“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?

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"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?

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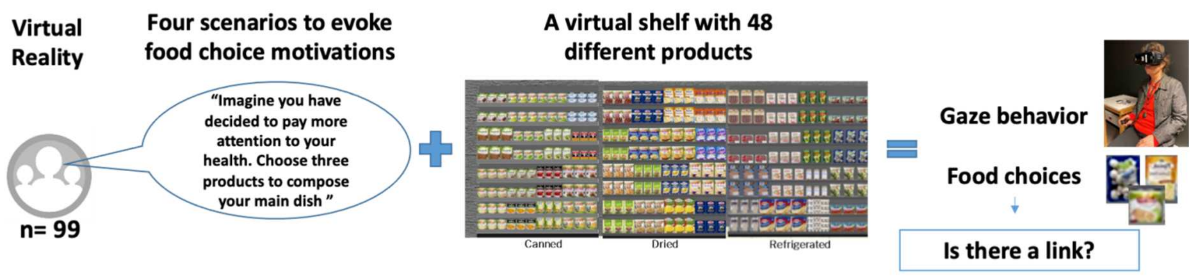
Abstract:

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

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

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

Graphical abstract:



Keywords: food choice; gaze behavior; Virtual reality (VR); Generalized Linear Mixed Model (GLMM); food motivations; consumers.

1. Introduction

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

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

Another component of the complexity of food choice that should be taken into account in experiments is that food choices are generally goal-driven. When asked to choose one item per product category, as in the study by Gidlöf et al. (2017), participants may make choices independently from one another. When choosing foods to prepare a meal, however, the factors underlying food choices may be even more complex, as they involve the creation of a dish. A dish is the combination of different food items on a plate, potentially eaten with other people (de Boer & Aiking, 2019), and its composition may take into consideration many different aspects (such as sensory properties, familiarity, nutritional content, health, etc.). When preparing a dish, products from different food groups are associated, and the choices are interrelated. A previous study showed that, for French people, a main dish generally comprises a meat product, together with a starch and a vegetable (Melendrez-Ruiz et al., 2019). This result led us to wonder whether the relationship between gaze behavior and food choice would be similar in the context of planning a main dish, where complex food motivations are involved. To study this relationship, a realistic experimental setup is necessary to reproduce as closely as possible the true complexity of bottom-up and top-down processes.

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

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

2. Materials and methods

2.1. Recruitment

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

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

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

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

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

2.2. Virtual reality (VR) set-up

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

2.3. Construction of the shelf in the virtual supermarket

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

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

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

2.4. Use of scenarios to evoke food-choice motivations

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

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

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

2.5. Organization of the session

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

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

Food-choice task

Participants remained connected to the VR set-up, in front of a shelf. The general instruction was to project themselves in a shopping context: “Imagine you are doing your grocery shopping in this supermarket, to prepare a meal that you would eat in your usual environment, at home on a weekday”. The first scenario was then presented on the screen, to evoke a motivation of choice. Participants had to observe the products displayed in front of them, and then choose three food products to compose a main dish, while taking into consideration the motivation evoked by the scenarios listed in Table 2. Participants were free to choose whatever three products they wanted from among the 48 products presented, with no indication of the food group that a given product belonged to. No mention was made of food groups to the participants. Once they had identified the product they wanted to choose, they used the hand controller to “grasp” the product that they were looking at. Participants were asked to validate their choice with the hand controller, which automatically placed the chosen product in the shopping cart. Once a participant had chosen three products to compose the first main dish, there was a pause of 10 seconds in front of a neutral environment (gray background) before a new scenario was presented. For a given participant, the same shelf arrangement was used for each scenario. Each participant had to choose three food products for each of the four scenarios. Once they had finished this task, the session was over, and they were instructed to remove the headset and give it back to the researcher.

2.6. Measures

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

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

The following measures were obtained for each participant:

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

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

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

2.7. Statistical analysis

2.7.1. Descriptive analysis

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

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

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

For fixation duration, we performed four one-way repeated-measure ANOVAS (one per scenario), with total fixation duration as the dependent variable, AOI (food groups) as the fixed factor, and participants as a random factor. The ANOVA was applied after checking that (i) observations were independent (or, more precisely, independent and identically distributed), (ii) the variables followed a multivariate normal distribution in the population (this assumption is not necessary if the sample size >= 25), and (iii) sphericity was respected. When applicable, multiple pairwise comparisons were carried out with a Tukey test.

