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► To cite this version:

Juliana Melendrez-Ruiz, Laurence Dujourdy, Isabelle Goisbault, Jean-Christophe Charrier, Kevin Pagnat, et al.. “You look at it, but will you choose it”: Is there a link between the foods consumers look at and what they ultimately choose in a virtual supermarket?. *Food Quality and Preference*, 2022, 98, pp.104510. 10.1016/j.foodqual.2021.104510 . hal-03525978

HAL Id: hal-03525978

<https://hal.inrae.fr/hal-03525978v1>

Submitted on 8 Jan 2024

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1 **“YOU LOOK AT IT, BUT WILL YOU CHOOSE IT”: IS THERE A LINK BETWEEN THE FOODS CONSUMERS LOOK AT AND**
2 **WHAT THEY ULTIMATELY CHOOSE IN A VIRTUAL SUPERMARKET?**

3
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10

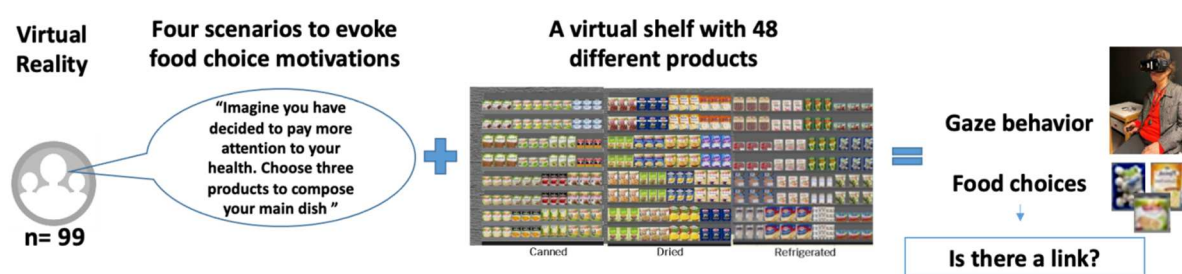
11 **Abstract:**

12 Eye-tracking studies [have shown](#) a link between gaze allocation and consumer food choices among
13 food products from the same category. However, in daily life, consumers usually make food choices
14 in more complex environments, with many options. Our study explores the link between gaze
15 behavior and food choices in a virtual supermarket, reproducing a realistic choice situation.

16 Participants (n=99) performed a food-choice task, [based on four scenarios evoking different](#)
17 [motivations \(health, environment, hedonic, and everyday\)](#). Participant gaze behavior was measured
18 [throughout](#). Participants had to choose three products from the 48 available in the virtual
19 supermarket, to create a main dish. To facilitate statistical analysis, the study was designed to include
20 [an equal number \(n=12\) of animal products, pulses, starches, and vegetables, representing four food](#)
21 [groups](#).

22 Product choices had a significantly positive link with fixation duration and significantly depended on
23 the scenario and food group. The link between fixation duration and choices was more complex than
24 expected. We identified three distinctive patterns, depending on product and scenario: (i) products
25 were briefly fixated but frequently chosen (e.g., vegetables in the health scenario); (ii) products were
26 fixated for longer but rarely chosen (e.g., pulses in the hedonic scenario); or (iii) fixation was similar
27 but choice differed across food groups. The motivation of choice related to each scenario had a clear
28 influence on the choice of products from specific food groups.

29 **Graphical abstract:**



30

31 **Keywords:** food choice; gaze behavior; Virtual reality (VR); [Generalized Linear Mixed Model \(GLMM\)](#);
32 food motivations; consumers.

33 1. Introduction

34 Previous eye-tracking studies have shown a link between gaze allocation and consumer food
35 choices (Danner et al., 2016; Gere et al., 2020; van der Laan et al., 2015; Vu et al., 2018). Some
36 authors have suggested that the product first fixated would be chosen (Duerschmid & Danner,
37 2018), but there is no consensus on such a result. Other authors have found that consumer food
38 choices were not always consistent with their first fixation, or even that the first fixation **did not**
39 **influence** choice (Gere et al., 2020; van der Laan et al., 2015). These authors suggest that the location
40 of the first fixation could be driven by visually salient products that attract the gaze, but that this
41 effect does not translate into the consumer's final choice. Instead, these studies found that product
42 choice was more probably driven by other fixation criteria. Indeed, when a product was chosen, it
43 had received a higher number of fixations and a longer fixation duration (Gere et al., 2020). Other
44 studies found that participants in an eye-tracking study increased their number of fixations and total
45 fixation duration when they had to choose a food product during the experiment (Danner et al.,
46 2016). It should be noted that most of the studies were performed for a specific food product or
47 category, and participants were presented with six to eight different choice sets, each composed of
48 four images from the same food product category (i.e., apple, beer, bread, chocolate, instant soup,
49 salad, sausage, or soft drink). Participants were asked to look at each image set and to choose the
50 product most appealing to them within each category (Danner et al., 2016; Gere et al., 2020).

51 However, in daily life, consumer food choices are made in complex environments, such as
52 grocery stores and supermarkets, which offer far more diversity. In these complex situations of
53 choice, a much greater number of options is available, and many factors **can influence consumers'**
54 **choices. Attention is primarily captured by physical characteristics of stimuli from the environment**
55 **(e.g., image saliency, shape, color, number of images, etc.), related to bottom-up processes.**
56 **However, with top-down processes, consumers can also "decide" to pay attention to specific**
57 **products (e.g., goal-driven attention, task instruction, individual preference, etc; Orquin & Mueller**
58 **Loose, 2013). Both processes influence final food choices.** This was evidenced in an eye-tracking
59 study carried out in a real supermarket, in which participants were instructed to do their regular
60 shopping, and buy a food item from the pasta, cereal, and yogurt categories. The authors found that
61 the gaze behavior of participants was influenced **by the characteristics of the products** (features and
62 attributes of a product presented to consumers) and **top-down processes** (e.g., related to individual
63 interests), highlighting the interaction between visual saliency and individual goals and preferences
64 (Gidlöf et al., 2017). In that experiment, another interesting result was that visual attention was the
65 most important predictor of choice of a product within the food categories studied, **obtaining similar**
66 **results to previous studies, but in a more realistic setting.** Other authors have highlighted the
67 influence of top-down process on food choices. For instance, local products are bought to support
68 the local community (Memery et al., 2015), while organic foods are chosen for health motivations
69 (Magnusson et al., 2003). So, under the instruction "ordinary shopping", participants may include
70 different drivers of choice that finally lead them to select a product.

71 Another component of the complexity of food choice that should be taken into account in
72 experiments is that food choices are generally goal-driven. When asked to choose one item per
73 product category, as in the study by Gidlöf et al. (2017), participants may make choices
74 independently from one another. When choosing foods to prepare a meal, however, the factors
75 underlying food choices may be even more complex, as they involve the creation of a dish. A dish is

76 the combination of different food items on a plate, potentially eaten with other people (de Boer &
77 Aiking, 2019), and its composition may take into consideration many different aspects (such as
78 sensory properties, familiarity, nutritional content, health, etc.). When preparing a dish, products
79 from different food groups are associated, and the choices are interrelated. A previous study showed
80 that, for French people, a main dish generally comprises a meat product, together with a starch and a
81 vegetable (Melendrez-Ruiz et al., 2019). This result led us to wonder whether the relationship
82 between gaze behavior and food choice would be similar in the context of planning a main dish,
83 where complex food motivations are involved. To study this relationship, a realistic experimental
84 setup is necessary to reproduce as closely as possible the true complexity of bottom-up and top-
85 down processes.

86 Conducting a study in a real-life retail environment, such as a supermarket, is a tricky
87 procedure, with many constraints (e.g., negotiating an agreement between researchers and store
88 managers, maintaining some control over the many possible environmental cues, etc.). To overcome
89 these issues, Virtual Reality (VR) can be used to control the environment for each participant, while
90 creating a higher ecological validity than in a laboratory setting (Hartmann & Siegrist, 2019). [Since](#)
91 [the early 2000s](#), virtual supermarkets have been developed to understand consumer food choices
92 and purchases, and are now considered to be valid tools to observe consumer behavior. The results
93 obtained with VR are comparable to those obtained in real-life store settings (Pizzi et al., 2019;
94 Siegrist et al., 2019; van Herpen et al., 2016; Waterlander et al., 2011; Waterlander et al., 2015). In
95 the present study, VR was used to mimic a supermarket, thus allowing us to observe consumer
96 behavior in a realistic food-choice environment. We combined VR with an eye-tracking device to
97 better understand consumer behavior in this shopping environment, [as previously tested by Meißner](#)
98 [and colleagues \(2017\)](#).

99 This study [was designed](#) to understand the link between gaze behavior (i.e., fixation duration and
100 number of fixations) and food group choices made by participants in a virtual supermarket, when
101 exposed to scenarios evoking different food motivations to create a main dish. [Our hypothesis was](#)
102 [that, in a complex environment of choice, the relationship between gaze behavior and food choice](#)
103 [would not be the same for all products, and would also depend on parameters extrinsic to the](#)
104 [products \(e.g., the situational motivation of choice\)](#). We sought to [investigate](#): (i) whether there is a
105 relationship between gaze behavior and food group choices when planning a main dish under
106 different food motivation scenarios; (ii) [if such a relationship is confirmed, whether gazing at a](#)
107 [product increases or decreases the choice of this product, and the strength of the relationship](#).

108

109 **2. Materials and methods**

110 **2.1. Recruitment**

111 Participants (N = 120, aged between 20 and 65) were recruited from the Chemosens
112 Platform's PanelSens database. This database complies with national data protection guidelines and
113 has been examined by French National authorities (Commission Nationale Informatique et Libertés –
114 CNIL – 135 n = 1.148.039). The study was conducted in accordance with the Declaration of Helsinki
115 and was approved by the local ethical committee of INSERM N°18-506 (Institutional Review Board
116 INSERM or CEEI, IRB00003888, IORG0003254, FWA00005831).

