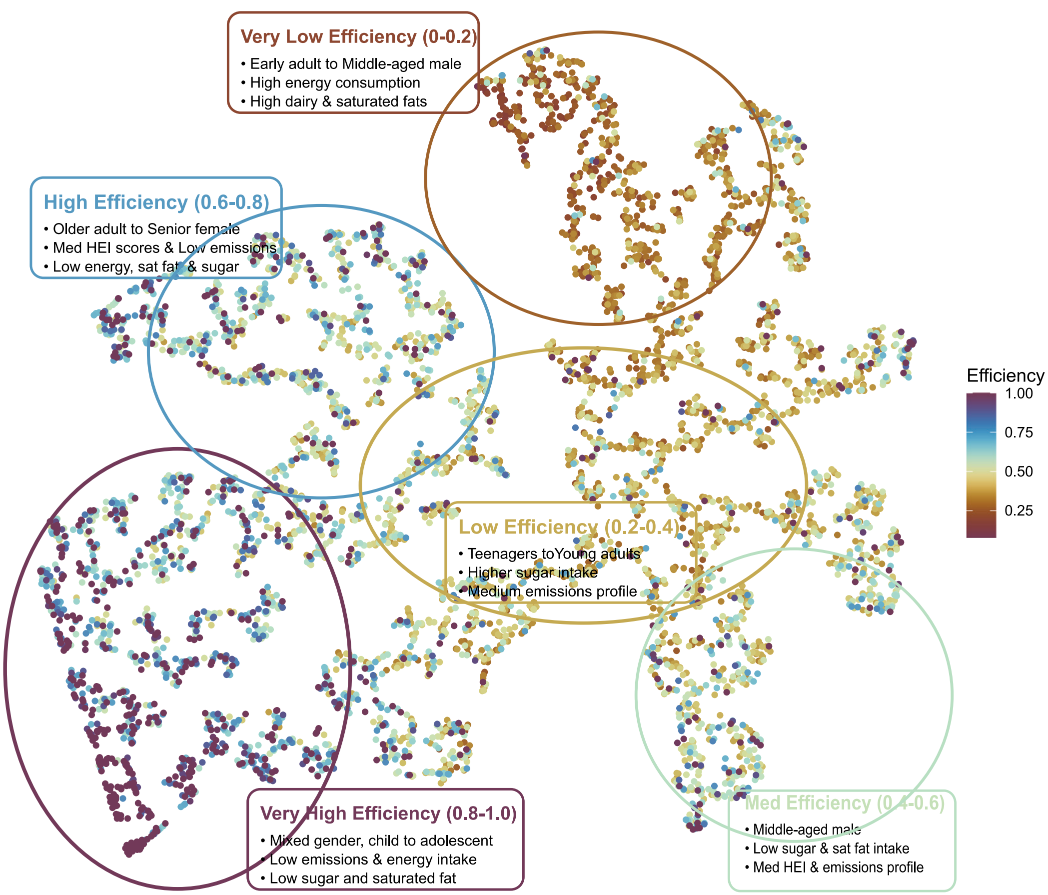

Fig. 2. t-SNE clustering of individual diets by 13 food components, colored by DEA efficiency score. Clusters are annotated with demographic and dietary characteristics.

interventions. In this section, we explore the elasticity of dietary quality, environmental impact, and dietary efficiency, using a composite measure that captures the trade-off between nutritional quality and environmental burden, with respect to these key drivers.

Table 1 shows that price elasticities are larger in magnitude than income elasticities, which indicates prices exert stronger influence. However, the effects from price often move in opposite directions, generating tradeoffs. When dietary prices are at the low and mid groups, the increase in price leads to nutrition improvements but also the raise of emissions, as households shift from ultra-cheap foods toward slightly higher quality yet emission intensive options. When price falls in the mid range, there is a “sweet spot”, where rising prices improve both nutrition and sustainability. Diets diversity toward more balanced baskets. For high price diets, the increases of price reduce both nutrition and emissions, as consumers cut back simultaneously on nutrient-dense and carbon-intensive items.