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

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

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

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

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

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

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

$$\begin{gathered}\boldsymbol{glmer(Foodchoice \sim DuFn\ +\ Scenario * FoodGroup\ +\ (1\ |Participant),}\\ \boldsymbol{data = df2, family = binomial, nAGQ = 10,}\\ \boldsymbol{control = glmerControl\ (optimizer =} \text{ bobyqa}))\end{gathered}$$

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

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

$$glmer(Foodchoice \sim DuFn + Combinations + (1 | Participant), data = df2, family = binomial, nAGQ = 10, control = glmerControl\ (optimizer = \text{bobyqa}))$$

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

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

$$Percent\ Change\ in\ the\ Odds = (Odds\ Ratio - 1) \times 100$$

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

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

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

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

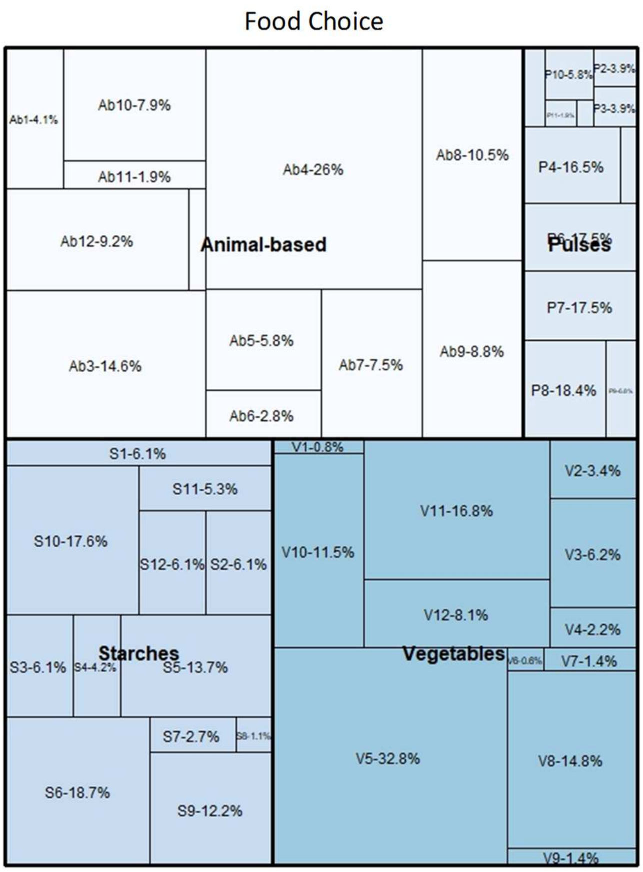
For linear mixed-effects models and non-parametric tests: “lmerTest” (Kuznetsova et al., 2017); “lme4” (Bates et al., 2015); “car” (Fox & Weisberg, 2019) calculates type-II or type-III analysis-of-variance tables for model objects produced by lme4; “DHARMa” (Hartig, 2021) uses a simulation-based approach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

3. Results

3.1. Descriptive analyses

3.1.1. Food choice per scenario

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



Ab1 Chicken Ham
Ab2 Corned Beef
Ab3 Cream
Ab4 Chicken Breast
Ab5 Cheese
Ab6 Ham
Ab7 Bacon
Ab8 Eggs
Ab9 Fish, fresh
Ab10 Sausages
Ab11 Tuna
Ab12 Beef
P1 White Beans, canned
P2 White Beans, box
P3 Red Beans, canned
P4 Red Beans, box
P5 Red Beans, refrigerated
P6 Brown Lentils, box
P7 Lentils, refrigerated
P8 Lentils, canned
P9 Green Lentils, Box
P10 Split peas
P11 Chickpeas, canned
P12 Chickpeas, box

