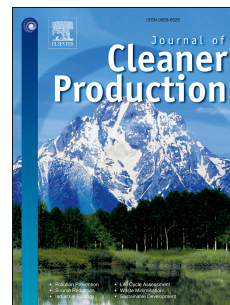


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Impact of different carbon labels on consumer inference

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Transparent Reporting

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Authorship contribution statement

Anna Kristina Edenbrandt: Conceptualization, Data collection, Methodology, Formal analysis, Funding acquisition, Writing - review & editing. **Daniele Asioli:** Writing - review & editing. **Jonas Nordström:** Conceptualization, Writing - review & editing.

Impact of different carbon labels on consumer inference

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 CO₂e-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.

Key words: carbon label; climate information; consumer inference; front-of-pack label, sustainability label

1 Introduction

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

16 A key prerequisite for a carbon label to be effective in shifting consumption in the direction of reduced
17 climate impact is that consumers understand the label, and that it helps them identify changes in their
18 purchase patterns towards reduced climate impact (Asioli et al., 2020). Only then can changes in
19 behaviour be achieved. Thus, the impact of a FoP label is affected by the inference the consumer makes
20 from a label (Grunert et al., 2010; Grunert and Wills, 2007). The characteristics of a labelling scheme
21 will affect the type and amount of information a label provides. An important determinant of the
22 inferences consumers make from a label is whether the information is descriptive or evaluative
23 (Hamlin, 2015). Descriptive labels convey the information, such as the exact amount of CO₂
24 equivalents from the production of one unit of a product, while an evaluative label relates this
25 information to a reference level, which simplifies the information. For labels that are evaluative, the
26 reference point against which the label is evaluated is crucial. This can be based on the overall
27 performance, encompassing all food categories, or it can focus on evaluating products within the same
28 category (Edenbrandt and Nordström, 2023). This study investigates how these key characteristics
29 affect consumers' ability to identify food products with the lowest climate impact.

30 A growing body of literature has investigated if and how consumers are affected in their consumption
31 choices by climate information on food products (Rondoni and Grasso, 2021). Early work on the topic
32 includes studies in the UK (Gadema and Oglethorpe, 2011; Upham et al., 2011), Finland (Hartikainen
33 et al., 2014; Koistinen et al., 2013) and a study across countries (Feucht and Zander, 2017). Typically,
34 studies on carbon labelling effects focus on one specific carbon label in one specific product category
35 (Aoki and Akai, 2022; Canavari and Coderoni, 2020; Carlsson et al., 2022; Chen et al., 2024;
36 Edenbrandt and Lagerkvist, 2021; Lohmann et al., 2022; Rondoni and Grasso, 2021; Sonntag et al.,
37 2023; Soregaroli et al., 2021; Win et al., 2024) or on meals in restaurants (Brunner et al., 2018; Casati
38 et al., 2023; Lohmann et al., 2022; Novak et al., 2024), where the evidence suggests that climate
39 information and carbon labels have some (albeit limited) impact on food choices. A number of studies
40 have included comparisons of different carbon label formats. Carlsson *et al.* (2021) conducted a choice
41 experiment on ready-made lasagne among Swedish respondents and found that color-coded labels have
42 a greater impact on choices than black-and-white labels. Similarly, Thøgersen and Nielsen (2016)
43 conducted a hypothetical choice experiment on coffee among Danish respondents, showing that colour-
44 coded footprint has a greater impact on preferences compared to black-and-white labels. Meyerding,
45 Schaffmann and Lehberger (2019) compared carbon labels with different levels of detail and found
46 larger effects for traffic light labels compared to labels that claim reduced emissions or carbon
47 neutrality. Fresacher and Johnson (2023) compare carbon labels with different appearance (colour, font
48 size).

