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Journal of Cleaner Production 494 (2025) 145020

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Impact of different carbon labels on consumer inference

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ARTICLE INFO

Handling Editor: Giovanni Baiocchi

Keywords:
Carbon label
Climate information
Consumer inference
Front-of-pack label
Sustainability label

ABSTRACT

Carbon labelling of food products serves as a demand-side tool with the potential to drive the essential shift in consumption patterns toward reducing climate impact. For carbon labels to influence food choices, they must enable consumers to recognize and adopt purchasing behaviour that lower their climate footprint. While inference plays a critical role in facilitating behavioural change, evidence remains sparse regarding how specific characteristics of carbon labels affect consumers' ability to accurately identify low-carbon products.

This study investigates how different carbon labels affect consumers' efficiency in identifying low-carbon-emitting food products. Three labels are evaluated: (i) '*Digit*' specifies the amount of CO_2e-emissions from the production of the product, (ii) '*Colour-Coded*' label indicates the overall climate impact from A to E, (iii) '*Logo*' identifies the lowest-emitting products within each product category.

Respondents in a survey in the United Kingdom were asked to identify the lowest-emitting food product in a set of tasks. All labels improved accuracy in the tasks when products from the same food category were included. Importantly, in the tasks that included products from different categories, the Digit outperformed both the Colour-Coded and the Logo labels. Notably, the Logo did not improve accuracy compared to no-label tasks. It is important that a carbon label informs about the overall climate impact rather than the within-category performance, should the label help consumers identify changes that contribute to significant reductions in climate impact.

1. Introduction

The climate impact from the global food system is immense, where food production accounts for one-third of the total greenhouse gas emissions (Crippa et al., 2021), and especially meat and dairy production are heavy emitters (Poore and Nemecek, 2018). Technological and systemic innovations, reductions in food loss and waste and changes in dietary patterns are all important measures to achieve major reductions in the greenhouse gas emissions (Clark et al., 2020; Moran et al., 2020). Front-of-Pack (FoP) carbon labelling on food is a demand-side instrument that seeks to shift consumers' food choices in a more climate friendly direction by reducing the existing information asymmetry between producers and consumers, making it more salient and providing incentives for producers to reduce emissions (Taufique et al., 2022; Vandenbergh et al., 2011). A key benefit of carbon labelling of products is that policy makers can rely either on third party initiatives and/or private firms, or, if judged necessary, can be implemented and controlled by government (Caswell and Anders, 2011). In the market, various private and third-party carbon labelling initiatives have surfaced (Pleinchamp, 2022; Retail-Detail, 2021), alongside ongoing policy-level efforts (European Commission, 2022; Lemken et al., 2021).

A key prerequisite for a carbon label to be effective in shifting consumption in the direction of reduced climate impact is that consumers understand the label, and that it helps them identify changes in their purchase patterns towards reduced climate impact (Asioli et al., 2020). Only then can changes in behaviour be achieved. Thus, the impact of a FoP label is affected by the inference the consumer makes from a label (Grunert et al., 2010; Grunert and Wills, 2007). The characteristics of a labelling scheme will affect the type and amount of information a label provides. An important determinant of the inferences consumers make from a label is whether the information is descriptive or evaluative (Hamlin, 2015). Descriptive labels convey the information, such as the exact amount of CO_2 equivalents from the production of one unit of a product, while an evaluative label relates this information to a reference level, which simplifies the information. For labels that are evaluative, the reference point against which the label is evaluated is crucial. This

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https://doi.org/10.1016/j.jclepro.2025.145020
Received 13 November 2023; Received in revised form 31 January 2025; Accepted 10 February 2025
Available online 12 February 2025

can be based on the overall performance, encompassing all food categories, or it can focus on evaluating products within the same category (Edenbrandt and Nordström, 2023). This study investigates how these key characteristics affect consumers' ability to identify food products with the lowest climate impact.

A growing body of literature has investigated if and how consumers are affected in their consumption choices by climate information on food products (Rondoni and Grasso, 2021). Early work on the topic includes studies in the UK (Gadema and Oglethorpe, 2011; Upham et al., 2011), Finland (Hartikainen et al., 2014; Koistinen et al., 2013) and a study across countries (Feucht and Zander, 2017). Typically, studies on carbon labelling effects focus on one specific carbon label in one specific product category (Aoki and Akai, 2022; Canavari and Coderoni, 2020; Carlsson et al., 2022; Chen et al., 2024; Edenbrandt and Lagerkvist, 2021; Lohmann et al., 2022; Rondoni and Grasso, 2021; Sonntag et al., 2023; Soregaroli et al., 2021; Chen et al., 2024) or on meals in restaurants (Brunner et al., 2018; Casati et al., 2023; Lohmann et al., 2022; Novak et al., 2024), where the evidence suggests that climate information and carbon labels have some (albeit limited) impact on food choices. A number of studies have included comparisons of different carbon label formats. Carlsson et al. (2021) conducted a choice experiment on ready-made lasagne among Swedish respondents and found that color-coded labels have a greater impact on choices than black-and-white labels. Similarly, Thøgersen and Nielsen (2016) conducted a hypothetical choice experiment on coffee among Danish respondents, showing that colour-coded footprint has a greater impact on preferences compared to black-and-white labels. Meyerding et al. (2019) compared carbon labels with different levels of detail and found larger effects for traffic light labels compared to labels that claim reduced emissions or carbon neutrality. Fresacher and Johnson (2023) compare carbon labels with different appearance (colour, font size).

An aspect that has received little attention in the literature is whether carbon labels, or more general climate information, induce changes in consumption pattern that contribute to significant reductions in greenhouse gas emissions. Such changes will require shifts between product categories (Poore and Nemecek, 2018), for example by shifting diet from animal-based food products to plant-based foods (Clark et al., 2020). While there is evidence regarding the impact from a specific label in a specific food category, less research has been conducted on the overall impact, such that products from different categories are included in the same study. An example of this is a study by Faccioli et al. (2022), which included multiple food product categories in a survey conducted in the UK. They found a reduction in GHG emissions following the presentation of a carbon label, mainly achieved by substitutions away from unprocessed beef. However, the study included only one type of carbon label, disabling insights on how the characteristics of carbon labels impact effects on consumption.

