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Consumers' environmental impact perceptions are sensitive to broad food categories purchased but not within-category purchasing patterns

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Abstract

Accelerating environmentally sustainable dietary shifts requires understanding consumer perceptions of their food shopping's environmental impact and of how perceptions align with actual impact. Yet existing work has been limited by a lack of real-world data. We address this by linking supermarket loyalty card data, product environmental impact estimates, and self-report measures for 947 UK shoppers. Self-reported and objectively assessed food shopping impacts were weakly correlated. Individuals purchasing more meat, and less plant-based food, correctly perceived their impact as higher but underestimated the extent. Those buying more meat believed meat was less environmentally harmful, potentially contributing to this underestimation. Perceptions were not sensitive to types of meat or dairy purchased, despite within-category choices strongly contributing to objective impact. Results indicate consumers have only a coarse understanding of their food shopping's environmental impact, highlighting potential benefits of interventions emphasising the magnitude of differences in product impacts both between and within categories.

Main

Food systems are a major contributor to environmental impacts, responsible for up to a third of global GHG emissions[1], 70% of freshwater withdrawals[2], and the majority of deforestation[3]. Even with supply-side efficiency gains and reductions in food waste, environmental impacts from food systems are projected to exceed safe planetary boundaries by 2050 without widespread dietary change among the public[4].

While people generally report favourable attitudes towards buying foods with a low environmental impact, translating attitudes into consistent behaviour change remains a challenge[5]. A burgeoning literature has examined motivations and barriers to sustainable food purchasing, with perceived cost and lack of knowledge frequently reported as obstacles[5,6].

Policy proposals for addressing barriers include information-provision strategies, such as displaying environmental impact labels on product packaging (eco-labels), carbon taxes on meat purchases, and subsidies on low-impact foods[7]. Food eco-labels have been gaining traction in the academic literature and policy discussions but have yet to be widely implemented, and questions remain about their optimal format[8-11].

Effective design and communication of demand-side interventions, such as eco-labels, requires a clear understanding of consumers' perceptions of their food shopping's environmental footprint and of how these perceptions correspond with actual impact. However, existing work has been limited by a lack of real-world behavioural data[5,12]. Moreover, estimating environmental impacts for the thousands of food products sold at major supermarkets presents a major technical challenge. Consequently, studies using actual purchase data have typically employed coarse proxies for environmental impact, such as proportion of expenditure on red meat or organic food[13,14]. These measures are unlikely to accurately capture an individual's environmental footprint, since organic versus conventional production is a weak predictor of a product's impact, and the impacts of food types within broad categories (including red meat) can vary widely[15].

Here we develop an objective measure of the environmental impact of individuals' food purchasing by linking loyalty card transaction data for the UK's largest supermarket retailer[16] (Tesco) to a dataset from Clark et al.[17] containing environmental impact estimates for thousands of supermarket food products. Though extensive, Clark et al.'s dataset does not cover all food products sold at Tesco. We greatly expand coverage by developing a detailed categorisation scheme designed to minimise within-category variability in environmental impacts (Methods). This enabled items in the shopping data without an existing impact score in Clark et al. to be assigned the average value across similar products. We used Clark et al.'s composite environmental impact scores per 100g, equally weighting GHG emissions, land

use, eutrophication potential, and water scarcity, to calculate an *environmental food purchasing index* (EFPI); representing a shopper's environmental impact per 100g of food purchased.

We linked shopping data, enriched with environmental impact values, to survey measures capturing perceived environmental impact of food shopping, self-reported dietary consumption, and beliefs about the environmental impact of different types of food. These linked data enabled us to (1) examine convergence between self-report measures and an objective behavioural indicator, (2) identify areas of alignment and misalignment by comparing how the composition of shoppers' baskets contributed to their subjectively perceived versus objectively assessed environmental impact, and (3) determine associations between purchasing behaviour and beliefs about the environmental impacts of different types of food.

Results

EFPI scores: Convergence with self-report measures

Objectively estimated EFPI scores and environmental impact of self-reported dietary consumption (calculated from food frequency questionnaire responses; see Methods) were log-transformed to reduce large positive skew (Supplementary Analyses, Fig. S1). EFPI scores had statistically robust but relatively weak associations with self-report measures of behaviour. Controlling for pre-registered covariates (number of people shopped for, self-reported percentage of grocery purchases made at Tesco, main household shopper status), EFPI scores (M = 0.94, SD = 0.34) positively correlated with perceived environmental impact of food shopping (M = 4.12, SD = 1.32; see Fig. S2 for distribution), r_p = .13, p < .001, n = 945; and with environmental impact of self-reported dietary consumption (M = 1.09, SD = 0.44), r_p = .24, p < .001, n = 944. Correlations with EFPI scores remained significant when

additionally controlling for total volume by purchase weight (perceived environmental impact, r_p = .09, p = .008; environmental impact of self-reported dietary consumption, r_p = .26, p < .001).

Objective EFPI scores were also associated with general reported dietary preferences of household members. Participants who reported shopping for one or more household members that followed a non-meat or low-meat diet (vegan, vegetarian, pescatarian, flexitarian; n = 173) had significantly lower EFPI scores (M = 0.80, SD = 0.31) than participants in omnivore-only households (M = 0.97, SD = 0.34); Welch's t-test, t(271.55) = 6.34, p < .001, d = 0.50, 95% CI [0.34, 0.67].

All relationships remained significant, with similar or slightly larger effect sizes, when analyses were restricted to regular shoppers (n = 754); defined as participants with purchases in at least six of the last 12 months (Table S1).

Food shopping compositions: Associations with EFPI scores and subjectively perceived impact

