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RESEARCH ARTICLE

The Impact of Gardening on Dietary Inflammation: Mixed-Effect Models and Propensity Score Analyses

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Introduction: Gardening has been found to increase vegetable intake and reduce BMI; this suggests that it may improve diets by lowering inflammatory content. The goal of this study goal was to evaluate the effect of gardening on Dietary Inflammatory Index scores.

Methods: Longitudinal data were collected annually between 2015 and 2018 from adults in low-income, urban neighborhoods of Cleveland and Columbus, Ohio. The authors measured the association between gardening and Dietary Inflammatory Index in the full data set using multivariable mixed-effect models with a random intercept for participant (Model 1; *n*=409). To further explore potential causation, the author used propensity score analyses in a subset of the data by building a 1-to-1 matched model (Model 2; *n*=339).

Results: Of 409 adults, 30.3% were gardeners with Dietary Inflammatory Index scores ranging from −6.228 to +6.225. Participating in gardening was associated with lower Dietary Inflammatory Index scores in the mixed-effects model (−0.45; 95% CI= −0.85, −0.04; Model 1) and the 1-to-1 matched model (−0.77; 95% CI= −1.40, −0.14; Model 2).

Conclusions: The analyses indicate that gardeners had lower Dietary Inflammatory Index scores than nongardeners, implying lower diet-driven inflammation. These findings highlight the potential for a causal relationship between gardening and Dietary Inflammatory Index, which should be confirmed in future studies. If this relationship is validated, strategies to increase gardening may be worth testing as primary prevention tools for diet-driven chronic disease.

INTRODUCTION

Gardening and gardening interventions have been found to improve diet diversity, increase vegetable consumption, and decrease BMI.[1−3] Although the physiologic mechanisms for how gardening may improve health are still being characterized, this paper addresses 1 potential pathway through reducing diet-driven inflammation. The Dietary Inflammatory Index (DII) is a literature-derived index that categorizes the inflammatory potential of a person's diet; higher DII scores indicate more proinflammatory diets.[4] Higher DII scores are associated with higher risk of chronic diseases, including obesity, cardiovascular disease, Type 2 diabetes, cancer, and all-cause mortality.[5] Given that inflammation is a known driver of many chronic diseases, diet and healthy lifestyle

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choices that reduce inflammation may subsequently reduce the incidence of these conditions[6,7] and warrant further investigation.

Prior studies of the relationship between gardening and nutrition are largely cross-sectional and often rely on low-accuracy methods of dietary assessments such as food screener questionnaires.[8−10] Previous work has leveraged general measures of dietary quality but, to the authors' knowledge, has not evaluated hypotheses specific to diet-driven inflammation or DII scores.[1,2,11,12]

Therefore, the authors sought to examine the relationship between gardening and dietary inflammation using both cross-sectional and longitudinal data. The authors used mixed-effect models and propensity score methods because they have complementary strengths and thus can provide convergent evidence for the causal relationship.

METHODS

Study Sample

The analyses describe part of the Future of Food in Your Neighborhood Study (foodNEST) from Mary Ann Swetland Center for Environmental Health.[13,14] This study was approved by the Case Western Reserve University IRB, and written informed consent was obtained from all participants. The sample included 409 participants enrolled in a prospective cohort study in 2015 and followed through 2018. Participants lived in low-income urban neighborhoods known to have limited access to stores selling fresh and healthy foods in Cleveland and Columbus, Ohio. Eligibility criteria and data collection procedures have been detailed previously.[14,15] In brief, participants were eligible if they lived in the targeted neighborhoods and were not considering moving for at least 1 year, were aged at least 18 years, spoke English, and were responsible for at least half of the household food shopping. A total of 1,395 residents were screened, of whom 655 (47%) were eligible, and 516 (79%) enrolled. Participants were then contacted with 3 phone calls in each of the next 3 years. The first phone call administered a survey (covariate data collection) and a 24-hour dietary recall. The second 2 phone calls consisted of repeat 24-hour dietary recalls, and all 3 phone calls were conducted within a 37-day window.

