# TECHNICAL METHODOLOGY REPORT:

## What if healthier food became the norm?

September 2026

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# 1. Introduction

This document provides details of the technical methodology underpinning the analysis presented in the main report. It sets out the data sources, analytical steps, assumptions and limitations of the approach.

## Scope and purpose of the analysis

This analysis examines the potential population health impacts on adults (aged 15+) in the United States of shifting retail food and drink sales towards relatively healthier products within food and drink categories. Using the most recent available sales, nutrition, dietary intake, mortality and demographic data, we modelled the resulting changes in dietary intake, deaths delayed and estimated the associated reduction in lost working-age earnings.

The work was conducted as part of a collaboration between ATNi (Access to Nutrition initiative), ShareAction and Nesta to support investor understanding of how improvements in the healthiness of manufacturers' portfolios could influence population health outcomes. Nesta developed the analytical approach in collaboration with ATNi and ShareAction and conducted the health and economic impact analysis.

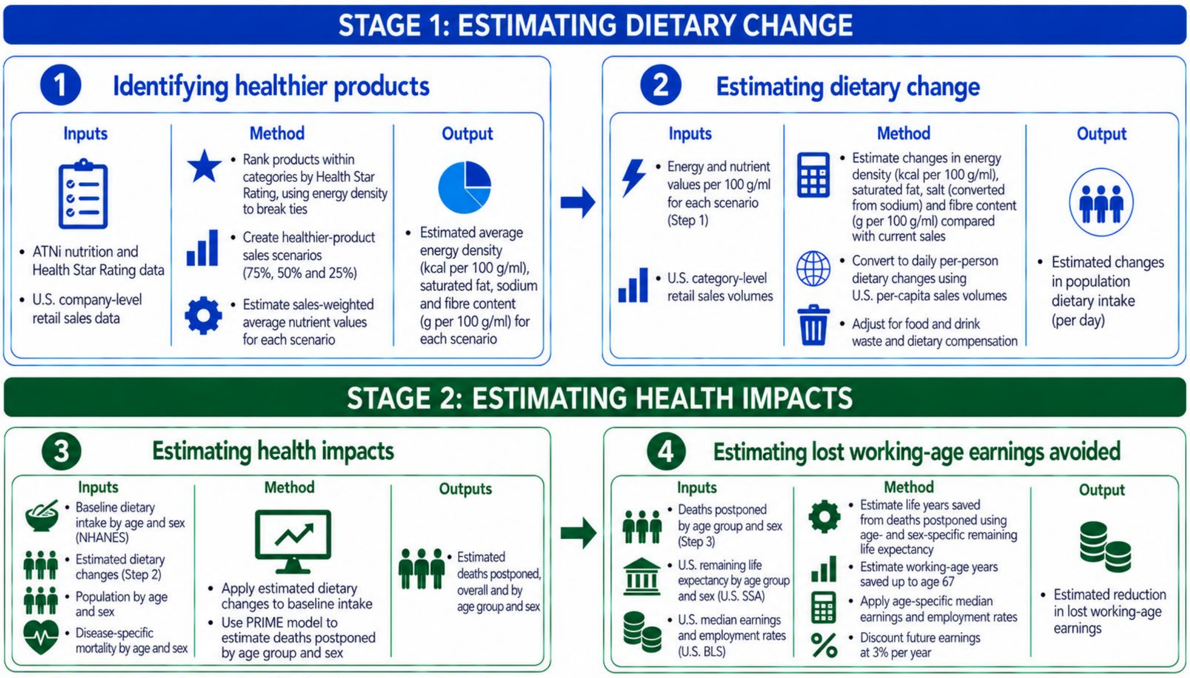
## Overview of approach

The analysis (click the headings below to jump to each section):

1. **Defining healthier-product scenarios:** Products within each food and drink category were ranked from healthiest to least healthy according to Health Star Rating (HSR). Where products share the same HSR, energy density (kcal per 100 g/ml) was used as a secondary ranking criterion.
2. **Estimating dietary shifts:** Scenarios were created in which all sales within each category were assumed to have a level of healthiness equivalent to the healthiest 25%, 50% or 75% of products within that category. U.S. food and drink sales data were then used to estimate how these scenarios would affect dietary intake among adults.
3. **Health impact modelling:** PRIME (the Preventable Risk Integrated ModEl) was used to estimate how these dietary changes could affect adult mortality across different age groups and by sex. Life years saved were then estimated using the number of deaths delayed and expected remaining life expectancy for each age group.
4. **Economic analysis:** Using our estimates of life years saved, we estimated the associated reduction in lost working-age earnings for each age group, based on median earnings and employment rates. This represents one component of the

potential economic benefits associated with the modelled food and drink sales-shifts.

The year of data sources used in this analysis ranged from 2021–2024. The results should therefore be interpreted as estimates of the potential impact in a typical recent year, rather than a specific calendar year.




Note: ATNi = Access to Nutrition initiative. NHANES = National Health and Nutrition Examination Survey.
U.S. SSA = U.S. Social Security Administration. BLS = U.S. Bureau of Labor Statistics. PRIME = Preventable Risk Integrated ModEl.

# 2. Defining healthier-product scenarios

The following steps were conducted in Python; code is available here.