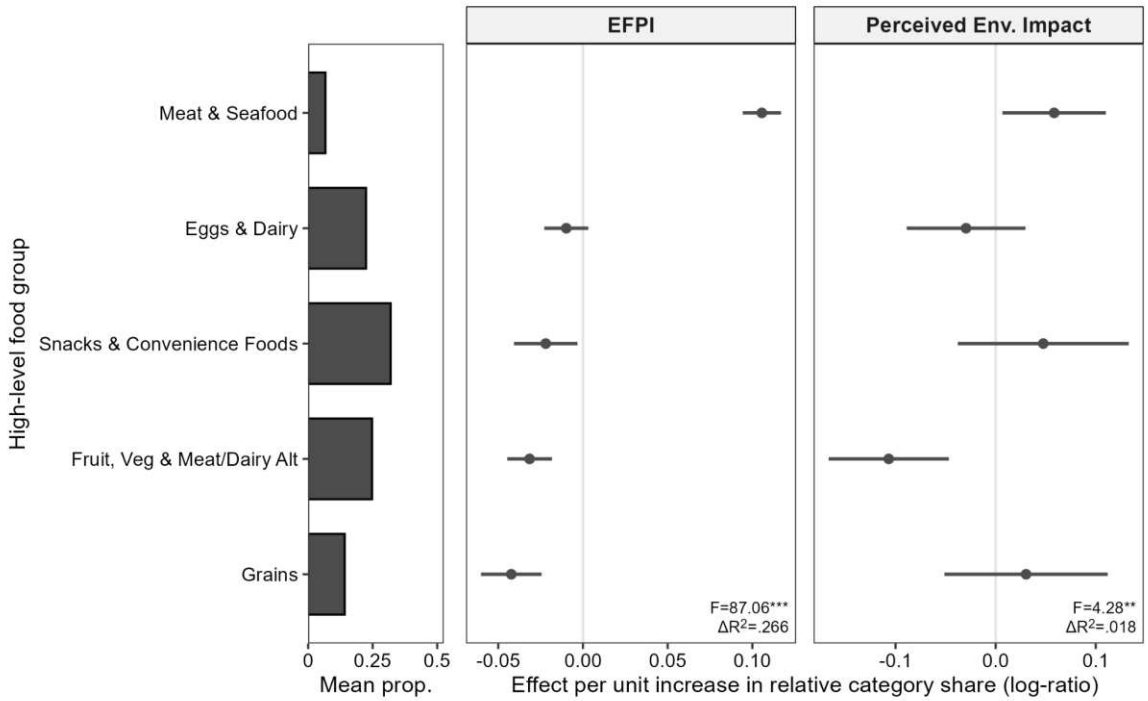
We examined how food shopping compositions at different levels of categorisation (high-level food groups and detailed subcategories) related to subjectively perceived versus objectively assessed environmental impact. High-level food groups were: (1) meat and seafood, (2) eggs and dairy, (3) fruit, vegetables and meat/dairy alternatives, (4) grains, and (5) snacks and convenience food (see Methods for grouping rationale). Compositional shares of food groups (by weight purchased) were modelled using isometric log-ratios (ILRs; see Methods). Subcategory purchasing patterns were examined using a two-stage approach. First, binary variables were created which indicated whether a participant purchased each subcategory. Second, subcategory compositional shares were computed for participants who purchased across a sufficient range of subcategories within a high-level food group.

Associations between food subcategory compositional shares and EFPI scores and perceived environmental impact of food shopping were examined in separate multiple linear regression analyses (controlling for shopping metrics covariates; see Methods).

High-level food group composition

The composition of high-level food groups in participants' shopping was significantly related to both EFPI scores and perceived environmental impact (Fig. 1). Higher EFPI scores were primarily associated with an increased share of meat and seafood, and higher perceived impact was associated with an increased share of meat and seafood, and a decreased share of fruit, vegetables, and meat/dairy alternatives (Fig. 1). The effect size for perceived impact was small ($\Delta R^2 = .018$), and standardised perceived impact ratings increased with share of meat and seafood far less strongly than standardised EFPI scores did (Fig. S3), suggesting participants underestimated the extent to which higher levels of meat and seafood purchasing increased their environmental footprint relative to others.

Fig 1: High-level food group composition associations with EFPI scores and perceived environmental impact of food shopping



Mean sample composition (left) and centred log-ratio (CLR) coefficients with 95% CIs (centre, right). Compositions were modelled with ILRs and re-expressed in CLR-space for interpretation (Methods). F-statistics and R^2 change values reflect joint effects of the ILR regression coefficients, controlling for covariates. See Supplementary Analyses (Table S2) for model statistics and ILR regression coefficients.

** $p < .01$ *** $p < .001$

Within-group purchasing patterns

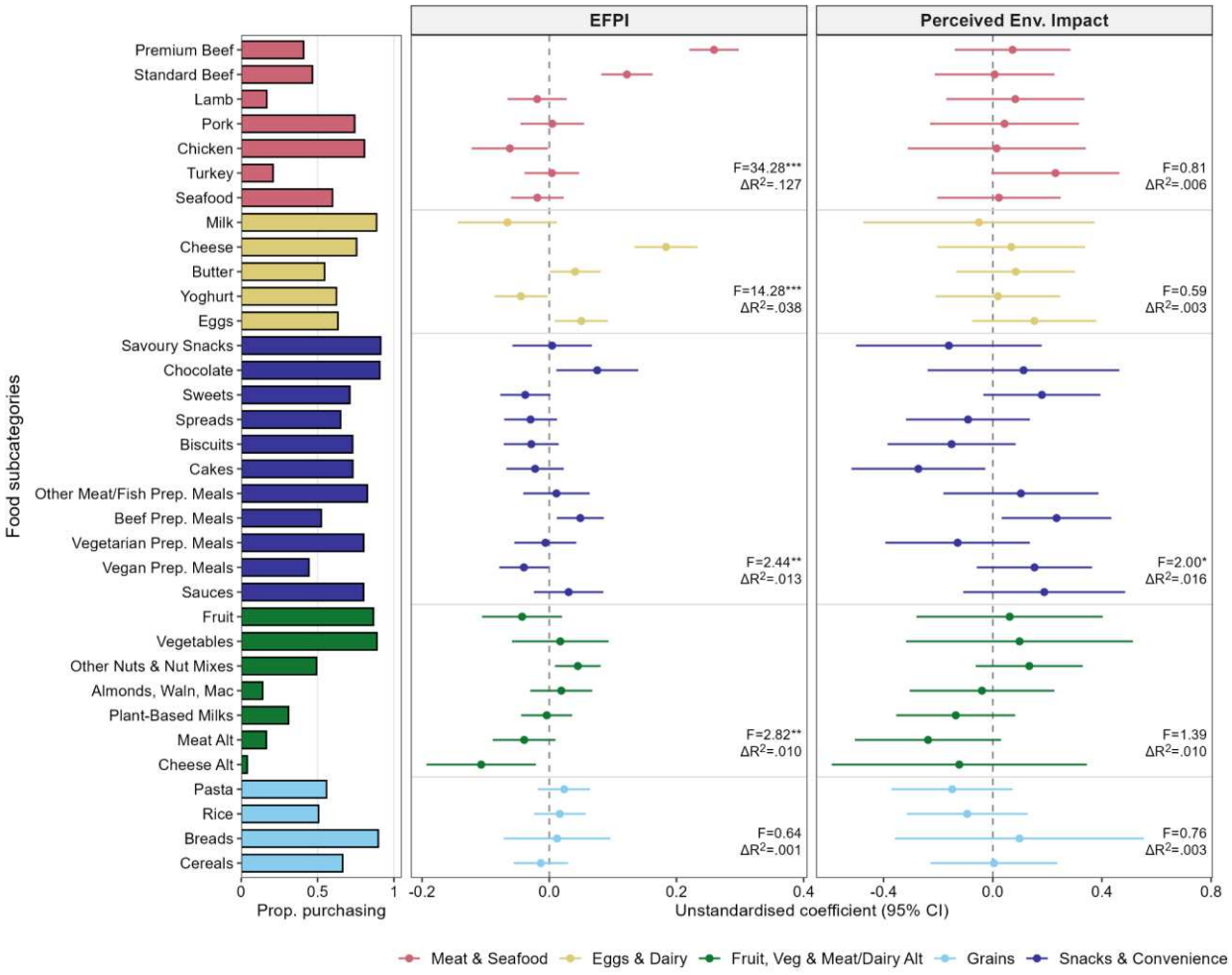
Binary purchase indicators for 34 detailed subcategories were entered into separate multiple linear regression models predicting EFPI scores and perceived environmental impact of food shopping. Analyses controlled for high-level food group composition, with regression coefficients thus representing the impact of purchasing a given subcategory while holding high-level food group purchase shares constant.