The analyses were limited to the 409 participants (79% of those enrolled) who had complete data from at least 2 of the 3 years of the study. A participant was considered to have complete dietary data if at least two 24-hour dietary recalls were conducted each year. Dietary intakes were seasonally standardized by assuring that each participant provided their recall within the same 37-day window of each year. Nutrition Data Systems for Research software was then used to estimate the intakes for 31 diet components at each assessment. These were averaged across the 2−3 assessments in that year, which were then multiplied by previously calculated inflammatory coefficients and summed as described below to yield 1 DII score[4] for each participant in each year.[4,14] Additional details are available in the authors' prior publications.[14,15]

Measures

The exposure of interest was gardening status, operationalized as a binary variable. In the survey, participants were asked, *Over the last 12 months, did you take part in any of the following activities in your neighborhood?* Potential responses were (1) *Cooking club or classes*, (2) *Nutrition or healthy eating class*, (3) *Weight loss class or program*, (4) *Exercise class or program*, (5) *Community gardening*, (6) *Home gardening*, (7) *Community arts event*, (8) *Neighborhood meetings*, (9) *Neighborhood events*, and (10) *Farmers markets*. Those who indicated yes to community gardening or home gardening at baseline were marked as gardeners; all others were marked as nongardeners. Although gardening status was reassessed each year, the sample size was insufficient to analyze participants who stopped or started gardening.

The outcome of interest was DII score. DII generally ranges from −9 to +8 ($\sim 25^{th}$ percentile: −2.4; $\sim 75^{th}$ percentile: +1.9).[4] Food components with an inflammatory effect score below 0 are considered anti-inflammatory, and those above 0 are considered proinflammatory. These inflammatory effect scores are based on the evidence from literature that links each diet component to the raising (or lowering) of circulating markers of inflammation (e.g., tumor necrosis factor-α, C-reactive protein, IL-1b, IL-4, IL-6, or IL-10).[4] The DII score was calculated from the 31 available components as described in the following Equation 1,[4]:

$$\mathrm{DII} = \sum_{j=1}^{N} \mathrm{Dietary\ component}_j \times \mathrm{Inflammatory\ Effect\ Score}_j \qquad (1)$$

where j indexes N dietary components.

Because overall energy consumption intake is thought to impact net inflammation, some scholars have argued that an energy-adjusted DII (E-DII) is necessary[16]; however, E-DII has not replaced DII to date. Similar outcomes have been found in studies utilizing both DII and E-DII.[17,18] Although some researchers utilize the E-DII scores in relation to health behaviors and health outcomes,[19−21] others do not adjust for energy and only utilize DII.[22−24] For this study, the authors present DII as the main outcome and include energy adjustments in the Appendix (available online).

Statistical Analysis

Mixed models are a common analytic approach to longitudinal data, and they implicitly control for confounders that are stable through the time course of study. The second approach based on propensity scores provides a complementary assessment that differs in its strategy for handling bias. Evaluating these data in 2 distinct ways is important because it allows for convergence. Because these methods do not depend on the same assumptions, their weaknesses do not align. The mixed-model approach has greater power and the ability to leverage within person changes in gardening status; the propensity score analysis accounts for temporality and features a more comprehensive approach to residual confounding. Thus, the 2 approaches can complement and corroborate each other. All analyses were computed in R Studio, Version 2023.06.2+561.

First, the authors used multivariable-adjusted linear mixed models to estimate the association between gardening status and DII score using all 3 years of data. This method compares gardening with DII within the same year over the 3 consecutive years of the study, which allows the authors to quantify DII changes with concurrent gardening. To maximize the effective sample size and reduce potential confounding,[14,25] the authors included a random intercept for each participant. Six of the 409 participants had 1 missing DII score, and the remaining participants had 3 values per person (1 per year). This design controls for within-participant characteristics that are stable during the study, which accounts for confounding. The authors utilized Satterthwaite's method *t*-tests (alpha=0.05) to draw conclusions on significance.

Model 1 adjusts for age (in years), education (high school or less, some college, college graduate or more), income (<$10,000; $10,001−$20,000; $20,001−$30,000; ≥$30,001), self-identified race (3 categories: Black, white, other), Supplemental Nutrition Assistance Program status (recipient versus not), and car available for shopping (yes/no). These variables were chosen because they may be common prior causes of exposure and outcome and thus may act as confounders. To handle this ambiguity,[26] the authors present adjusted and unadjusted results to clarify that the conclusions are not changed by these adjustment differences. The E-DII sensitivity analyses found in the Appendix (available online) also adjust for total daily energy intake (kcal).