An important gap in the current literature on carbon labels concerns inference; that is, the degree to which the carbon labels affect consumers' accuracy in identifying purchase patterns that are lower in carbon emissions. Importantly, a carbon label will influence consumer purchase behaviour, and ultimately the climate, if it provides the information needed to alleviate information asymmetry and if it is understood by consumers. The impact of label characteristics on consumer inference has been explored in the area of health FoP, finding that more simplifying labels, such as traffic light labels and logos, are better understood by consumers than more detailed labels (Bauer and Reisch, 2019; Borgmeier and Westenhoefer, 2009; Campos et al., 2011; Egnell et al., 2018; Shrestha et al., 2023). While insights from the health FoP literature provide useful insights regarding carbon labels, this area is different in one major aspect. The climate impact from food products is associated with a high degree of asymmetric information in the current market context. In contrast, it is mandatory to display the nutritional content on the back of food products in many countries (EU, 2011), which implies a low degree of asymmetric information, and the purpose of health FoP is rather to make the existing information more salient and simplified. Despite that inference is a precursor to behavioural changes, there is to our knowledge no evidence on how carbon label characteristics impact consumer accuracy in identifying products that are lower in carbon emissions.

The present study investigates how carbon labels with different characteristics affect consumers' ability to identify food products with the lowest climate impact. Importantly, we investigate this ability both overall and within specific food categories. We conducted an online survey among 750 respondents in the United Kingdom, where the accuracy in correctly identifying the lowest emitting food products was tested for three different carbon labels. The labels investigated include a purely descriptive label, an evaluative label that indicates the overall performance, and an evaluative label that indicates the performance within the specific food category. We tested whether inference vary between these labels; that is, if there are differences in the degree to which consumers can correctly identify products with low climate impact.

The question of carbon labelling and sustainability labelling is high on the political agenda and is an area where private initiatives are evolving on the market (Lemken et al., 2021). At this stage, it is important to gain insights on how the characteristics of a carbon label may influence the effect from the labelling system. The present study makes two main contributions. First, we provide insights regarding whether carbon labels are successful at communicating the climate impact of food products in a way that is understandable to the consumer. We provide guidance on how key characteristics of carbon labels affect inference. Second, while the literature on consumer understanding and preferences regarding carbon labels typically focus on a specific product category, we investigate how different characteristics of carbon labels affect inference both overall (across different food categories) and within specific food categories. This study contributes with policy guidance, since policy decisions regarding characteristics of a carbon labelling system are likely to impact the inference and ultimately consumer purchase decisions.

2. Background on carbon labelling: market implementations and policy context

The first carbon label that could be displayed on food products was introduced in 2006 by Carbon Trust, a private company initiated by government in the United Kingdom (Liu et al., 2016). The British retailer Tesco began to carbon footprint label products in 2007, but the initiative was discontinued in 2012 due to low involvement from other retailers and high labelling costs (Vaughan, 2012). A lot has happened in the area since then, and different types of carbon labels have been introduced in different countries (Liu et al., 2016). For example, as part of the Farm to Fork strategy, the European commission is set to present a sustainable food labelling framework (European Commission, 2022). Meanwhile, several third-party initiatives have been piloted recently. The Eco-score labelling scheme was launched in France in 2021 by a group of private food operators (La Fourche, Marmiton, FoodChéri, Seazon, Eco2Initiative, Scan up, Yuka, Etiquettable, Frigo magic and Open Food Facts) (Open Food facts, 2021). The design of this label has similarities to the European Nutriscore scheme by providing an overall sustainability score from A to E (Eco-score, 2022). In France, Eco-score is used (so far, mainly online) when purchasing food, ordering food or choosing recipes. Lidl has implemented a pilot project with Eco-score in Germany, Belgium, the Netherlands and Scotland (Andersson and Nordström, 2023). The Belgian Colruyt Group has also made the Eco-score available in its app and on its website and is working to provide all its own brand products with the Eco-score printed on the packaging (Colruyt Group, 2023). The first labelled products appeared in Belgian stores in the summer of 2021 (Retail-Detail, 2021). So far, it is relatively unusual to see Eco-scores on products in physical stores.

Another initiative is the Planet-score, which addresses sustainability more broadly (IFOAM, 2022; ITAB et al., 2021). Like the Eco-score, the

Planet score provides an overall sustainability score from A to E. The label also contains information about how the product is assessed in terms of climate impact, pesticide use, impact on biological diversity and animal welfare. Since 2022, the Planet-score has been available on products in French stores and has also started to be used in other European countries such as Germany, Belgium, the Netherlands, Spain, Italy and the UK (Pleinchamp, 2022). In Denmark, the government nominated a group of representatives from the food sector, to propose a climate label of food. The group suggest a Colour-Coded label with scores from A to E (The Danish Veterinary and Food Administration, 2023), similar to the Nutri-score and Eco-score labels.

For restaurants, Klimato started to develop a label and a tool for restaurants to calculate the carbon footprint for meals in 2017. The label has three levels – low, medium and high – indicated by a symbol, and also show the meal's carbon footprint (CO_2e) with a digit. No colour-coding is used. The label is used in countries including Sweden, Norway and the UK (Klimato, 2023).

There are competing views in the debate regarding carbon and sustainability labelling schemes (Lemken et al., 2021), and a key question is whether a carbon (or sustainability) label should indicate the overall performance of a product or if it should evaluate how products perform within the specific food category.

3. Theoretical framework and hypotheses

Our point of departure is the theoretical framework presented in Grunert and Wills (2007) and further developed by Grunert et al. (2010). For FoP labels to affect food choices, an individual must first be exposed to the label and then take the information from the label into account when making the decision. Importantly, provided such exposure and awareness, consumer understanding of the label mediates the impact a label may have on consumption decisions. The inference made from the label measures the degree to which consumers can correctly identify products based on their climate impact.

An important determinant to the inference consumers makes from a label is how the information is conveyed (Grunert and Wills, 2007). Edenbrandt and Nordström (2023) identified two characteristics of a carbon label that are expected to impact the inference consumers make. First, the *assessment criteria* refers to whether the information conveyed is descriptive or evaluative. A purely descriptive label displays the exact amount of carbon emission equivalents (CO_2e) from the production of one unit of the product. Second, for labels that are evaluative, the *level of reference* decides what the evaluation is based on, and these reference levels can be defined on the overall climate impact or in more narrow reference groups (specific food categories).