The set of binary purchase variables for the seven meat and seafood subcategories were jointly related to EFPI scores, accounting for 12.7% of the variance. This was driven by higher EFPI scores among participants who purchased premium or standard beef (Fig. 2). In

contrast, meat and seafood binary purchase variables did not jointly predict perceived environmental impact (Fig. 2). A one-sided 95% CI upper bound on ΔR^2 of .008 indicates that plausible effect sizes for the relationship are small. A similar pattern was observed for eggs and dairy, where the corresponding binary purchase indicators were jointly related to EFPI scores (driven by higher impacts among participants who purchased cheese; Fig. 2), but not to perceived impact of food shopping (one-sided 95% CI upper bound on $\Delta R^2 = .006$).

Snacks and convenience food was the only high-level food group where subcategories purchased significantly predicted perceived environmental impact, albeit weakly—accounting for 1.6% of the variance. Conditional on overall share of snacks and convenience food, purchasing of beef-based convenience foods was associated with a higher perceived impact, while purchasing cakes was associated with a lower perceived impact (Fig. 2). Snacks and convenience food binary purchase indicators were also jointly related to EFPI scores, with purchasing of beef-based prepared foods and chocolate associated with a higher impact.

Fig 2: Association of subcategory binary purchase indicators with EFPI scores and perceived environmental impact of food shopping



Proportion of participants who purchased each subcategory (left panel) and unstandardised linear regression coefficients (with 95% CIs) for the effect of purchasing a given subcategory on EFPI scores (centre panel) and perceived environmental impact of food shopping (right panel). F-statistics and R^2 change values reflect joint effects for the set of binary purchase indicators relating to a high-level food group.

* $p < .01$, ** $p < .01$, *** $p < .001$

For within-group compositional shares, we restricted analyses to participants who purchased from more than half of the subcategories within a high-level food group, and amalgamated (e.g., premium beef and standard beef > beef) or excluded (lamb, turkey) low-frequency subcategories (see Methods). This minimised the prevalence of zero purchase values for

compatibility with compositional data analysis. Separate multiple linear regression analyses were performed for each of the five within-group compositions by each dependent variable.

Results (Fig. S4) generally aligned with the binary purchase indicator regressions. Within-group composition of meat and seafood subcategories strongly predicted EFPI scores, $F(3, 560) = 101.27$, $p < .001$, accounting for 20.2% of the variance. This was primarily driven by an increased share of beef relative to chicken in within-group compositions associated with higher EFPI scores (pairwise log-ratio: $b = 0.15$, $SE = 0.01$, 95% CI [0.13, 0.17]). In contrast, meat and seafood subcategory composition was not significantly associated with perceived environmental impact, $F(3, 559) = 1.13$, $p = .338$, $\Delta R^2 = .005$ (one-sided 95% CI upper bound on $\Delta R^2 = .015$), and perceived impact did not vary by relative share of beef versus chicken (pairwise log-ratio: $b = -0.02$, $SE = 0.07$, 95% CI [-0.15, 0.11]).

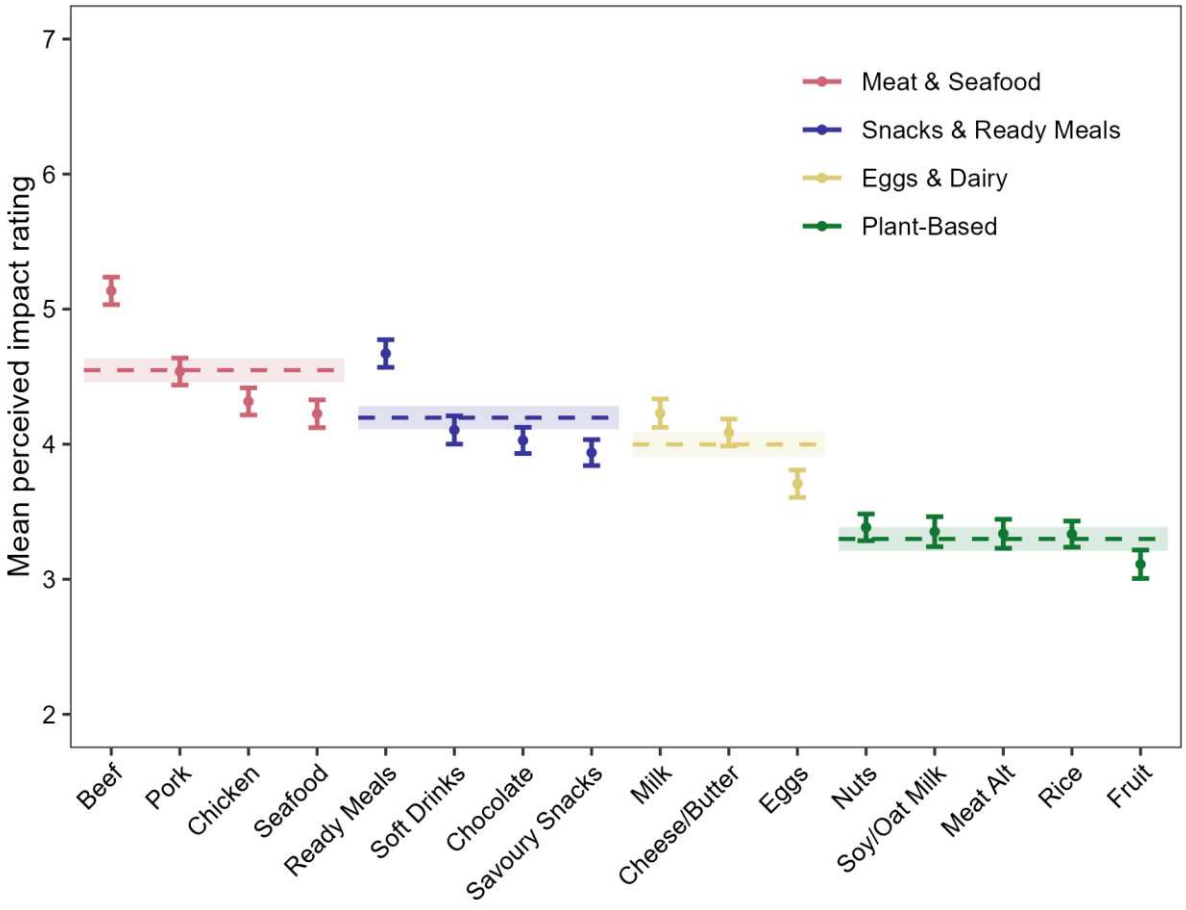
Within-group composition of eggs and dairy was a moderate predictor of EFPI scores, $F(4, 638) = 23.78$, $p < .001$, accounting for 7.9% of the variance. Within-group compositions associated with higher EFPI scores contained an increased share of cheese relative to milk (pairwise log-ratio: $b = 0.09$, $SE = 0.01$, 95% CI [0.07, 0.12]). Conversely, eggs and dairy subcategory composition was not significantly associated with perceived environmental impact, $F(4, 636) = 0.48$, $p = .749$, $\Delta R^2 = .003$ (one-sided 95% CI upper bound on $\Delta R^2 = .006$), and perceived impact did not vary by relative share of cheese versus milk (pairwise log-ratio: $b = 0.003$, $SE = 0.06$, 95% CI [-0.11, 0.12]).