In addition, the authors used propensity score matching methods to identify evidence of causation while addressing temporality and the potential for residual confounding.[27] This method utilizes gardening at baseline to predict DII in the following year. The propensity score was estimated as the probability of the exposure (gardening) given 27 covariates that likely impact gardening status (measures of demographics, family composition, financial security, physical health, food perceptions, and food accessibility) (Appendix Table 1, available online) measured at baseline (2015−2016). It is recommended to include all measured baseline characteristics in propensity score models to best balance exposure groups and account for both true and potential confounders.[27] The outcome, DII, was measured 12 months later (2016−2017). The propensity score analysis was limited to the 339 participants (82.9% of all participants) with data for both time periods. Of those 339 participants, 108 (30.3%) were gardeners, and 231 (69.7%) were not. The propensity score was then used for matching and weighting to estimate the impact of gardening on DII. To compare gardeners with nongardeners on DII, the authors examined the covariate balance with 2 approaches: 1-to-1 propensity-matched pairs without replacement and propensity weighting to obtain average treatment effect on the treated estimates, which can be found in the Appendix (available online). After matching, the authors used a generalized model (alpha=0.05) to examine the association between gardening and DII on the matched pairs.

RESULTS

Characteristics of all 409 participants have been published previously,[13,14] and details of the subset of 339 participants are provided in Table 1. Within the subset at baseline, the majority of participants were female (76.4%), were non-White (70.2%), and had annual incomes below $30,000 (82.3%). On average, participants were aged 51 years. Almost one third of participants (30.3%) were gardeners. DII scores in the sample ranged from −6.228 to +6.225. Several covariates varied considerably between gardeners and nongardeners as seen in Table 1, including education; annual income; age; race; renting home; Supplemental Nutrition Assistance Program status; Special Supplemental Nutrition Program for Women, Infants, and Children status; employment status; neighborhood perceptions; transportation method for shopping; and effort to eat fresh and healthy foods.

In Model 1, an unadjusted mixed-effect model, being a gardener was associated with a lower DII score by 0.44 points (95% CI= −0.75, −0.12) than being a nongardener. The estimated effect size was similar after adjusting for age, education, income, race, and having a car available for shopping, with a lower DII by 0.45 points (95% CI= −0.85, −0.04) (Table 2) for gardeners than for nongardeners. In sensitivity analyses adjusted only for total daily energy intake, these associations were stronger,

Table 1. Participant Characteristics in the Data Subset, Comparing Nongardeners With Gardeners Prior to Propensity Score Matching