S1 Wheat
S2 Bulgur
S3 Couscous
S4 Chestnuts
S5 Pasta
S6 Whole-wheat Pasta
S7 Polenta
S8 Potatoes
S9 Quinoa
S10 Basmati Rice
S11 Long-grain Rice
S12 Round-grain Rice
V1 Artichokes
V2 Carrots, canned
V3 Carrots, fresh
V4 Mushrooms, canned
V5 Mushrooms, fresh
V6 Brussels Sprouts
V7 Spinach
V8 Green Beans
V9 Green Peas
V10 Radishes
V11 Salad Leaves
V12 Tomatoes

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

As shown in Figure 3, in the control condition (3a), participants chose mainly animal products (44%), followed by starches (28%), vegetables (23%), and finally pulses (5%). Very similar choices were made in the hedonic scenario (3d), where animal-based products were most often chosen (50%), followed by starches (27%), vegetables (17%), and pulses (7%). In the environment scenario (3b), both vegetables and animal products were mostly chosen, in equal proportions (34%), followed by starches (19%), and pulses (13%). Finally, in the health scenario (3c), vegetables were most often chosen (47%), followed by animal products (29%), starches (15%), and pulses (9%). When the choices of a food group decreased from one scenario to another, it did not necessarily mean that the choice of all the foods of this group decreased. Rather, it could result from a different distribution of choices for one food in particular, since specific products chosen within each food group changed in relation to the scenario. The most salient example was for the animal-based food group, with a frequent choice of chicken in the control scenario and a frequent choice of eggs in the environment scenario.