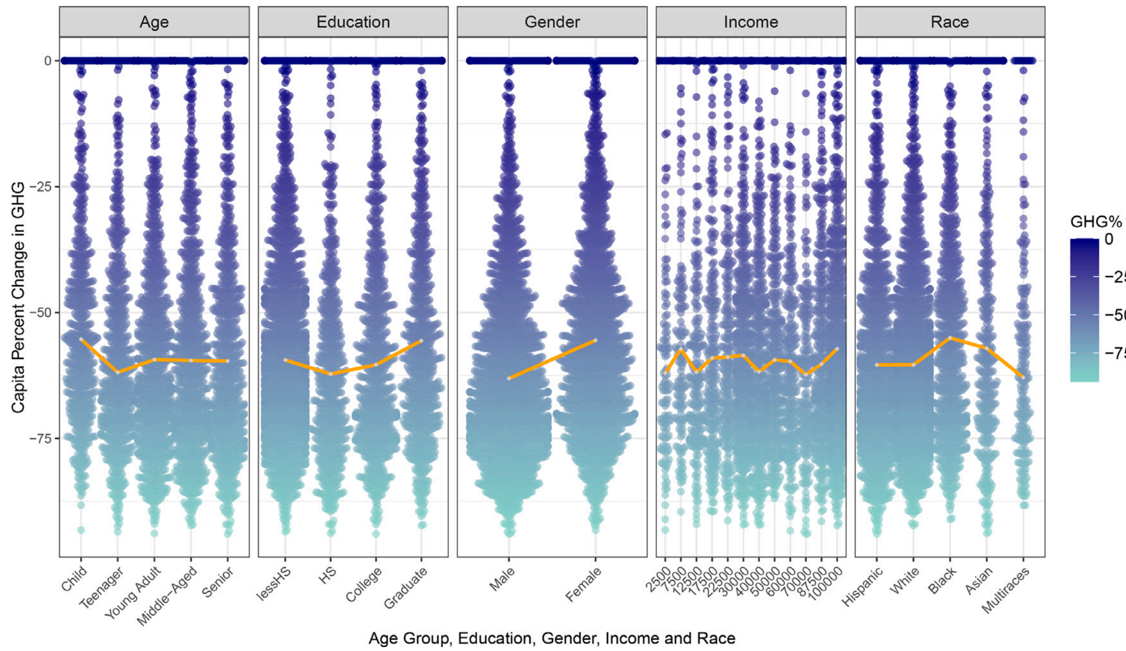

Fig. 3. Median percentage change in per capita GHG emissions when all individuals reach the efficiency frontier, by demographic group.

Income elasticities are smaller in magnitude but more consistent in direction, showing a progression across the income distribution. For low income group, additional income worsens both nutrition and emissions, reflecting a shift toward cheap, calorie-dense foods (refined grains, added sugars, oils, processed meats) that lower diet quality and harm environment at the same time. Among mid income groups, income growth improves diet quality toward fruits, vegetables, whole grains, dairy, seafood, and plant proteins but also adds resource-intensive items (more animal products), thus emissions increase alongside HEI. However, at high income households, they can afford premium, health-conscious diets (fresh produce, lean proteins, nuts, whole grains) and diets shift toward plant-forward or balanced patterns that are both healthier and less carbon-intensive. High-income groups are more likely to adopt "efficient frontier" diets.

While the regression results above capture broadly linear and quadratic relationships, the effect of education on dietary outcomes was better captured by a more flexible specification. Supplementary Table 3 presents the results of two Generalized Additive Models (GAMs) analyzing the determinants of the Healthy Eating Index (HEI) and Greenhouse Gas Emissions (MGHG). The smooth term for education is highly significant in both models (EDF = 4.771 and 4.186, $p < 0.001$), indicating a nonlinear relationship between education and both HEI and MGHG. This suggests that the effect of education on dietary choices and environmental impact is complex and varies across different levels of education.