Variable	All (N=339)	Nongardeners (*n*=231)	Gardeners (*n*=108)	Standardized mean differences	*p*-value
Education, *n* (%)				0.553	<0.001
High school graduate or less	205 (60.5)	157 (68.0)	48 (44.4)		
Some college	88 (26.0)	55 (23.8)	33 (30.6)		
College graduate or more	46 (13.6)	19 (8.2)	27 (25.0)		
Income, *n* (%)				0.422	0.005
<$10,000	116 (34.2)	90 (39.0)	26 (24.1)		
$10,001–$20,000	109 (32.2)	76 (32.9)	33 (30.6)		
$20,001–$30,000	54 (15.9)	34 (14.7)	20 (18.5)		
≥$30,001	60 (17.7)	31 (13.4)	29 (26.9)		
Age, mean (SD)	51.62 (12.87)	50.48 (12.48)	54.06 (13.38)	0.277	0.016
Sex, female, *n* (%)	259 (76.4)	175 (75.8)	84 (77.8)	0.048	0.786
Self-identified race, White, *n* (%)	101 (29.8)	44 (19.0)	57 (52.8)	0.751	<0.001
Cohabit, *n* (%)	92 (27.1)	55 (23.8)	37 (34.3)	0.232	0.059
People in household, mean (SD)	2.38 (1.50)	2.45 (1.54)	2.23 (1.41)	0.145	0.220
Rent home, *n* (%)	207 (61.1)	164 (71.0)	43 (39.8)	0.661	<0.001
SNAP use, *n* (%)	219 (64.6)	160 (69.3)	59 (54.6)	0.305	0.012
WIC use, *n* (%)	25 (7.4)	22 (9.5)	3 (2.8)	0.284	0.046
Other federal financial assistance use, *n* (%)	169 (49.9)	120 (51.9)	49 (45.5)	0.132	0.312
Employment status, *n* (%)				0.347	0.037
Employed	131 (38.6)	84 (36.4)	47 (43.5)		
Not working	72 (21.2)	57 (24.7)	15 (13.9)		
Retired	40 (11.8)	22 (9.5)	18 (16.7)		
Unable to work	96 (28.3)	68 (29.4)	28 (25.9)		
Hypertension, *n* (%)	133 (39.2)	92 (39.8)	41 (38.0)	0.038	0.835
CVD, n (%)	22 (5.6)	14 (6.1)	8 (7.4)	0.054	0.816
Diabetes or prediabetes, *n* (%)	47 (13.9)	31 (13.4)	16 (14.8)	0.040	0.859
Overweight or obese, *n* (%)	103 (30.4)	70 (30.3)	33 (30.6)	0.005	1.000
Cancer, *n* (%)	11 (3.2)	10 (4.3)	1 (0.9)	0.214	0.187
Kidney disease, *n* (%)	5 (1.5)	3 (1.3)	2 (1.9)	0.044	1.000
Your neighborhood is the kind of place you'd like to live, *n* (%)				0.392	0.016
Strongly agree	103 (30.4)	63 (27.3)	40 (37.0)		
Tend to agree	127 (37.5)	81 (35.1)	46 (42.6)		
Tend to disagree	52 (15.3)	41 (17.7)	11 (10.2)		
Strongly disagree	57 (16.8)	46 (19.9)	11 (10.2)		

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Table 1. Participant Characteristics in the Data Subset, Comparing Nongardeners With Gardeners Prior to Propensity Score Matching (*continued*)

Variable	All (N=339)	Nongardeners (*n*=231)	Gardeners (*n*=108)	Standardized mean differences	*p*-value
Mode of transport for food shopping, *n* (%)				0.416	0.011
Family or friend drive	92 (27.1)	70 (30.3)	22 (20.4)		
Personal vehicle	188 (55.5)	116 (50.2)	72 (66.7)		
Public transit or Uber/taxi	21 (6.2)	19 (8.2)	2 (1.9)		
Walk or bike	38 (11.2)	26 (11.3)	12 (11.1)		
During the summer and fall seasons, how often do you buy food at a farmer's market or produce stand? n (%)				0.286	0.207
Weekly or more	47 (13.9)	28 (12.1)	19 (17.6)		
Every 2 weeks	39 (11.5)	25 (10.8)	14 (13.0)		
Monthly	62 (18.3)	43 (18.6)	19 (17.6)		
Few times a year	66 (19.5)	41 (17.7)	25 (23.1)		
Never	125 (36.9)	94 (40.7)	31 (28.7)		
Diet restrictions, *n* (%)				0.239	0.117
Food allergies	79 (23.3)	53 (22.9)	26 (24.1)		
None	184 (54.3)	133 (57.6)	51 (47.2)		
Other	76 (22.4)	45 (19.5)	31 (28.7)		
A large selection of fruits and vegetables is available in your neighborhood, *n* (%)				0.226	0.260
Strongly agree	132 (38.9)	93 (40.3)	39 (36.1)		
Tend to agree	133 (39.2)	67 (29.0)	28 (25.9)		
Tend to disagree	67 (19.8)	28 (12.1)	22 (20.4)		
Strongly disagree	48 (14.2)	43 (18.6)	19 (17.6)		
The fresh fruits and vegetables in your neighborhood are of high quality, *n* (%)				0.199	0.388
Strongly agree	91 (26.8)	62 (26.8)	29 (26.9)		
Tend to agree	95 (28.0)	95 (41.1)	38 (35.2)		
Tend to disagree	50 (14.7)	40 (17.3)	27 (25.0)		
Strongly disagree	62 (18.3)	34 (14.7)	14 (13.0)		
I think that fresh and healthy foods are expensive, *n* (%)				0.058	0.886
Strongly agree	152 (44.8)	103 (44.6)	49 (45.4)		
Tend to agree	103 (30.4)	69 (29.9)	34 (31.5)		
Tend to disagree	0 (0)	0 (0)	0 (0)		
Strongly disagree	84 (24.8)	59 (25.5)	25 (23.1)		