117 The inclusion criteria for the study were to be resident in Dijon, to read, write, and speak
118 French fluently, and to buy food in a supermarket at least once a month. The exclusion criteria were
119 to have visual problems, to need thick eyeglasses with strong corrective lenses, to be prone to
120 dizziness, or to follow a restrictive food diet (e.g., vegetarian, vegan, without gluten, without lactose,
121 without pork, etc.).

122 Participants were invited to join the study under the pretext of participation in a virtual
123 reality (VR) experiment. They were not informed that their gaze toward products was being
124 recorded, in order to avoid bias by focusing attention on their gaze behavior. At the end of the study,
125 an investigation questionnaire was used to confirm that participants had not understood the real
126 purpose of the study. Once participants had completed this questionnaire, they were fully debriefed
127 about the true objective of the study and received a €20 voucher.

128 Twenty-one participants were excluded from the study after data collection. For nineteen of
129 them, a technical problem had prevented data from being correctly recorded. One participant did
130 not follow the instructions correctly, and one participant had guessed the real aim of the study. Table
131 1 shows the characteristics of the 99 participants finally included in the study.

132 **Table 1.** Distribution of participants in the study by age range and gender.

Age	Women	Men	Total
20-35	16	14	30
36-50	21	18	39
51-65	14	16	30
Total	51	48	99

133

134 **2.2. Virtual reality (VR) set-up**

135 The VR set-up consisted of a Gear VR headset powered by Oculus, using a Samsung Galaxy S8
136 cellphone. A Samsung hand controller was connected via Bluetooth. The field of view in the headset
137 was 101°, with an image resolution of 1480 x 1440 for each eye. For eye-tracking data, an innovative
138 technique called “VR tracking” was used in this study. It differs from classical “eye” or “head”
139 tracking, in that it uses a point at the center of the screen to catch the attention of participants,
140 allowing them to interact with the environment. This approach is similar to that used in video games:
141 the point is always at the center of the screen, and this gaze pointer is managed by the movement of
142 the participant’s head. The field of vision of participants wearing the headset is more restricted than
143 usual (60°), thus naturally making respondents move their heads more. This system does not record
144 the xy coordinates (as conventional eye-trackers do), but the objects (products) that will be identified
145 as an area of interest. With this technology, not only were we able to track the central point but also
146 a certain area around that point, so that it reflects what the eye usually “catches” when looking at a
147 shelf. A specific application was created to record the virtual eye-tracking data. Further information
148 regarding the technical aspects are reported elsewhere (Melendrez-Ruiz et al., 2021).

149

150 **2.3. Construction of the shelf in the virtual supermarket**

151 All products presented in this study are real brands commonly found in French supermarkets.
 152 They were photographed and then integrated into the virtual supermarket using a specific 3D
 153 software program. All indications about expiry date and price were removed. All the products were
 154 presented in multiple exemplars, to fill a shelf seemingly as large as a real-life supermarket shelf.

155 The shelf was constructed by grouping in the same visual space products commonly found in
 156 three specific areas of French supermarkets (i.e., dried, canned, and refrigerated fresh products).
 157 Each type of product was in a specific zone of the virtual shelf: the left part of the shelf was
 158 dedicated to canned products, the dried products were presented in the center, and the refrigerated
 159 fresh products were on the right (Figure 1). The three zones were presented in this order to all the
 160 participants, but the distribution of products within each zone was different across participants (for
 161 further details, see (Melendrez-Ruiz et al., 2021). There were 48 different food products on the shelf,
 162 with an equal number (n=12) of animal-based products, pulses, starches, and vegetables. The notion
 163 of food groups was never presented to participants, but the study was designed to take into account
 164 these four food groups.

165



166 **Figure 1.** Example of display on the shelf, from left to right: canned, dried, and refrigerated
 167 shelves.
 168
 169

170 **2.4. Use of scenarios to evoke food-choice motivations**

171 Four scenarios were created to evoke four particular motivations under which participants
 172 were invited to make food choices in the virtual supermarket (Table 2). The order in which scenarios
 173 were presented was balanced across participants.

174

175 **Table 2.** Scenarios used to evoke a motivation for choice

Scenario Title*	Script	To Represent
Everyday	Imagine you have decided to do your daily grocery shopping in this supermarket. Choose three products available on these shelves to compose your main dish	The control condition
Health	Imagine you have decided to pay more attention to your	Taking health

	health. Choose three products available on these shelves to compose your main dish	issues into consideration
Environment	Imagine you have decided to pay more attention to preserving the environment. Choose three products available on these shelves to compose your main dish	Taking environmental impact into consideration
Hedonic	Imagine you have decided to pay more attention to what you enjoy. Choose three products available on these shelves to compose your main dish	The pleasure of eating

176 * The titles of the scenarios were not mentioned to participants. They will only be used to refer to
177 the scenarios in this paper.

178

179 2.5. Organization of the session

180 The participants came to the laboratory for one session that lasted about 15 minutes. A
181 researcher received one participant at a time, in a neutral room of the laboratory. Before starting the
182 study, participants signed a consent form. At the beginning of each session, a brief explanation was
183 given regarding the material to be used (the headset and the hand controller). The researcher helped
184 the participant to put on and adjust the headset. Participants were seated in a chair throughout the
185 experiment. Once the participants were ready, they were asked to read aloud the instructions that
186 appeared in the virtual headset, to ensure that they carefully read and understood all the
187 instructions.

188 The session was divided into two parts: a training phase (before starting the measurements),
189 and a food-choice task. The training phase was necessary to teach participants how to use the
190 controller, to move around the virtual environment, to pick up products from the virtual shelf, and to
191 put them in the shopping cart. The virtual shelf used for this training phase contained hair and body
192 care products, with no brands or names.

193 *Food-choice task*

194 Participants remained connected to the VR set-up, in front of a shelf. The general instruction
195 was to project themselves in a shopping context: "Imagine you are doing your grocery shopping in
196 this supermarket, to prepare a meal that you would eat in your usual environment, at home on a
197 weekday". The first scenario was then presented on the screen, to evoke a motivation of choice.
198 Participants had to observe the products displayed in front of them, and then choose three food
199 products to compose a main dish, while taking into consideration the motivation evoked by the
200 scenarios listed in Table 2. Participants were free to choose whatever three products they wanted
201 from among the 48 products presented, with no indication of the food group that a given product
202 belonged to. No mention was made of food groups to the participants. Once they had identified the
203 product they wanted to choose, they used the hand controller to "grasp" the product that they were
204 looking at. Participants were asked to validate their choice with the hand controller, which
205 automatically placed the chosen product in the shopping cart. Once a participant had chosen three
206 products to compose the first main dish, there was a pause of 10 seconds in front of a neutral
207 environment (gray background) before a new scenario was presented. For a given participant, the

208 same shelf arrangement was used for each scenario. Each participant had to choose three food
209 products for each of the four scenarios. Once they had finished this task, the session was over, and
210 they were instructed to remove the headset and give it back to the researcher.
211

212 **2.6. Measures**

213 We obtained two types of behavioral measurement: implicit measures (data collected by
214 eye-tracking), and explicit measures (triplet of products selected). Both measures were recorded
215 continuously during the food-choice task, in each of the four scenarios.

216 For the eye-tracking measures, each product displayed on the shelf was defined as an area of
217 interest (AOI). The shelf contained forty-eight AOIs. For the analysis, each AOI was sorted into a food
218 group (i.e., pulses, starches, animal-based products, or vegetables).

219 The following measures were obtained for each participant:

- 220 • Total fixation duration (DuF): the sum of all fixation durations within an AOI (seconds).
- 221 • Total number of fixations (NbF): number of fixations within an AOI (frequency).

222

223 Gazes shorter than 200 ms were not considered as fixations (Widdel, 1984). A fixation
224 duration was calculated when participants gazed at the same AOI at least two consecutive times, for
225 a total period of 200 ms.

226

227 The frequencies of choice for each product, in each scenario, were calculated from the data
228 obtained during the food-choice task.

229 **2.7. Statistical analysis**

230 **2.7.1. Descriptive analysis**

231 First, the results from the food-choice task and gaze behavior were studied independently. Food
232 choices were descriptively analyzed using a mosaic plot, in which the area of boxes in the plot is
233 proportional to the cell frequencies of the contingency table. To analyze eye-tracking data, two
234 boxplots were constructed to display distribution for fixation duration and for the number of
235 fixations. A Spearman's rank-order correlation was then carried out to evaluate the relationship
236 between the two eye-tracking measures.

237 **2.7.2. Statistical analysis: differences across scenarios among food choices and gaze** 238 **behavior**

239 To compare food choices in each scenario, we calculated the frequency of choice for each food group
240 in the four different scenarios. We performed four different Friedman tests (one per scenario),
241 followed by multiple pairwise comparisons, and a two-tailed Nemenyi test (Hollander et al., 2014).
242 The Friedman test is a nonparametric statistical procedure designed to compare more than two
243 samples that are related (Corder & Foreman, 2014).

244 For fixation duration, we performed four one-way repeated-measure ANOVAS (one per scenario),
245 with total fixation duration as the dependent variable, AOI (food groups) as the **fixed factor**, and
246 participants as a **random factor**. The ANOVA was applied after checking that (i) observations were
247 independent (or, more precisely, independent and identically distributed), (ii) the variables followed

248 a multivariate normal distribution in the population (this assumption is not necessary if the sample
249 size ≥ 25), and (iii) sphericity was respected. When applicable, multiple pairwise comparisons were
250 carried out with a Tukey test.

