Using consumption and reward simulations to increase the appeal of plant-based foods

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ABSTRACT

The production of meat is a main contributor to current dangerous levels of greenhouse gas emissions. However, the shift to more plant-based diets is hampered by consumers finding meat-based foods more attractive than plant-based foods. How can plant-based foods best be described to increase their appeal to consumers? Based on the grounded cognition theory of desire, we suggest that descriptions that trigger simulations, or re-experiences, of eating and enjoying a food will increase the attractiveness of a food, compared to descriptions emphasizing ingredients. In Study 1, we first examined the descriptions of ready meals available in four large UK supermarkets (N = 240). We found that the labels of meat-based foods contained more references to eating simulations than vegetarian foods, and slightly more than plant-based foods, and that this varied between supermarkets. In Studies 2 and 3 (N = 170, N = 166, pre-registered), we manipulated the labels of plant-based and meat-based foods to either include eating simulation words or not. We assessed the degree to which participants reported that the description made them think about eating the food (i.e., induced eating simulations), and how attractive they found the food. In Study 2, where either sensory or eating context words were added, we found no differences with control labels. In Study 3, however, where simulation-based labels included sensory, context, and hedonic words, we found that simulation-based descriptions increased eating simulations and attractiveness. Moreover, frequent meat eaters found plant-based foods less attractive, but this was attenuated when plant-based foods were described with simulation-inducing words. We suggest that language that describes rewarding eating experiences can be used to facilitate the shift toward healthy and sustainable diets.

1. Introduction

The production of meat is a main contributor to unsustainable levels of greenhouse gas emissions and environmental degradation. Producing meat, fish, eggs, and dairy uses ca. 83% of the world's farmland, and contributes more than 56% of food's different greenhouse gas emissions, while these foods provide only 37% of all protein and 18% of calories consumed (Poore & Nemecek, 2018). In Europe, 65% of agricultural land is used for livestock, which contributes heavily to environmental degradation through air and water pollution, global warming, biodiversity loss, and soil acidification (Leip et al., 2015). Meat production specifically is the single most important source of methane (Poore & Nemecek, 2018). Compared to plant-based protein sources, such as beans and lentils, the production of beef and other red meat requires 20 times more land and emits 20 times more greenhouse gas emissions per unit of edible protein.

To curb climate change, we need "huge and immediate changes to reduce demand for environmentally unsustainable products" (Marteau, 2017). Specifically, shifting diets toward more plant-based foods is crucial to reduce the environmental impact of food production. Indeed, a recent paper suggested that Western countries would need to reduce beef consumption by 90% and consume five times mores beans and lentils to sustain the planet (Springmann et al., 2018). A change in diet would also have substantial public health benefits, because the consumption of red meat is associated with an increased risk for coronary heart disease, stroke, and colorectal cancer (e.g., Bechthold et al., 2019; Schwingshackl et al., 2018). A recent analysis of 15 commonly consumed foods showed that red meat is not only associated with the

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largest negative impact on the environment; it is also associated with the largest increase in disease risk (Clark, Springmann, Hill, & Tilman, 2019). Thus, shifting consumer behaviour away from meat and towards plant-based foods would have multiple environmental and health benefits (Farchi, De Sario, Lapucci, Davoli, & Michelozzi, 2017).

How can this shift in consumer behaviour be achieved? Meat consumption is guided by nonconscious processes, such as habits and perceived pleasure (Graça, Truninger, Junqueira, & Schmidt, 2019; Rees et al., 2018; Schösler, Boer, & Boersema, 2012). Interventions solely focusing on conscious processes such as knowledge are therefore not likely to lead to major shifts in consumer's meat eating behaviour (see Bianchi, Dorsel, Garnett, Aveyard, & Jebb, 2018, for a review). Instead, interventions should target nonconscious determinants of behaviour (Marteau, 2017), for example through changes in the choice environment, which can affect habits. In line with this approach, increasing the availability of vegetarian and plant-based dishes has been shown to decrease choices of meat in cafeteria settings (Garnett, Balmford, Sandbrook, Pilling, & Marteau, 2019). Similarly, reducing the portion size of meat served also reduced meat consumption (Bianchi, Garnett, Dorsel, Aveyard, & Jebb, 2018), without affecting customer satisfaction (Reinders, Huitink, Dijkstra, Maaskant, & Heijnen, 2017). Recent work has also shown that omnivore consumers, that is, those who typically eat meat in their diets, are more likely to choose vegetarian dishes in restaurants when these are presented in between other dishes on the menu, as compared to in a separate section (Bacon & Krpan, 2018). Similarly, people chose vegetarian dishes more when vegetarian dishes were labelled as "social choices" or "environmentally friendly" choices, compared to when they were labelled as "vegetarian" (Krpan & Houtsma, 2020). These findings suggest that making meat alternatives a regular alternative and making them appear more enjoyable can motivate consumers to choose them.