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Table 1. Participant Characteristics in the Data Subset, Comparing Nongardeners With Gardeners Prior to Propensity Score Matching (*continued*)

Variable	All (N=339)	Nongardeners (*n*=231)	Gardeners (*n*=108)	Standardized mean differences	*p*-value
I am a healthy eater, n (%)				0.199	0.242
Strongly agree	112 (33.0)	76 (32.9)	36 (33.3)		
Tend to agree	133 (39.2)	85 (36.8)	48 (44.4)		
Tend to disagree	0 (0)	0 (0)	0 (0)		
Strongly disagree	94 (27.7)	70 (30.3)	24 (22.2)		
How often do you make conscious efforts to try and eat a fresh and healthy diet? n (%)				0.428	0.002
Most of the time	110 (32.4)	63 (27.3)	47 (43.5)		
Quite often	113 (33.3)	76 (32.9)	37 (34.3)		
Never to now and again	116 (34.2)	92 (39.8)	24 (22.2)		

CVD, cardiovascular disease; SNAP, Supplemental Nutrition Assistance Program; WIC, Special Supplemental Nutrition Program for Women, Infants, and Children.

Table 2. Summary of the Analyses With Estimates on DII Scores for Gardeners Compared With Those for Nongardeners

Model	DII estimate	95% CI
Model 1: mixed model[a]	−0.45	(−0.85, −0.04)
Model 2: 1-to-1 propensity score matched	−0.77	(−1.40, −0.14)
Unadjusted mixed model	−0.44	(−0.75, −0.12)

[a]Adjusted for age (in years), education (3 level ordinal scale: 1=high school or less, 2=some college, and 3=college graduate or more), income (4 level ordinal scale: 1= <\$10,000, 2=\$10,001−\$20,000, 3=\$20,001−\$30,000, and 4= ≥\$30,001), self-identified race (3 categories: Black, White, other), SNAP status (recipient versus not), and car available for shopping (yes/no).
DII, Diet Inflammatory Index; SNAP, Supplemental Nutrition Assistance Program.

with gardeners having a lower DII of 0.65 points (95% CI= −0.89, −0.41; not displayed); after adjusting for age, education, income, race, having a car available for shopping, and total daily energy intake, gardeners had a lower DII score by 0.49 points (95% CI= −0.77, −0.20) (Appendix Table 2, available online) than nongardeners.

With 108 propensity-matched pairs, Model 2 demonstrated that gardeners had a lower DII score than nongardeners by 0.77 points (95% CI= −1.40, −0.14) (Table 2). The average treatment effect on the treated weighted propensity analysis yielded relatively weak results in balancing covariates and is described in Appendix Table 3 (available online). Appendix Figures 1 and 2 (available online) illustrate the distributions of both propensity score analyses through Love plots,[28] which are visualizations displaying covariate balance before and after adjustment. Covariate balance was evaluated with standardized mean differences, given in Table 1.

Energy-adjusted results are presented in Appendix Table 2 (available online). In this case, the authors included total energy intake (kcal) as a covariate in the same year as the DII scores (2016−2017, because this is considered an optional component of outcome rather than a determinant of propensity to garden).

DISCUSSION

The analyses identified evidence of a relationship between gardening and lower dietary inflammation using 2 complementary analytic approaches. The mixed-effect models (Method 1) have the advantage of evaluating all available data for more power, and the random intercept per participant generates intrinsic control for participant characteristics that are stable throughout the 3 years of the study (both measured and unmeasured characteristics). In short, people who change their gardening status can impact these models, and thus these results partly reflect within person changes in DII when gardening. The propensity score model (Method 2) addresses confounding by comparing gardeners with nongardeners who had roughly the same propensity to garden. This approach has less power but has established validity in the context of causal reasoning.[29] The matching model (Method 2) corroborated the mixed-model (Method 1) findings. The inability for the propensity score−weighted model to appropriately balance covariates is an interesting pattern that has been described in the literature,[29] and it suggests that the putative effect may not exist among those who are extremely unlikely to change their gardening status. In other words, gardening may improve the inflammatory content of diets only among those who are likely to make this behavior change. This suggests that future research should seek to identify which subgroups of the population are likely to change gardening status (i.e., start or stop gardening) and thus may benefit from gardening interventions. Attention should be given to interventions that equitably expand gardening access and highlight resources that remove barriers to gardening such as time, knowledge, finances, and availability of space.[30] Overall, these approaches have distinct strengths and weaknesses with respect to causal reasoning, and here, they corroborate each other.[31] However, the authors acknowledge that these results are not definitive in establishing a causal association between gardening and DII but instead provide initial evidence warranting further study.