251 **2.7.3. A model to explain the relation between gaze behavior and food choices**

252 Generalized linear models (GLMs) represent a class of fixed effects regression models for different
253 types of dependent variables (e.g., continuous, count, or dichotomous). Linear regression, logistic
254 regression, and Poisson regression are all types of GLMs (Hedeker, 2005). A Generalized Linear
255 Mixed Model (GLMM) includes random effects in addition to the usual fixed effects used in a GLM
256 (Agresti, 2015). Within the GLMM framework, a mixed logistic regression was applied to our data in
257 order to study the relationship between participants' food choices (0/1) and fixation duration. We
258 constructed our model with four fixed effects, Fixation Duration (a continuous variable), Scenario (a
259 categorical variable), Food Group (a categorical variable), and interaction between Scenario and Food
260 Group, and one random effect, Participants (a categorical variable) (Eq. 1). Data points are not
261 independent because they are produced by the same participant. In such cases, the data is
262 considered hierarchical, and statistical models should incorporate the structural features of the data
263 they work upon. With respect to regression modelling, hierarchical structures are incorporated by
264 the notion of random effects.

265 A logistic regression for Y (FoodChoice) can be written as follows:

$$266 \text{logit}(Y) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \gamma X_2 X_3 + B_4 X_4 + \epsilon$$

267 with $X_1 = \text{DuFn}$, $X_2 = \text{Scenario}$, $X_3 = \text{FoodGroup}$, and $X_4 = \text{Participant}$; α is the intercept, $\beta_{1,2,3}, \gamma, B_4$ are
268 the model coefficients, and ϵ is the error term.

269 **Equation 1.** A mathematical formula for the mixed logistic regression was used with our data.

270 Equation 1 can be translated into the following formula in R (Eq.2).

```
271 glmer(Foodchoice ~ DuFn + Scenario * FoodGroup + (1 | Participant),  
272 data = df2, family = binomial, nAGQ = 10,  
273 control = glmerControl(optimizer = bobyqa))
```

274 **Equation 2.** Mixed logistic regression formula used to test the effect of Fixation Duration, Scenario,
275 Food Group, and the interaction between Scenario and Food Group. The `glmer` package (`lme4`
276 library) fits a generalized linear mixed-effects model (GLMM). Both fixed effects and random effects
277 are specified via the model formula.

278 In the model (Eq.2), we found a significant effect of the Scenario*Food Group interaction over
279 participants' food choices (model results and residual graphs are available as supplementary
280 material). This outcome made the interpretation of the individual effect of scenario and food group
281 more difficult because we could not interpret the effect of each factor separately (Scenario and Food
282 Group). We had to cross the different levels for each factor. Thus, we concatenated the Food Group
283 and Scenario variables to run another model with this combination. As observed in Equation 3,
284 fixation duration and the sixteen combinations Scenario - Food Group were entered as fixed effects,
285 with Participants as random effects. For the analysis of the model, the combination Control Scenario
286 and Animal-Based Food Group was considered as reference.

```
287 glmer(Foodchoice ~ DuFn + Combinations + (1 |Participant),  
288 data = df2, family = binomial, nAGQ = 10,  
289 control = glmerControl(optimizer = bobyqa))
```

290 **Equation 3.** Mixed logistic regression R formula used to test the effect of Fixation Duration and the
291 Scenario-Food Group combination.

292 To run the models, the fixation duration was normalized (DuFn) *as suggested by the residual analysis*.
293 The optimizer bobyqa was used to ensure the convergence of the model. The purpose of bobyqa is to
294 minimize a function of many variables by a trust region method that forms quadratic models by
295 interpolation (Powell, 2009). Ten outlier values were identified and validated in the analysis of
296 residuals. The indices of those residuals were obtained to discern the DuFn outlier values and remove
297 them from the data set. An *ANOVA table was retrieved from the model*. To better interpret the
298 Estimate Coefficient obtained in the model, which is on a logit scale, we calculated the Odds Ratios
299 (OR) that correspond to the exponential of the regression coefficient e^x . As the fixation duration is a
300 continuous variable, we did not interpret the value of the Odds Ratio but rather its sign, and also
301 whether it was significantly different from one. Then we calculated the percentage change in the
302 odds using the following formula (Eq. 4).

$$303 \text{Percent Change in the Odds} = (\text{Odds Ratio} - 1) \times 100$$

304 **Equation 4.** Formula to calculate the percentage of change in the odds ratio

305 Finally, to explore whether significant patterns were found in the residuals from the model, we
306 checked Pearson's χ^2 residuals and the Deviance (G2). Before application, we verified and validated
307 all the conditions of application (Harrison et al., 2018).

308 To assess the performance of the model, we created a random training data set using our own data
309 (80% for training and 20% for validation). We tested the model using these data to check the
310 prediction of the model. In addition, we used a confusion matrix to calculate the accuracy, precision,
311 and recall of the model (Ozdemir, 2016).

312 The alpha risk was set at 5% for all hypothesis tests. Calculations used XLSTAT for Windows
313 (Addinsoft, version 2020-1) and RStudio Version 1.2.5042 (RStudio Team, 2020) for both univariate
314 and multivariate analyses. The R-4.0.0 program (R Core Team, 2020) was also used with the following
315 packages: for data manipulation and visualization: “dplyr”(Wickham et al., 2021); “ggplot2”
316 (Wickham, 2009) for boxplots and mosaic plots obtained with the treemap package “treemap”
317 (Tennekes, 2017).

318 For linear mixed-effects models and non-parametric tests: “lmerTest” (Kuznetsova et al., 2017);
319 “lme4” (Bates et al., 2015); “car” (Fox & Weisberg, 2019) calculates type-II or type-III analysis-of-
320 variance tables for model objects produced by lme4; “DHARMA” (Hartig, 2021) uses a simulation-
321 based approach to create readily interpretable scaled (quantile) residuals for fitted (generalized)
322 linear mixed models; “ez” (Lawrence, 2016) was used to perform the Friedman rank-sum test;
323 “PMCMR ” (Pohlert, 2014) was used to calculate pairwise multiple comparisons between mean rank
324 sums; “dfoptim” (Varadhan et al., 2020) was used to provide derivative-free optimization algorithms.
325 These algorithms do not require gradient information and can be used to solve non-smooth

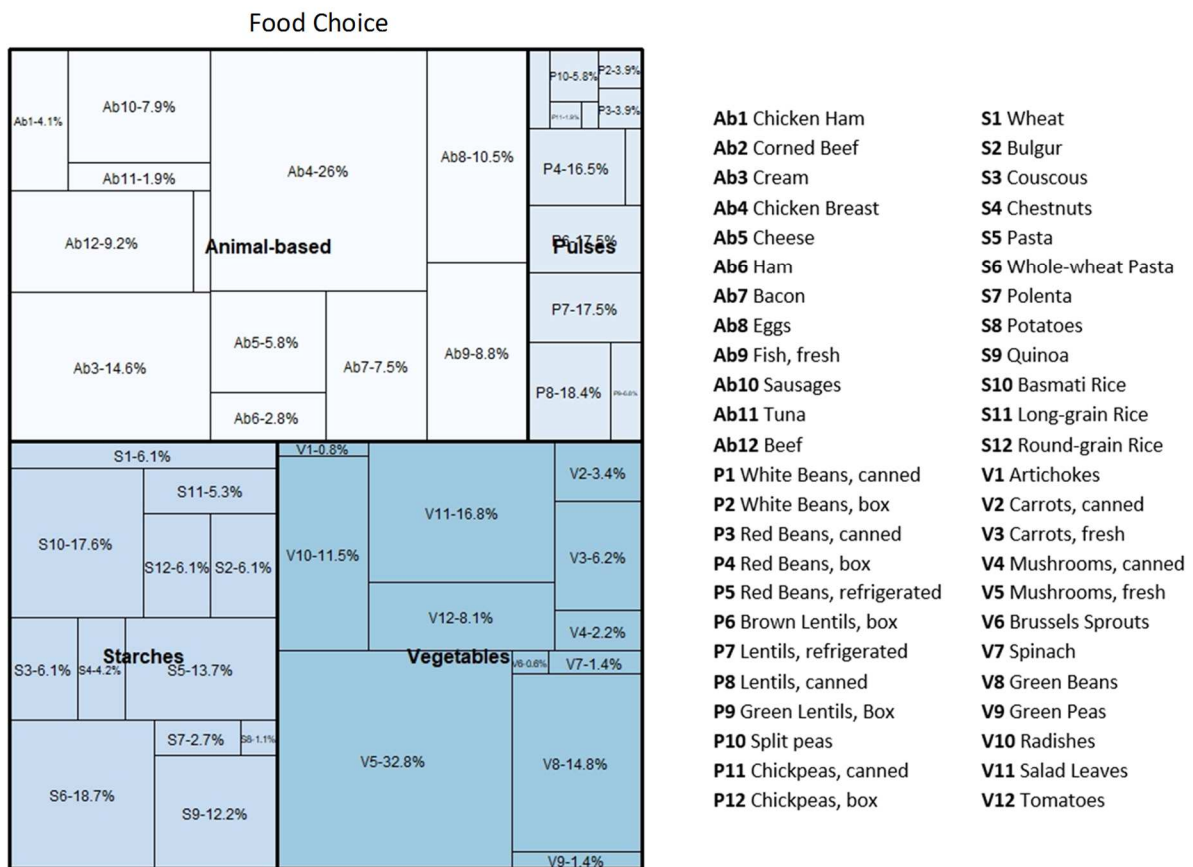
326 optimization problems. The “caret” package (Kuhn, 2020) contains functions to streamline the model
 327 training process for complex regression and classification problems.