## Identification of healthier product groupings

Product-level Health Star Rating (HSR) and nutrient composition data were obtained from the dataset used to produce the ATNi Global Index for 2024, which contained 16,287 packaged food and drink products available in the US across 24 food and drink categories, and from 24 food and drink companies. Six categories (dairy, plant-based dairy, meat and seafood substitutes, processed meat and seafood, ready meals, and soup) were excluded because corresponding estimated retail sales data were either unavailable or could not be directly mapped to the ATNi categories due to differences in category classifications in the 2024 Euromonitor International data. This left 9,724 products, from 24 food and drink companies across 18 categories, for inclusion in the analysis (Table 1). The analysis therefore does not cover all packaged food and beverage categories. The companies whose products were included in the modelling account for an estimated 37% of the total US packaged food and beverage market by sales value in 2024, excluding alcohol, baby food and foods for special medical purposes (this market share estimate relates to the companies' overall packaged food and beverage sales and is not restricted to the product categories included in the modelling). The nutritional characteristics of products from these companies were used to estimate changes within the 18 included categories, which were then extrapolated to total US retail sales volumes within those categories.

The purpose of this step was to identify the healthiest 75%, 50% and 25% of products within each category, which formed the basis of the healthier-product scenarios modelled in the analysis. In each scenario, all sales within a category were assumed to be distributed across the corresponding group of healthier products. For example, in the 75% scenario, sales were distributed across the healthiest 75% of products, effectively excluding the least healthy 25%. In the 25% scenario, sales were distributed across only the healthiest 25% of products, excluding the least healthy 75%.

The Health Star Rating (HSR) system, a nutrient profiling model developed by the Australian and New Zealand governments, was used to identify relatively healthier products within each category. HSR assigns products a star rating from 0.5 to 5 stars (in 0.5-star increments) using category-specific algorithms that balance nutrients associated with poorer health outcomes (including energy, saturated fat, total sugars and sodium) against beneficial components (including fruit, vegetables, nuts and legumes, fibre and protein). Category-specific nutrient thresholds and scoring rules are applied to calculate the final rating. These characteristics are combined to provide an overall indication of nutritional quality, with higher star ratings representing a more favourable nutritional profile. Products with an HSR of 3.5 stars or more are generally considered healthier choices. However, no absolute HSR threshold was used in this modelling exercise.

Instead, products were ranked by HSR within each category to identify the relatively healthier and less healthy products.

Within each category, products were ranked by HSR to identify the healthiest 25%, 50% and 75% of products. Because HSR is limited to 10 possible values, many products shared the same value. Where this occurred, products were secondarily ranked by energy density (kcal per 100g/ml), with less energy dense products ranked more favourably. For example, in a category containing 1,000 products, the 500 highest-ranked products according to HSR (using energy density to break ties) comprised the top 50% grouping.

While the 24 companies represented in the dataset account for an estimated 37% of the total US packaged food and beverage market by sales value, coverage varied considerably across the individual product categories included in the analysis, ranging from 72% of US retail sales for carbonates to 12% for baked goods (Table 1). While market coverage is therefore relatively low for some categories, many of the companies included also manufacture supermarket own-brand products that are often nutritionally similar to their branded ranges. The dataset may therefore be more representative of the nutritional characteristics of the wider market than branded market share coverage alone would suggest.

**Table 1. Food and drink categories included in the analysis.** 'Estimated U.S market share coverage' is the share of total 2024 U.S retail sales value within each category accounted for by companies represented in the ATNi Global Index dataset, based on Euromonitor International Passport data for 2024.

| Category | Number of products | Number of companies | Estimated U.S market share coverage |
|---|---|---|---|
| **Baked goods** | 882 | 4 | 12% |
| **Bottled water** | 217 | 4 | 24% |
| **Breakfast cereals** | 249 | 2 | 36% |
| **Carbonates** | 628 | 3 | 72% |
| **Concentrates** | 180 | 2 | 46% |
| **Confectionery** | 2,662 | 4 | 56% |
| **Ice cream** | 841 | 4 | 42% |
| **Juice** | 335 | 3 | 27% |
| **Other hot drinks** | 17 | 1 | 56% |
| **Processed fruit and vegetables** | 182 | 2 | 34% |

| | | | |
|---|---|---|---|
| **RTD coffee** | 27 | 1 | 12% |
| **RTD tea** | 61 | 2 | 50% |
| **Rice, pasta and noodles** | 325 | 4 | 17% |
| **Sauces, dips and condiments** | 816 | 4 | 30% |
| **Savoury snacks** | 1,222 | 9 | 64% |
| **Sports drinks** | 198 | 2 | 89% |
| **Sweet biscuits** | 813 | 7 | 51% |
| **Sweet spreads** | 69 | 2 | 17% |

## Estimating scenario nutrient values

This step aimed to estimate the average nutrient values (energy, saturated fat, sodium and fibre) of food and drink sales within each category under different healthier-product scenarios.

Two different types of sales data from the Euromonitor International Passport database for 2024 for the United States were used in the analysis for different purposes:

- Company-level retail revenue within each category was used to estimate product sales when calculating average nutrient content per 100 g of products sold within each category, because product-level sales volumes were unavailable.
- Category-level sales volumes were then used later in the analysis to estimate how changes in the nutrient composition of products sold within each category would translate into changes in population dietary intake.

Only retail sales were included because comparable out-of-home (i.e. "on-trade" or 'foodservice', as defined by Euromonitor) sales data were not available across all food and drink categories.