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

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

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

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

97 Background on carbon labelling: market implementations and 98 policy context

99 The first carbon label that could be displayed on food products was introduced in 2006 by Carbon
100 Trust, a private company initiated by government in the United Kingdom (Liu et al., 2016). The British
101 retailer Tesco began to carbon footprint label products in 2007, but the initiative was discontinued in
102 2012 due to low involvement from other retailers and high labelling costs (Vaughan, 2012). A lot has
103 happened in the area since then, and different types of carbon labels have been introduced in different
104 countries (Liu et al., 2016). For example, as part of the Farm to Fork strategy, the European commission
105 is set to present a sustainable food labelling framework (European Commission, 2022). Meanwhile,
106 several third-party initiatives have been piloted recently. The Eco-score labelling scheme was launched
107 in France in 2021 by a group of private food operators (La Fourche, Marmiton, FoodChéri, Seazon,
108 Eco2Initiative, Scan up, Yuka, Etiquettable, Frigo magic and Open Food Facts) (Open Food facts,
109 2021). The design of this label has similarities to the European Nutriscore scheme by providing an
110 overall sustainability score from A to E (Eco-score, 2022). In France, Eco-score is used (so far, mainly
111 online) when purchasing food, ordering food or choosing recipes. Lidl has implemented a pilot project
112 with Eco-score in Germany, Belgium, the Netherlands and Scotland (Andersson and Nordström, 2023).
113 The Belgian Colruyt Group has also made the Eco-score available in its app and on its website and is
114 working to provide all its own brand products with the Eco-score printed on the packaging (Colruyt
115 Group, 2023). The first labelled products appeared in Belgian stores in the summer of 2021 (Retail-
116 Detail, 2021). So far, it is relatively unusual to see Eco-scores on products in physical stores.

117 Another initiative is the Planet-score, which addresses sustainability more broadly (IFOAM, 2022;
118 ITAB et al., 2021). Like the Eco-score, the Planet score provides an overall sustainability score from
119 A to E. The label also contains information about how the product is assessed in terms of climate
120 impact, pesticide use, impact on biological diversity and animal welfare. Since 2022, the Planet-score
121 has been available on products in French stores and has also started to be used in other European
122 countries such as Germany, Belgium, the Netherlands, Spain, Italy and the UK (Pleinchamp, 2022). In
123 Denmark, the government nominated a group of representatives from the food sector, to propose a
124 climate label of food. The group suggest a Colour-Coded label with scores from A to E (The Danish
125 Veterinary and Food Administration, 2023), similar to the Nutri-score and Eco-score labels.

126 For restaurants, Klimato started to develop a label and a tool for restaurants to calculate the carbon
127 footprint for meals in 2017. The label has three levels – low, medium and high – indicated by a symbol,
128 and also show the meal's carbon footprint (CO₂e) with a digit. No colour-coding is used. The label is
129 used in countries including Sweden, Norway and the UK (Klimato, 2023).

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

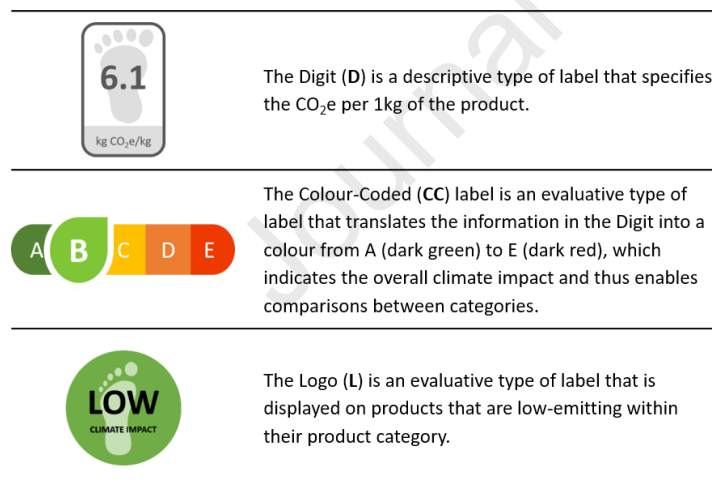
134 Theoretical framework and hypotheses