We select three labels that vary with respect to the assessment and the level of reference, and which will be tested in this study (Fig. 1). The first label is a 'Digit' that specifies the CO_2e from the production of 1 kg product. This represents a descriptive assessment criteria. To some extent, this is similar to the early carbon label implemented in the UK by Tesco, and the meal labelling developed by Klimato. The second is a 'Colour-Coded' (CC) type of label which indicates the *overall* performance on a scale from A (green) to E (red). This represents an evaluative assessment criterion, with the level of reference on overall impact across all food categories. The CC label holds similarities to the European Nutriscore label and the recently proposed environmental labels (Eco-score and Planet-score), which are also evaluative in their assessment criteria and that to a certain degree assess the overall nutritional quality and sustainability respectively. Note that the evaluative nature of the label implies a simplification of the descriptive assessment, and the use of five categories implies a less fine-grained level of detail compared to the Digit, disabling identification of smaller differences that occur within each category. The third label is a 'Logo' which is displayed on the best (least carbon-emitting) food products within a product category. This represents an evaluative assessment criteria, where the level of reference is defined within food categories. This Logo is similar to the RSPCA animal welfare label in the UK, and to health FoP food labels such as Nordic Keyhole, Health Tick and Choices Logo (Bauer and Reisch, 2019). Such labels provides guidance on good alternatives *within* a product category.

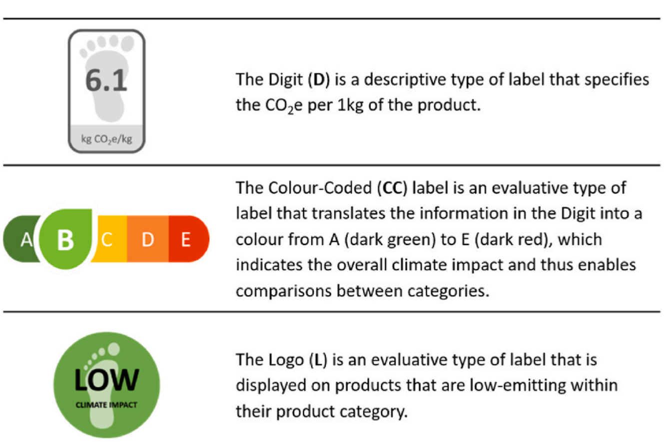

Fig. 1. Carbon label formats used in this study.

It is worth noting that the three carbon label formats are selected for their differences in the assessment criteria and in the level of reference, but also for their policy relevance. For example, it would be possible to include a CC-type of label based on within category evaluation, or a Logo type of label that is based on overall evaluation. However, the debate regarding carbon labelling has largely evolved around variants of the three label types included in this study.

3.1. Hypotheses: within food category inference accuracy

The exact amount of carbon emissions from the production of a food product is a credence attribute meaning that it is not possible for the consumer to evaluate upon inspection or consumption, as it depends on factors such as technology use, management practices, and place of production (Springmann et al., 2018). A credible source of information, in the form of a label, could alleviate this asymmetric information between producers and consumers. Therefore, we expect that carbon labels improve consumers' ability to identify products that are lower emitting.

H1a. *Within* food-category consumer inference is more accurate with a descriptive carbon label (Digit) than with no label.

H1b. *Within* food-category consumer inference is more accurate with an evaluative between-category evaluative carbon label (CC) than with no label.

H1c. *Within* food-category consumer inference is more accurate with evaluative within-category carbon label (Logo) than with no label.

The Digit, CC and Logo all provide the information necessary to accurately identify the lowest emitting product within a product category. Thus, we do not hypothesise differences in consumers' level of accuracy among the different labels.

3.2. Hypotheses: overall (between category) inference accuracy

With a label that is purely descriptive, consumers will be able to identify the lowest carbon-emitting food product, both within and across food product categories; they simply need to compare numbers (such as the CO_2e per 1 kg of the product). The evaluative between-category label (CC) provides a simplification of the Digit by dividing food products into categories. This simplification provides guidance regarding the lowest carbon-emitting product, both within food categories and overall. Finally, while the evaluative within-category label (Logo) simplifies the information and enables identification within specific food categories, it will not help consumers identify the lowest carbon-emitting food products overall. A food product that is low-emitting in a high-emitting food category will be labelled with the logo, while a much lower-emitting product in the low-emitting category will not be labelled if it is not among the lower emitting within the category. In summary, regarding the overall inference from carbon labels (between category comparisons), we hypothesise that.

H2a. *Overall* (between-category) consumer inference is more accurate with descriptive carbon label (D) than with no label.

H2b. *Overall* (between-category) consumer inference is more accurate with the between-category evaluative carbon label (CC) than with no label.

For the within-category evaluative label (Logo), we do not expect differences in accurately identifying low-emitting products compared to no label. Since we do not expect differences between the Logo and a no-label condition, H2a and H2b extend to the following hypotheses.

H2c. *Overall* (between-category) consumer inference is more accurate with descriptive carbon label (D) than the evaluative within-category carbon label (Logo).

H2d. *Overall* (between-category) consumer inference is more accurate with between-category evaluative carbon label (CC) than the evaluative within-category carbon label (Logo).

3.3. Hypotheses: ease of understanding and label perception

While the Digit provides the most precise information, evidence from the health FoP labelling literature reveals that quantitative and descriptive information is more demanding for individuals to interpret (Bauer and Reisch, 2019). Following dual system theory of behaviour, individuals decision making involve deliberate cognition, where the relevant information is carefully considered, and automatic thinking, where the decision maker use rules of thumb that enable fast decisions even when the task is complex (heuristic mode) (Dhar and Gorlin, 2013). In low-involvement choice tasks, which are often the case in food choices, individuals tend to apply heuristics (Hauser, 2014). This suggests that evaluative labels, which seek to simplify the information, may be faster and easier to interpret by the consumer compared to more detailed and descriptive label formats (Bauer and Reisch, 2019). In this study, the CC label is a simplification of the Digit on the overall level, while the Logo is a simplification of the information in the Digit on the within-product level. Thus, we expect that the simplifying labels are associated with higher stated level of understanding of the labels.