Fig. 4 displays the estimated smooth functions of education from two Generalized Additive Models (GAMs), illustrating its nonlinear relationships with both dietary quality and environmental impact. The left panel shows how education affects the Healthy Eating Index (HEI), revealing a highly nonlinear effect at higher education levels. The right panel presents education's relationship with greenhouse gas emissions (GHG) from diet choices, showing a more complex pattern. Initially, emissions increase with education, before declining at much higher education levels. The shaded light blue regions represent 95% confidence intervals, with wider bands at the lower extremes of the education distribution indicating greater uncertainty in these regions. These nonlinear patterns, captured by the high effective degrees of freedom (EDFs) in both models (4.186 and 4.771 respectively), demonstrate that the relationship between education and dietary choices is highly nonlinear at high level of education requiring a 4th degree polynomial to capture it. The reduction in efficiency as education increases from low levels, is much steeper than the increase at higher levels of education.

5. Discussion

This study introduces a novel, data-driven optimization approach to assess the balance between nutritional quality and environmental impact in real-world diets. By applying this method, we identified substantial gaps between many diets and the best-observed practices: most individuals consume diets that are simultaneously less healthy and more environmentally costly than necessary. Unlike scenario-based projections, this method grounds analysis in actual dietary behavior, offering realistic pathways for transition.

Our findings reinforce the global evidence that plant-forward diets deliver the most favorable tradeoffs. Fruits, vegetables, whole grains, legumes, and seafood and plant proteins consistently aligned with higher Healthy Eating Index (HEI) scores and lower greenhouse gas (GHG) emissions. This aligns with other analyses (Grummon et al., 2023; Stylianou et al., 2021), including the EAT–Lancet Commission, which call for dietary transitions that emphasize plant-based diversity and reduced reliance on animal-source foods. Our price-elasticity findings extend this picture: while higher diet quality is frequently accompanied by higher cost in the U.S. Conrad et al. (2023), our results show this relationship is non-monotonic rather than uniform, with a mid-price range in which nutrition and emissions improve together.

At the same time, we found strong socioeconomic disparities in diet performance. These results reflect not only personal choices but also deeper structural factors: such as food environments, affordability, targeted marketing, and cultural norms that shape dietary behavior. Comparable disparities are seen globally, where disadvantaged populations often face limited access to affordable, nutritious foods and carry disproportionate burdens of both diet-related disease and environmental harms.

The estimated 50% median reduction in per capita GHG emissions if all diets matched the best-observed diets highlights the scale of their climate mitigation potential. Globally, such dietary shifts are essential to meeting planetary health targets, including the Paris Agreement and the Sustainable Development Goals. Importantly, our results show that the largest potential improvements lie with groups whose current diets have the lowest relative performance: teenagers, lower-education