328 **3. Results**

329 3.1. Descriptive analyses

330 3.1.1. Food choice per scenario

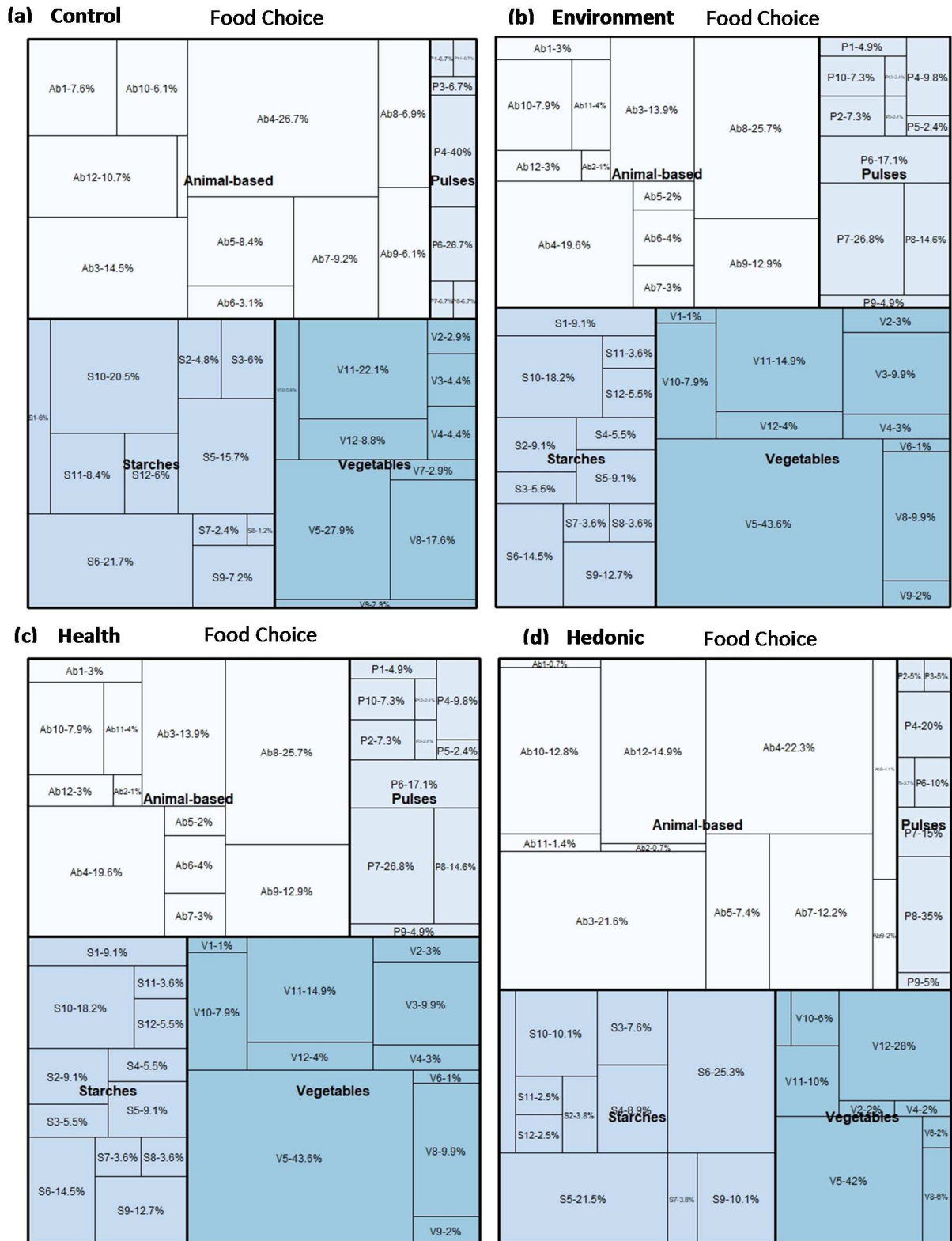
331 Figure 2 represents food choices with a mosaic plot taking all scenarios together: a greater
 332 proportion of the choice was toward animal food products (39%), followed by vegetables (30%),
 333 starches (22%), and pulses (9%). The products that were most often chosen for each food group were
 334 chicken breast, fresh mushrooms, whole-wheat pasta, and canned lentils, respectively.



335
 336 **Figure 2.** The mosaic plot of food choices over all scenarios and a list of the products. Note that some
 337 tiles have no labels. The text labels are not shown when they cannot fit within a tile without being
 338 shrunk below a minimum size, by default 4 points.

339 As shown in Figure 3, in the control condition (3a), participants chose mainly animal products (44%),
 340 followed by starches (28%), vegetables (23%), and finally pulses (5%). Very similar choices were made
 341 in the hedonic scenario (3d), where animal-based products were most often chosen (50%), followed
 342 by starches (27%), vegetables (17%), and pulses (7%). In the environment scenario (3b), both
 343 vegetables and animal products were mostly chosen, in equal proportions (34%), followed by
 344 starches (19%), and pulses (13%). Finally, in the health scenario (3c), vegetables were most often
 345 chosen (47%), followed by animal products (29%), starches (15%), and pulses (9%). When the choices

346 of a food group decreased from one scenario to another, it did not necessarily mean that the choice
347 of all the foods of this group decreased. Rather, it could result from a different distribution of choices
348 for one food in particular, since specific products chosen within each food group changed in relation
349 to the scenario. The most salient example was for the animal-based food group, with a frequent
350 choice of chicken in the control scenario and a frequent choice of eggs in the environment scenario.



351
 352 **Figure 3.** Mosaic plots for the number of choices in (a) control condition, (b) environment, (c) health,
 353 and (d) hedonic scenarios. Note that some tiles have no labels. The text labels are hidden when they
 354 cannot fit within a tile without being shrunk below a minimum size (by default 4 points). **Ab1** Chicken
 355 Ham; **Ab2** Corned Beef; **Ab3** Cream; **Ab4** Chicken Breast; **Ab5** Cheese; **Ab6** Ham; **Ab7** Bacon; **Ab8** Eggs; **Ab9** Fish, fresh;
 356 **Ab10** Sausages; **Ab11** Tuna; **Ab12** Beef; **P1** White Beans, canned; **P2** White Beans, box; **P3** Red Beans, canned; **P4** Red

357 Beans, box; **P5** Red Beans, refrigerated; **P6** Brown Lentils, box; **P7** Lentils, refrigerated; **P8** Lentils, canned; **P9** Green Lentils,
 358 Box; **P10** Split peas; **P11** Chickpeas, canned; **P12** Chickpeas, box; **S1** Wheat; **S2** Bulgur; **S3** Couscous; **S4** Chestnuts; **S5** Pasta;
 359 **S6** Whole-wheat Pasta; **S7** Polenta; **S8** Potatoes; **S9** Quinoa; **S10** Basmati Rice; **S11** Long-grain Rice; **S12** Round-grain Rice;
 360 **V1** Artichokes; **V2** Carrots, canned; **V3** Carrots, fresh; **V4** Mushrooms, canned; **V5** Mushrooms, fresh; **V6** Brussels Sprouts;
 361 **V7** Spinach; **V8** Green Beans; **V9** Green Peas; **V10** Radishes; **V11** Salad Leaves; **V12** Tomatoes.

362

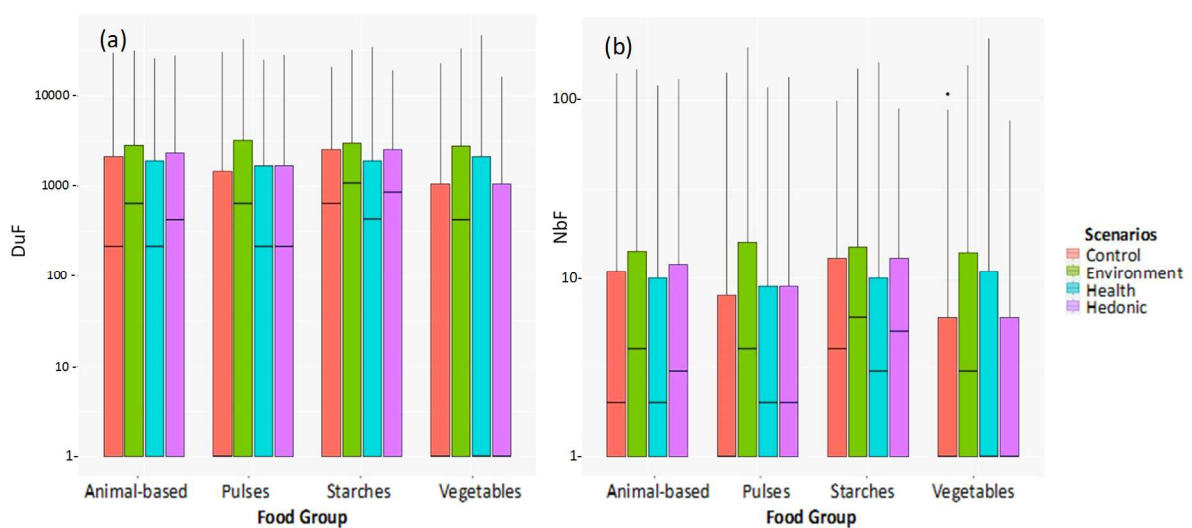
363 To identify any statistical difference between the frequency of choice of each food group across
 364 scenarios, we performed a Friedman test for each food group (4 in total), followed by multiple
 365 pairwise comparisons (two-tailed Nemenyi test). We found that consumers chose animal-based
 366 products ($p < 0.0001$) and starches ($p < 0.0001$) significantly more often in the everyday and hedonic
 367 scenarios than in the health and environment scenarios. By contrast, vegetables ($p < 0.0001$) were
 368 chosen significantly more often in the health and environment scenarios than in the hedonic and
 369 everyday scenarios. The pulse food group was chosen significantly more often in the environment
 370 scenario than in the everyday scenario. A graph representing these results is available in the
 371 supplementary material (Supplemental Figure B).