H3a. Stated level of consumer understanding is higher for the Logo than the Digit.

H3b. Stated level of consumer understanding is higher for the CC than the Digit.

We further explore whether the perceived certainty in identifying the lowest carbon-emitting products varies between the labels.

In line with the conceptual model of Grunert and Wills (2007), consumers' use of a label depends not only on the inference, but also on the liking of the label. Some labels are perceived as moralizing or patronizing, which reduces the liking and the probability that the consumer will use the label in their decisions (Grunert and Wills, 2007). We explore whether the following aspects of label perception vary between the labels: (i) consumer liking, (ii) consumers' wish to see the label when purchasing food, and (iii) the degree to which consumers perceive the label as patronizing. Finally, general knowledge about climate impact from food can be expected to impact label inference accuracy (Grunert and Wills, 2007). We explore how prior knowledge relates to accuracy in identifying low emitting products and how this varies between the labels.

4. Material and methods

4.1. Data collection and participants

Data were collected in an online survey with three treatment groups (Digit, CC, Logo), which included tasks where respondents were asked to indicate the food product with the lowest CO_2e emissions. To establish the required sample size, we conducted power analysis, assuming an $\alpha = 0.05$ and power of 0.80. We assumed mean differences in the probability of correct identification of the lowest emitting product of 0.1 for the labelling treatments compared to no label (control group). This difference was based on a study on FoP health labels (Borgmeier and Westenhoefer, 2009),[1] since we did not find any study on environmental labels with a similar study design. The estimated number of participants needed per treatment group was 231, but since we include four observations per individual, the number of individuals needed to detect a difference of 0.1 was 145. We used 250 individuals per treatment, which gave us room to test for differences in specific food categories.

Ethical clearance was obtained from [omitted to maintain anonymized reviewing] prior to data collection. The study was pre-registered prior to data collection.[2] To increase respondent engagement, a statement of consequentiality (policy relevance) was included in the introduction of the survey (Johnston et al., 2017).

Data were collected from a representative sample of consumers in the UK from a panel managed by TGM Research during March 2023 using a web-based survey. The UK, as the first country to introduce a carbon label, and several of the earliest studies on consumer preferences and carbon labels (Gadema and Oglethorpe, 2011; Upham et al., 2011) offers a unique context for this study. Currently, the UK lacks a large-scale, widely recognized carbon label on food products, with only various private initiatives that are not widely familiar to consumers. This setting allows us to explore consumer understanding and inference of carbon labels, providing insights relevant to both the UK and other markets considering similar strategies. Age and gender were used to stratify the sample to resemble the UK population in the measured characteristics. Participation in the panel was voluntary and participants are awarded points, which are transferred to vouchers, as reward for their participation. Participation in the survey was voluntary and respondents were informed that they could withdraw at any point without giving a reason. Only individuals who gave their consent and were at least 18 years old proceeded with the survey. Respondents who stated that they rarely or never purchase food were screened out. The distributed survey invitation described the purpose of the study in general terms and did not mention the topic of climate impact, to reduce the potential selection bias of including individuals with special interest in the subject (Newman et al., 2021).

Several measures were undertaken to ensure the data quality of the responses. The first part of the survey included an attention check question where respondents were asked to select a specific response, and respondents who failed were screened out ($n = 59$). Respondents who finished the survey in less than 3 min were regarded as speeders because pre-tests of the survey suggested that this was an unrealistically short time if respondents had read all the questions. Screening out speedy responses ($n = 49$) gave a sample of 750. Finally, following the final tasks on carbon label perception, respondents were asked if they considered their responses to be of high quality, or if they believed we should discard their responses. Including only respondents who indicated that they considered their responses should be considered resulted in a final sample of 715. Descriptive statistics of the sample are presented in Table S1 in Supplementary Materials. There are not statistically significant differences in the presented individual characteristics

[1] In Borgmeier and Westenhoefer (2009), the differences ranged from 0.05 to 0.17.

[2] https://aspredicted.org/JK2_4S9.

among the treatment groups.

4.2. Survey design

The survey consisted of three parts. First, respondents were introduced to the survey and gave their consent to participate, and indicated their gender and age followed by questions on general food habit questions and self-rated level of knowledge about climate impact of food in general.

The second part of the survey included tasks of identifying the least emitting product among a set of food products. These tasks included four product categories: meat (pork loin steaks, beef mince, lamb chops), vegetables (tomato, carrots, green beans), starchy carbohydrates (rice, pasta, potato) and ready-made sandwiches (tuna and cucumber, egg and ham, cheese and tomato). These are all products that consumers are familiar with, and that many consume on a regular basis in the UK (Espinoza-Orias and Azapagic, 2018). Overall, these food products cover both high-emitting categories (meat) and low-emitting categories (vegetables and starchy carbohydrates) (Poore and Nemecek, 2018). We included ready-made sandwiches, as we expect it to be more difficult for individuals to assess the climate impact for this product category, due to the inclusion of several different ingredients in the same product. The ready-made sandwiches included are among the most commonly sold sandwich types in the UK (Espinoza-Orias and Azapagic, 2018). The list of the food products investigated in this study, including the CO_2e per kg and the carbon labels displayed, are presented in Table S2.

Each respondent was randomly assigned to one of three treatments (Digit, CC, Logo). Within each treatment, every respondent answered one block of control tasks and one block of treatment tasks (Fig. 2).

In the first block (control), there was a brief text that explained the climate impact from food and the measure CO_2e per kg product (Fig. S1). Respondents were presented with eight tasks, where each tasks presented three different food products and respondents were asked to indicate the product with the lowest climate impact. The order of the food products (left/middle/right) within each task was randomized. The first four tasks consisted of one task for each food category (meat, vegetables, starchy carbohydrates, ready-made sandwiches). The order of presentation among the categories was randomized. These tasks represented within-category identification of the lowest emitting product. The last four tasks consisted of products from different food categories (for example, lamb chops, carrots, rice). These tasks represented overall (between-category) identification of the lowest emitting product. For these tasks, there are many possible combinations of products from the different food categories. We randomly drew 24 of these combinations of products, and each respondent was presented with four tasks.[3] The order of presentation for these tasks was randomized. Following the tasks of selecting the lowest emitting products, respondents indicated their certainty in their responses (‘*How certain were you in your identification of the products with the lowest climate impact?*’ on a five-point scale ranging from ‘very uncertain’ to ‘very certain’, and an additional option of ‘I don’t know’).