Energy density (kcal per 100g/ml), saturated fat (g/100g), sodium (mg/100g) and fibre (g/100g) were included in the analysis because these are the dietary factors modelled within PRIME. As the PRIME model requires salt intake in grams rather than sodium in milligrams, sodium values were converted from milligrams to grams and multiplied by 2.54 to express them as salt. Protein and sugar were not included because they are not modelled by PRIME. While PRIME can also model changes in fruit and vegetable intake, estimates of fruit and vegetable content were not available within the ATNi dataset and are not routinely reported on food and drink packaging. Estimating these values was therefore considered outside the scope of the analysis and would have introduced additional uncertainty. As the healthier-product scenarios would be expected on average to increase fruit and vegetable intake, which is associated with better health outcomes, excluding this pathway means that the analysis may underestimate their potential health benefits.

## Estimating product-level sales

The analysis aimed to account for differences in how much products are sold, rather than simply calculating the average nutrient values of all products available on the market. Without doing so, niche products with very low sales volumes would contribute equally to nutrient value averages as products sold in much larger quantities, potentially overstating or understating estimated dietary shifts associated with healthier-product scenarios. For example, a niche "healthier" cereal product with very low sales volumes would contribute equally to category averages as a bestselling cereal product if sales volumes were not taken into account.

Because product-level sales volume data were unavailable, company-level retail revenue within each category was used as a proxy for product sales. Revenue was distributed evenly across all products sold by a company within a category. For example, if a company generated $1 million in ice cream sales and sold 10 ice cream products, each product was assigned estimated sales of $100,000. The same approach to estimating and distributing sales was applied consistently to both the baseline and modelled scenarios.

This approach makes two major assumptions:

1. **Company-level retail revenue is broadly proportional to sales volume within categories.** While this assumption is unlikely to hold exactly because product prices vary, companies selling larger quantities of products will generally generate higher revenues, making revenue a pragmatic proxy for relative sales volume. The net impact of this assumption on estimated health outcomes is uncertain and will depend on the relationship between product price, sales volume and nutritional quality within each category.
2. **Sales are distributed equally across products within each company's portfolio in each category.** While this assumption does not reflect differences in sales between products within the same company and category, it does account for differences in sales between companies and is therefore likely to provide a more realistic estimate of product-level sales than assuming all products sell equally. Whether this assumption leads to over- or underestimation of dietary shifts for healthier sales scenarios depends on whether higher-selling products are, on average, healthier or less healthy than lower-selling products within a company's portfolio in the same category. Previous analyses suggest that sales are often concentrated among less healthy products. If this is the case, assuming equal sales across products may make company portfolios appear healthier than they are in reality, meaning the estimated health gains associated with shifting sales towards healthier products may be conservative. However, the magnitude of any resulting bias is likely to vary between companies and categories and cannot be determined with certainty.

## Estimating healthier-product scenarios

Estimated product-level sales were used to calculate estimated sales-weighted average nutrient values across all products for energy density, saturated fat, fibre, and salt within each category for the previously defined groupings:

- 25% healthiest products *(more ambitious – excludes the least healthy 75% of products)*,
- 50% healthiest products (excludes the least healthy 50% of products),
- 75% healthiest products (*less ambitious* -excludes the least healthy 25% of products),
- 100% of products (representing the current category average)

The three healthier-product scenarios assumed that all sales within each category had a level of healthiness equivalent to the corresponding 25%, 50% or 75% grouping. These scenarios therefore represent decreasingly ambitious shifts in sales away from less healthy products and towards healthier alternatives.

The main report focuses on the 50% scenario. Under this scenario, all sales within each category were assumed to shift to the healthiest 50% of products available in that category. These products were not necessarily healthy *per se* (e.g. above the HSR threshold of 3.5 stars); rather, they represented the relatively healthier half of products within each category based on their HSR. (Appendix 2 in the main report also presents results for the 25% scenario (more ambitious) and the 75% scenario (less ambitious)).

# 3. Estimating dietary shifts

## Estimating nutrient shifts per 100g/ml

For each category and healthier-product scenario, the estimated baseline sales weighted average for energy density (kcal per 100 g/ml), saturated fat, salt (converted from sodium) and fibre content (g per 100 g/ml) was subtracted from the corresponding category-average values for the healthier-product scenarios. The resulting differences represented the estimated nutrient shift associated with moving category sales towards relatively healthier products per 100g/ml sold.

For example, if the estimated category-average energy density was 250 kcal/100g under current sales and 220 kcal/100g under the 25% healthier-product scenario, the estimated nutrient shift would be a reduction of 30 kcal/100g.

## Estimating population dietary change

Data from the Euromonitor International Passport database for the United States were used to estimate population-level dietary change. Category-level retail sales data, reported as annual per-capita sales volumes (kilograms for solid products and litres for liquid products), were used to convert estimated nutrient shifts per 100g/ml into estimated daily per-person dietary changes by multiplying the nutrient shifts by annual per-capita sales volumes and dividing by 365. For example, if the estimated energy density within a category decreased by 30 kcal/100g and average annual retail sales for that category were 5 kg per person, this would equate to an estimated reduction of approximately 4.1 kcal per person per day.

### Food and drink wastage

Not all food and drink purchased is ultimately consumed. To account for this we reduced the daily per person dietary change estimates by household waste estimates of 21% for food (United States Department of Agriculture, 2010 data) and 7% for drinks (UK Government Department for Environment, Food and Rural Affairs, 2008 data). While these sources are relatively old and the drinks estimate is based on UK rather than US data, they were the most suitable estimates identified for this analysis at the time of writing.