372 The mean time spent by consumers to choose three products per scenario was 62.5 seconds in the
 373 everyday scenario, 67.8 seconds in the health scenario, 90.4 seconds in the environment scenario,
 374 and 63.1 seconds in the hedonic scenario.

375

376 3.1.2. Gaze behavior per scenario

377 The fixation duration (DuF) and the total number of fixations (NbF) toward each food group were
 378 measured during the food-choice task, across the different scenarios (Figure 4). Similar distributions
 379 were found for both gaze measures. A Spearman correlation between DuF and NbF was calculated. It
 380 was strongly and significantly positive ($r_s = 1.000$, $p = < 0.0001$). Since both measures provided similar
 381 information, to simplify further analyses, we decided to continue with the analysis of fixation
 382 duration alone.



383

384 **Figure 4.** Boxplots for (a) Fixation duration, and (b) Number of fixations, for each food group across
 385 scenarios. For better visualization, the y axis is in a logarithmic scale.

386

387 4. Differences across scenarios for gaze behavior and food choices

388

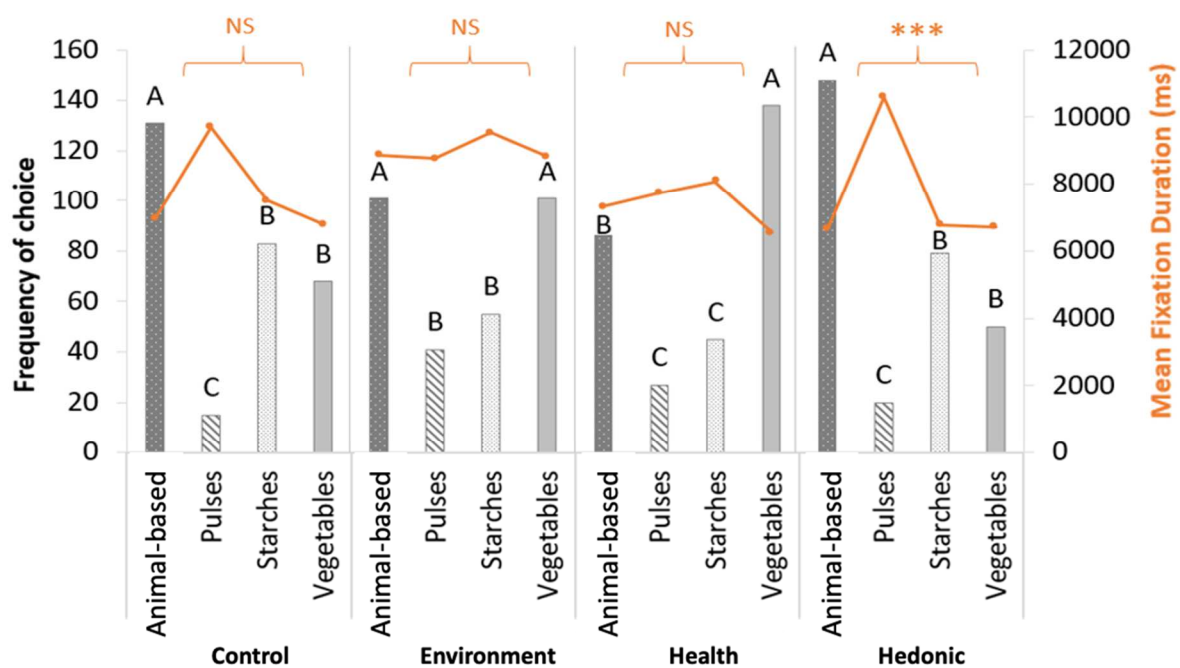
389 4.1. Fixation duration and frequency of choice food group and scenario

390 Regarding fixation duration, three out of the four repeated-measure ANOVAs showed no significant
391 differences between total fixation duration across the four food groups for the control, environment,
392 and health scenarios (Figure 5, right y-axis). The repeated-measure ANOVA for the hedonic scenario
393 showed significant differences between the total fixation duration across food groups ($p= 0.009$).
394 Pairwise comparisons, obtained by a Tukey test, highlighted the fact that participants spent
395 significantly more time looking at products from the pulses food group ($p= 0.001$) compared to all the
396 other food groups.

397 Participants chose products from each food group differently across the four scenarios (Figure 5, left
398 y-axis). In the control ($p < 0.0001$) and hedonic ($p < 0.0001$) scenarios, animal-based products were
399 chosen significantly more often than all the other food groups, and pulses were the products chosen
400 significantly less often. In the environment scenario ($p < 0.0001$), vegetables and animal-based
401 products were chosen significantly more often than pulses and starches. In the health scenario,
402 participants chose vegetables significantly more often than all the other food groups ($p < 0.0001$),
403 while starches and pulses were the products chosen significantly least often.

404 Based on results from the Friedman and the repeated-measure ANOVAs, Figure 5 indicates that
405 pulses were observed for a significantly longer time in the hedonic scenario, but this did not translate
406 into a higher frequency of choice toward these products. On the contrary, animal-based products in
407 this scenario were frequently chosen but the total fixation duration was not as high as for pulses.
408 Even though fixation durations were not different across food products in the other scenarios, as
409 shown in Figure 5, similar tendencies can be seen: food groups that had shorter fixation times were
410 chosen more frequently by participants in the control condition (animal-based), and in the health
411 scenario (vegetables). By contrast, for the environment scenario, the fixation duration was similar
412 across the different food groups.

413



414
 415 **Figure 5.** Frequency of choice (bars) and mean fixation duration (line chart) for each food group
 416 across the four scenarios. Within each scenario, similar letters for different food groups indicate that
 417 the frequency of choice was comparable among food products (two-tailed Nemenyi test; $p < 0.05$).
 418 Orange brackets indicate either no significant effect (NS), or a significant difference (***) in fixation
 419 duration.

420

421 5. Model to explain the relation between gaze behavior and food choices

422 To study the relationship between fixation duration and food choice (0/1), a [mixed logistic regression](#)
 423 was run with binomial data.

424 The ANOVA of the model highlighted a significant effect of fixation duration (F
 425 (1) = 1599.94, $p < 0.001$) and the combination Scenario – Food Group (F (15) = 341.42, $p < 0.001$) over
 426 consumer food choices.

427 As indicated in Table 3, the application of the [mixed logistic regression](#) showed that the effect of
 428 fixation duration on food choices was significant ($\beta = 21.38$, $SE = 0.53$, z (18998) = 39.99, $p < 0.001$). We
 429 found a main effect for the combination of the control scenario with pulses ($\beta = -2.847$, $SE = 0.35$, z
 430 (18998) = -8.022, $p < 0.001$), starches ($\beta = -0.859$, $SE = 0.181$, z (18998) = -4.733, $p < 0.001$), and vegetables
 431 ($\beta = -0.555$, $SE = 0.187$, z (18998) = -2.964, $p < 0.01$). Regarding the odds ratios and their percentage
 432 change, these results suggest that for a unit increase in the choice ([changing from 0 no choice, to 1 a](#)
 433 [choice](#)) of an animal-based product in the control scenario (combination used as reference), the odds
 434 of choosing a product in this control scenario is reduced for pulses (94%), starches (58%), and
 435 vegetables (43%).

436 Each combination of the environment scenario with food groups was significant: animal-based
 437 products ($\beta = -0.898$, $SE = 0.179$, z (18998) = -5.012, $p < 0.001$), pulses ($\beta = -2.348$, $SE = 0.243$, z (18998) = -
 438 9.661, $p < 0.001$), starches ($\beta = -1.563$, $SE = 0.204$, z (18998) = -7.679, $p < 0.001$), and vegetables ($\beta = -0.710$,

439 SE=0.175, z (18998) =-4.057, p<0.001). In this scenario, the odds of choosing any food product were
 440 reduced for pulses (90%), followed by starches (79%), animal-based products (59%), and vegetables
 441 (51%), compared to a unit increase in the choice of an animal-based product in the control scenario.

442 The combination of the health scenario was significant with animal-based products ($\beta=-0.495$,
 443 SE=0.177, z (18998) =-2.793, p<0.01), pulses ($\beta=-2.068$, SE=0.264, z (18998) =-7.838, p<0.001), and
 444 starches ($\beta=-1.456$, SE=0.215, z (18998) =-6.763, p<0.001). In this scenario, the odds of choosing a
 445 product decreased for pulses (87%), starches (77%), and animal-based products (39%), while it non-
 446 significantly increased by 0.25% for vegetables, compared to the choice of animal-based products in
 447 the control scenario.

448 Similarly, a significant effect was found regarding the combination of the hedonic scenario with:
 449 pulses ($\beta=-2.481$, SE=0.309, z (18998) =-8.015, p<0.001), starches ($\beta=-0.729$, SE=0.178, z (18998) =-
 450 4.091, p<0.001), and vegetables ($\beta=-0.697$, SE=0.199, z (18998) =-3.522, p<0.001). In this scenario,
 451 the odds of choosing decreased for pulses (92%), starches (52%), and vegetables (50%), but it
 452 increased notably, by 19%, for animal-based products, compared to the choice of animal-based
 453 products in the control scenario.

454

455 **Table 3.** Results of the [mixed logistic regression](#) to test the effect of Fixation Duration, and the
 456 combination of Scenarios - Food Groups on consumer food choices. The combination control
 457 scenario–animal-based products is used as reference.