Here, we take a complementary approach and focus on the language used to label and describe plant-based foods in order to make plant-based meat alternatives more attractive. Most people like eating meat, and enjoyment of meat is one of the main barriers of following a plant-based diet (Corrin & Papadopoulos, 2017; Macdiarmid, Douglas, & Campbell, 2016; Pohjolainen, Vinnari, & Jokinen, 2015). Therefore, to enable a shift to plant-based alternatives, their immediate attractiveness needs to be increased. We examine how this can be achieved for restaurant meals, and for ready-meals, which are a major part of the British food industry (Mahon, Cowan, & McCarthy, 2006). We take the perspective of the grounded cognition theory of desire (Papies, Barsalou, & Rusz, 2020; Papies & Barsalou, 2015) and suggest that if a consumer simulates eating and enjoying a food, this will increase the food's attractiveness. Therefore, describing plant-based foods with labels that induce simulations of eating and enjoying a food should boost their appeal.

The grounded cognition theory of desire aims to explain how motivation for appetitive stimuli, including foods and drinks, arises in the cognitive system (Papies, Best, Gelibter, & Barsalou, 2017; Papies, Barsalou, & Rusz, 2020; Papies & Barsalou, 2015). The theory suggests that every time a person eats a food, this creates a rich, comprehensive memory of this eating episode (a "situated conceptualisation"; Barsalou, 2009). Such episodes include not only information about the taste, texture, and enjoyment of a food, but also information about other internal states (e.g., feeling hungry or satiated, feeling happy, wanting to diet, or feeling socially connected) and external context (e.g., sounds, other objects and people present, occasion, time and location, etc). When the person later encounters a food cue, such as the food itself, a food image or word, or an associated context cue that forms part of the situated conceptualisation (e.g., a brand name, eating location), this can activate other elements of the previously encoded eating memory. The person then simulates, or re-experiences, these other, associated elements (e.g., thoughts about its taste, texture, or pleasure from eating). In other words, such information is not merely cognitively associated, but once activated through associative pathways, non-present elements can

be re-enacted, or simulated, such as the taste, texture, or pleasure of eating a food. This way, the picture of a freshly grilled burger, for example, can trigger a simulation of the action of picking it up to take a bite, of its rich and smokey flavour, its chewy mouthfeel, and the direct reward experienced from eating it. The image can also trigger a simulation of being in a pub with good friends, feeling relaxed on a weekend, and having a sip from a cold drink. Such simulations effortlessly provide useful information about expected taste and enjoyment of a food, and thus support goal-directed behaviour (e.g., going to the pub, ordering a burger). Importantly, the theory suggest that such consumption and reward simulations can also create desire in the absence of hunger, such as when a food image or advertisement activates rewarding food memories that a person would then like to re-experience. In other words, the grounded cognition theory of desire suggests that food cues can trigger simulations of eating and enjoying the food, especially if this food has previously been rewarding, and that these simulations can increase the perceived attractiveness and desire for the food.

Recent research provides some initial support for these hypotheses, for example in behavioural work using a so-called feature listing task (McRae, Cree, Seidenberg, & Mcnorgan, 2005; Papies, 2013). Here, when participants were asked to list the "features that are typically true" of different foods, words for attractive foods triggered more eating-simulation words than words for neutral foods (Papies, 2013). Thus, for an attractive food like chips (UK: crisps), participants were more likely to describe its taste, texture, and situations for eating it ("salty", "crunchy", "tasty" "at night"). In contrast, for a neutral food like rice, participants were more likely to list visual features or words describing production and preparation methods (e.g., "small", "white", "grains", "has to be cooked"). These results suggest that when asked to describe an attractive food, participants spontaneously simulated eating and enjoying it in a relevant eating situation, whereas such simulations were less likely for the neutral food.