### Dietary compensation

The analysis assumed that individuals partially compensate for reductions in parts of their diet by increasing consumption elsewhere in the diet. A compensation rate of 23% was applied based on evidence from meta-analyses examining changes in energy density and total energy intake. In other words, for every 100 fewer calories consumed from the product category, an additional 23 calories would be consumed in another category. For example, if the estimated reduction in energy intake was 4.1 kcal per person per day, applying the 21% household waste assumption reduced this to approximately 3.2 kcal per person per day. Applying the 23% dietary compensation assumption further reduced the estimated reduction in energy intake from 3.2 kcal to approximately 2.5 kcal per person per day.

In the absence of evidence on nutrient-specific dietary compensation, we assumed that, where overall calorie intake decreased, compensation was applied proportionally across all nutrients i.e. estimated reductions in saturated fat and salt were then also reduced by 23%. This assumes non-nutrient-specific dietary compensation, where individuals compensate for reductions in calorie intake by increasing overall food consumption rather than selectively increasing specific nutrients.

Compensation was applied only where calorie intake decreased and only to reductions in nutrient intake, not increases. For example, if a healthier-product scenario reduced calorie intake but increased fibre intake (positive from a health perspective), the estimated increase in fibre was not scaled down. This reflects the assumption that a reduction in calorie intake would be unlikely to encourage compensatory behaviours resulting in lower consumption of certain nutrients that increased as part of the healthier-product scenario.

Please see Appendix B for estimated daily dietary shifts for healthier-product scenarios.

## Sensitivity analysis

Household waste and dietary compensation assumptions are among the largest sources of uncertainty within the analysis and have a direct and large effect on the estimated size of dietary intake changes. A sensitivity analysis was therefore conducted to test the impact of these assumptions on final outputs. This involved running additional models without the household waste adjustment, without the dietary compensation adjustment, and without both adjustments together, across the following scenarios:

- the 25% and 75% healthier-product scenarios,
- two food and drink categories likely to be of greatest interest to several corporate stakeholders (Carbonates and RTD tea),
- and the combined “all categories together” scenario.

These scenarios were intended to test the influence of the assumptions on the model, rather than represent plausible upper or lower estimates of the true impacts. The sensitivity analysis showed that the assumptions around food and drink wastage and dietary compensation reduced estimated deaths delayed by around 22–30% for all categories combined, relative to a scenario with no wastage or dietary compensation. Across the individual categories examined, the reduction ranged from approximately 25% to 42%. However, the overall conclusions were unchanged, with the model continuing to predict substantial health gains under all sensitivity scenarios (see Appendix C for outputs of the sensitivity analysis).

# 4. Health impact modelling

The number of deaths delayed under the healthier-product scenarios was estimated using the Preventable Risk Integrated ModEl (PRIME), a widely used, spreadsheet-based scenario modelling tool that estimates how changes in behavioural risk factors (diet, physical activity, tobacco and alcohol) affect adult mortality. For this analysis, only dietary risk factors were modelled. We use the term 'deaths delayed' rather than 'deaths avoided' because the model estimates deaths that would otherwise have occurred being postponed to a later point in time, rather than permanently prevented.

Python was used to automate the creation and population of the PRIME spreadsheets and extraction of model outputs.

The following data were entered into the PRIME model.

## PRIME Inputs

### Dietary intake data

Baseline dietary intake data by age and sex for energy, saturated fat, fibre and salt were entered into the PRIME model. This data was obtained from NHANES (August 2021-August 2023), which, to our knowledge, was the most recent nationally representative US dietary intake data available at the time of analysis with dietary intake estimates split by sex and age group. NHANES age groups did not align exactly with those used in PRIME. Where necessary, dietary intake estimates from a single NHANES age group were applied to multiple adjacent PRIME age groups. For example, the NHANES estimate for adults aged 20–29 years was applied to the PRIME age groups 20–24 and 25–29 years.

Saturated fat intake within PRIME is expressed as a percentage of total energy intake. This was calculated using mean saturated fat intake (grams) and mean total energy intake (kcal) from NHANES data. NHANES reports mean values and standard errors for saturated fat intake and total energy intake separately but does not report the standard deviation of saturated fat as a percentage of total energy intake, which is required by the PRIME model. Standard deviations for saturated fat intake and total energy intake were first derived from the reported standard errors and sample sizes. The standard deviation of saturated fat as a percentage of total energy intake was then approximated using the delta method, a standard statistical approach for estimating the variance of a ratio from the variances and covariance of its numerator and denominator.

Because NHANES publishes only summary statistics, the covariance between saturated fat intake and total energy intake could not be estimated and was assumed to be zero. In practice, saturated fat intake and total energy intake are likely to be positively correlated because saturated fat contributes to total energy intake. Under this method, assuming zero covariance is therefore likely to overestimate the variance of saturated fat as a percentage of total energy intake, resulting in wider (more conservative) uncertainty intervals around the PRIME model outputs.

These baseline dietary intake estimates represented the current diet against which the healthier-product scenarios were modelled. For each scenario, the estimated changes in energy, saturated fat, fibre and salt were applied uniformly across all age and sex groups to generate the corresponding counterfactual dietary intake entered into PRIME.