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

141 An important determinant to the inference consumers makes from a label is how the information is
142 conveyed (Grunert and Wills, 2007). Edenbrandt and Nordström (2023) identified two characteristics

143 of a carbon label that are expected to impact the inference consumers make. First, the *assessment*
 144 *criteria* refers to whether the information conveyed is descriptive or evaluative. A purely descriptive
 145 label displays the exact amount of carbon emission equivalents (CO₂e) from the production of one unit
 146 of the product. Second, for labels that are evaluative, the *level of reference* decides what the evaluation
 147 is based on, and these reference levels can be defined on the overall climate impact or in more narrow
 148 reference groups (specific food categories).

149 We select three labels that vary with respect to the assessment and the level of reference, and which
 150 will be tested in this study (Figure 1). The first label is a ‘Digit’ that specifies the CO₂e from the
 151 production of 1 kg product. This represents a descriptive assessment criteria. To some extent, this is
 152 similar to the early carbon label implemented in the UK by Tesco, and the meal labelling developed
 153 by Klimato. The second is a ‘Colour-Coded’ (CC) type of label which indicates the *overall*
 154 performance on a scale from A (green) to E (red). This represents an evaluative assessment criterion,
 155 with the level of reference on overall impact across all food categories. The CC label holds similarities
 156 to the European Nutriscore label and the recently proposed environmental labels (Eco-score and Planet-
 157 score), which are also evaluative in their assessment criteria and that to a certain degree assess the
 158 overall nutritional quality and sustainability respectively. Note that the evaluative nature of the label
 159 implies a simplification of the descriptive assessment, and the use of five categories implies a less fine-
 160 grained level of detail compared to the Digit, disabling identification of smaller differences that occur
 161 within each category. The third label is a ‘Logo’ which is displayed on the best (least carbon-emitting)
 162 food products within a product category. This represents an evaluative assessment criteria, where the
 163 level of reference is defined within food categories. This Logo is similar to the RSPCA animal welfare
 164 label in the UK, and to health FoP food labels such as Nordic Keyhole, Health Tick and Choices Logo
 165 (Bauer and Reisch, 2019). Such labels provides guidance on good alternatives *within* a product
 166 category.



167

168 **Figure 1. Carbon label formats used in this study.**

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

174 **3.1 Hypotheses: Within food category inference accuracy**

175 The exact amount of carbon emissions from the production of a food product is a credence attribute
 176 meaning that it is not possible for the consumer to evaluate upon inspection or consumption, as it
 177 depends on factors such as technology use, management practices, and place of production
 178 (Springsmann et al., 2018). A credible source of information, in the form of a label, could alleviate this

179 asymmetric information between producers and consumers. Therefore, we expect that carbon labels
180 improve consumers' ability to identify products that are lower emitting:

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

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

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

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

190 **3.2 Hypotheses: Overall (between category) inference accuracy**

191 With a label that is purely descriptive, consumers will be able to identify the lowest carbon-emitting
192 food product, both within and across food product categories; they simply need to compare numbers
193 (such as the CO₂e per 1kg of the product). The evaluative between-category label (CC) provides a
194 simplification of the Digit by dividing food products into categories. This simplification provides
195 guidance regarding the lowest carbon-emitting product, both within food categories and overall.
196 Finally, while the evaluative within-category label (Logo) simplifies the information and enables
197 identification within specific food categories, it will not help consumers identify the lowest carbon-
198 emitting food products overall. A food product that is low-emitting in a high-emitting food category
199 will be labelled with the logo, while a much lower-emitting product in the low-emitting category will
200 not be labelled if it is not among the lower emitting within the category. In summary, regarding the
201 overall inference from carbon labels (between category comparisons), we hypothesise that:

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

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

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

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

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

213 **3.3 Hypotheses: Ease of understanding and label perception**

214 While the Digit provides the most precise information, evidence from the health FoP labelling literature
215 reveals that quantitative and descriptive information is more demanding for individuals to interpret
216 (Bauer and Reisch, 2019). Following dual system theory of behaviour, individuals decision making
217 involve deliberate cognition, where the relevant information is carefully considered, and automatic
218 thinking, where the decision maker use rules of thumb that enable fast decisions even when the task is
219 complex (heuristic mode) (Dhar and Gorlin, 2013). In low-involvement choice tasks, which are often
220 the case in food choices, individuals tend to apply heuristics (Hauser, 2014). This suggests that
221 evaluative labels, which seek to simplify the information, may be faster and easier to interpret by the
222 consumer compared to more detailed and descriptive label formats (Bauer and Reisch, 2019). In this

223 study, the CC label is a simplification of the Digit on the overall level, while the Logo is a simplification
 224 of the information in the Digit on the within-product level. Thus, we expect that the simplifying labels
 225 are associated with higher stated level of understanding of the labels.

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

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

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

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

239 Material and methods

240 4.1 Data collection and participants

241 Data were collected in an online survey with three treatment groups (Digit, CC, Logo), which included
 242 tasks where respondents were asked to indicate the food product with the lowest CO₂e emissions. To
 243 establish the required sample size, we conducted power analysis, assuming an $\alpha=0.05$ and power of
 244 0.80. We assumed mean differences in the probability of correct identification of the lowest emitting
 245 product of 0.1 for the labelling treatments compared to no label (control group). This difference was
 246 based on a study on FoP health labels (Borgmeier and Westenhoefer, 2009),¹ since we did not find any
 247 study on environmental labels with a similar study design. The estimated number of participants needed
 248 per treatment group was 231, but since we include four observations per individual, the number of
 249 individuals needed to detect a difference of 0.1 was 145. We used 250 individuals per treatment, which
 250 gave us room to test for differences in specific food categories.

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

255 Data were collected from a representative sample of consumers in the UK from a panel managed by
 256 TGM Research during March 2023 using a web-based survey. The UK, as the first country to introduce
 257 a carbon label, and several of the earliest studies on consumer preferences and carbon labels (Gadema
 258 and Oglethorpe, 2011; Upham et al., 2011) offers a unique context for this study. Currently, the UK
 259 lacks a large-scale, widely recognized carbon label on food products, with only various private
 260 initiatives that are not widely familiar to consumers. This setting allows us to explore consumer
 261 understanding and inference of carbon labels, providing insights relevant to both the UK and other
 262 markets considering similar strategies. Age and gender were used to stratify the sample to resemble

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

² https://aspredicted.org/JK2_4S9

263 the UK population in the measured characteristics. Participation in the panel was voluntary and
264 participants are awarded points, which are transferred to vouchers, as reward for their participation.
265 Participation in the survey was voluntary and respondents were informed that they could withdraw at
266 any point without giving a reason. Only individuals who gave their consent and were at least 18 years
267 old proceeded with the survey. Respondents who stated that they rarely or never purchase food were
268 screened out. The distributed survey invitation described the purpose of the study in general terms and
269 did not mention the topic of climate impact, to reduce the potential selection bias of including
270 individuals with special interest in the subject (Newman et al., 2021).