In the second block (label treatment), respondents were introduced to the carbon label of their treatment group (Digit, CC, Logo). The label description is provided in Fig. S2. Following the introduction to the label, respondents indicated how well they understood the label (1 = ‘I don’t understand this at all’ to 5 = ‘I absolutely understand this’). Next, the tasks from the control block were repeated with the carbon label included (examples of tasks are shown in the lower panel of Fig. 2), followed by the question on their perceived certainty in their responses.

The third part of the survey consisted of questions regarding their perception of the label. They indicated their agreement to the following statements on a five-point scale ranging from ‘strongly disagree’ to ‘strongly agree’: ‘I like the carbon label’, ‘I find the carbon label patronizing’, ‘I wish to see the carbon label when purchasing groceries’. Finally, we included questions on food consumption habits, including both general and specific measures and additional background information (education, household size).

[3] One of the randomly drawn combinations was replaced because it was almost identical to one of the other combinations.

4.3. Data analysis

The main outcome variable of interest is the inference from the carbon label, measured by correct identification of the lowest emitting products. This is a binary variable (Y) that takes the value one for tasks where the individual correctly identified the lowest emitting product, and zero otherwise. Our main questions of interest are to compare the inference between the control condition and the label conditions and to compare the inference between the different label conditions. Thus, for hypotheses 1 and 2, we estimated the following model:

$$Y_{itm} = \beta_0 + \beta_1 Label_{itm} + \varepsilon_{itm} \tag{1}$$

in which i denotes individuals, t tasks and m treatment group ($m = 0$ is control tasks where the *Label*-variable takes the value zero). β_1 is the label treatment effect.

To test hypothesis 1a-c, if within food category inference is more accurate with the carbon labels than no label, we estimated model (1) based on data on the within-food category tasks. Thus, $t = 1, \ldots, 4$, since each individual was presented with one task for each food category (meat, vegetables, starchy carbohydrates, ready-made sandwiches). We estimated separate models for each of the three treatment groups, since each respondent first answered control (no label) tasks followed by treatment tasks for one of the labels (Digit, CC, Logo).

To test hypothesis 2a and 2b, if the overall (between category) inference is more accurate with the carbon labels than no label, we estimated model (1) based on observations from the overall (mix of category) tasks. In each model, β_1 is the effect of the specified label compared to no label (control).

Finally, we tested if the overall (between category) inference is more accurate with the Digit than the Logo (H2c) and the CC than the Logo (H2d). We estimated model (1) based on observations from the two label treatments that are to be compared, while excluding the no-label tasks for each individual. In these models, β_1 is the effect of the specified label compared to the baseline label.

For all models, we clustered the errors at the individual level. Given the binary form of the dependent variable, logit or probit models could be estimated. Although such models provide advantages related to prediction and efficiency in standard errors, we proceeded with linear probability models (LPM), as this provides simpler interpretation while predictions are not part of this study analysis (Gomila, 2021). We present results from LPM in the results section, while in a set of sensitivity analyses we estimate the same models with logit specifications.

We tested if the self-reported understanding of the Logo was higher than for the Digit (H3a) and for the CC than the Digit (H3b). The dependent variable (Y), the self-reported understanding, was measured on a five-point scale and we tested for differences in means across the treatment groups by estimating the following model:

$$Y_{im} = \beta_0 + \beta_1 Logo_{im} + \beta_2 CC_{im} + \varepsilon_{im} \tag{2}$$

Responses from all three treatments are included and we expected both β_1 (H3a) and β_2 (H3b) to be positive.

Finally, while not guided by hypothesis, we explored if perceptions vary between the different labels. We estimate model (2) for each of the dependent variables liking, wish to use the label, and if it is perceived as patronizing. For ease of interpretation, the response variables are treated as continuous. In a set of sensitivity analysis, we estimate the models with ordered logit models. We investigate the role of prior knowledge in the accuracy. For each treatment group and type of task (within-food category tasks and mix of food categories tasks), we esti-

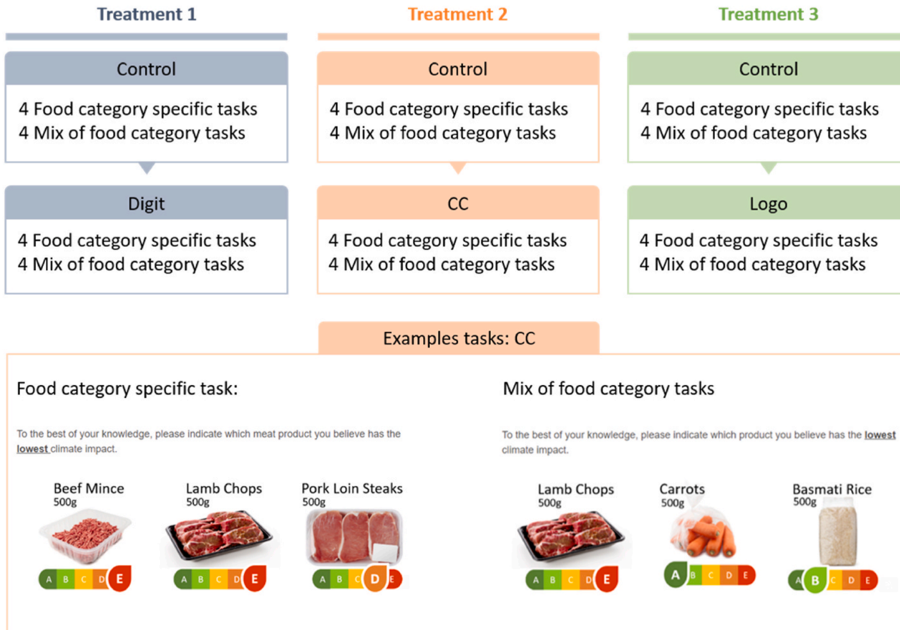

Fig. 2. Overview of study design and example of tasks in Colour-Coded (CC) treatment. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

mate the following model:

$$Y_{itm} = \beta_0 + \beta_1 High\ knowledge_i + \beta_2 Low\ knowledge_i + \beta_3 Label_{itm} + \beta_4 Label_{itm} * High\ knowledge_i + \beta_5 Label_{itm} * Low\ knowledge_i + \varepsilon_{itm} \quad (3)$$

β_1 and β_2 are the estimated differences in accuracy in identifying the lowest carbon-emitting food products for individuals with high or low levels of knowledge, relative to individuals with medium levels of knowledge, in the absence of a label. β_3 estimates the effect from the label, while the interaction terms β_4 and β_5 indicate whether the effect from the label varies with prior knowledge. All analyses are conducted using STATA 15.