### Population size data

Population estimates by age group and sex were entered into the PRIME model using data from United Nations Department of Economic and Social Affairs (UN DESA) World Population Prospects (2023).

### Disease mortality data

Disease-specific mortality by age group and sex was entered into the PRIME model using 2023 estimates from the Institute for Health Metrics and Evaluation Global Burden of Disease (GBD) study.

In most cases, there was a direct mapping between disease categories used in the PRIME model and those available within the GBD dataset. However, PRIME disease categories do not always align exactly with GBD classifications. Where exact matches were not possible, PRIME disease categories were mapped to the closest appropriate GBD category. In some cases, GBD categories group diseases together with adjacent but rarer conditions, while in other cases they are more narrowly defined than the corresponding PRIME category. Where a choice existed between a similar but narrower or broader disease category, we generally selected the narrower category to reduce the risk of overestimating mortality impacts (see Appendix A for full mapping between PRIME disease categories and GBD mortality categories).

PRIME estimates deaths delayed both overall and by disease. For this analysis, we extracted the overall estimate alongside disease-specific estimates for cardiovascular diseases (CVD) and diabetes. Within CVD, estimates for stroke and hypertensive disease were also extracted. These disease-specific results represent a subset of the outcomes modelled by PRIME. We also extracted the estimated number of deaths delayed through changes in obesity. These are not mutually exclusive of the disease-specific estimates, as obesity is an intermediate risk factor through which dietary changes can affect several disease outcomes, including CVD and diabetes. For example, a CVD death delayed as a result of a reduction in obesity would be captured in both estimates. The estimates should therefore not be summed.

## Category-specific and combined modelling

Health impacts were estimated for each food and drink category individually, as well as for all categories combined. Combined impacts were modelled directly within PRIME rather than derived by summing category-level estimates. This was necessary because the relationship between the size of dietary changes and their estimated impact on mortality in PRIME is non-linear. As a result, the health impact of simultaneous changes across multiple food categories cannot be estimated accurately by simply adding the category-level estimates.

For combined-category scenarios, the estimated changes in energy, saturated fat, fibre and salt across all categories were aggregated and entered into PRIME as a single dietary shift. This allowed the model to estimate the total health impact of simultaneous improvements across all categories while accounting for these non-linear relationships.

## Monte Carlo simulation

PRIME's built-in Monte Carlo simulation was used to estimate uncertainty around the model outputs. The simulation runs the model more than 5,000 times, drawing slightly different values from the uncertainty distributions specified for model parameters on each iteration. This produces an estimate of the mean number of deaths delayed together with a 95% uncertainty interval for deaths delayed.

PRIME outputs uncertainty intervals for total deaths delayed, but not for deaths delayed by age group. Life years saved and monetised values were estimated separately using deaths delayed by age group, so corresponding uncertainty intervals could not be derived directly from PRIME outputs. We therefore report indicative lower and upper bound estimates only, based on applying the proportional uncertainty around total deaths delayed. These should not be interpreted as exact 95% uncertainty intervals.

**Table 2. Summary of data sources**

| Type of data | Source | Year |
| --- | --- | --- |
| Product nutrition | Access to Nutrition Initiative (ATNi) Global Index packaged food and beverage database for the US | 2024 |
| Sales and volume | Euromonitor International Passport database | 2024 |
| Dietary intake | NHANES | 2021–2023 |

| | | |
|---|---|---|
| Population size | United Nations Department of Economic and Social Affairs World Population Prospects | 2023 |
| Disease mortality | Institute for Health Metrics and Evaluation, Global Burden of Disease Study | 2023 |
| Life expectancy | United States Social Security Administration actuarial life tables | 2023 |
| Median earnings | U.S Bureau of Labor Statistics, Median Weekly Earnings | 2024 |
| Employment Rates | US Bureau of Labor Statistics, Employment Rate | 2024 |

# 5. Economic analysis

In addition to the health impacts, we estimated the reduction in lost working-age earnings associated with the modelled food and drink sales shifts.

The PRIME model estimates deaths delayed by age group and sex. Life years saved were estimated by calculating expected remaining life expectancy for each age group using United States Social Security Administration actuarial life tables[1], multiplying this by the estimated number of deaths delayed within each group, and summing across all age and sex groups. This approach assumes that individuals whose deaths are delayed have the same expected remaining life expectancy as the population average for their age group.

We then estimated the additional earnings associated with these additional years of life based on age-specific median earnings and employment rates from the U.S. Bureau of Labor Statistics. Each age group was assigned a starting age based on the mid-point of its age bracket, rounded to the nearest whole year (for example, age 18 for the 15–20 group). For each additional year of life before retirement age 67, we applied the median earnings and employment rate corresponding to the cohort's age in that year (i.e. as a cohort aged, we updated median earnings and employment rate to reflect its new age bracket). We assumed median earnings and employment rates for each age group remain fixed over time. Future earnings were discounted using a 3% annual discount rate to express them in present-value terms, reflecting the standard economic principle that benefits received in the future are valued less than equivalent benefits received today. The 3% rate was chosen to align with US Government guidance for health-related economic analysis. The estimated earnings across all working years saved were then summed to calculate the total reduction in lost working-age earnings. The resulting estimate captures earnings that would otherwise be lost through premature mortality. It does not include other potential economic impacts, such as sickness absence, productivity while at work or healthcare costs, nor costs associated with increased longevity.

[1] based on the midpoint of each PRIME five-year age group (with a midpoint age of 90 years assumed for the 85+ age group).