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

282 **4.2 Survey Design**

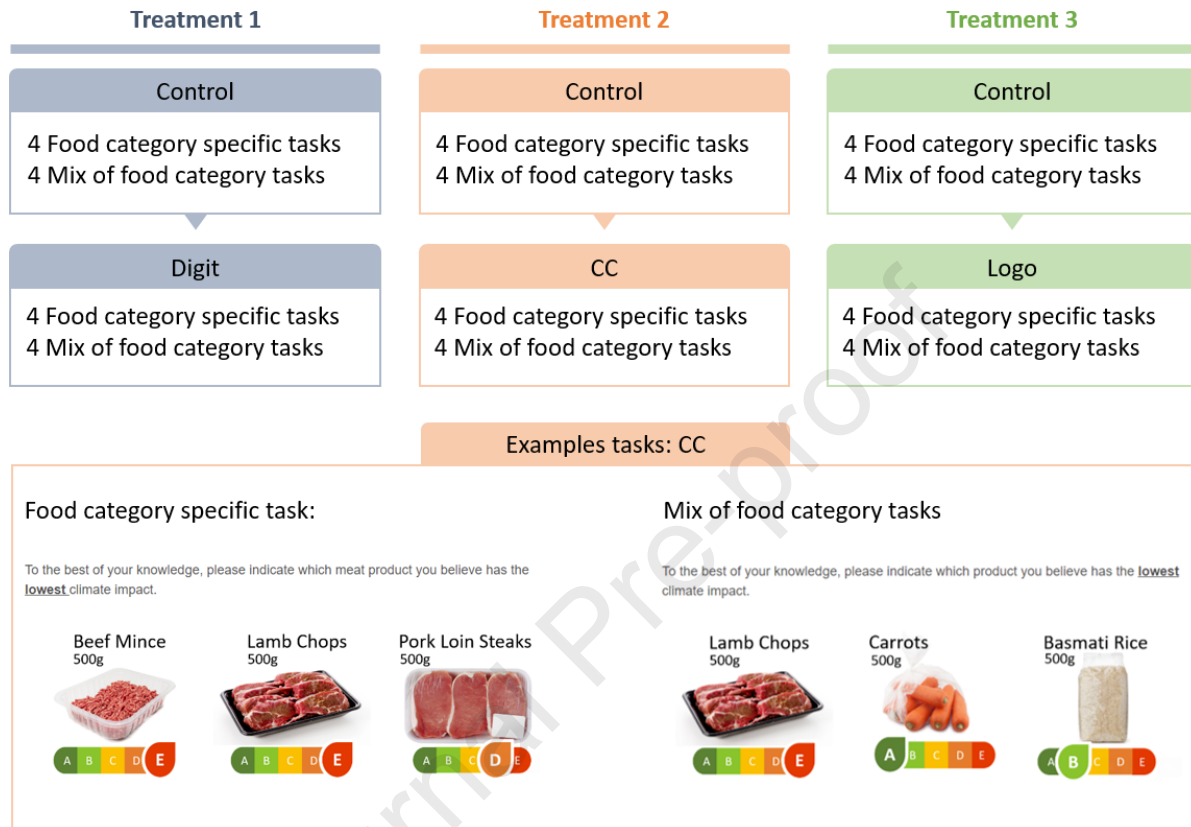
283 The survey consisted of three parts. First, respondents were introduced to the survey and gave their
284 consent to participate, and indicated their gender and age followed by questions on general food habit
285 questions and self-rated level of knowledge about climate impact of food in general.

286 The second part of the survey included tasks of identifying the least emitting product among a set of
287 food products. These tasks included four product categories: meat (pork loin steaks, beef mince, lamb
288 chops), vegetables (tomato, carrots, green beans), starchy carbohydrates (rice, pasta, potato) and ready-
289 made sandwiches (tuna and cucumber, egg and ham, cheese and tomato). These are all products that
290 consumers are familiar with, and that many consume on a regular basis in the UK (Espinoza-Orias and
291 Azapagic, 2018). Overall, these food products cover both high-emitting categories (meat) and low-
292 emitting categories (vegetables and starchy carbohydrates) (Poore and Nemecek, 2018). We included
293 ready-made sandwiches, as we expect it to be more difficult for individuals to assess the climate impact
294 for this product category, due to the inclusion of several different ingredients in the same product. The
295 ready-made sandwiches included are among the most commonly sold sandwich types in the UK
296 (Espinoza-Orias and Azapagic, 2018). The list of the food products investigated in this study, including
297 the CO₂e per kg and the carbon labels displayed, are presented in Table S2.