Fixed effects Factors	Levels	Estimate (model coefficient)	SE	Z value	Pr(> z)	Odds ratio	Percentage (%) changes
	(Intercept)	-3.475	0.138	-25.258	< 2e-16 ***	0.031	-96.902
Gaze Behavior	DuFn	21.389	0.535	39.999	< 2e-16 ***	1.945e9	N/A
	Control - Pulses	-2.847	0.355	-8.022	1.04e-15 ***	0.058	-94.200
	Control - Starches	-0.859	0.181	-4.733	2.21e-06 ***	0.424	-57.622
	Control - Vegetables	-0.555	0.187	-2.964	0.003034 **	0.574	-42.582
	Environment -Animal- based	-0.898	0.179	-5.012	5.40e-07 ***	0.407	-59.260
Combined Scenario - Food Group	Environment - Pulses	-2.348	0.243	-9.661	< 2e-16 ***	0.096	-90.443
	Environment - Starches	-1.563	0.204	-7.679	1.60e-14 ***	0.209	-79.057
	Environment - Vegetables	-0.710	0.175	-4.057	4.96e-05 ***	0.492	-50.835
	Health - Animal-based	-0.495	0.177	-2.793	0.005223 **	0.610	-39.021
	Health - Pulses	-2.068	0.264	-7.838	4.56e-15 ***	0.126	-87.351
	Health - Starches	-1.456	0.215	-6.763	1.35e-11 ***	0.233	-76.689
	Health - Vegetables	0.003	0.160	0.016	0.987	1.003	0.259
	Hedonic - Animal-based	0.174	0.155	1.122	0.262	1.190	19.008
	Hedonic - Pulses	-2.481	0.309	-8.015	1.10e-15 ***	0.084	-91.631
	Hedonic - Starches	-0.729	0.178	-4.091	4.29e-05 ***	0.482	-51.752
	Hedonic - Vegetables	-0.697	0.199	-3.522	0.000428 ***	0.498	-50.233

458

459

460

461 *5.1.1. Model residuals and performance*

462 Residuals from the model were analyzed to explore whether any significant pattern remained
463 (Figure C in supplementary material). Neither Pearson χ^2 residuals nor Deviance indicated a lack of fit
464 (p values greater than 0.05). Regarding model performance, we tested the model on random data to
465 evaluate whether the model prediction was correct (own dataset with 80% for training and 20% for
466 validation). Results from the confusion matrix highlighted an accuracy of 94%, with a precision of
467 60%, and a recall of 26%. These results support the idea that we have developed a model with a good
468 percentage of performance.

469 **6. Discussion**

470 This study aimed to understand the link between gaze behavior (i.e., fixation duration and
471 number of fixations) and food group choices made by participants in a virtual supermarket when
472 exposed to scenarios evoking different food motivations to create a main dish. In the following
473 discussion, we will first explain the relationship between gaze and food choice, and then we will use
474 the results of our *mixed logistic regression* to predict food choice.

475

476 6.1. What is the relationship between gaze behavior and food choice?

477 From the GLM model, we found that product choices were significantly linked to fixation
478 duration, which is in accordance with previous studies (Danner et al., 2016; Gere et al., 2020; van der
479 Laan et al., 2015; Vu et al., 2018). Furthermore, a cross-dataset study found a positive relationship
480 between gaze and choice, where a longer gaze increased the probability of choice (Thomas et al.,
481 2019). However, with our experimental set-up, we identified three distinct tendencies regarding
482 fixation duration and choice, influenced by the scenario presented and the food group to which a
483 product belongs. Within a given scenario, some food groups were (i) either briefly fixated but very
484 frequently chosen by participants (e.g., vegetables in the health scenario), (ii) fixated for a long time
485 but rarely chosen (e.g., pulses in the hedonic scenario), or (iii) fixation duration was similar but the
486 frequency of choice varied among the food groups. How can we explain this discrepancy between
487 gaze behavior and food choices and their (sometimes) opposite relationships? To answer this
488 question, we first need to understand the potential reasons underlying each behavior.

489 *Why do some products not need to be fixated for a long time to be chosen?*

490 Our results suggest that participants could consider some products as adapted to a specific
491 situation, without much visual attention. It has been found that participants involved in a repetitive
492 task improve their ability to selectively use information and thus decrease their number of fixations
493 (Haider & Frensch, 1999). Learning allows people to become more efficient at a task, thus reducing
494 the total number of fixations needed to take a decision (Orquin et al., 2013). One eye-tracking study
495 highlighted that food purchases in a real supermarket reflect habitual behavior, as most participants
496 tend to choose their usual product directly without much deliberation or comparison (Machín et al.,
497 2020). In our study, participants were probably very used to choosing vegetables for health
498 motivation, and animal-based products for their everyday dish preparation, and for a hedonic
499 motivation. Consequently, they did not need long fixation times toward these products when

500 choosing similar conditions. This result is in accordance with results from a French cohort study,
501 which found that individuals motivated to eat a healthy diet have a higher intake of fruits and
502 vegetables and a lower intake of animal products, particularly meat, cheese, and milk (Ducrot et al.,
503 2017). Animal-based products, especially meat, are shown to have a central place in the construction
504 of French dishes (Melendrez-Ruiz et al., 2019), and are often consumed for hedonic motivations
505 (Ellies-Oury et al., 2019; Poquet et al., 2017). In this sense, these two food groups (vegetables and
506 animal-based) can be considered as staple products within their corresponding scenarios, and thus
507 we could hypothesize that a product typically chosen in a specific context would not need long
508 fixations to be selected.

509 *Why are some products frequently fixated but not necessarily chosen?*

510 It has been suggested that attention plays a role in decision-making. Attention for a specific
511 item among different alternatives would increase the preference for this item and the importance
512 attributed to it (Orquin & Mueller Loose, 2013; Van Loo et al., 2018). This is called the downstream
513 effect. Our results suggest that some products captured visual attention (numerous fixations) but
514 were not frequently selected (i.e., pulses in the hedonic and control scenarios). This result reveals
515 that what consumers look at does not necessarily translate into what they ultimately choose. In the
516 case of pulses, a previous study showed that they suffer from a negative image, are disliked, and are
517 considered difficult to cook by French consumers (Melendrez-Ruiz, Buatois, et al., 2019). Moreover,
518 the consumption of pulses is very low in France, with only 2 kg/person/per year (Agrete, 2019),
519 which could result in some unfamiliarity with these products among French people. It has been
520 shown that previous exposure and other memory-based factors, such as product familiarity, can
521 influence fixation time (Atalay et al., 2012). In accordance with this observation, our results also
522 suggest that less familiarity increased fixation duration. We could also argue that the higher fixation
523 of pulses was caused by the characteristics of the products themselves, such as the color of the
524 packaging, saliency, or location (bottom-up factors). Yet, if this were true, we would find similar
525 tendencies in all scenarios, which was not the case. Another possible explanation could be that
526 participants in our study considered pulses as “inappropriate” products to fulfill the objective of the
527 scenario (motivation). The fact that pulses were fixated in certain situations suggests that they
528 entered into the consideration set as an alternative but, when making the final choice, participants
529 decided to choose other products that seemed more suitable to them for that motivation. This could
530 indicate that even an eye-catching product would be less likely to be selected when it is unfamiliar to
531 the consumer, and when it is considered unsuited to a specific situation.

532

533 *Why do some products have similar fixation durations but different choice frequencies?*

534 Regarding the environment scenario, we did not observe a marked relationship between
535 gaze behavior and food choice, as in the other scenarios previously discussed. On the contrary, we
536 found that fixation duration was similar across all food groups in this scenario, while the choices
537 between food groups differed significantly. The total time taken by participants to make the three
538 food choices in this scenario was about 50% longer than in other scenarios (around 90 seconds
539 compared to an average of 65 seconds for the other scenarios). This time increase might be related
540 to a perceived difficulty to choose the more “eco-friendly” products among all the possible options.
541 Decision difficulty can increase the number of fixations (Orquin & Mueller Loose, 2013). Similarly,

542 multiple comparisons made by participants between alternatives and attributes make greater
543 demands on working memory, which might also increase the total number of fixations needed to
544 make a choice (Orquin & Mueller Loose, 2013). Participants in our study had to reflect thoroughly
545 before making their final choices, thus increasing visual attention toward all food products, but still
546 resulting in the choice of some specific products rather than any others. We suppose from these
547 results that choosing a food product while considering the environment does not seem to be a
548 commonplace motivation of food choice for participants. This factor could represent a challenge
549 when focusing on more sustainable food choices.

550 *Gaze behavior – Food choices: is there a possible gap?*

551 As stated by Van Loo et al., (2018), even if visual attention and food choices are related, the
552 directionality of this relationship remains unclear. With our study, we provide evidence to explain the
553 different types of links between gaze behavior and food choices. We could argue that even if fixation
554 duration has a significant effect on consumer food choices, the relationship is not always direct, as it
555 could depend on the motivation for the food choice, and the food group to which a product belongs.
556 Under certain circumstances, there could perhaps be a gap between gaze behavior and food choices.
557 This gap could be similar to the attitude/or intention–behavior gap, which examines people’s
558 attitudes/intentions to predict future behavior, and explains why people often tend to have a
559 positive attitude or intention that does not translate into a corresponding behavior (Glasman &
560 Albarracín, 2006). In future studies of gaze behavior and food choices, it will be necessary to explore
561 the nature and extent of their relationship, and the processes underlying the influence of gaze
562 allocation on choice. This would provide information about cases where food choice can be predicted
563 by gaze allocation, and thus bridge the gap between gaze behavior and food choices.