Snacks and convenience food within-group composition was significantly associated with EFPI scores, $F(9, 706) = 2.99$, $p = .002$, $\Delta R^2 = .023$, but not perceived environmental impact of food shopping, $F(9, 705) = 1.78$, $p = .068$, $\Delta R^2 = .020$. Higher EFPI scores were predicted by a greater within-group share of beef-based prepared foods and sauces, and a smaller share of cakes (Fig. S4).

Purchasing compositions and food category environmental impact judgements

We used perceived environmental impact ratings elicited for 16 food types to examine associations between purchasing behaviour and beliefs about the environmental impact of different types of food. Perceived impact of high-level food groups was calculated based on mean perceived impact ratings across corresponding food types (Fig. 3). The four composite measures had good internal reliability (meat and seafood; $\alpha = .86$; eggs and dairy; $\alpha = .86$; snacks and ready meals; $\alpha = .82$; plant-based foods; $\alpha = .86$). Descriptive statistics are reported in Figure 3.

Fig 3: Perceived environmental impact ratings for subcategories and high-level food groups

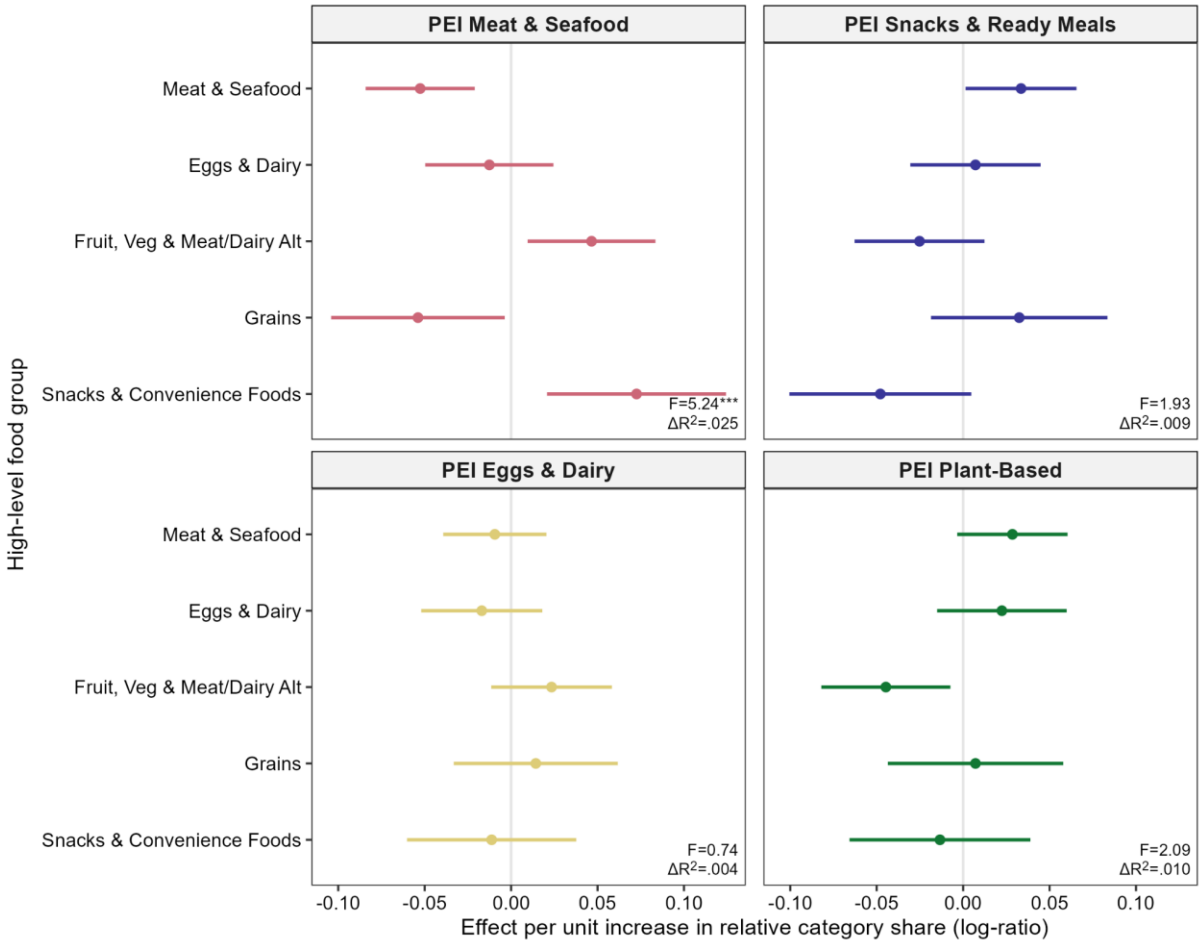


Dashed horizontal lines represent mean ratings for high-level food groups. Circles represent mean values for individual food types. Error bars and bands are 95% CIs.

Category perceived impact measures were z-scored within-participants, with higher scores indicating a participant perceived a given category as more environmentally harmful relative to other categories. Separate multiple linear regression analyses for each z-scored perceived impact measure showed that high-level food group composition was significantly associated with relative perceived impact of meat and seafood, but not of eggs and dairy, snacks and ready meals, or plant-based foods (Fig. 4). Those who purchased greater shares of meat/seafood and grains, and decreased shares of fruit, vegetables and meat/dairy alternatives, and snacks and convenience food, also perceived meat and seafood to have a lower environmental impact.

Equivalent relationships between purchasing patterns and relative perceived impact ratings were generally not evident for individual meat and seafood subcategories (see Method, and Tables S9-S10), though there was some indication that participants with a greater share of seafood among their meat and seafood purchases judged seafood as less impactful and pork as more impactful (Fig. S5).