# 6. Key assumptions and limitations

The analysis should be interpreted in light of several important assumptions and limitations. Below we reiterate some of the most important assumptions and limitations:

## Scope of food and drink sales included

The analysis only covers a subset of food and drink sales. It is based on an extrapolation of retail sales of 24 F&B manufacturing companies, which represent an estimated 37% of the US packaged food and beverage market in 2024. It focuses on retail sales within a subset of food and drink categories (18 out of a total of 24 categories) included in the Access to Nutrition Initiative (ATNi) Global Index dataset and does not capture food consumed through restaurants, takeaways, cafés or other out-of-home settings. It relies on company and category-level, rather than product-level sales data. Food consumed at home (retail) accounts for approximately 68% of total calorie intake in the US, while out-of-home food contributes around 32%. As a result, the analysis does not capture the potential health impacts of healthier products across the whole food system.

## Temporal alignment of data sources

The analysis uses the most recent suitable data available for each input, with data sources ranging from 2021 to 2024. Together, these provide a recent basis for estimating the potential health impacts of the modelled sales shifts. The results should therefore be interpreted as reflecting recent historical conditions rather than conditions in a specific calendar year. As the most recent data used are from 2024, the analysis does not capture changes that have occurred since then.

## Population scope

The analysis was limited to people aged 15 and over and therefore did not estimate health impacts among children under 15. As a result, the estimated health gains do not capture potential benefits arising from improvements in childhood diets and may underestimate the total population health impact of healthier food and drink sales.

## Nutrients included in the modelling

The PRIME model requires estimates of changes in energy, saturated fat, fibre and sodium intake. Consequently, the analysis focuses on changes in these nutrients and does not capture potential health effects associated with other nutritional characteristics of foods, including protein, added sugars, or micronutrients. The analysis also does not account for the degree of food processing. The estimated health impacts therefore reflect the dietary factors included in the model and do not capture all possible nutritional effects of dietary change.

While added sugars were not modelled explicitly, many of the health effects of sugar intake relevant to the diseases included in PRIME are likely captured indirectly through changes in energy intake and associated effects on obesity-related disease risk. However, the model may not fully capture health impacts arising from changes in sugar intake that operate independently of calorie consumption.

## Hypothetical dietary scenarios

The scenarios modelled represent hypothetical shifts in sales towards relatively healthier products within categories. They do not represent forecasts of consumer behaviour, industry reformulation or policy impacts. The analysis estimates the potential health impacts of these dietary shifts, rather than the likelihood of them occurring in practice.

The analysis also relies on several simplifying assumptions to translate changes in food sales into changes in dietary intake. These include assumptions about food and drink wastage and the extent to which consumers compensate for reductions in calorie intake by consuming additional food elsewhere in their diet. While these assumptions were informed by the best available evidence, and the resulting dietary shifts were reviewed by a registered nutritionist to assess whether they represented broadly plausible changes in purchasing and consumption patterns, actual behaviours are likely to vary across foods, individuals and contexts.

# Health Star Rating (HSR) limitations

The Health Star Rating (HSR) system was used to identify relatively healthier products within categories. HSR is a widely used nutrient profiling model applied extensively in research, policy and industry settings. The Access to Nutrition initiative (ATNi) also used a Delphi process involving stakeholders from industry, academia, civil society, investors and policymakers to review a range of nutrient profiling approaches, identifying HSR as one of the three most credible models (alongside Nutri-Score and the UK NPM) available for assessing the relative healthiness of food and drink products.

However, like all nutrient profiling models, HSR has limitations. One criticism of HSR is that it is possible, within certain limits[2], to improve rating values through reformulation that increases positive components such as fibre, protein or fruit, vegetable, nut and legume (FVNL) content, even where products remain relatively high in calories, saturated fat or sugar.

A related implication is that products with higher HSR do not necessarily contain healthier levels of every nutrient included in the health model. Consequently, some dietary shifts modelled resulted in less favourable changes in individual nutrients. For example, energy

[2] The Health Star Rating (HSR) system does include built-in gateway rules, caps, and automatic ratings designed to limit manipulation.

density increased in some scenarios for rice, pasta and noodles, sweet spreads, savoury snacks and processed fruit and vegetables (Appendix B). In some cases, these less favourable nutrient changes outweighed improvements in other nutrients, resulting in the PRIME model estimating increases rather than decreases in deaths. This was the case for the 75% and 50% scenarios for rice, pasta and noodles and sweet spreads. These counterintuitive results may also partly reflect the fact that PRIME model does not directly model changes in some factors included in HSR, such as protein, nuts and legumes, and total sugar.

HSR uses category-specific algorithms and nutrient weightings. As a result, products with the same HSR from different categories are not necessarily nutritionally equivalent. While this may be a limitation for analyses comparing products across categories, this was not an issue for the present analysis which used HSR only to rank products within the same category.

Alternative nutrient profiling models would likely identify somewhat different sets of products as healthier. However, there is currently no single nutrient profiling model that is universally accepted as the definitive measure of product healthiness. HSR was selected because it provides a transparent, widely used and holistic assessment of product nutritional quality that can be applied consistently across a broad range of food and drink categories.

## PRIME model limitations

The PRIME model estimates health impacts based on epidemiological studies linking dietary factors to disease outcomes, through relative risk estimates derived from meta-analyses. As with any such model, the results depend on the quality, applicability and assumptions of the underlying evidence base.