Neuroimaging research has shown that viewing attractive compared to neutral food images during a brain scan leads to stronger activations in brain areas that are also involved in actual eating, such as primary taste, reward, and motor areas (for reviews, see Chen, Papies, & Barsalou, 2016; van der Laan, de Ridder, Viergever, & Smeets, 2011). Exposure to attractive food also triggers stronger salivation than neutral food (Keesman, Aarts, Vermeent, Häfner, & Papies, 2016; Nederkoorn, Smulders, & Jansen, 2000), especially when participants are instructed to imagine eating it (Keesman et al., 2016). Eating simulations can also be triggered by more subtle cues, as demonstrated by Elder and Krishna (2012). Here, when advertisements showed a food in such a way that one could easily imagine eating it, for example yoghurt accompanied by spoon with the handle pointing to one's dominant hand compared to the other direction, this increased simulations of eating the food as well as purchase intentions. Together, these findings suggest that attractive foods trigger eating simulations, and that this in turn can increase the appeal of foods.

Can this process be used to increase the appeal of plant-based foods? Initial evidence suggests that this may be possible. Turnwald and Crum (2019) compared taste-focused labels with health-focused labels for vegetable dishes. They found that taste-focused labels increased choices and made the dishes appear tastier compared to health-focused labels, and also compared to shorter labels simply stating the name of the vegetable (Turnwald et al., 2019). However, eating simulations were not measured, and the foods were mostly well-known vegetables, which might be more acceptable to consumers than fully plant-based dishes. Still, Turnwald and Crum's findings are in line with the possibility that increasing rewarding eating simulations through labels will increase desire, even for relatively novel or healthy foods.

Here we build on this idea. Previous work has shown that healthy restaurant dishes are often described with less exciting, less indulgent language compared to unhealthy dishes (Turnwald, Jurafsky, Conner, & Crum, 2017). Therefore, we first investigate if the same could be true for plant-based foods. We examine the labels and descriptions of a large

number of meat-based, vegetarian, and plant-based ready meals to assess the number of words related to rewarding eating simulations. We then apply simulation-inducing labels to plant-based foods to test whether simulation labels increase the attractiveness of plant-based foods, compared with equally long control labels. We also test whether simulation labels increase eating simulations. In sum, we address two research questions: 1) To what degree are eating simulation words being used in descriptions of meat-based, vegetarian, and plant-based ready meals in the UK? 2) Can the use of simulation words in labels and descriptions increase the attractiveness of plant-based foods?

We present three studies to answer these questions. Study 1 examines the descriptions of a large number of meat-based, vegetarian and plant-based ready-meals available in the UK to assess the use of simulation-based language in these descriptions. Studies 2 and 3 then test experimentally whether differences in the language used in food descriptions affect consumers' spontaneous eating simulations and the perceived attractiveness of foods, such that descriptions that refer to rewarding eating experiences increase simulations and attractiveness.

2. Study 1

In this study, we analysed the words used in descriptions of meat-based, vegetarian, and plant-based ready-meals available in UK supermarkets. We were interested in the degree to which simulation-words are used in such descriptions. We predicted that meat-based foods would be described more heavily in terms of sensory and action features that reflect the actual eating experience and could therefore trigger eating simulations, compared to vegetarian and plant-based foods.

All study materials, data, and analysis code can be found on the Open Science Framework (OSF) under https://osf.io/kygup/?view_only=22226a4824d145bab15bc7ce58097681.

2.1. Method

2.1.1. Sample

We aimed to collect a representative sample of food labels from four popular supermarkets in the UK, with different sociodemographic profiles. From each supermarket, we aimed to select 20 meat-based, 20 plant-based, and 20 vegetarian foods (total $N = 240$). One supermarket did not offer 20 vegetarian options, which is why we sampled 23 plant-based and 17 vegetarian foods. Another did not offer 20 plant-based options, which is why we sampled 17 plant-based and 23 vegetarian foods. We included food items if they were ready made meals (e.g., pasta dishes, pizza) or if they comprised a large part of a meal (e.g., burger patties). To be included, the preparation required for the consumption of a meal had to be limited to simple cooking in a microwave or an oven to only include easily prepared meals requiring minimal effort. The sample included both supermarket's own brand, as well as other brands' products from chilled and frozen sections. We selected foods from a wide range of categories (e.g., curry, salad, bake) to obtain a large variety of meals, based on local availability and price range. When there were multiple dishes available for a category, we randomly selected one option. We did not conduct an a priori power analysis.