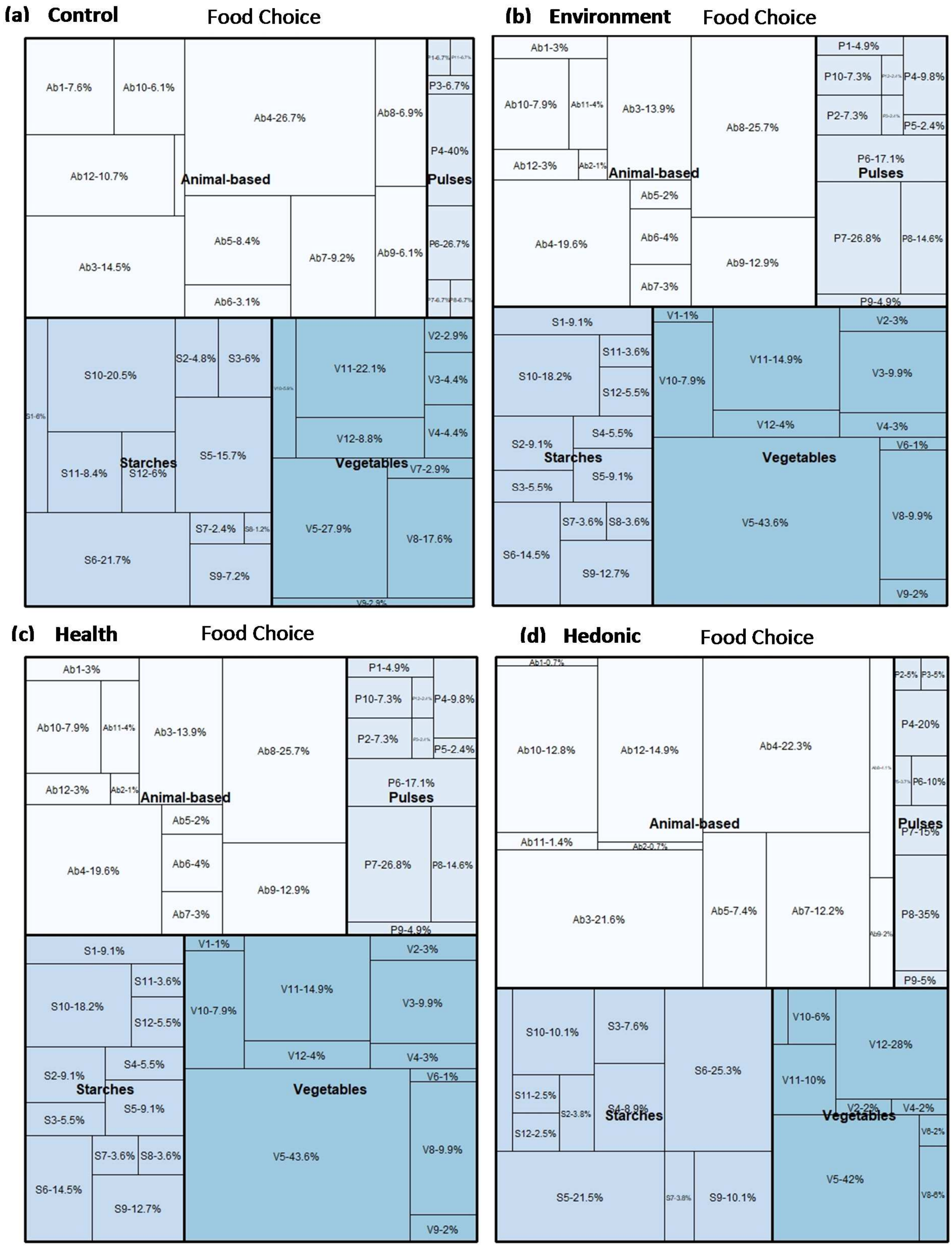


Figure 3. Mosaic plots for the number of choices in (a) control condition, (b) environment, (c) health, and (d) hedonic scenarios. Note that some tiles have no labels. The text labels are hidden when they cannot fit within a tile without being shrunk below a minimum size (by default 4 points). **Ab1**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

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

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

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

3.1.2. Gaze behavior per scenario

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

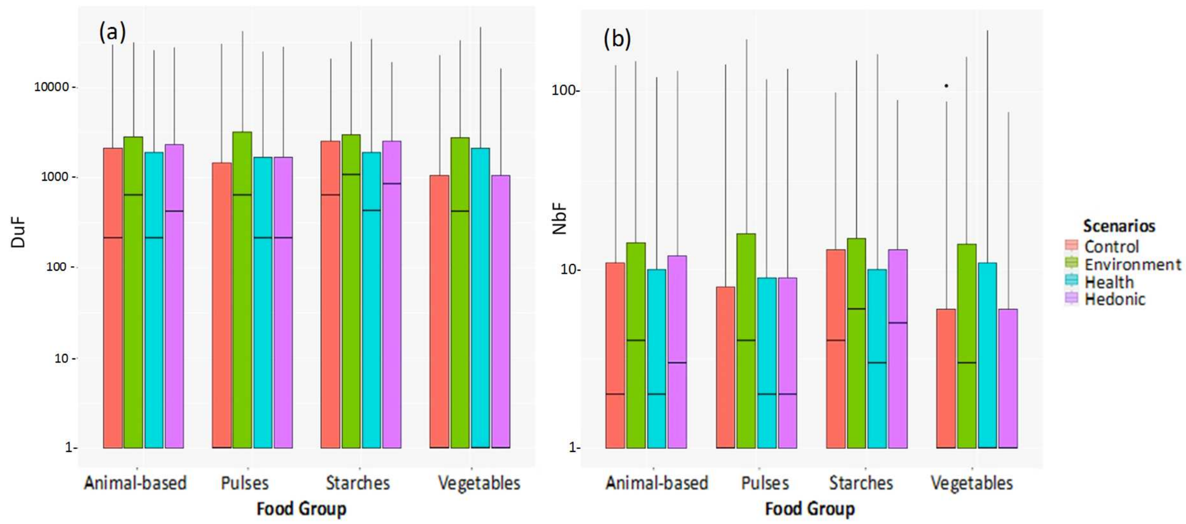


Figure 4. Boxplots for (a) Fixation duration, and (b) Number of fixations, for each food group across scenarios. For better visualization, the y axis is in a logarithmic scale.