564

565 6.2. Predicting food choice from results of [the mixed logistic regression](#) developed here

566 In the development of [our model](#), we used as reference the combination between control
567 scenario and animal-based products, as these represent the basis for the most common everyday
568 meal in the French diet. For people who tend to choose animal-based products (e.g., beef, chicken,
569 or fish), as the main ingredient of their everyday meal, the model shows how choices could be
570 oriented in different situations, when specific motivations are involved. Our model suggests that the
571 more a person chooses animal-based foods for an everyday meal, the lower the probability that this
572 person would choose other products rich in proteins, such as pulses, whatever the food-choice
573 motivation. This could represent a challenge when seeking to reduce meat consumption, as animal-
574 based products often play a central role in western diets. Thus, shifting consumer food choices
575 toward more sustainable products implies a change in consumer habits, which could be quite difficult
576 for meat-eaters. By contrast, we found two scenarios where the odds of participants choosing
577 animal-based products would decrease: first to preserve the environment (-59%), and then for health
578 reasons (-39%). This finding is encouraging, as it demonstrates that the French population is
579 becoming more aware of the environmental impact of meat production. This result could represent
580 an opportunity for dietary changes. The decrease in the choice of meat for health motivation is more
581 surprising, since the consumption of animal-based products, especially meat, has long been
582 considered to contribute to good health (Poquet et al., 2017). While the environment-oriented
583 scenario used in our study referred to long-term altruistic motivations, the health scenarios

584 corresponded more to a self-centered motivation, with long-term consequences (Aschemann-Witzel,
585 2015). A self-centered motivation is usually more efficient in shaping behaviors than an altruistic
586 motivation. These results can thus be considered as a positive signal for the reduction of meat
587 consumption in favor of a more sustainable diet.

588 **6.3 Limitations of the study**

589 Our study also encountered some limitations. We are aware that there might be some
590 differences between VR and real-life gaze behavior of participants. It is true that, in a real
591 supermarket, consumers are usually exposed to a much higher number of options to choose from,
592 which is not exactly the case here. In our study, by comparison with the literature, we increased the
593 number of products and food groups, while being careful to balance as much as possible other
594 variables that may affect consumer gaze behavior (e.g., the same number of products in each food
595 group, color packaging, format, etc). Nevertheless, we were not able to propose as many product
596 references as in real supermarkets. Furthermore, in our study, we discussed the data by food group;
597 some differences might also be driven by food products. For instance, within a food group, there are
598 healthier or less healthy products (red meat vs white meat); this factor could be considered for
599 further studies. Finally, we cannot exclude the possibility that, for a given scenario, participants may
600 have created dishes using food products that they may not usually combine to form a dish, or that
601 they may not necessarily enjoy.

602

603 **7. Conclusions and implications for further studies**

604 Overall, our results show that there is some relation between gaze behavior and choices, but
605 that this link is more complex than expected. In our study, not only fixation duration, but also the
606 motivations (scenario presented), and the food group to which the product belongs influenced
607 participants' food choices. We found three different tendencies for the relationship between gaze
608 and choice, depending on the motivation: (i) a low fixation on a group of products, but a very
609 frequent choice of these products; (ii) frequent fixations but infrequent choice of a group of
610 products; (iii) no relation between fixations and choice, where similar fixation frequencies led to
611 different frequencies of choice. While the first tendency is probably explained by great familiarity
612 with a group of products, the explanations for the second and third tendencies show the important
613 role of working memory, resulting from the difficulty of decision-making in certain situations, or
614 between multiple alternative sets, but also the unfamiliarity and perceived inappropriateness of a
615 product for a particular choice motivation. These results indicate that less working memory is
616 required to select familiar foods due to repeated experience with a product, thus reducing gaze
617 fixations. Further studies will be necessary to explore this potential gap between gaze allocation and
618 food choice, related to familiarity with the product.

619

620 **Funding:** This work was supported by grants from the Carnot institute Qualiment[®], ANR PUNCH
621 (ANR-15-CE21-0014); the Conseil Régional Bourgogne, Franche-Comté (PARI grant) and the FEDER
622 (European Funding for Regional Economic Development).

623 **Acknowledgments:** The authors thank Cecile Schneider for her help in the collection of data, and
624 Carmela Chateau-Smith for English proofreading. We thank H el ene Aubrier and Alexiane Lu, from the
625 Strategir group, for their help.

626 **Conflicts of Interest:** The authors have no conflict of interest to disclose.

627 **References**

628 Agreste. (2019). *Alimentation. Consommation alimentaire (quantit )* (pp. 112–114) [GraphAgri 2019].
629 Le Service statistique minist riel de l’agriculture. [https://agreste.agriculture.gouv.fr/agreste-](https://agreste.agriculture.gouv.fr/agreste-web/download/publication/publie/GraFra2020Chap10.2/Graf2038%20-%20Consommation%20alimentaire.pdf)
630 [web/download/publication/publie/GraFra2020Chap10.2/Graf2038%20-](https://agreste.agriculture.gouv.fr/agreste-web/download/publication/publie/GraFra2020Chap10.2/Graf2038%20-%20Consommation%20alimentaire.pdf)
631 [%20Consommation%20alimentaire.pdf](https://agreste.agriculture.gouv.fr/agreste-web/download/publication/publie/GraFra2020Chap10.2/Graf2038%20-%20Consommation%20alimentaire.pdf)

632 Agresti, A. (2015). *Foundations of linear and generalized linear models*. John Wiley & Sons Inc.

633 Aschemann-Witzel, J. (2015). Consumer perception and trends about health and sustainability:
634 Trade-offs and synergies of two pivotal issues. *Current Opinion in Food Science*, 3, 6–10.
635 <https://doi.org/10.1016/j.cofs.2014.08.002>

636 Atalay, A. S., Bodur, H. O., & Rasolofoarison, D. (2012). Shining in the Center: Central Gaze Cascade
637 Effect on Product Choice. *Journal of Consumer Research*, 39(4), 848–866.
638 <https://doi.org/10.1086/665984>

639 Bates, D., M achler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using
640 lme4. *Journal of Statistical Software*, 67(1). <https://doi.org/10.18637/jss.v067.i01>

641 Corder, G. W., & Foreman, D. I. (2014). *Nonparametric statistics: A step-by-step approach* (Second
642 edition). Wiley.

643 Danner, L., de Antoni, N., Gere, A., Sipos, L., Kov acs, S., & D urrschmid, K. (2016). Make a choice!
644 Visual attention and choice behaviour in multialternative food choice situations. *Acta Alimentaria*,
645 45(4), 515–524. <https://doi.org/10.1556/066.2016.1111>

646 de Boer, J., & Aiking, H. (2019). Strategies towards healthy and sustainable protein consumption: A
647 transition framework at the levels of diets, dishes, and dish ingredients. *Food Quality and Preference*,
648 73, 171–181. <https://doi.org/10.1016/j.foodqual.2018.11.012>

649 Ducrot, P., M ejean, C., Fassier, P., All es, B., Hercberg, S., & P eneau, S. (2017). Associations between
650 motives for dish choice during home-meal preparation and diet quality in French adults: Findings
651 from the NutriNet-Sant  study. *British Journal of Nutrition*, 117(6), 851–861.
652 <https://doi.org/10.1017/S0007114517000666>

653 Duerrschmid, K., & Danner, L. (2018). Eye Tracking in Consumer Research. In G. Ares & P. Varela-
654 Tomasco (Eds.), *Methods in consumer research. Volume 2: Alternative approaches and special*
655 *applications*. Woodhead Publishing, an imprint of Elsevier.

656 Ellies-Oury, M.-P., Lee, A., Jacob, H., & Hocquette, J.-F. (2019). Meat consumption – what French
657 consumers feel about the quality of beef? *Italian Journal of Animal Science*, 18(1), 646–656.
658 <https://doi.org/10.1080/1828051X.2018.1551072>

659 Fox, J., & Weisberg, S. (2019). *An R companion to applied regression* (Third edition). SAGE.

660 Gere, A., Danner, L., Dürschmid, K., Kókai, Z., Sipos, L., Huzsvai, L., & Kovács, S. (2020). Structure of
661 presented stimuli influences gazing behavior and choice. *Food Quality and Preference*, *83*, 103915.
662 <https://doi.org/10.1016/j.foodqual.2020.103915>

663 Gidlöf, K., Anikin, A., Lingonblad, M., & Wallin, A. (2017). Looking is buying. How visual attention and
664 choice are affected by consumer preferences and properties of the supermarket shelf. *Appetite*, *116*,
665 29–38. <https://doi.org/10.1016/j.appet.2017.04.020>

666 Glasman, L. R., & Albarracín, D. (2006). Forming attitudes that predict future behavior: A meta-
667 analysis of the attitude-behavior relation. *Psychological Bulletin*, *132*(5), 778–822.
668 <https://doi.org/10.1037/0033-2909.132.5.778>

669 Haider, H., & Frensch, P. A. (1999). Eye movement during skill acquisition: More evidence for the
670 information-reduction hypothesis. *Journal of Experimental Psychology: Learning, Memory, and*
671 *Cognition*, *25*(1), 172–190. <https://doi.org/10.1037/0278-7393.25.1.172>

672 Harrison, X. A., Donaldson, L., Correa-Cano, M. E., Evans, J., Fisher, D. N., Goodwin, C. E. D., Robinson,
673 B. S., Hodgson, D. J., & Inger, R. (2018). A brief introduction to mixed effects modelling and multi-
674 model inference in ecology. *PeerJ*, *6*, e4794. <https://doi.org/10.7717/peerj.4794>

675 Hartig, F. (2021). *DHARMA: Residual Diagnostics for Hierarchical (Multi-Level / Mixed) Regression*
676 *Models*. [R package version 0.4.1]. <https://CRAN.R-project.org/package=DHARMA>

677 Hartmann, C., & Siegrist, M. (2019). Virtual reality and immersive approaches to contextual food
678 testing. In *CONTEXT: the effects of environment on product design and evaluation*.
679 <http://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN=1908134>

680 Hedeker, D. (2005). Generalized Linear Mixed Models. In B. S. Everitt & D. C. Howell (Eds.),
681 *Encyclopedia of Statistics in Behavioral Science* (p. bsa251). John Wiley & Sons, Ltd.
682 <https://doi.org/10.1002/0470013192.bsa251>

683 Hollander, M., Wolfe, D. A., & Chicken, E. (2014). *Nonparametric statistical methods* (Third edition).
684 John Wiley & Sons, Inc.