2.1.2. Procedure and materials

We collected the labels and descriptions of the foods from the supermarket websites. For foods not available on the website, we took photos of the food in the store (Glasgow, UK). We then coded words contained in the first paragraph, which was usually a phrase of ca. twelve words. We divided labels into their smallest meaningful units. For example, "crisp wholegrain ultra-thin stonebaked pizza topped with houmous-style sauce" became "crisp", "wholegrain", "ultra-thin", "stonebaked", "pizza", "topped", "houmous-style", "sauce".

We coded words in the food descriptions according to a hierarchical coding scheme (Papies, Tatar, et al., 2020). The scheme has been designed to assign food features to categories according to whether the

features refer to situations in which the food is consumed (consumption situations), to situations in which the food is present but not being consumed (non-consumption situations), or whether they are situation-independent. These three main categories are further divided into sub-categories. Consumption situation features are assigned to the subcategories of sensory and action system features (taste, flavour, texture, temperature, action words), contextual features (e.g., internal and external context words, such as emotional context or physical, social or time setting), and immediate positive or negative consequences of consumption (e.g., hedonic consequences, such as delicious; bodily consequences, such as filling). Non-consumption situation features are assigned to the subcategories of origins and production (e.g., from China), preparation (e.g., steamed), and purchase and accessibility (e.g., expensive). Situation-independent features are assigned to the subcategories of ingredients and content (e.g., tomatoes), visual features (e.g., round), linguistic and category information (e.g., snack), and general evaluation (e.g., bad).

One author coded each feature of each food label, assigning features to categories. A second author double coded 10% of all foods. Interrater reliability ($\kappa = 0.69$) indicated substantial agreement (McHugh, 2012). The two coders then discussed and resolved discrepancies and applied these coding decisions to the remaining food labels.

2.2. Results

Foods had an average of 9.8 total features ($SD = 3.6$). Meat-based foods had the highest number of total features ($M = 11.6$, $SD = 3.7$), followed by vegetarian foods ($M = 9.2$, $SD = 3.3$) and plant-based foods ($M = 8.6$, $SD = 2.9$). We conducted all analyses in R (version 3.6.1; R Core Team, 2019); we processed and visualized data with packages of the *tidyverse* (version 1.2.1; Wickham, 2017).

2.2.1. Confirmatory analyses

We first tested the hypothesis that meat-based foods would have a higher proportion of sensory and action features than plant-based and vegetarian foods. Proportions were calculated by dividing the number of features per category by the total number of features for a food. Because we were analyzing proportions, we could not rely on a linear model that assumed a Gaussian distribution; such models regularly result in biased estimates (Jaeger, 2008). In addition, there was substantial variation on the total number of features between supermarkets (see Fig. 1). To account for these differences and the non-Gaussian data distribution, we fitted binomial mixed-effects models with the *glmer* function of the *lme4* package (version 1.1.-21; Bates, Maechler, Bolker, & Walker, 2015). Following current best practices, we employed a maximal random effects structure (Barr, Levy, Scheepers, & Tily, 2013), predicting proportion with a fixed effect for food type (sum-to-zero coded), a random intercept for supermarket, and a random slope for food type varying across supermarkets. We obtained p-values based on Likelihood Ratio Tests, as implemented in the *mixed* function of the *afex* package (version 0.25–1, Singmann, Bolker, Westfall, & Aust, 2019). The model met all assumptions for a binomial regression model and displayed excellent fit, as assessed with the model diagnostics implemented with the *DHARMa* package (version 0.2.6; Hartig, 2019). For details on the diagnostics see the analysis reports on the OSF.

Contrary to our prediction, the overall effect of food type on sensory and action features was not significant, $\chi^2 (2) = 5.01$, $p = .082$.

2.2.2. Exploratory analyses

However, to better understand the pattern of results as shown in Fig. 2, we conducted pairwise comparisons between the conditions within the confirmatory model with the *emmeans* command in the *emmeans* package (version 1.4.2; Lenth, 2019), adjusting our alpha for multiple comparisons ($\alpha = 0.05/3 = 0.017$).