4. Differences across scenarios for gaze behavior and food choices

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

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

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

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

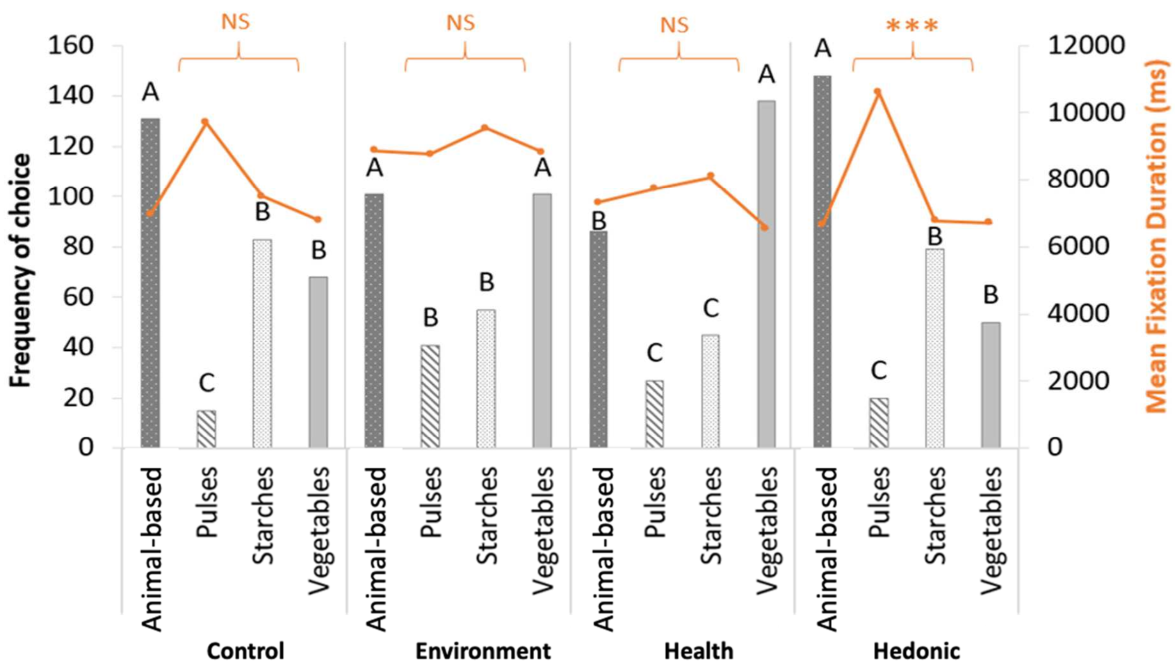


Figure 5. Frequency of choice (bars) and mean fixation duration (line chart) for each food group across the four scenarios. Within each scenario, similar letters for different food groups indicate that the frequency of choice was comparable among food products (two-tailed Nemenyi test; p<0.05). Orange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

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

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

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

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

Each combination of the environment scenario with food groups was significant: animal-based products (β=-0.898, SE=0.179, z (18998) =-5.012, p<0.001), pulses (β=-2.348, SE=0.243, z (18998) =-9.661, p<0.001), starches (β=-1.563, SE=0.204, z (18998) =-7.679, p<0.001), and vegetables (β=-0.710, SE=0.175, z (18998) =-4.057, p<0.001). In this scenario, the odds of choosing any food product were reduced for pulses (90%), followed by starches (79%), animal-based products (59%), and vegetables (51%), compared to a unit increase in the choice of an animal-based product in the control scenario.

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

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

Table 3. Results of the mixed logistic regression to test the effect of Fixation Duration, and the combination of Scenarios - Food Groups on consumer food choices. The combination control 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
Combined Scenario - Food Group	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
	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

5.1.1. Model residuals and performance

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

6. Discussion

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

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

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

Why do some products not need to be fixed for a long time to be chosen?

Our results suggest that participants could consider some products as adapted to a specific situation, without much visual attention. It has been found that participants involved in a repetitive task improve their ability to selectively use information and thus decrease their number of fixations (Haider & Frensch, 1999). Learning allows people to become more efficient at a task, thus reducing the total number of fixations needed to take a decision (Orquin et al., 2013). One eye-tracking study highlighted that food purchases in a real supermarket reflect habitual behavior, as most participants tend to choose their usual product directly without much deliberation or comparison (Machín et al., 2020). In our study, participants were probably very used to choosing vegetables for health motivation, and animal-based products for their everyday dish preparation, and for a hedonic motivation. Consequently, they did not need long fixation times toward these products when choosing similar conditions. This result is in accordance with results from a French cohort study, which found that individuals motivated to eat a healthy diet have a higher intake of fruits and vegetables and a lower intake of animal products, particularly meat, cheese, and milk (Ducrot et al., 2017). Animal-based products, especially meat, are shown to have a central place in the construction of French dishes (Melendrez-Ruiz et al., 2019), and are often consumed for hedonic motivations (Ellies-Oury et al., 2019; Poquet et al., 2017). In this sense, these two food groups (vegetables and animal-based) can be considered as staple products within their corresponding scenarios, and thus we could hypothesize that a product typically chosen in a specific context would not need long fixations to be selected.