Table 1
Consumer accuracy in identifying the lowest emitting product in tasks with products from same food category.

	Label - Control comparisons			Label comparisons		
	Digit vs. Control	CC vs. Control	Logo vs. Control	Digit vs. Logo	Digit vs. CC	Logo vs. CC
Digit	0.42 (23.22)					
CC		0.42 (22.23)			0.00 (0.22)	
Logo			0.38 (21.29)	−0.04 (1.77)		−0.04 (2.01)
Intercept	0.49 (30.28)	0.50 (30.91)	0.50 (33.16)	0.91 (66.31)	0.91 (66.31)	0.92 (68.23)
Observations	1856	1928	1936	1896	1892	1932
Individuals	232	241	242	474	473	483
F	539.10	494.19	453.38	3.15	0.05	4.04

Note: Dependent variable takes a value of 0 or 1. Intercept represents the share of correct responses in the base group, and the parameters are interpreted as the difference in share of correct responses in the treatment groups. Robust t-values in parenthesis.

5. Results

5.1. Consumer inference accuracy within food category

Table 1 shows consumer accuracy in identifying the lowest carbon-emitting food product in tasks with products from same food category (model 1). First, we can see that, on average, the share of correctly identified products among the within-category questions is 0.50 in the control group, which implies that the share of correct responses is higher than random choices (0.33).[4] Second, the share of correct responses is higher for all carbon labels compared to the control group; 0.91 in the Digit treatment, 0.92 in the CC treatment and 0.88 in the Logo treatment. Results are consistent when applying logit models (Table S4). This provides support for our first hypotheses (H1a-c: *Within*-category inference more accurate with carbon label (Digit, CC, Logo) than no label). We note that all labels provide respondents with the necessary information to accurately identify the least emitting product within each category. The finding of less than 100% accuracy in the label treatments suggests that approximately 10% in each treatment did not understand the label or did not engage in the tasks. Fig. S3 presents the share of consumer correct responses by food category. The share of correct responses is higher for the carbon label treatments than for the control treatment, in all food categories. Thus, the support for the first set of hypothesis, that all three labels increase accuracy, holds for all food categories.

Since all labels provide the necessary information to correctly identify the lowest emitting product within the food categories, we did not expect the label treatment effects to vary across treatments. To explore this, we estimate model (1) where we include the treatment tasks only for the different label treatment groups (‘Label comparisons’ in Table 1). Overall, the results are in line with our expectations that there is not statistically significant differences in accuracy between the Digit and the Logo or the Digit and the CC label. Although there is a

[4] The share of correct responses in the within category control tasks is not statistically significantly different in the control tasks across the treatment groups (Digit = 0.49, CC = 0.50 and Logo = 0.50). Tests for differences are available in Table S3.

statistical difference at a 5 per cent significance level in accuracy between the Logo and the CC, the difference is small in magnitude.

5.2. Overall consumer inference accuracy

We investigate the accuracy in identification of the lowest emitting product, where products from three different food categories were included in each task. The share of correct responses in the control tasks is 0.63,[5] which is higher than random choice, and it is notably higher than in the within-category tasks. This suggests that individuals have some prior knowledge on the greater differences in carbon emissions between food categories and are able to identify products in the lower carbon-emitting food categories.

Table 2 presents the results for the overall (mixed product) tasks, where model (1) is estimated based on the between-category tasks. The second hypothesis (H2a) is supported, as the inference is more accurate with the descriptive carbon label (Digit) than no label, where the share of correctly identified products is 0.95 ($p < 0.001$). We further find support for H2b, since in the CC-treatment, the share of correct responses is 0.77, which is significantly higher than in the control tasks ($p < 0.001$).

We did not expect that the Logo would change the accuracy compared to the control, since the label criteria is based on comparison within food categories. Indeed, we found that the share of correct responses is 0.61 in the Logo treatment, which is not statistically different from the 0.64 in the control condition ($p = 0.142$).

Given the properties of the different carbon labels, we hypothesise a higher accuracy with the Digit than the Logo (H2c), as well as a higher accuracy with the CC label than the Logo (H2d). The share of correct responses is significantly lower (34 percentage points) with the Logo than the Digit (model 4 in Table 2), while the share is 16 percentage points lower when compared to the CC (model 6 in Table 2). Thus, there is support for both H2c and H2d.

We also see that the Digit outperforms the CC label, with a 17 percentage point higher accuracy (model 5). It should be acknowledged that the CC is based on a set of evaluative criteria (thresholds for the different colours), and the Digit thus provides more detailed information. In the CC treatment there were tasks where the lowest-emitting product displayed the same colour as the second-lowest-emitting product (when the CO_2e for both products were below the same threshold). In such tasks, the label did not provide guidance on the correct response. This is in line with how this type of simplifying label functions, and it explains the lower rate of correct responses for the CC label than the Digit. Results for the overall (between food category) consumer inference accuracy are the same when applying logit model specifications (Table S6).

Table 2
Accuracy in identifying the lowest emitting product in tasks with products from different food categories.

	Label - Control comparisons			Label comparisons		
	Digit vs. Control	CC vs. Control	Logo vs. Control	Digit vs. Logo	Digit vs. CC	Logo vs. CC
Digit	0.32 (15.68)					
CC		0.14 (6.52)			−0.17 (9.24)	
Logo			−0.03 (1.47)	−0.34 (17.85)		−0.16 (7.80)
Intercept	0.62 (32.49)	0.63 (34.28)	0.64 (35.49)	0.95 (81.28)	0.95 (81.28)	0.77 (52.09)
Observations	1856	1928	1936	1896	1892	1932
Individuals	232	241	242	474	473	483
F	246.01	42.49	2.17	318.78	85.44	60.81

Note: Dependent variable takes a value of 0 or 1. Intercept represents the share of correct responses in the base group, and the parameters are interpreted as the difference in share of correct responses in the treatment groups. Robust t-values in parenthesis.