Fig 4: Associations between high-level food group composition and environmental impact judgements



CLR coefficients with 95% confidence intervals, indicating the expected change in the corresponding category perceived impact measure associated with a one-unit increase in the natural log of a component relative to the geometric mean of the composition. PEI = perceived environmental impact. ILR regression coefficients are reported in Table S8.

*** $p < .001$

Discussion

We used supermarket loyalty card purchase data and product environmental impact estimates[17] to develop an objective behavioural indicator (EFPI) representing the environmental footprint of individuals' food shopping, based on GHG emissions, land use, eutrophication potential, and water scarcity. By linking objective impact scores, shopping

metrics, and survey responses, we identified (1) statistically robust but relatively weak associations between self-reported behaviour and objectively assessed environmental impacts; (2) perceived environmental impact of food shopping was somewhat sensitive to share of high-level food categories purchased but not within-category purchasing patterns for meat and dairy, despite within-category patterns strongly contributing to objective impact; and (3) consumers with a greater share of meat and seafood in their shopping, and less plant-based food, believed meat and seafood was less environmentally harmful.

A point of alignment between perceived and objective impacts was that higher values for both were predicted by a greater share of meat and seafood among overall food purchases, and a lower share of fruit, vegetables, and meat/dairy alternatives. However, perceived impact was much less strongly tied to meat purchase share than objective impact was, suggesting shoppers may underestimate the extent to which purchasing more meat increases their environmental footprint relative to other people's. Furthermore, purchasing more beef relative to lower-impact meats, and more cheese relative to milk, strongly contributed to objectively assessed impact but perceptions were not sensitive to these within-category distinctions.

This limited sensitivity to within-category purchasing patterns is consistent with recent evidence that when judging the environmental impact of different foods, consumers appear to mainly distinguish products by whether they are meat or plant-based and their level of processing[18]. When asked to judge the environmental impact of individual food types in the present study, participants did, on average, rate beef as more environmentally harmful than other meats and seafood, suggesting they had some awareness of relative differences in impact. However, nearly half of participants believed chicken had an equal or higher impact compared to beef, and 21% rated beef higher by only a single point (Fig. S6). Moreover, over 80% of participants incorrectly believed that milk had an equal or higher impact compared to

cheese (Fig. S6). Contrary to these small and inconsistent differences in participants' judgements of different types of meat and dairy, GHG emissions per kg of beef (from a beef herd) are estimated to be 10 times or more higher than chicken, and cheese 7-8 times higher than milk[15,17]. Since beef and cheese represent only a small share of meat and dairy purchase volumes, respectively[20,21], clear communication of the extent, not only the direction, of these differences may be important for increasing consumer awareness that even relatively infrequent purchases can substantially contribute to their environmental footprint. Notably, the currently dominant approach of using ordinal impact scores (e.g., A-E grade) for eco-labels[19] conveys limited information about magnitude, with more fine-grained rating systems (e.g., 0-100 numerical scores) potentially worthy of further consideration.

Another key finding was that individuals purchasing more meat and seafood (or grains), and less fruit, vegetables, and meat/dairy alternatives (or snacks and convenience food) believed meat and seafood had a lower environmental impact. Since meat purchasing is a primary driver of objective impact, this may contribute to underestimation of environmental footprint among consumers buying more meat products. These relationships could indicate that what people buy biases their environmental impact beliefs, perhaps underpinned by a motivation to maintain cognitive consistency between pro-environmental attitudes and behavioural self-perceptions[22,23]. In particular, individuals with a higher share of meat (and less plant-based food) in their shopping may be motivated to downplay meat's environmental impact, while those buying larger amounts of highly processed products (an alternative dimension along which consumers could view themselves as environmentally unfriendly[18]) may be motivated to emphasise meat as the main issue in food sustainability. Alternatively, it is possible the relationships reflect that real-world food purchasing behaviour is shaped by environmental impact beliefs; for instance, individuals may buy less meat when they perceive it as especially environmentally harmful. Regardless of causal direction, the observed associations

indicate possible benefits of information-provision strategies, whereby increasing awareness of the size of meat's environmental impact relative to other food categories could either directly shape purchasing decisions, or highlight to consumers where their behaviour is inconsistent with their attitudes.

Despite the novel insights provided by the current research, there are important limitations. Firstly, our environmental impact measure was based on product environmental impact values from Clark et al[17], who estimated scores by combining food commodity global averages[15,24] with product ingredients lists. Consequently, our EFPI measure was not sensitive to variation in environmental impacts across different producers. This limitation reflects the current state of the field, with product-specific environmental impact values for the vast range of products available at supermarket retailers not yet available.

Secondly, our shopping data came from a single retailer, meaning we had incomplete coverage of participants' food purchases. Since variability in total environmental impact (i.e., product volumes multiplied by associated impact scores) could reflect differences in coverage across participants, we used a weighted mean environmental impact measure and also controlled for self-reported percentage of shopping done at Tesco and total weight purchased. An important limitation of our weighted mean EFPI measure is that it does not fully capture differences in environmental impact intensities across individuals. For instance, participants with comparable food shopping compositions but different purchase volumes (e.g., due to food waste) would have had similar EFPI scores, which would not be reflective of their comparative environmental footprints.

In summary, our research indicates consumers have only a coarse understanding of the environmental impact of their food purchases, with perceptions somewhat sensitive to share of high-level food groups purchased but not within-category choices across meat or dairy

subcategories. Information-provision campaigns that emphasise the magnitude—not just the direction—of differences across meat and dairy subtypes could strengthen consumers' awareness of what contributes to their environmental footprint, with potential benefits in encouraging within-category dietary shifts to lower-impact options; especially for meat, where different varieties are often substitutable in diets. Beyond these specific findings, the approach outlined here can be employed by other researchers seeking to examine environmentally sustainable purchasing behaviour, with potential to advance the field through increased use of measures capturing naturally occurring behaviour.

Methods

Supermarket loyalty card purchase data

Food purchasing data were customer-level Tesco Clubcard transaction datasets provided by study participants (see Data collection). Tesco Clubcard is the most well-penetrated supermarket loyalty card scheme in the UK, present in over 80% of households[25]. Tesco has a dedicated online data request tool allowing customers to request the transfer of their shopping data to a third party, with requests typically fulfilled within 1-2 days via an automated email with the data download link. Accessing store card data from other major UK supermarkets is more practically challenging since requests must be made via email or online contact forms, accompanied by proof of identity documentation, and retailers may take up to one month to fulfil requests.