The epidemiological studies underpinning the model identify associations between dietary risk factors and disease outcomes and do not necessarily establish that these relationships are causal. They are subject to potential sources of bias and uncertainty, including measurement error, residual confounding and differences between study populations. While PRIME draws on the best available evidence and has been widely used in public health research, the estimated health impacts should be interpreted as indicative estimates under a defined set of assumptions rather than precise predictions of real-world outcomes.

In addition, PRIME captures only the dietary risk factors and disease pathways included within the model. Potential health impacts operating through other nutritional components or disease pathways are not reflected in the estimates.

## Life expectancy following delayed deaths

The estimate of life-years saved assumes that individuals whose deaths are delayed have the same expected remaining life expectancy as the population average for their age group. In practice, these individuals may have different underlying health profiles and life expectancies, meaning the estimated number of life-years saved may be higher or lower than would occur in practice.

# Appendix

## Appendix A. Full mapping between PRIME disease categories and GBD mortality categories

| PRIME disease category | GBD mortality category used | Notes on mapping |
|---|---|---|
| C25: Pancreas | Pancreatic cancer | Direct equivalent |
| C50: Breast | Breast cancer | Direct equivalent |
| C18–20: Colorectum | Colon and rectum cancer | Different naming convention |
| C16: Stomach | Stomach cancer | Direct equivalent |
| C34: Bronchus and lung | Tracheal, bronchus, and lung cancer | Slightly broader; includes tracheal cancer |
| C00–C14: Lip, oral cavity and pharynx | Lip and oral cavity cancer; Nasopharynx cancer; Other pharynx cancer | Sum of multiple GBD categories |
| C54.1: Endometrium | Uterine cancer | Slightly broader; includes rare uterine sarcoma |
| C23: Gallbladder | Gallbladder and biliary tract cancer | Slightly broader; includes adjacent biliary tract cancers |
| C64: Kidney | Kidney cancer | Direct equivalent |
| C67: Bladder cancer | Bladder cancer | Direct equivalent |
| C22: Liver cancer | Liver cancer | Direct equivalent |
| C53: Cervix cancer | Cervical cancer | Different naming convention |
| C15: Oesophagus | Esophageal cancer | GBD uses US spelling |
| I10–I15: Hypertensive disease | Hypertensive heart disease | Narrower category used to avoid double counting of chronic kidney disease due to hypertension which is captured under chronic kidney disease. |

| | | |
|---|---|---|
| E11, E14: Diabetes | Type 2 diabetes mellitus | Narrower category used to exclude type 1 diabetes |
| J40–J44: Chronic obstructive pulmonary disease | Chronic obstructive pulmonary disease | Direct equivalent |
| K70, K74: Liver disease | Cirrhosis and other chronic liver diseases | Broader category including additional chronic liver diseases |
| I50: Heart failure | Cardiomyopathy and myocarditis | Narrower category used to reduce risk of double counting with other cardiovascular diseases |
| I71: Aortic aneurysm | Aortic aneurysm | Direct equivalent |
| I26: Pulmonary embolism | Pulmonary arterial hypertension | Closest available GBD category |
| N18: Chronic renal failure | Chronic kidney disease | Different naming convention |
| I20–I25: Ischaemic heart diseases | Ischemic heart disease | GBD uses US spelling |
| I60–I69: Cerebrovascular diseases | Stroke | Slightly narrower category capturing the majority of deaths |
| I05–I09: Rheumatic heart disease | Rheumatic heart disease | Direct equivalent |

## Appendix B. Estimated daily dietary shifts for healthier-product scenarios

### 25% healthiest products scenario

| Category | Kcal | Sat Fat | Fibre | Salt |
|---|---|---|---|---|
| Baked Goods | -63.7059 | -2.43283 | 5.000937 | -0.14113 |
| Bottled Water | -2.85959 | 0 | -0.0084 | -0.02729 |
| Breakfast Cereals | -4.66693 | -0.07215 | 0.437501 | -0.0763 |
| Carbonates | -59.3996 | 0 | -0.0021 | -0.0136 |
| Concentrates | -0.21298 | 0.000112 | -4.9E-05 | -0.00131 |
| Confectionery | -44.7336 | -2.21454 | -0.364 | -0.03809 |
| Ice Cream | -19.5219 | -1.00358 | 0.185999 | -0.01815 |
| Juice | -5.44595 | -0.00148 | 0.058162 | 0.0989 |
| Other Hot Drinks | -0.17409 | -0.0038 | 0.031997 | -0.00115 |
| Processed Fruit and Vegetables | 21.58207 | -0.03611 | 1.554332 | -0.09561 |
| RTD Coffee | -1.18121 | -0.01759 | -0.00179 | -0.00213 |
| RTD Tea | -3.01068 | 0 | 0 | -0.00075 |
| Rice, Pasta and Noodles | 18.80342 | -0.09804 | 1.582087 | -0.05111 |
| Sauces, Dips and Condiments | -64.0402 | -0.80984 | 0.06872 | -1.0254 |
| Savoury Snacks | -2.29197 | -1.05099 | 2.530253 | -0.30278 |
| Sports Drinks | -8.48504 | -0.00256 | -0.00256 | -0.01133 |
| Sweet Biscuits, Snack Bars and Fruit Snacks | -7.1434 | -0.54995 | 1.025231 | -0.01873 |
| Sweet Spreads | 0.625522 | -0.14398 | 0.075434 | 0.017879 |
| **TOTAL** | **-245.862** | **-8.43733** | **12.17174** | **-1.70809** |