5.3. Consumer ease of understanding and perception of carbon labels

The average score for the stated level of understanding of the carbon labels (on a scale from 1 = 'I don't understand it at all' to 5 = 'I absolutely understand it') is 3.10 for the Digit, while it is 0.27 points higher for the CC ($p < 0.05$), and 0.21 points higher for the Logo ($p = 0.06$) (means are presented in Table 3, while tests for differences across label treatments are available in Table S7). Thus, the simplifying and evaluative labelling formats (CC and Logo) are perceived as easier to understand than the descriptive and detailed label (Digit). Note that the question of consumer understanding of the carbon label was posed following the introduction of the label, but prior to using the label in the inference tasks. Thus, their responses are not affected by their experience from using the carbon label in the following tasks.

Respondents were asked about their level of certainty in the responses to the tasks of identifying the products with the lowest carbon emissions (on a scale from 1 = 'very uncertain' to 5 = 'very certain', 10 respondents were excluded because they indicated 'I don't know'). The average score for the Digit is 3.90, which is 0.27 points higher than the CC label ($p < 0.05$) and 0.74 points higher than the Logo ($p < 0.001$) (Table 3 and Table S7).

Finally, we investigated the differences in consumer perceptions for the different carbon labels. Table 3 shows that there are little differences in the perceptions of the different labels. The wish to see the label in a shopping situation is similar across the labelling formats. None of the labels are perceived as very patronizing (average score of 2.3 on a scale from 1 to 5), and there are no differences across labels. Only the degree of liking varies across the labels; while there is a high degree of liking (average score of 4.0 for the Digit and the CC label), this is significantly lower for the Logo (average score 2.1 less). The main findings presented in Table 3 hold when the models are estimated with ordered logit models. Results for these models can be found in Table S7.

Half respondents (47 per cent) reported having a fair level of knowledge about the climate impact from food, while 18 per cent indicated a good level of knowledge. Only three per cent rated their knowledge levels to be excellent and seven per cent rated their

Table 3
Average scores for understanding, certainty and perception of carbon labels.

	Understanding[a]	Certainty[b]	Patronizing[c,f]	Liking[d,f]	Wish to see[e,f]
CC	3.37 (1.29)	3.63 (1.13)	2.30 (1.00)	4.02 (0.85)	3.83 (1.00)
Logo	3.32 (1.11)	3.16 (0.96)	2.42 (1.01)	3.78 (0.85)	3.70 (1.01)
Digit	3.10 (1.31)	3.90 (1.07)	2.32 (1.09)	3.99 (0.90)	3.87 (1.02)

Note: Standard deviations in parenthesis.
[a] 1 = 'I don't understand this at all' to 5 = 'I absolutely understand this'.
[b] 'How certain were you in your identification of the products with the lowest climate impact?' (1 = 'very uncertain' to 5 = 'very certain').
[c] 'I find the carbon label patronizing'.
[d] 'I like the carbon label'.
[e] 'I wish to see the carbon label when purchasing groceries'.
[f] 1 = 'strongly disagree' to 5 = 'strongly agree'.

[5] The share of correct responses are not statistically significantly different in the control tasks across the treatment groups; digit (0.62), CC (0.63) and Logo (0.64).

knowledge as very poor (Table S9).[6] Given the small number of respondents at the extreme ends of the knowledge spectrum, we combined these categories into three broader groups: low, medium, and high knowledge. Individuals who rated their knowledge as high did not perform better at identifying the lowest-emitting products in the control tasks (Table S10a). This finding is not unexpected for the within-category tasks, as the differences in carbon emissions between variants within each food product category are relatively small. Surprisingly, no significant difference in accuracy was found for the between-category tasks either, despite the fact that general knowledge about the climate impact of different food groups (e.g., meat vs. starches) should allow for accurate identification. Furthermore, self-reported knowledge did not explain the influence of the labels on product selection.

6. Discussion

This study investigated how different carbon labels affect consumers' efficiency in identifying low-carbon-emitting food products, where the included labels were the descriptive 'Digit', the 'Colour-Coded' (CC) label, and the 'Logo'. In the tasks where only products from the same food category were included, each of the carbon labels increased the accuracy significantly, from 50 per cent correctly identified products without a carbon label to around 90 per cent when the carbon labels were present, with only minor differences in the performance between the labels.

In the tasks where products from different categories were included, consumer accuracy in identifying the lowest emitting food products was approximately 63 per cent without any label. The presence of the Digit improved the accuracy the most (32 percentage points), followed by the CC (14 percentage points), while the Logo resulted in no improvement in accuracy. We are not aware of previous studies on consumer inference from different carbon labels. Existing research that compares labels primarily focuses on consumer willingness to pay for labelled products in a specific food category (Carlsson et al., 2021; Thøgersen and Nielsen, 2016). However, findings on consumer inference from health-related labels align with our results. Studies show that traffic light labels significantly improve accuracy in identifying the healthiest products (Egnell et al., 2018), while best-in-class logos tend to perform the worst (Borgmeier and Westenhoefer, 2009). As nutrition-related information depends on several parameters such as amount of fat, salt, sugar and dietary fibre it is difficult to summarize this information to a single digit.

The descriptive label (Digit) provides the most precise information, while evaluative labels (CC and Logo) aim to make the information easier to use. In line with the purpose of evaluative labels, the CC and Logo were rated to be more understood compared to the Digit. However, the level of certainty in the tasks of identifying the least-emitting products was highest for the Digit and lowest for the Logo. This can be explained by the difficulty in identifying the lowest-emitting product when products from different categories were included in the task; a situation where the Logo provides no assistance. Thus, while simplifying labels provides an appearance that is easier to understand, they imply greater difficulty when used due to the lack of detail.

While inference from a label is key to the impact it may have on actual use and purchase decisions, the perceptions of a label are likely important determinants of whether a consumer decides to use a label (Grunert and Wills, 2007). Many consumers expressed a wish to see the carbon labels when purchasing food, and this did not vary between labels. We found no differences in the degree to which the labels were perceived as patronizing. Only the degree of liking varied across the labels, where the Digit and the CC were better liked compared to the Logo.