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

301 In the first block (control), there was a brief text that explained the climate impact from food and the
302 measure CO₂e per kg product (Figure S1). Respondents were presented with eight tasks, where each
303 tasks presented three different food products and respondents were asked to indicate the product with
304 the lowest climate impact. The order of the food products (left/middle/right) within each task was
305 randomized. The first four tasks consisted of one task for each food category (meat, vegetables, starchy
306 carbohydrates, ready-made sandwiches). The order of presentation among the categories was
307 randomized. These tasks represented within-category identification of the lowest emitting product. The
308 last four tasks consisted of products from different food categories (for example, lamb chops, carrots,
309 rice). These tasks represented overall (between-category) identification of the lowest emitting product.
310 For these tasks, there are many possible combinations of products from the different food categories.

311 We randomly drew 24 of these combinations of products, and each respondent was presented with four
 312 tasks.³ The order of presentation for these tasks was randomized. Following the tasks of selecting the
 313 lowest emitting products, respondents indicated their certainty in their responses (*'How certain were*
 314 *you in your identification of the products with the lowest climate impact?'* on a five-point scale ranging
 315 from 'very uncertain' to 'very certain', and an additional option of 'I don't know').



316
 317 **Figure 2. Overview of study design and example of tasks in Colour-Coded (CC) treatment.**

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

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

330 4.3 Data analysis

331 The main outcome variable of interest is the inference from the carbon label, measured by correct
 332 identification of the lowest emitting products. This is a binary variable (Y) that takes the value one for

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

333 tasks where the individual correctly identified the lowest emitting product, and zero otherwise. Our
 334 main questions of interest are to compare the inference between the control condition and the label
 335 conditions and to compare the inference between the different label conditions. Thus, for hypotheses
 336 1 and 2, we estimated the following model:

$$337 \quad Y_{itm} = \beta_0 + \beta_1 \text{Label}_{itm} + \varepsilon_{itm} \quad (1)$$

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

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

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

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

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

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

$$363 \quad Y_{im} = \beta_0 + \beta_1 \text{Logo}_{im} + \beta_2 \text{CC}_{im} + \varepsilon_{im} \quad (2)$$

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

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

$$372 \quad Y_{itm} = \beta_0 + \beta_1 \text{High knowledge}_i + \beta_2 \text{Low knowledge}_i + \beta_3 \text{Label}_{itm} + \beta_4 \text{Label}_{itm} * \\ 373 \quad \text{High knowledge}_i + \beta_5 \text{Label}_{itm} * \text{Low knowledge}_i + \varepsilon_{itm} \quad (3)$$

374 β_1 and β_2 are the estimated differences in accuracy in identifying the lowest carbon-emitting food
 375 products for individuals with high or low levels of knowledge, relative to individuals with medium
 376 levels of knowledge, in the absence of a label. β_3 estimates the effect from the label, while the

377 interaction terms β_4 and β_5 indicate whether the effect from the label varies with prior knowledge. All
 378 analyses are conducted using STATA 15.

379 Results

380 5.1 Consumer inference accuracy within food category

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

396 **Table 1. Consumer accuracy in identifying the lowest emitting product in tasks with products**
 397 **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

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

401
 402 Since all labels provide the necessary information to correctly identify the lowest emitting product
 403 within the food categories, we did not expect the label treatment effects to vary across treatments. To
 404 explore this, we estimate model (1) where we include the treatment tasks only for the different label
 405 treatment groups ('Label comparisons' in Table 1). Overall, the results are in line with our expectations
 406 that there is not statistically significant differences in accuracy between the Digit and the Logo or the

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.

407 Digit and the CC label. Although there is a statistical difference at a 5 per cent significance level in
408 accuracy between the Logo and the CC, the difference is small in magnitude.

409 **5.2 Overall consumer inference accuracy**

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

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

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

425 Given the properties of the different carbon labels, we hypothesise a higher accuracy with the Digit
426 than the Logo (H2c), as well as a higher accuracy with the CC label than the Logo (H2d). The share
427 of correct responses is significantly lower (34 percentage points) with the Logo than the Digit (model
428 4 in table 2), while the share is 16 percentage points lower when compared to the CC (model 6 in
429 table 2). Thus, there is support for both H2c and H2d.

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).