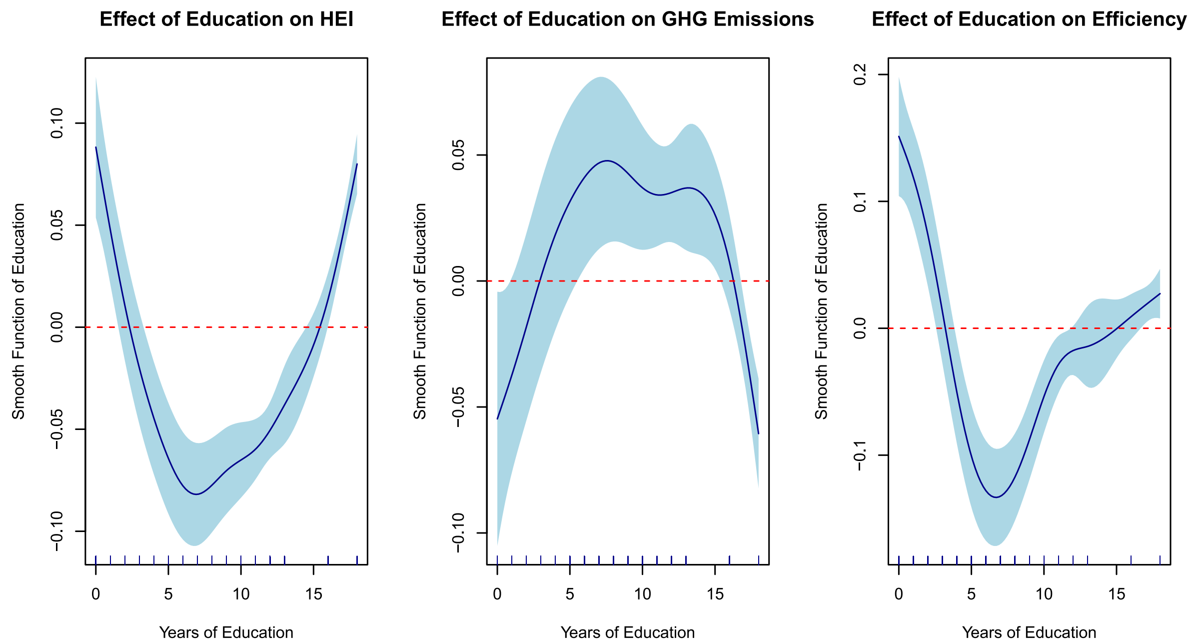

Fig. 4. Estimated GAM smooth functions of education on Healthy Eating Index, GHG emissions, and dietary efficiency. Shaded regions denote 95% confidence intervals.

populations, and males. This suggests that equity-focused interventions could yield environmental and health co-benefits, aligning with international calls for a just transition in food systems.

Policy responsiveness varied across socioeconomic contexts, underscoring the need for tailored interventions. The price elasticities suggest one plausible mechanism for this variation: at low and mid price levels, rising prices were associated with both nutritional improvement and higher emissions, consistent with households shifting from the cheapest available foods toward modestly higher-quality but more emission-intensive options. Within a mid-range "sweet spot", however, rising prices were associated with improvement in both nutrition and emissions, suggesting that diets in this range diversify toward more balanced food baskets rather than simply trading one outcome for the other. At high price levels, rising prices were associated with declines in both outcomes, consistent with consumers cutting back simultaneously on nutrient-dense and carbon-intensive items. For very low incomes, raising income alone risks worsening both nutrition and environmental outcomes. At middle incomes, income growth improves health but also increases emissions, creating tradeoffs that calls for targeted price interventions such as subsidies for sustainable nutritious foods and taxes on carbon-intensive items to realign dietary choices (Guerriero et al., 2020; Gillies et al., 2021; Ammann et al., 2023). At high incomes, by contrast, further income growth tends to reinforce healthier and more sustainable diets, simultaneously improving nutritional quality and lowering emissions.

Our analysis of education effects revealed non-linear trends: emissions rose with education through low-to-middle levels before declining at the highest levels, while HEI and efficiency showed a corresponding dip before improving. One possible explanation, consistent with the income findings above, is that moderately educated individuals are more likely to adopt resource-intensive diets. The decline in emissions at the highest education levels may then reflect greater awareness of sustainability and more deliberate dietary choices. We also see that diet quality and environmental outcomes improved markedly only at the highest levels of education. These results suggest that policies promoting education alone may not yield broad improvements in dietary sustainability. These tiered responses imply that no single lever is sufficient: integrated policy portfolios that combine price, income, and education strategies are needed.

Despite its strengths, this study has several limitations. Some of these limitations are common to diet-related life-cycle assessment and survey-based sustainability studies, but they are important to state because they affect the interpretation of individual dietary footprints. It relies on post processed LCA data (Stylianou et al., 2021), which may not fully reflect regional variations (Dubey et al., 2019; Faghmous and Kumar, 2014; Schau and Fet, 2008). Key factors such as trade flows, storage, and transportation emissions were not explicitly modeled (Aceves-Martins et al., 2023). In addition, the Healthy Eating Index is an aggregate scoring system with component thresholds and caps; equal differences in HEI do not necessarily imply equal differences in nutritional adequacy or health benefit. The DEA approach also shows some deficiencies. The DEA frontier is constructed through linear programming as a piecewise-linear surface formed from observed diets and their convex combinations (Charnes et al., 1978; Banker et al., 1984). This is a standard feature of DEA rather than a problem unique to this application, but its implications are important for interpretation. The approach is most reliable when the observed diet space is sufficiently rich to approximate the range of feasible nutrition–emissions combinations. When data are sparse, noisy, or contain unusual diets, the frontier may be shaped by a small number of observations, and the resulting benchmark may be more sensitive to outliers or gaps in the observed sample. This also means that the reference point for an inefficient diet may be a synthetic combination of observed diets rather than a dietary pattern directly reported by an individual. Such composite benchmarks are useful for measuring relative performance, but they should not be interpreted mechanically as feasible behavioral prescriptions. Other DEA formulations, including non-radial, slacks-based, directional-distance, robust, or bootstrapped DEA models, may embody different assumptions that are better suited to particular dietary questions, especially when undesirable outputs, nutrient thresholds, food-substitution constraints, or uncertainty in LCA estimates are central. Further methodological work is needed to compare these specifications in dietary applications and to assess how sensitive health–environment efficiency scores are to alternative frontier assumptions. The DEA score should therefore be interpreted as a relative benchmark of joint dietary performance under the chosen data and model specification, rather than as an absolute or behaviorally complete measure of dietary sustainability.