Plant-based foods were described with a lower proportion of sensory and action features ($M = 0.10$, $SD = 13$) than meat-based foods ($M = $
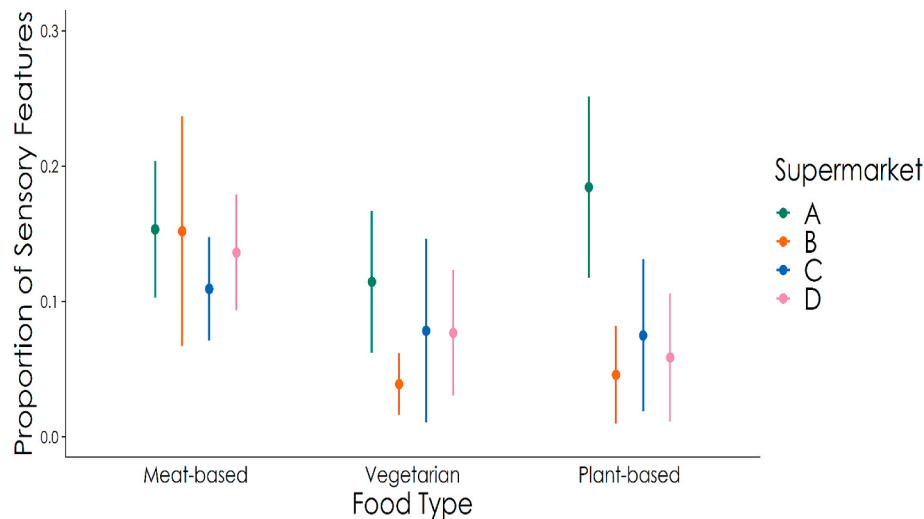
Fig. 1. Mean proportion of sensory features for food type for each of the four supermarkets. Points represent means; bars of these points represent the 95% CI of the within-subject standard error (Morey, 2008), calculated with the Rmisc package (version 1.5; Hope, 2013).
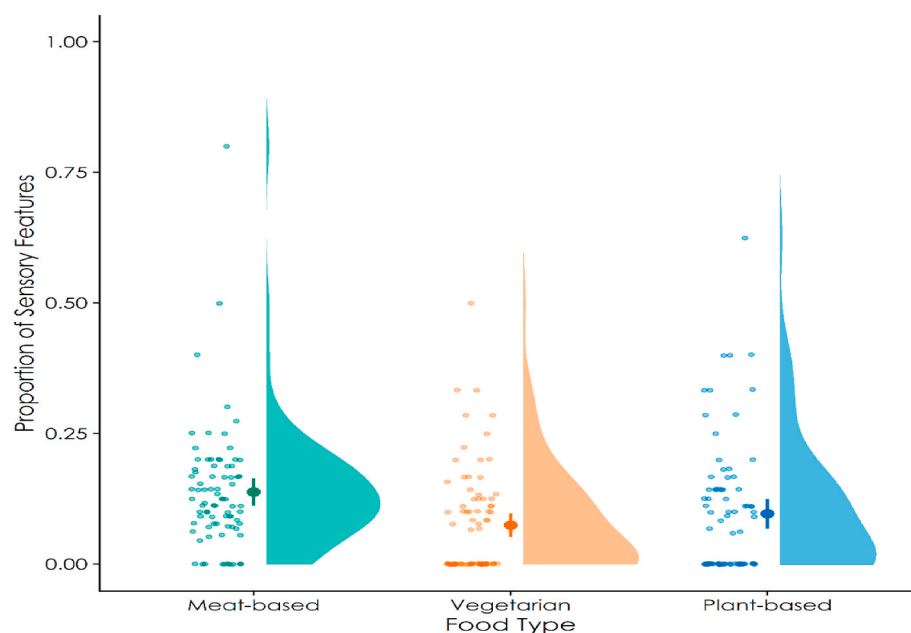

Fig. 2. Raincloud plots of the raw data associated with our analysis of the difference in the proportion of sensory and action features between food types. Points represent each raw data point; density plots represent the distribution. Large circles represent the group means; bars of these points represent the 95%CI. All raincloud plots based on Allen, Poggiali, Whitaker, Marshall, and Kievit (2018).

0.14, $SD = 0.12$), but this difference was not significant, $b = 0.62$, $SE = 0.34$, $p = .064$. Vegetarian food descriptions had a lower proportion of sensory and action features ($M = 0.07$, $SD = 0.10$) than meat-based foods, $b = 0.63$, $SE = 0.23$, $p = .005$. The difference between descriptions of plant-based and vegetarian foods was not significant, $b = 0.01$, $SE = 0.25$, $p = .967$.

2.2.3. Further exploratory analyses

In addition, we explored potential differences between descriptions with regard to the three main feature categories in three additional binomial mixed-effects models. For an overview of the proportions, see Table 1. For a visualization, see Fig. 3.

2.2.3.1. Consumption situation features.
The overall effect of food type on proportion of consumption situation features was significant, χ^2 (2)

Table 1
Proportions of features by feature category and food category.