430 **Table 2. Accuracy in identifying the lowest emitting product in tasks with products from**
 431 **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

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

435

436 We also see that the Digit outperforms the CC label, with a 17 percentage point higher accuracy
 437 (model 5). It should be acknowledged that the CC is based on a set of evaluative criteria (thresholds
 438 for the different colours), and the Digit thus provides more detailed information. In the CC treatment
 439 there were tasks where the lowest-emitting product displayed the same colour as the second-lowest-
 440 emitting product (when the CO₂e for both products were below the same threshold). In such tasks,
 441 the label did not provide guidance on the correct response. This is in line with how this type of
 442 simplifying label functions, and it explains the lower rate of correct responses for the CC label than
 443 the Digit. Results for the overall (between food category) consumer inference accuracy are the same
 444 when applying logit model specifications (Table S6).

445 5.3 Consumer ease of understanding and perception of carbon labels

446 The average score for the stated level of understanding of the carbon labels (on a scale from 1 = 'I
 447 don't understand it at all' to 5 = 'I absolutely understand it') is 3.10 for the Digit, while it is 0.27 points
 448 higher for the CC ($p < 0.05$), and 0.21 points higher for the Logo ($p = 0.06$) (means are presented in Table
 449 3, while tests for differences across label treatments are available in Table S7). Thus, the simplifying
 450 and evaluative labelling formats (CC and Logo) are perceived as easier to understand than the
 451 descriptive and detailed label (Digit). Note that the question of consumer understanding of the carbon
 452 label was posed following the introduction of the label, but prior to using the label in the inference
 453 tasks. Thus, their responses are not affected by their experience from using the carbon label in the
 454 following tasks.

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

	Understanding ^a	Certainty ^b	Patronizing ^{c*}	Liking ^{d*}	Wish to see ^{e*}
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	3.90	2.32	3.99	3.87

(1.31)

(1.07)

(1.09)

(0.90)

(1.02)

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

460

461 Respondents were asked about their level of certainty in the responses to the tasks of identifying the
 462 products with the lowest carbon emissions (on a scale from 1 = 'very uncertain' to 5 = 'very certain',
 463 10 respondents were excluded because they indicated 'I don't know'). The average score for the Digit
 464 is 3.90, which is 0.27 points higher than the CC label ($p < 0.05$) and 0.74 points higher than the Logo
 465 ($p < 0.001$) (Table 3 and Table S7).

466 Finally, we investigated the differences in consumer perceptions for the different carbon labels. Table
 467 3 shows that there are little differences in the perceptions of the different labels. The wish to see the
 468 label in a shopping situation is similar across the labelling formats. None of the labels are perceived as
 469 very patronizing (average score of 2.3 on a scale from 1 to 5), and there are no differences across labels.
 470 Only the degree of liking varies across the labels; while there is a high degree of liking (average score
 471 of 4.0 for the Digit and the CC label), this is significantly lower for the Logo (average score 2.1 less).
 472 The main findings presented in Table 3 hold when the models are estimated with ordered logit models.
 473 Results for these models can be found in Table S7.

474 Half respondents (47 per cent) reported having a fair level of knowledge about the climate impact from
 475 food, while 18 per cent indicated a good level of knowledge. Only three per cent rated their knowledge
 476 levels to be excellent and seven per cent rated their knowledge as very poor (Table S9).⁶ Given the
 477 small number of respondents at the extreme ends of the knowledge spectrum, we combined these
 478 categories into three broader groups: low, medium, and high knowledge. Individuals who rated their
 479 knowledge as high did not perform better at identifying the lowest-emitting products in the control
 480 tasks (Table S10a). This finding is not unexpected for the within-category tasks, as the differences in
 481 carbon emissions between variants within each food product category are relatively small.
 482 Surprisingly, no significant difference in accuracy was found for the between-category tasks either,
 483 despite the fact that general knowledge about the climate impact of different food groups (e.g., meat
 484 vs. starches) should allow for accurate identification. Furthermore, self-reported knowledge did not
 485 explain the influence of the labels on product selection.