### 50% healthiest products scenario

| Category | Kcal | Sat Fat | Fibre | Salt |
|---|---|---|---|---|
| Baked Goods | -49.8892 | -2.44612 | 2.281036 | -0.07694 |
| Bottled Water | -2.55283 | 0 | -0.0084 | -0.02927 |
| Breakfast Cereals | -3.12622 | -0.04547 | 0.302968 | -0.03427 |
| Carbonates | -29.3875 | 0 | -0.00081 | -0.00829 |
| Concentrates | -0.17984 | 9.72E-05 | 6.1E-06 | -0.00065 |
| Confectionary | -27.4254 | -1.59743 | -0.30158 | -0.02388 |
| Ice Cream | -10.926 | -0.69604 | 0.040595 | -0.00846 |
| Juice | -4.12025 | -0.00148 | -0.00176 | 0.012646 |
| Other Hot Drinks | -0.11064 | -0.00353 | 0.017731 | 0.000476 |
| Processed Fruit and Vegetables | -2.63632 | -0.05935 | 0.54448 | -0.0923 |
| RTD Coffee | -0.60489 | -0.00669 | 2.91E-05 | -0.00087 |

| | | | | |
|---|---|---|---|---|
| RTD Tea | -1.99079 | 0 | 0 | -0.00019 |
| Rice, Pasta and Noodles | 18.26856 | -0.10513 | 0.83882 | -0.04931 |
| Sauces, Dips and Condiments | -55.7842 | -0.61803 | -0.07109 | -0.87431 |
| Savoury Snacks | 2.601562 | -0.87527 | 1.129498 | -0.28456 |
| Sports Drinks | -6.56468 | -0.00256 | -0.00256 | -0.0091 |
| Sweet Biscuits, Snack Bars and Fruit Snacks | -3.45659 | -0.60379 | 0.512665 | 0.004617 |
| Sweet Spreads | 3.460947 | -0.07414 | 0.07877 | 0.006199 |
| **TOTAL** | **-174.424** | **-7.13493** | **5.36039** | **-1.46846** |

## 75% healthiest products scenario

| Category | Kcal | Sat Fat | Fibre | Salt |
|---|---|---|---|---|
| Baked Goods | -40.8463 | -1.91092 | 1.301755 | -0.04887 |
| Bottled Water | -2.40841 | 0 | -0.0084 | -0.02965 |
| Breakfast Cereals | -1.18076 | -0.01111 | 0.201505 | -0.02003 |
| Carbonates | -15.8055 | 0 | -0.00084 | -0.00886 |
| Concentrates | -0.14028 | 7.38E-05 | 0.000134 | -0.00061 |
| Confectionary | -12.5081 | -0.95215 | -0.2322 | -0.0142 |
| Ice Cream | -4.83895 | -0.43208 | 0.020814 | -0.00106 |
| Juice | -2.82819 | 0.000418 | -0.00291 | -0.01182 |
| Other Hot Drinks | -0.05842 | -0.00349 | 0.005798 | 0.00026 |
| Processed Fruit and Vegetables | -5.20281 | -0.04392 | 0.223881 | -0.06427 |
| RTD Coffee | -0.26333 | -0.00164 | -0.00038 | -0.0005 |
| RTD Tea | -0.88316 | 0 | 0 | 8.73E-05 |
| Rice, Pasta and Noodles | 11.89554 | -0.09988 | 0.35728 | -0.03889 |
| Sauces, Dips and Condiments | -37.247 | -0.43523 | -0.09459 | -0.73063 |
| Savoury Snacks | 2.022804 | -0.78387 | 0.576619 | -0.17942 |
| Sports Drinks | -4.38516 | -0.00256 | -0.00256 | -0.00878 |
| Sweet Biscuits, Snack Bars and Fruit Snacks | -1.2032 | -0.35656 | 0.01598 | 0.023233 |
| Sweet Spreads | 0.846235 | -0.12767 | 0.015346 | 0.001504 |
| **TOTAL** | **-115.035** | **-5.16059** | **2.377227** | **-1.1325** |

## Appendix C. Sensitivity Analysis Outputs

| Category | Scenario | 0% Compensation, 0% Wastage | 0% Compensation, 21% Wastage | 23% Compensation, 0% Wastage | 23% Compensation, 21% Wastage |
|---|---|---|---|---|---|
| Baked Goods | 25% | 106,174 | 95,794 | 94,538 | 76,576 |
| Baked Goods | 75% | 54,212 | 48,901 | 45,499 | 36,563 |
| Carbonates | 25% | 39,037 | 37,059 | 31,516 | 29,487 |
| Carbonates | 75% | 12,175 | 11,344 | 9,542 | 8,886 |
| RTD Tea | 25% | 2,762 | 2,486 | 2,122 | 1,654 |
| RTD Tea | 75% | 753 | 669 | 569 | 434 |
| All categories | 25% | 266,839 | 249,332 | 241,307 | 208,451 |
| All categories | 75% | 147,832 | 135,252 | 125,144 | 103,627 |

ATNi (Access to Nutrition initiative)
Arthur van Schendelstraat 650
3511 MJ Utrecht
The Netherlands
+31 (0)6 429 51 655
info@atni.org
www.atni.org



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