Why are some products frequently fixated but not necessarily chosen?

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

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

Regarding the environment scenario, we did not observe a marked relationship between gaze behavior and food choice, as in the other scenarios previously discussed. On the contrary, we found that fixation duration was similar across all food groups in this scenario, while the choices between food groups differed significantly. The total time taken by participants to make the three food choices in this scenario was about 50% longer than in other scenarios (around 90 seconds compared to an average of 65 seconds for the other scenarios). This time increase might be related to a perceived difficulty to choose the more “eco-friendly” products among all the possible options. Decision difficulty can increase the number of fixations (Orquin & Mueller Loose, 2013). Similarly, multiple comparisons made by participants between alternatives and attributes make greater demands on working memory, which might also increase the total number of fixations needed to make a choice (Orquin & Mueller Loose, 2013). Participants in our study had to reflect thoroughly before making their final choices, thus increasing visual attention toward all food products, but still resulting in the choice of some specific products rather than any others. We suppose from these results that choosing a food product while considering the environment does not seem to be a commonplace motivation of food choice for participants. This factor could represent a challenge when focusing on more sustainable food choices.

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

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

6.2. Predicting food choice from results of the mixed logistic regression developed here

In the development of our model, we used as reference the combination between control scenario and animal-based products, as these represent the basis for the most common everyday meal in the French diet. For people who tend to choose animal-based products (e.g., beef, chicken, or fish), as the main ingredient of their everyday meal, the model shows how choices could be oriented in different situations, when specific motivations are involved. Our model suggests that the more a person chooses animal-based foods for an everyday meal, the lower the probability that this person would choose other products rich in proteins, such as pulses, whatever the food-choice motivation. This could represent a challenge when seeking to reduce meat consumption, as animal-based products often play a central role in western diets. Thus, shifting consumer food choices toward more sustainable products implies a change in consumer habits, which could be quite difficult for meat-eaters. By contrast, we found two scenarios where the odds of participants choosing animal-based products would decrease: first to preserve the environment (-59%), and then for health reasons (-39%). This finding is encouraging, as it demonstrates that the French population is becoming more aware of the environmental impact of meat production. This result could represent an opportunity for dietary changes. The decrease in the choice of meat for health motivation is more surprising, since the consumption of animal-based products, especially meat, has long been considered to contribute to good health (Poquet et al., 2017). While the environment-oriented scenario used in our study referred to long-term altruistic motivations, the health scenarios corresponded more to a self-centered motivation, with long-term consequences (Aschemann-Witzel, 2015). A self-centered motivation is usually more efficient in shaping behaviors than an altruistic motivation. These results can thus be considered as a positive signal for the reduction of meat consumption in favor of a more sustainable diet.

6.3 Limitations of the study

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

7. Conclusions and implications for further studies

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

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References

Agreste. (2019). *Alimentation. Consommation alimentaire (quantité)* (pp. 112–114) [GraphAgri 2019]. Le Service statistique ministériel de l'agriculture. https://agreste.agriculture.gouv.fr/agreste-web/download/publication/publie/GraFra2020Chap10.2/Graf2038%20-%20Consommation%20alimentaire.pdf

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

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

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

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

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

Danner, L., de Antoni, N., Gere, A., Sipos, L., Kovács, S., & Dürrschmid, K. (2016). Make a choice! Visual attention and choice behaviour in multialternative food choice situations. *Acta Alimentaria*, *45*(4), 515–524. https://doi.org/10.1556/066.2016.1111

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

Ducrot, P., Méjean, C., Fassier, P., Allès, B., Hercberg, S., & Péneau, S. (2017). Associations between motives for dish choice during home-meal preparation and diet quality in French adults: Findings from the NutriNet-Santé study. *British Journal of Nutrition*, *117*(6), 851–861. https://doi.org/10.1017/S0007114517000666

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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