Tesco Clubcard data contains timestamped records of all Clubcard transactions made by a customer over the last 10 years. Analyses reported here relate to food purchased during the full 12-month period prior to the study launch (July 2024 – June 2025). For each transaction, product names, quantity purchased, and price paid were provided. Product names were represented only by a text string, with no unique identifying code or category information

included. Product weight was not included as a separate field but was usually specified in the product name (e.g., Chicken breast 500g). Where not specified, we estimated weight by extracting pack quantity from the text string and multiplying by the typical per-piece weight for that food type. For example, “Free Range Eggs 10 Pack” was assigned a weight of 650g, based on the pack quantity of 10 multiplied by a standard per-egg weight of 65g. To calculate overall purchase weight by product, pack weights were multiplied by total quantity purchased over the 12-month period.

Environmental impact estimates

Product environmental impact estimates were based on a dataset developed by Clark et al.[17], who combined food commodity “cradle-to-retail” data from LCA studies[15,24] with algorithmically estimated ingredient proportions for individual supermarket food products. Product environmental impact values per 100g are provided for GHG emissions (kg CO_2 eq), land use (m^2), eutrophication potential (g PO_4 eq), scarcity-weighted water use (litres), and a composite environmental score equally weighting the four underlying indicators on a normalised scale (0 = no impact, 100 = highest impact).

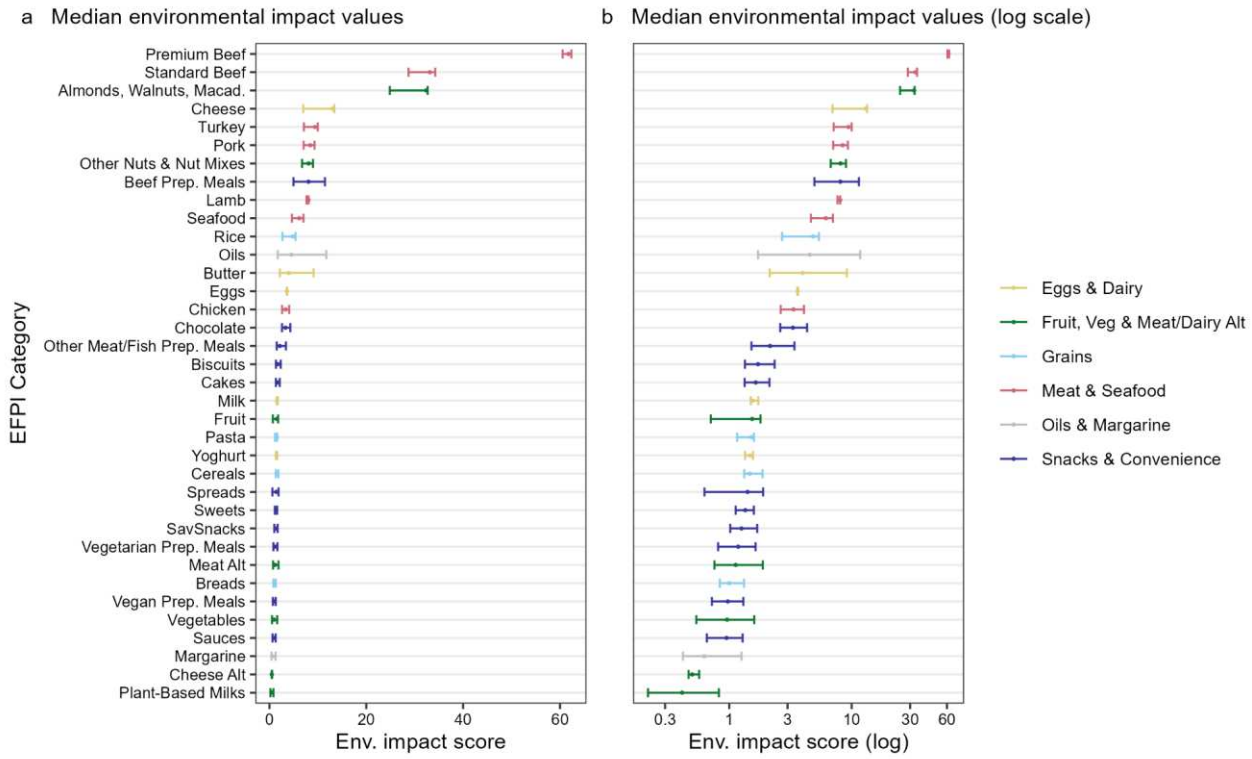
Clark et al.'s dataset contains ~11k unique Tesco products that were available from the Tesco website in 2019. This captures a relatively small proportion of food products sold by Tesco across a 12-month period during 2024-2025, given the frequent addition of new items. To expand coverage, we developed a detailed food classification scheme that enabled items in the shopping data with no exact match in Clark et al. to be assigned the average value across similar products. The classification scheme was developed through an iterative process. First, we classified products from Clark et al.’s dataset into typical supermarket food categories (e.g., red meat, poultry, ready meals) using regular expression (regex) pattern matching of the product name text string. We then assessed the distribution of composite environmental impact scores within each category, subdividing high-variance categories (e.g., red meat >

346 beef, lamb, pork; poultry > chicken, turkey; dairy > milk, butter, cheese; grains > bread, rice,
347 pasta). Within-category variability was subsequently examined for the revised categories,
348 which were subdivided again where necessary. For example, beef product impacts were still
349 too heterogeneous because Clark et al. assigned higher values to steak and steak mince
350 compared to beef mince, meatballs, and burgers; likely reflecting different impacts for beef
351 from beef herds versus beef from dairy herds[15]. We therefore subdivided beef into premium
352 beef (steak or steak mince) and standard beef (e.g., beef mince, burgers).

353 The goal of minimising within-category variability was balanced against the need for
354 categories to be substantively meaningful to enable analysis of food purchasing patterns, and
355 for it to be possible to classify products based only on their text string in the transaction data.
356 Consideration was also given to the expected purchase volumes of food categories. For
357 instance, it may have been possible to reduce within-category variance in oils by separating
358 olive oil and vegetable oils, but this would be highly unlikely to materially change overall
359 environmental footprint scores given these products represented a small fraction of purchases.
360 The list of 36 food categories with their median composite environmental impact scores and
361 variances is shown in Figure 5.

362 Once the transaction data had been collected, we used regex pattern classification to assign
363 food products to one of the 36 pre-defined categories using product name text strings.
364 Classification accuracy was checked manually, focusing on products with substantial sales
365 volume.

Fig. 5: Median impact values for EFPI categories on linear and log scales



Plots show median environmental impact scores and interquartile ranges for the 36 EFPI categories, colour-coded by high-level food group. Both plots show the same data, on (a) linear and (b) logarithmic (base 10) scales. Potatoes and processed vegetables (e.g., oven chips) are included in the vegetables category; cream products are included in the milk category.