Food type	Consumption		Non-consumption		Situation independent	
	M	SD	M	SD	M	SD
Meat-based	.15	.14	.17	.12	.68	.16
Plant-based	.13	.17	.10	.10	.77	.19
Vegetarian	.08	.11	.14	.13	.78	.17

$= 7.31$, $p = .026$. Meat-based food descriptions had a higher proportion of consumption situation features than plant-based foods, but this difference was not significant, $b = 0.42$, $SE = 0.36$, $p = .248$. Meat-based food descriptions had a significantly higher proportion than vegetarian food descriptions, $b = 0.66$, $SE = 0.21$, $p = .002$. The difference between plant-based and vegetarian food descriptions was not
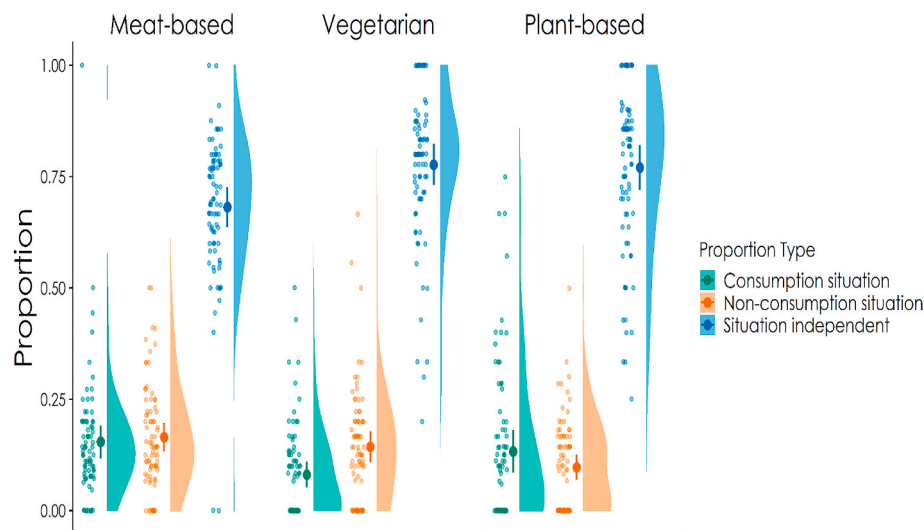
Fig. 3. Raincloud plots of the raw data associated with our analysis, showing the proportions of words associated with each of the main categories for each of the three food types. Points represent each raw data point; density plots represent the distribution. Large points represent means; bars of these points represent the 95% CI of the within-subject standard error.

significant, $b = 0.24$, $SE = 0.28$, $p = .389$. The model met all assumptions and displayed good fit.

2.2.3.2. Non-consumption situation features. The overall effect of food type on proportion of non-consumption situation features was significant, χ^2 (2) $= 7.51$, $p = .024$. Meat-based food descriptions had a significantly higher proportion of non-consumption situation features compared to plant-based food descriptions, $b = 55$, $SE = 0.16$, $p < .001$, but not compared to vegetarian food descriptions, $b = 0.13$, $SE = 0.15$, $p = .381$. The difference between plant-based and vegetarian food descriptions was significant, $b = -0.41$, $SE = 0.19$, $p = .026$, but not when correcting for multiple testing ($\alpha = 0.05/3 = 0.017$). The model met all assumptions and displayed good fit.

2.2.3.3. Situation-independent features. The effect of food type on proportion of situation-independent features was significant, χ^2 (2) $= 6.70$, $p = .033$). Meat-based food descriptions had a slightly lower proportion of situation-independent features than plant-based foods, $b = -0.54$, $SE = 0.22$, $p = .015$, and a significantly lower proportion than vegetarian foods, $b = -0.40$, $SE = 0.12$, $p < .001$. Plant-based and vegetarian foods did not significantly differ from each other, $b = 0.14$, $SE = 0.21$, $p = .517$. The model met all assumptions and displayed good fit.

2.3. Summary and discussion

Specific comparisons in this observational study showed that the descriptions of meat-based ready meals available in UK supermarkets contained a higher proportion of sensory and action words (such as words referring to taste and texture), compared to vegetarian foods, although not significantly higher when compared to plant-based foods. We also saw descriptively that the food language varied between supermarkets, with three of the supermarkets using fewer sensory and action words for plant-based foods compared to meat-based foods, and one supermarket showing the opposite pattern. Overall, meat-based foods contained a lower proportion of situation-independent words (such as words referring to ingredients, health, or food categories).