486 Discussion

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

493 In the tasks where products from different categories were included, consumer accuracy in identifying
 494 the lowest emitting food products was approximately 63 per cent without any label. The presence of
 495 the Digit improved the accuracy the most (32 percentage points), followed by the CC (14 percentage
 496 points), while the Logo resulted in no improvement in accuracy. We are not aware of previous studies
 497 on consumer inference from different carbon labels. Existing research that compares labels primarily

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).

498 focuses on consumer willingness to pay for labelled products in a specific food category (Carlsson et
499 al., 2021; Thøgesen et al., 2016). However, findings on consumer inference from health-related labels
500 align with our results. Studies show that traffic light labels significantly improve accuracy in
501 identifying the healthiest products (Egnell et al., 2018), while best-in-class logos tend to perform the
502 worst (Borgmeister et al., 2019). As nutrition-related information depends on several parameters such
503 as amount of fat, salt, sugar and dietary fibre it is difficult to summarize this information to a single
504 digit.

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

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

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

530 Several future research avenues could be identified. First, this study compares three different labels
531 that were judged as policy-relevant and covered distinctly different approaches to present carbon
532 emission information on FoP labels. Future studies may investigate how the design features, such as
533 colour and position on products affect the ease of use and choices. Second, this study examines a key
534 precursor to food consumption choices; the label's ability to inform consumers. A label can only enable
535 consumers to make low-carbon choices if it helps them accurately identify low-carbon options.
536 Building on the findings of this study, future research should explore the extent to which consumer
537 inference from different labelling schemes mediates their impact on actual consumption. We
538 recommend that future studies expand the scope of prior research, which has often focused on a single
539 product category (Canavari and Coderoni, 2020; Carlsson et al., 2021; Edenbrandt et al., 2021;
540 Rondoni and Grasso, 2021; Thøgersen and Nielsen, 2016), by investigating the effects of various labels
541 on purchasing patterns across a broader range of product categories. Third, it is important to recognize
542 that the accuracy in identifying the lowest-emitting products is high with both the Digit and the CC
543 labels in the survey context. However, in a real market setting, where numerous competing sources of
544 information compete for consumer attention, the salience of a carbon label is likely to diminish.
545 Consequently, the share of correct responses in such a setting would likely be significantly lower.
546 Nevertheless, we have no reason to believe that the conclusions regarding the relative performance of

547 the labels would differ between the real market context and the survey environment of this study.
548 Fourth, this study is conducted in a European country (UK), and future studies may extend the research
549 to other countries. Notably, much of the existing research on climate labels is conducted in European
550 and North American contexts (Rondini and Grasso, 2021) with an increasing number of studies
551 emerging from different Asian countries (Aoki and Akai, 2022; Chen et al. 2024). However, research
552 remains largely concentrated in high- and middle-income countries, and future studies should extend
553 the research to a more diverse set of cultures and economic settings.

554 Conclusions

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

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

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

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

589 A key argument in favour of simplifying rather than detailed FoP labels is that they are easier to
590 understand and use, particularly in choice tasks involving food, which are typically low involvement
591 (Bauer and Reisch, 2019). The findings from this study challenge these arguments. While the stated
592 understanding is higher for the most simplifying labels, the perceived certainty in inference is

593 significantly higher with the more detailed labels (Digit and CC), and these labels are also more liked
594 than the most simplifying ‘best-in-class’ Logo.

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

599

600 Writing process

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

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Journal Pre-proof

Impact of different carbon labels on consumer inference

- Consumer accuracy in identifying lowest carbon-emitting food product is investigated.
- Carbon label design affects accuracy in identifying lowest emitting products.
- All labels improve accuracy *within* food categories.
- Descriptive label superior when products from different categories are evaluated simultaneously.
- Evaluative label that indicates overall performance superior to best-in-class logo.
- Best-in-class logo is the least liked type of carbon label.

Declaration of interests

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.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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