Table 1
Environmental impact, diet quality and efficiency models.

	Dependent variable:		
	Log MGHG (1)	Log HEI Score (2)	Log Efficiency (3)
White	−0.009 (0.017)	−0.017 (0.011)	0.016 (0.015)
Black	−0.062*** (0.023)	−0.041*** (0.015)	0.049** (0.020)
Asian	0.014 (0.030)	0.076*** (0.020)	0.150*** (0.026)
Multi-Races	0.055* (0.030)	−0.030 (0.020)	0.011 (0.026)
Log Income	0.306** (0.119)	−0.241*** (0.080)	0.120 (0.104)
Log Income Squared	−0.016*** (0.006)	0.014*** (0.004)	−0.006 (0.005)
Energy Convention	0.381*** (0.029)	−0.206*** (0.019)	−0.977*** (0.025)
Log Price	1.247*** (0.137)	0.399*** (0.092)	−0.823*** (0.120)
Log Price Squared	−0.176*** (0.031)	−0.051** (0.021)	0.199*** (0.027)
Gender (Female)	−0.057*** (0.012)	0.040*** (0.008)	0.031*** (0.011)
Education	−0.004*** (0.001)	0.005*** (0.001)	0.002** (0.001)
Constant	−4.727*** (0.648)	5.826*** (0.437)	6.999*** (0.567)
Observations	4157	4157	4157
R^2	0.312	0.116	0.371
Adjusted R^2	0.310	0.114	0.369
Residual Std. Error (df = 4145)	83.531	56.346	73.172
F Statistic (df = 11; 4145)	170.647***	49.587***	221.852***

* p < 0.1
** p < 0.05
*** p < 0.01

6. Conclusion

This study introduces a joint efficiency score, derived from Data Envelopment Analysis, that benchmarks individual diets against the best-observed combination of nutritional quality and environmental impact achieved by comparable diets in the U.S. population. We find that most diets fall well short of this frontier, with a median potential reduction in per capita GHG emissions exceeding 50% if all individuals adopted efficient dietary patterns. The largest gains lie with groups whose current diets have the lowest relative performance, suggesting that equity-focused interventions could yield environmental and health co-benefits, aligning with international calls for a just transition in food systems.

Beyond identifying these gaps, our analysis of income, price, and education shows that no single policy lever is sufficient: their effects on the nutrition–environment trade-off are non-monotonic and vary across the socioeconomic distribution. Price and income gains improve both outcomes only within specific ranges, while education's benefits emerge only at the highest levels. These tiered responses imply that integrated policy portfolios are needed, rather than uniform interventions assumed to work the same way for everyone.

CRediT authorship contribution statement

Wen Qi: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Giovanni Baiocchi:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization.

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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.

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During the preparation of this work, the authors used a large language model only for language polishing, grammar correction, and improving the clarity of wording. The tool was not used to generate research ideas, design the study, conduct the analysis, interpret the results, or draw conclusions. All AI-assisted text was carefully reviewed, edited, and verified by the authors, who take full responsibility for the content of the manuscript.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jclepro.2026.149143.

Data availability

This study uses publicly available data; sources are cited in the text. Processed data and analysis code are available upon request.

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