Environmental food purchasing index (EFPI)

Products with an exact match in Clark et al. were assigned the corresponding environmental impact score per 100g, while those without an exact match (~80% of sales volume) were assigned the median environmental impact value for the EFPI category they were classified with. The EFPI was calculated as a participant's weighted mean environmental impact per 100g of food purchased across the 12-month period preceding the study launch. This weighted mean approach is coherent with the compositional nature of dietary intake, with higher consumption of some foods typically implying lower intake of others[26,27]. Notably, this assumption does not hold for soft drinks or alcohol, since their consumption elicits minimal compensatory adjustment in food intake[28,29]. We therefore excluded drinks categories (except milk/milk alternatives) from the analyses. This was particularly important

for soft drinks as they represent a large share of purchase volume and have very low environmental impact values per 100ml[17], meaning their inclusion would have spuriously diluted weighted mean EFPI scores.

Survey measures

Survey items used in the present report are reported in Table 1. A full list of measures included in the survey is available from the OSF project page (https://osf.io/g9uxb/overview?view_only=8bf44bf804d440179b8fd8a77d530078). Perceived environmental impact of food shopping was the composite of two Likert-style items (Table 1). Environmental impact of self-reported dietary consumption was based on responses to a food frequency questionnaire (FFQ), adapted from the EPIC-Norfolk cohort study[30]. Our FFQ included 36 food types, plus soft drinks and tea and coffee, which were excluded from the dietary impact calculation to align with the EFPI measure. FFQ food types closely matched the EFPI categories except that in the FFQ, beef and nuts were each single categories rather subdivided; subtypes of plant-based milk (almond, soy, oat) were separate items; cream/ice cream and milk were separate items; and oil was excluded. Participants reported typical consumption frequencies for foods during the past year (Table 1). We multiplied self-reported consumption frequencies by standard portion sizes[31] to estimate monthly consumption volumes by food type. Median impact values for the corresponding EFPI food category (Fig. 5) were used to calculate weighted mean environmental impact scores per 100g of self-reported dietary consumption. For beef and nuts, we weighted assigned impact scores by relative volume shares of premium beef versus standard beef, and almonds, macadamias, and walnuts versus other nuts, based on the transaction data.

Table 1. Survey items and response options

Measure	Item(s)	Response options
Main household shopper	Generally, who does the food shopping for your household?	1 = I do all or most of the shopping; 2 = I share the responsibility fairly equally with someone else; 3 = Someone else does all or most of the food shopping (screened out)
Household dietary patterns	Please indicate how many people in your household (including yourself) follow each dietary pattern [Omnivore, pescatarian, vegetarian, vegan, flexitarian]	1, 2, 3, 4, 5+
Number of people shopped for	How many people (including yourself) are you typically shopping for when you do your grocery shopping at Tesco?	1, 2, 3, 4, 5+
Self-reported % shopping done at Tesco	In a typical month, what percentage of your total grocery purchases do you estimate are made at Tesco?	0-100 sliding scale
Perceived environmental impact of food shopping ($\alpha = .85$)	1. Overall, my grocery shopping in the past year has been environmentally friendly. [RC] 2. When grocery shopping in the past year, I have mostly bought food products with a low environmental impact. [RC]	7-point scale; strongly disagree to strongly agree RC = Reverse-coded so that higher values reflect lower environmental friendliness/ higher perceived impact
Food frequency questionnaire	Please indicate how often, on average, you have eaten each of these foods during the past year. [36 food types, plus soft drinks and tea & coffee]	Never or less than once a month, 1-3 per month, once a week, 2-4 per week, 5-6 per week, once a day, 2-3 per day, 4+ per day
Food frequency questionnaire - milks	Please indicate, how much of these milks you typically drank each day during the past year**,** including with tea, coffee, cereals etc. [Cow's milk, oat milk, soya milk, almond milk]	None, quarter of a pint, half a pint, three quarters of a pint, one pint, more than a pint

Perceived environmental impact of food types	Please now indicate how much of an environmental impact you think each of the following food products have. [Beef, pork, chicken, fish and seafood, cheese/butter, milk, eggs, chocolate, savoury snacks, rice, prepared meals, nuts, soy/oat milk, meat alternatives, fruit, soft drinks]	7-point scale (very low impact to very high impact) plus "don't know"

Data collection

Ethics

Ethics approval was obtained from [redacted for anonymous peer review] Ethics Committee. Participants were fully informed as to the nature of the data they would be asked to provide and consented to take part.

Participants

A pre-registered target sample size of 1000 participants was set (https://osf.io/7s5kr/overview?view_only=749bac5559bb40b9b814df826466a7a3), providing statistical power of over $\beta = .80$ to detect effect sizes as small as $r = .10$, in two-tailed Pearson's correlation tests ($\alpha = .05$), assuming a participant exclusion rate of approximately 10% (power analysis was performed in G*Power[32]).

UK adult participants who reported being the main grocery shopper in their household (or sharing the responsibility equally with someone else) and regularly using a Tesco Clubcard were recruited via Qualtrics online research panels. Qualtrics performed quota sampling using UK census distributions for age, gender, and geographic region to target a representative sample; though quotas were relaxed for the 65+ age group due to recruitment difficulties (see Table S11 for a full breakdown of demographic characteristics). During data collection, survey respondents were replaced by Qualtrics if we did not receive their Clubcard transaction data (n = 737), or if the respondent was identified as a duplicate submission based

on their email address (n = 110) or transaction history (n = 34). Matched Clubcard and survey data were collected from 1008 participants. Sixty-one participants were excluded because their Clubcard data contained no food purchases over the previous 12 months, leaving a remaining sample of 947 (45.5% men, 54.5% women, 1% other/non-binary).

Procedure

Prospective participants were pre-screened by Qualtrics so that only individuals who reported regularly using a Tesco Clubcard and being the main grocery shopper in their household (or sharing the responsibility equally with someone else) were invited to participate. These questions were repeated as pre-screeners at the start of the survey, with individuals who did not meet the study criteria informed they were ineligible for participation.

Participants first provided informed consent and completed multiple comprehension checks to ensure understanding of the study and the data they would be required to provide. They were then provided with detailed instructions on how to request transfer of their Clubcard data via the online Tesco data portability tool. Upon submitting the third-party data access request, participants were provided with a unique reference code by Tesco, which they entered in a survey field. This enabled us to link survey responses to Clubcard transaction datasets received from Tesco. In the main part of the survey, participants first reported dietary preferences of household members, number of people shopped for, Clubcard use by others in the household, and percentage of purchases made at Tesco. Subsequently, they completed the FFQ and then rated the environmental impact of 16 food types. Participants then completed the two items capturing perceived environmental impact of food shopping.