Gardening has recently been viewed as a nature-based solution to noncommunicable diseases, namely diet-driven chronic diseases.[2,32] The results indicate that gardeners had lower DII scores than nongardeners, by as much as 0.77 points. With every 1 point increase in DII, risk for cardiovascular disease and mortality increases by 8%,[33] highlighting that the effect of gardening may be clinically meaningful for health outcomes. There has been a described lack of studies designed to alter DII and inflammation's effect on cardiometabolic risk factors,[34] which this research addresses. Gardening is a nonpharmacologic intervention that has the potential to decrease dietary inflammation and mitigate risk for chronic disease. Although not studied in this work, it may also achieve other benefits, such as community building and physical activity.

The results of this study provide evidence that gardening may have nutritional and anti-inflammatory benefits. These results are consistent with recent evidence of community gardening interventions increasing total vegetable intake[3] and dietary fiber.[2] Gardening is becoming recognized as a useful strategy for improving health; however, the gardening literature has been limited by diet quality measures, and most do not include gold-standard dietary data (Nutrition Data Systems for Research analysis of 3 averaged 24-hour recalls). Building the connection between gardening and specific diet quality measures such as dietary inflammation with demonstrated clinical health outcomes is important to estimating the potential utility of gardening-based public health interventions.

Establishing causal links between gardening and nutritional benefits may help build an evidence base to support garden-based interventions in practice. This study shares a novel and important way of understanding the beneficial nutrition outcomes associated with gardening. Because gardeners may have lower dietary inflammation, infrastructure to make gardening more accessible has the potential to not only decrease dietary inflammation but also decrease risk for inflammation- and diet-related chronic diseases, such as cardiovascular disease and Type 2 diabetes. Gardening interventions may provide a nonpharmacologic approach to preventing chronic disease.

Limitations

This study is strengthened by the use of propensity score methods, an approach novel to nutrition and gardening research. However, the results have several limitations. The 1-to-1 matched propensity score model balanced covariates well but not propensity scores, whereas the propensity score weighted model balanced propensity scores well but not covariates, which is a notable limitation of the study sample. This may result from the fact that these results were secondary findings to the larger foodNEST study, meaning that the study questions were not designed to collect information on covariates directly relevant to gardening. In addition, gardening status in this study was measured by a single question that did not clarify the type or amount of gardening done. Future studies should consider a more robust measure of gardening and a comprehensive set of covariates to explore the potential causal connection between gardening and nutritional benefits as well as changes in gardening status over time. This study is also limited to English-speaking participants. Continued exploration of community-based, nonpharmacologic interventions for diet-related chronic conditions among diverse populations are needed.