These findings suggest that the language used to label and describe ready meals in the UK differs depending on whether the meal contains meat or not, at least in the four supermarkets examined here. Specifically, the overall pattern of the data suggests that meat-based foods are more likely to be described with words that can trigger consumption and reward simulations, and could contribute to a dish's appeal this way. In

Study 2, we therefore examined experimentally whether such differences in the language used to described foods indeed increases their attractiveness, and whether they affect consumption simulations.

3. Study 2

In this study, we manipulated the descriptions of meat-based and plant-based foods. The descriptions were either neutral or manipulated to contain words that would highlight either sensory features, contextual features, or health-positive features (Turnwald, Boles, & Crum, 2017). For each food, participants rated their subjective desire (likelihood to order the dish) as well as the degree to which the descriptions made them simulate eating the food. We predicted that both sensory and context descriptions would lead to increased desire and simulations compared to neutral descriptions for plant-based foods. We hypothesized no difference between health-positive and neutral descriptions. In addition, we predicted that meat-based foods would be rated as more desirable than plant-based foods, regardless of description type. We further expected that sensory and context descriptions would increase desire more for plant-based than for meat-based dishes, compared to neutral descriptions. Last, we hypothesized that the intention to reduce eating meat would positively correlate with desire for plant-based foods.

3.1. Method

Following calls for more robust science (Munafò et al., 2017; Nosek, Ebersole, DeHaven, & Mellor, 2018), we preregistered hypotheses, sampling plan, exclusion criteria, and our confirmatory analysis plan. The preregistration, all study materials, data, and analysis code can be found on the OSF, https://osf.io/kygup/?view_only=22226a4824d14 5bab15bc7ce58097681.

3.1.1. Design

We conducted an online experiment with a 4 (description type: context vs. health-positive vs. neutral vs. sensory) 2 (food type: plant-based vs. meat-based) within-participants design.

3.1.2. Sample

We aimed to detect a smallest effect size of interest of $d_z = 0.2$ in a one-tailed paired-samples t-test (Lakens, Scheel, & Isager, 2018). To achieve 80% power at $\alpha = 0.05$ for H_1, we needed to recruit 156 participants. To account for possible dropout and exclusions, we

preregistered to collect a sample 10% larger, resulting in a target sample size of 172. A total of 183 participants opened our survey on research participant recruitment website Prolific (www.prolific.co). Respondents had to fulfil five inclusion criteria: They had to (1) live in the UK, (2) be between 18 and 70 years old, (3) consume an omnivorous diet, (4) have no current eating disorder or a history of eating disorders, and (5) not be on weight-loss or other restrictive diet. Four participants did not fulfil the inclusion criteria. We had two preregistered exclusion criteria: (1) We excluded eight additional participants because they did not finish the survey; (2) one participant gave identical ratings on each trial. Thus, our final sample consisted of $N = 170$ participants (age range = 18–68, $M_{age} = 32$, $SD_{age} = 11$, 56 men). Participants received £1.40 for their participation. Studies 2 and 3 were approved by the Ethics Committee of the College of Science and Engineering at the University of Glasgow.

3.1.3. Materials

We selected 20 plant-based and 20 meat-based meals that could be ordered in a restaurant. We chose a broad range of types of dishes (e.g., soups, burgers, curries) and the proportion of dish type was equal for both types of food (e.g., three plant-based and three meat-based soups). Each dish description had a neutral version (i.e., the neutral condition) that merely referred to situation-independent features such as ingredients (e.g., lamb, lentils), the food category (e.g., burger, chilli), and sides (e.g., served with tomato salsa). For the context condition, we added information to the neutral descriptions about contextual features (e.g., cold day, pub) and features signalling immediate positive consequences (e.g., satisfying, feel-good). For the sensory condition, we added information about taste and flavour (e.g., sweet, tangy) and texture (e.g., crispy, smooth). For the health-positive condition, we added information about long-term positive health consequences (e.g., nutritious, protein-packed). We did not match neutral descriptions in length with the other conditions. See Table 2 for examples. The food descriptions did not explicitly state that a dish was vegetarian, plant-based, or vegan.

We counterbalanced the assignment of condition to food across participants. This way, a specific food was not associated with only one condition for all participants. Instead, participants were randomly assigned to one of four counterbalancing conditions, such that each food was assigned to one of the four conditions equally. Thus, each participant saw a total of 40 descriptions: five for each description type condition for plant-based foods and five for each description type condition for meat-based foods. Therefore, we could rule out that possible effects were bound to a specific food and generalize to other foods in the analysis.