685 Kuhn, M. (2020). *caret: Classification and Regression Training*. [R package version 6.0-86].
686 <https://CRAN.R-project.org/package=caret>

687 Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package: Tests in Linear
688 Mixed Effects Models. *Journal of Statistical Software*, *82*(13). <https://doi.org/10.18637/jss.v082.i13>

689 Lawrence, M. A. (2016). *Easy Analysis and Visualization of Factorial Experiments*.
690 <http://github.com/mike-lawrence/ez>

691 Machín, L., Curutchet, M. R., Gugliucci, V., Vitola, A., Otterbring, T., de Alcantara, M., & Ares, G.
692 (2020). The habitual nature of food purchases at the supermarket: Implications for policy making.
693 *Appetite*, *155*, 104844. <https://doi.org/10.1016/j.appet.2020.104844>

694 Magnusson, M. K., Arvola, A., Hursti, U.-K. K., Åberg, L., & Sjöden, P.-O. (2003). Choice of organic
695 foods is related to perceived consequences for human health and to environmentally friendly
696 behaviour. *Appetite*, *40*(2), 109–117. [https://doi.org/10.1016/S0195-6663\(03\)00002-3](https://doi.org/10.1016/S0195-6663(03)00002-3)

697 Meißner, M., Pfeiffer, J., Pfeiffer, T., & Oppewal, H. (2017). Combining virtual reality and mobile eye
698 tracking to provide a naturalistic experimental environment for shopper research. *Journal of Business*
699 *Research*. <https://doi.org/10.1016/j.jbusres.2017.09.028>

700 Melendrez-Ruiz, J., Buatois, Q., Chambaron, S., Monnery-Patris, S., & Arvisenet, G. (2019). French
701 consumers know the benefits of pulses, but do not choose them: An exploratory study combining
702 indirect and direct approaches. *Appetite*, *141*, 104311. <https://doi.org/10.1016/j.appet.2019.06.003>

703 Melendrez-Ruiz, J., Chambaron, S., Buatois, Q., Monnery-Patris, S., & Arvisenet, G. (2019). A central
704 place for meat, but what about pulses? Studying French consumers' representations of main dish
705 structure, using an indirect approach. *Food Research International*, *123*, 790–800.
706 <https://doi.org/10.1016/j.foodres.2019.06.004>

707 Melendrez-Ruiz, J., Goisbault, I., Charrier, J.-C., Pagnat, K., Dujourdy, L., Arvisenet, G., & Chambaron,
708 S. (2021). An exploratory study combining eye-tracking and virtual reality: Are pulses good “eye-
709 catchers” in virtual supermarket shelves? *Frontiers in Virtual Reality*.

710 Memery, J., Angell, R., Megicks, P., & Lindgreen, A. (2015). Unpicking motives to purchase locally-
711 produced food: Analysis of direct and moderation effects. *European Journal of Marketing*, *49*(7/8),
712 1207–1233. <https://doi.org/10.1108/EJM-02-2014-0075>

713 Orquin, J. L., Bagger, M. P., & Mueller Loose, S. (2013). Learning affects top down and bottom up
714 modulation of eye movements in decision making. *Judgment and Decision Making*, *8*(6), 700–716.
715 Scopus.

716 Orquin, J. L., & Mueller Loose, S. (2013). Attention and choice: A review on eye movements in
717 decision making. *Acta Psychologica*, *144*(1), 190–206. <https://doi.org/10.1016/j.actpsy.2013.06.003>

718 Ozdemir, S. (2016). *Principles of Data Science*.
719 <http://sbiproxy.uqac.ca/login?url=https://international.scholarvox.com/book/88843515>

720 Pizzi, G., Scarpi, D., Pichierri, M., & Vannucci, V. (2019). Virtual reality, real reactions?: Comparing
721 consumers' perceptions and shopping orientation across physical and virtual-reality retail stores.
722 *Computers in Human Behavior*, *96*, 1–12. <https://doi.org/10.1016/j.chb.2019.02.008>

723 Pohlert, T. (2014). *The Pairwise Multiple Comparison of Mean Ranks Package (PMCMR)*, R package.
724 <https://CRAN.R-project.org/package=PMCMR>

725 Poquet, D., Chambaron-Ginhac, S., Issanchou, S., & Monnery-Patris, S. (2017). Interroger les
726 représentations sociales afin d'identifier des leviers en faveur d'un rééquilibrage entre protéines
727 animales et végétales: Approche psychosociale. *Cahiers de Nutrition et de Diététique*, *52*(4), 193–201.
728 <https://doi.org/10.1016/j.cnd.2017.05.002>

729 Powell, M. J. D. (2009). *The BOBYQA algorithm for bound constrained optimization without*
730 *derivatives* (p. 39) [DAMTP 2009/NA06]. Centre for Mathematical Sciences, University of Cambridge,
731 UK. http://www.damtp.cam.ac.uk/user/na/NA_papers/NA2009_06.pdf

732 R Core Team. (2020). *R: A language and environment for statistical computing*. R Foundation for
733 Statistical Computing. <https://www.R-project.org/>

734 RStudio Team. (2020). *RStudio: Integrated Development for R*. RStudio, PBC.
735 <http://www.rstudio.com/>.

736 Siegrist, M., Ung, C.-Y., Zank, M., Marinello, M., Kunz, A., Hartmann, C., & Menozzi, M. (2019).
737 Consumers' food selection behaviors in three-dimensional (3D) virtual reality. *Food Research*
738 *International*, *117*, 50–59. <https://doi.org/10.1016/j.foodres.2018.02.033>

739 Tennekes, M. (2017). *treemap: Treemap visualization*. [R package version 2.4-2]. [https://CRAN.R-](https://CRAN.R-project.org/package=treemap)
740 [project.org/package=treemap](https://CRAN.R-project.org/package=treemap)

741 Thomas, A. W., Molter, F., Krajbich, I., Heekeren, H. R., & Mohr, P. N. C. (2019). Gaze bias differences
742 capture individual choice behaviour. *Nature Human Behaviour*, 3(6), 625–635.
743 <https://doi.org/10.1038/s41562-019-0584-8>

744 van der Laan, L. N., Hooge, I. T. C., de Ridder, D. T. D., Viergever, M. A., & Smeets, P. A. M. (2015). Do
745 you like what you see? The role of first fixation and total fixation duration in consumer choice. *Food*
746 *Quality and Preference*, 39, 46–55. <https://doi.org/10.1016/j.foodqual.2014.06.015>

747 van Herpen, E., van den Broek, E., van Trijp, H. C. M., & Yu, T. (2016). Can a virtual supermarket bring
748 realism into the lab? Comparing shopping behavior using virtual and pictorial store representations
749 to behavior in a physical store. *Appetite*, 107, 196–207. <https://doi.org/10.1016/j.appet.2016.07.033>

750 Van Loo, E. J., Grebitus, C., Nayga, R. M., Verbeke, W., & Roosen, J. (2018). On the Measurement of
751 Consumer Preferences and Food Choice Behavior: The Relation Between Visual Attention and
752 Choices. *Applied Economic Perspectives and Policy*, 40(4), 538–562.
753 <https://doi.org/10.1093/aep/ppy022>

754 Varadhan, R., Borchers, H. W., & Bechard, V. (2020). *dfoptim: Derivative-Free Optimization*. [R
755 package version 2020.10-1]. <https://CRAN.R-project.org/package=dfoptim>

756 Vu, T. M. H., Tu, V. P., & Duerrschmid, K. (2018). Eye-tracking test design influences the relationship
757 between gazing behaviour and evaluation decision. *Die Bodenkultur: Journal of Land Management,*
758 *Food and Environment*, 68(4), 261–270. <https://doi.org/10.1515/boku-2017-0021>

759 Waterlander, W. E., Jiang, Y., Steenhuis, I. H. M., & Ni Mhurchu, C. (2015). Using a 3D Virtual
760 Supermarket to Measure Food Purchase Behavior: A Validation Study. *Journal of Medical Internet*
761 *Research*, 17(4), e107. <https://doi.org/10.2196/jmir.3774>

762 Waterlander, W. E., Scarpa, M., Lentz, D., & Steenhuis, I. H. (2011). The virtual supermarket: An
763 innovative research tool to study consumer food purchasing behaviour. *BMC Public Health*, 11(1),
764 589. <https://doi.org/10.1186/1471-2458-11-589>

765 Wickham, H. (2009). *Ggplot2: Elegant graphics for data analysis*. Springer.

766 Wickham, H., François, R., Henry, L., & Müller, K. (2021). *dplyr: A Grammar of Data Manipulation* [R
767 package version 1.0.5]. <https://CRAN.R-project.org/package=dplyr>

768 Widdel, H. (1984). Operational Problems in Analysing Eye Movements. In *Advances in Psychology*
769 (Vol. 22, pp. 21–29). Elsevier. [https://doi.org/10.1016/S0166-4115\(08\)61814-2](https://doi.org/10.1016/S0166-4115(08)61814-2)

770