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SUPPLEMENTARY MATERIALS

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REFERENCES

1. Garcia MT, Ribeiro SM, Germani ACCG, Bógus CM. The impact of urban gardens on adequate and healthy food: a systematic review. *Public Health Nutr.* 2018;21(2):416–425. https://doi.org/10.1017/S1368980017002944.
2. Litt JS, Alaimo K, Harrall KK, et al. Effects of a community gardening intervention on diet, physical activity, and anthropometry outcomes in the USA (CAPS): an observer-blind, randomised controlled trial. *Lancet Planet Health.* 2023;7(1):e23–e32. https://doi.org/10.1016/S2542-5196(22)00303-5.
3. Alaimo K, Beavers AW, Coringrato E, et al. Community Gardening increases vegetable intake and seasonal eating from baseline to harvest: results from a mixed methods randomized controlled trial. *Curr Dev Nutr.* 2023;7(5):100077. https://doi.org/10.1016/j.cdnut.2023.100077.
4. Shivappa N, Steck SE, Hurley TG, Hussey JR, Hébert JR. Designing and developing a literature-derived, population-based dietary inflammatory index. *Public Health Nutr.* 2014;17(8):1689–1696. https://doi.org/10.1017/S1368980013002115.
5. Marx W, Veronese N, Kelly JT, et al. The dietary inflammatory index and human health: an umbrella review of meta-analyses of observational studies. *Adv Nutr.* 2021;12(5):1681–1690. https://doi.org/10.1093/advances/nmab037.
6. Tsoupras A, Lordan R, Zabetakis I. Inflammation, not cholesterol, is a cause of chronic disease. *Nutrients.* 2018;10(5):604. https://doi.org/10.3390/nu10050604.
7. Nomikos T, Fragopoulou E, Antonopoulou S, Panagiotakos DB. Mediterranean diet and platelet-activating factor; a systematic review. *Clin Biochem.* 2018;60:1–10. https://doi.org/10.1016/j.clinbiochem.2018.08.004.
8. Kegler MC, Prakash R, Hermstad A, Williamson D, Anderson K, Haardörfer R. Home gardening and associations with fruit and vegetable intake and BMI. *Public Health Nutr.* 2020;23(18):3417–3422. https://doi.org/10.1017/S1368980020001329.
9. Barnidge EK, Hipp PR, Estlund A, Duggan K, Barnhart KJ, Brownson RC. Association between community garden participation and fruit and vegetable consumption in rural Missouri. *Int J Behav Nutr Phys Act.* 2013;10:128. https://doi.org/10.1186/1479-5868-10-128.
10. Robinson-Oghogho JN, Thorpe RJ. Garden access, race and vegetable acquisition among U.S. adults: findings from a national survey. *Int J Environ Res Public Health.* 2021;18(22):12059. https://doi.org/10.3390/ijerph182212059.
11. Tharrey M, Darmon N. Urban collective garden participation and health: a systematic literature review of potential benefits for free-living adults. *Nutr Rev.* 2021;80(1):6–21. https://doi.org/10.1093/nutrit/nuaa147.
12. Spees CK, Braun AC, Hill EB, et al. Impact of a tailored nutrition and lifestyle intervention for overweight cancer survivors on dietary patterns, physical activity, quality of life, and cardiometabolic profiles. *J Oncol.* 2019;2019:1503195. https://doi.org/10.1155/2019/1503195.
13. Freedman DA, Clark JK, Lounsbury DW, et al. Food system dynamics structuring nutrition equity in racialized urban neighborhoods. *Am J Clin Nutr.* 2022;115(4):1027–1038. https://doi.org/10.1093/ajcn/nqab380.
14. Ciesielski TH, Ngendahimana DK, Roche A, Williams SM, Freedman DA. Elevated dietary inflammation among supplemental nutrition assistance program recipients provides targets for precision public health intervention. *Am J Prev Med.* 2021;61(2):192–200. https://doi.org/10.1016/j.amepre.2021.02.007.
15. Freedman DA, Bell BA, Clark J, et al. Small improvements in an urban food environment resulted in no changes in diet among residents. *J Community Health.* 2021;46(1):1–12. https://doi.org/10.1007/s10900-020-00805-z.
16. Hébert JR, Shivappa N, Wirth MD, Hussey JR, Hurley TG. Perspective: the Dietary Inflammatory Index (DII)-lessons learned, improvements made, and future directions. *Adv Nutr.* 2019;10(2):185–195. https://doi.org/10.1093/advances/nmy071.
17. DiNatale JC, Azarmanesh D, Hébert JR, Wirth MD, Pearlman J, Crowe-White KM. Relationship between Non-Energy-Adjusted and Energy-Adjusted Dietary inflammatory Index and the Healthy Eating Index-2015: an analysis of the National Health and Nutrition Examination Survey (NHANES) 2015−2018. *Ann Med.* 2023;55(2):2236551. https://doi.org/10.1080/07853890.2023.2236551.
18. Mokhtary N, Mousavi SN, Sotoudeh G, Qorbani M, Kalantar Z, Koohdani F. Association between dietary inflammatory indices (DII, EDII) and obesity with consideration of Insertion/Deletion Apo B polymorphism in type 2 diabetic patients. *Obes Med.* 2020;19:100241. https://doi.org/10.1016/j.obmed.2020.100241.
19. Shakya PR, Melaku YA, Shivappa N, et al. Dietary inflammatory index (DII®) and the risk of depression symptoms in adults. *Clin Nutr.* 2021;40(5):3631–3642. https://doi.org/10.1016/j.clnu.2020.12.031.
20. Shu Y, Wu X, Wang J, Ma X, Li H, Xiang Y. Associations of dietary inflammatory index with prediabetes and insulin resistance. *Front Endocrinol.* 2022;13:820932. https://doi.org/10.3389/fendo.2022.820932.
21. Zhao L, Sun Y, Liu Y, Yan Z, Peng W. A J-shaped association between Dietary Inflammatory Index (DII) and depression: a cross-sectional study from NHANES 2007−2018. *J Affect Disord.* 2023;323:257–263. https://doi.org/10.1016/j.jad.2022.11.052.
22. Zhou N, Xie ZP, Liu Q, et al. The dietary inflammatory index and its association with the prevalence of hypertension: a cross-sectional study. *Front Immunol.* 2022;13:1097228. https://doi.org/10.3389/fimmu.2022.1097228.
23. Liu H, Tan X, Liu Z, et al. Association between diet-related inflammation and COPD: findings from NHANES III. *Front Nutr.* 2021;8:732099. https://doi.org/10.3389/fnut.2021.732099.
24. Syed Soffian SS, Mohammed Nawi A, Hod R, et al. Meta-analysis of the association between Dietary Inflammatory Index (DII) and colorectal cancer. *Nutrients.* 2022;14(8):1555. https://doi.org/10.3390/nu14081555.
25. Ciesielski TH, Schwartz J, Bellinger DC, et al. Iron-processing genotypes, nutrient intakes, and cadmium levels in the Normative Aging