Notably, in the control tasks, accuracy of identifying the lowest emitting product was higher when products from different product categories were included compared to tasks within the same category. This suggests that consumers possess some general knowledge about which product categories are lower-emissions. However, accuracy in the tasks with no carbon labels present did not vary with self-reported general knowledge about climate impact of food. Moreover, self-reported knowledge did not explain differences in label understanding. These findings are surprising, particularly as evidence suggest that individuals with greater general knowledge of nutrition understand health labels better (Campos et al., 2011). A potential explanation could be that the knowledge level in this study was self-reported; the results might have differed if objective knowledge had been measured. Exploring the role of objective versus subjective knowledge, and how this influences the inference and use of carbon labels, could be a valuable avenue for future research.

Several future research avenues could be identified. First, this study compares three different labels that were judged as policy-relevant and covered distinctly different approaches to present carbon emission information on FoP labels. Future studies may investigate how the design features, such as colour and position on products affect the ease of use and choices. Second, this study examines a key precursor to food consumption choices; the label's ability to inform consumers. A label can only enable consumers to make low-carbon choices if it helps them accurately identify low-carbon options. Building on the findings of this study, future research should explore the extent to which consumer inference from different labelling schemes mediates their impact on actual consumption. We recommend that future studies expand the scope of prior research, which has often focused on a single product category (Canavari and Coderoni, 2020; Carlsson et al., 2021; Edenbrandt et al., 2021; Rondoni and Grasso, 2021; Thøgersen and Nielsen, 2016), by investigating the effects of various labels on purchasing patterns across a broader range of product categories. Third, it is important to recognize that the accuracy in identifying the lowest-emitting products is high with both the Digit and the CC labels in the survey context. However, in a real market setting, where numerous competing sources of information compete for consumer attention, the salience of a carbon label is likely to diminish. Consequently, the share of correct responses in such a setting would likely be significantly lower. Nevertheless, we have no reason to believe that the conclusions regarding the relative performance of the labels would differ between the real market context and the survey environment of this study. Fourth, this study is conducted in a European country (UK), and future studies may extend the research to other countries. Notably, much of the existing research on climate labels is conducted in European and North American contexts (Rondoni and Grasso, 2021) with an increasing number of studies emerging from different Asian countries (Aoki and Akai, 2022; Chen et al., 2024). However, research remains largely concentrated in high- and middle-income countries, and future studies should extend the research to a more diverse set of cultures and economic settings.

7. Conclusions

For a carbon label to influence consumption patterns, it must help consumers identify changes in their purchasing habits that lead to reduced climate impact. Despite the critical role that inference plays in driving behavioural change, there is limited evidence on how the specific features of carbon labels influence consumers' ability to accurately recognize low-carbon products. This study suggests that there are large differences in the inference from different types of carbon labels. While all three labels achieved high levels of correct inference when comparing similar products, the overall inference was not improved compared to no label when using a 'best-in-class' Logo. Although this is not surprising, given the criteria of such a label, the results do highlight the limitations with labels that evaluative performance within-categories.

An evident advantage of carbon labels is their ability to help

[6] The level of knowledge is not different to a statistically significant degree across the treatment groups (χ^2-test: $p = 0.443$, Table S8).

consumers infer the carbon impact of different products, potentially influencing their purchasing decisions if their preferences align with the information provided. Beyond this direct benefit, carbon labels can also serve an educational purpose by enabling consumers to learn and update their understanding of the carbon footprint of various products. Policy makers should thus acknowledge that a labelling system functions not only as a point-of-purchase information tool but also as a means of educating consumers, potentially driving long-term behavioural change. This study demonstrates that the most substantial educational impact is achieved with detailed labels (Digit), followed by between-category colour-coded labels (CC), while best-in-class evaluative labels (Logo) fail to achieve this effect. Crucially, to reduce asymmetric information and fulfil the educational potential of labels, they should be applied to all products, not only those with a low climate impact. From a policy perspective, this highlights the necessity of mandatory carbon labelling. Voluntary schemes, even for the most effective formats like the Digit and CC, risk devolving into best-in-class format, which this study has demonstrated is significantly less effective in aiding consumer understanding. It should be noted that while mandatory labelling with Digit or CC is superior from an educational perspective, such labelling requirements are also associated with costs that must be considered in the policy decisions (Edenbrandt and Nordström, 2023).

Edenbrandt and Lagerkvist (2022) show that a high level of general knowledge about the climate impact of food is associated with lower emission food purchase patterns. From the perspective of policy design, it is promising that the carbon labels examined in this study enable individuals with low general climate knowledge to identify low-carbon-emitting food products as effectively as those with higher knowledge.

In addition to the direct guidance, and the longer-term education of consumers, carbon labels may provide incentives for firms to reduce carbon emissions, as they enable firms that produce higher quality (lower carbon emitting) products to communicate this to consumers in a credible way. This incentive is present for all three labels.

A key argument in favour of simplifying rather than detailed FoP labels is that they are easier to understand and use, particularly in choice tasks involving food, which are typically low involvement (Bauer and Reisch, 2019). The findings from this study challenge these arguments. While the stated understanding is higher for the most simplifying labels, the perceived certainty in inference is significantly higher with the more detailed labels (Digit and CC), and these labels are also more liked than the most simplifying ‘best-in-class’ Logo.

In conclusion, the findings from this study suggest that a descriptive and detailed carbon label (Digit) and a label that evaluates the overall (across food categories) performance of a product (CC) outperform the ‘best-in-class’ Logo, measured both by their impact on consumer accuracy in identifying low-emitting food products and by the liking of the labels.

8. Writing process

During the preparation of this work the authors used ChatGPT-4 to correct the grammar. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Transparent reporting

Preregistration of the study is available at: https://aspredicted.org/JK2_4S9.

CRediT authorship contribution statement

Anna Kristina Edenbrandt: Writing – review & editing, Writing – original draft, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Daniele Asioli:** Writing – review & editing. **Jonas Nordström:** Writing – review & editing, Conceptualization.

Funding statement

Edenbrandt is grateful for funding from the Swedish Research Council - FORMAS (Grant number 2021-02055).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2025.145020.

Data availability

Data will be made available on request.

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