Analytical approach

High-level food group compositional analysis

For analyses of high-level food groups, EFPI categories were aggregated into superordinate food groups broadly aligning with major food categories[33]. We separated out protein foods since prior work indicates people strongly differentiate between meat and non-meat products in their mental categorisations[18,34]. Eggs were grouped with dairy; nuts with fruit and vegetables; and meat and seafood was its own category. Because zeros are not valid in compositional data analysis due to the calculation of log-ratios, we avoided creating high-level food groups purchased by only a small proportion of participants as these would require a large number of replacements with imputed non-zero values. Accordingly, we grouped meat/dairy alternatives with fruit, nuts, and vegetables; and excluded oils and margarine spreads from compositional analyses (~0.9% of total purchase volume). The mapping of EFPI subcategories to high-level food groups is shown in Figure 5.

Participants who purchased from only one of the five high-level food groups (n = 31) were excluded from compositional data analyses since comparative shares cannot be meaningfully computed for single-part compositions. Of the remaining 916 participants, most (83%) purchased across all five food groups. We calculated proportions for high-level food groups by summing purchase volumes (by weight purchased) across the underlying EFPI categories and dividing by total volume. Zero purchase proportions (5.8% of total values) were replaced with nominal non-zero values using multiplicative replacement using the *zCompositions* package[35] in *R* (detection limits were set to minimum observed purchase proportions by food group). Proportions were subsequently converted to ILRs using the default sequential binary partitioning basis in the *compositions* package[36], with the input matrix ordered as (1) meat and seafood, (2) eggs and dairy, (3) grains, (4) fruit, vegetables, and meat/dairy alternatives, (5) snacks and convenience food. ILRs fully represent a D-part composition with D - 1 orthonormal coordinates, where D is the number of components in the composition[37]. In contrast to raw proportions, ILRs are compatible with standard statistical tests based on

Euclidean geometry and do not produce singular covariance matrices when used in multivariate analysis.

Associations with EFPI scores and perceived environmental impact of food shopping were examined with separate multiple linear regression analyses. For each analysis, the four ILRs representing the five-part high-level food group composition were added to a regression model alongside shopping metrics covariates. Covariates included here and in all regression models were number of people shopped for, self-reported percentage of grocery shopping done at Tesco, main shopper in household status, and total weight purchased (log-transformed due to large positive skew). We controlled for total weight purchased because compositional shares differed by purchase weight, with snacks and convenience food far more prevalent in baskets of low-volume shoppers (Fig. S8). The full model was compared to a covariates-only model using an omnibus F-test to assess whether the ILRs significantly improved model fit. Since ILR regression coefficients are difficult to interpret in terms of original compositional parts[38], we re-expressed coefficients and their variance-covariance matrix in CLR-space using the *ilr2clr* and *ilrvar2clr* functions in the *compositions* package.

Within-group subcategory analysis

Analysis of within-group compositions is challenging due to the large number of zero purchase volumes at the subcategory level. For instance, among meat and seafood shoppers, zeros represented 46% of total purchase proportions across the seven corresponding EFPI categories. To avoid an unacceptably high rate of imputed values, we probed within-group purchasing patterns using a two-stage approach, first examining whether or not a given EFPI category was purchased at all, and then examining within-group compositions for the subset of participants who purchased from more than half of the subcategories within a given high-level group.

For the binary purchase indicator regression analyses, omnibus F-tests were conducted to examine whether the set of purchase indicators relating to each high-level food group jointly predicted each dependent variable. Where the joint test was significant, individual regression coefficients were examined to determine whether purchasing a given subcategory was significantly associated with the dependent variable, conditional on high-level food group composition and covariates.

Samples sizes for the within-group compositional analyses were: meat and seafood (n = 575), eggs and dairy (n = 654), snacks and convenience food (n = 727), fruit, vegetables, and meat/dairy alternatives (n = 543), grains (n = 526). Amalgamated subcategories were: beef (premium beef, standard beef), vegetarian/vegan prepared food (vegan prepared food, vegetarian prepared food), meat/dairy alternatives (cheese alternatives, meat alternatives, plant-based milks), nuts (almonds, macadamias, walnuts; other nuts). Lamb and turkey, purchased by only 16% and 20% of the sample, respectively, were excluded from the meat and seafood subcategory composition analysis. This approach minimised the prevalence of zero purchases to 8.0% of total values for meat and seafood; 13.6% for eggs and dairy; 13.1% for snacks and convenience food; 14.4% for fruit, vegetables, and meat/dairy alternatives; and 9.8% for grains. Within-group purchase proportions were calculated as each subcategory purchase volume (by weight) divided by the total high-level food group volume. Imputation of zero purchase values and calculation of ILRs followed the same approach as for the high-level food group composition. For each regression analysis, ILRs representing a given within-group composition were added to a model alongside shopping metrics covariates plus high-level food group composition ILRs. Statistical significance of the within-group composition was assessed with an omnibus F-test of their ILR coordinates.

Perceived environmental impact of food types

For analyses of associations between high-level food group compositional shares and their relative perceived impact ratings (z-scored within-participants), participants were excluded if they did not rate the impact of at least one food type within each high-level food group on the 1-7 scale, with "don't know" responses coded as missing (11.6% of sample excluded). The percentage of "don't know" responses was similar across food groups (range 7-9%). Multiple linear regression analyses were conducted, where each relative perceived impact measure was a dependent variable in separate models. ILRs representing high-level food group compositional shares were the primary predictor variables. For each dependent variable, the full model was compared to a covariates-only model using an omnibus F-test to determine whether high-level food group composition significantly predicted perceived impact judgements.

To examine whether judgements about the impact of specific meat and seafood subcategories related to within-category purchasing patterns, we calculated within-participant z-scores across beef, pork, chicken, and seafood. Participants were excluded if they did not rate all four meat and seafood types on the 1-7 scale (13.5% of sample excluded). The percentage of "don't know" responses was similar across meat and seafood types (range 9-10%). We conducted multiple linear regression analyses on each of the z-scored perceived impact measures, with meat and seafood subcategory binary purchase indicators as the primary predictor variables. For participants who purchased from three or more subcategories across beef, chicken, pork, and seafood, we additionally performed separate multiple linear regression analyses examining associations between meat and seafood subcategory compositional shares and each z-scored perceived impact measure.

Pre-registration

This study was pre-registered prior to data collection (https://osf.io/7s5kr/overview?view_only=749bac5559bb40b9b814df826466a7a3). The

present paper reports pre-registered hypothesis tests for associations between self-reported behaviour and EFPI scores. Additional pre-registered analyses examining links with psychological models of behaviour will be reported separately.

Data availability

The following datasets are available from the OSF project page: (1) Qualtrics Clubcard Survey Dataset; (2) Transaction Data Monthly Summary; (3) Product Classifications (https://osf.io/g9uxb/overview?view_only=8bf44bf804d440179b8fd8a77d530078). Participant Tesco Clubcard transaction data files cannot be shared due to risk of re-identification.

Code availability

Analysis code for reproducing all results and figures reported in the main text and supplementary materials are available from the OSF project page (https://osf.io/g9uxb/overview?view_only=8bf44bf804d440179b8fd8a77d530078)

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