Study: evidence of sensitive subpopulations in cadmium risk assessment. *Environ Int.* 2018;119:527–535. https://doi.org/10.1016/j.envint.2018.06.040.

26. Digitale JC, Martin JN, Glymour MM. Tutorial on directed acyclic graphs. *J Clin Epidemiol.* 2022;142:264–267. https://doi.org/10.1016/j.jclinepi.2021.08.001.
27. Austin PC. An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behav Res.* 2011;46(3):399–424. https://doi.org/10.1080/00273171.2011.568786.
28. Greifer N. *Using love.plot to Generate Love Plots*. Vienna, Austria: The Comprehensive R Archive Network, R Foundation; 2023. https://cran.r-project.org/web/packages/cobalt/vignettes/love.plot.html. Accessed October 24, 2023.
29. Shiba K, Kawahara T. Using propensity scores for causal inference: pitfalls and tips. *J Epidemiol.* 2021;31(8):457–463. https://doi.org/10.2188/jea.JE20210145.
30. Schupp JL, Som Castellano RL, Sharp JS, Bean M. Exploring barriers to home gardening in Ohio households. *Local Environ.* 2016;21(6):752–767. https://doi.org/10.1080/13549839.2015.1017807.
31. Ciesielski TH, Pendergrass SA, White MJ, et al. Diverse convergent evidence in the genetic analysis of complex disease: coordinating omic, informatic, and experimental evidence to better identify and validate risk factors. *BioData Min.* 2014;7:10. https://doi.org/10.1186/1756-0381-7-10.
32. South EC, Kondo MC, Razani N. Nature as a community health tool: the case for healthcare providers and systems. *Am J Prev Med.* 2020;59(4):606–610. https://doi.org/10.1016/j.amepre.2020.03.025.
33. Shivappa N, Godos J, Hébert JR, et al. Dietary inflammatory index and cardiovascular risk and mortality-a meta-analysis. *Nutrients.* 2018;10(2):200. https://doi.org/10.3390/nu10020200.
34. Hariharan R, Odjidja EN, Scott D, et al. The dietary inflammatory index, obesity, type 2 diabetes, and cardiovascular risk factors and diseases. *Obes Rev.* 2022;23(1):e13349. https://doi.org/10.1111/obr.13349.