3.1.4. Procedure

The experiment was delivered via the online study software Qualtrics (https://www.qualtrics.com). Participants first read a study information sheet before indicating that they fulfilled the inclusion criteria and giving informed consent. Afterwards, they reported their current levels of hunger and thirst ("How do you feel right now?") on 100-point visual

analogue scale (VAS) for the items "Hungry" and "Thirsty" ranging from "not at all" to "extremely" ($M_{hunger} = 44$, $SD_{hunger} = 28$ and $M_{thirst} = 51$, $SD_{thirst} = 24$). Then, we instructed participants that they would rate 40 different dishes on how much they would like to order each dish based on the description. Participants could indicate their desire for a dish on a 100-point VAS ("Would you order this dish?"), ranging from "I would certainly not order it" to "I would certainly order it" ($M_{raw} = 52$, $SD_{raw} = 32$).[1] Participants then proceeded to rate their desire for all 40 foods. Next, to assess simulations, we instructed participants that we would like to know how much they thought about what a dish would taste like and how much they imagined what it would feel like to eat a dish. For the same 40 dishes as previously, they responded to two items that were intended to measure simulations ("I spontaneously thought about what it would taste like" and "I imagined what it would feel like to eat it") on a 100-point VAS ranging from "not at all" to "very much". As preregistered, we took the mean of those two items as a measure of simulations ($M_{raw} = 60$, $SD_{raw} = 26$).

In the next section, participants provided demographic information, beginning with age, sex, height ($M_{cm} = 171$, $SD_{cm} = 11$), and weight ($M_{kg} = 74$, $SD_{kg} = 18$). Eight participants reported not to follow an omnivore diet, although they indicated to be omnivores when responding to the inclusion criteria at the beginning of the study. When we asked participants how many of their meals in a week contain meat ($M = 7.2$, $SD = 3.8$), six out of those eight reported to occasionally eat meat; two reported no meat consumption. Because these two indicated to be omnivores at the beginning of the survey, they might occasionally eat meat, which is why we did not exclude them.[2] Next, we assessed participants' intention to reduce eating meat with the question "Are you currently trying to change your diet to reduce your meat consumption?" on a 100-point VAS ranging from "not at all trying" to "certainly trying" ($M = 37$, $SD = 32$). Last, participants reported on food allergies, language comprehension difficulties during the study, food likes and dislikes, what they thought the study was about, and technical problems during the study, before they were debriefed and thanked. The median duration of the experiment was around 15 min.

3.2. Results

In the analysis, we deviated from our preregistered analyses. We had preregistered to conduct paired-samples *t*-test and repeated-measures ANOVAs. However, these approaches do not take into account the variance associated with foods, which can lead to a higher false-positive rate (e.g., Bolker et al., 2009). Therefore, we regarded a deviation from our preregistered analysis plan as necessary to obtain more accurate results (Szollosi et al., 2020). We constructed mixed-effects models with a maximal effects structure for all hypotheses (Barr et al., 2013). For all models, we obtained p-values based on F-tests with Satterthwaite approximation for degrees of freedom for Type III Sums of Squares (Luke, 2017). The two main outcomes, desire and simulations, were conceptually similar and empirically related (r = 0.47), warranting correction for multiple testing. In total, we conducted five confirmatory tests with either simulations or attractiveness as outcome. To control our familywise error rate, we therefore applied a Bonferroni correction, such that we only considered effects to be significant at α = 0.05/5 = 0.01.

3.2.1. Main effect of description type for plant-based foods

3.2.1.1. Confirmatory. Our first three hypotheses predicted that for plant-based foods, both context and sensory descriptions would cause higher desire and simulations than neutral descriptions, and that health-

Table 2
Examples of Food Descriptions used in Study 2.

	Plant-based foods	Meat-based foods
Neutral	Chickpea curry with tomatoes and red peppers	Pulled pork burger with coleslaw, coriander and jalapeños
Sensory	**Fragrant** chickpea curry with tomatoes and **juicy** red peppers	**Juicy** pulled pork burger with coleslaw, coriander and **spicy** jalapeños
Context	**Celebratory** chickpea curry with tomatoes and **refreshing** red peppers	**Family feast** pulled pork burger with **satisfying** coleslaw, coriander and jalapeños
Heath-positive	**Nutrient-rich** chickpea curry with tomatoes and red peppers	**Iron rich** pulled pork burger with coleslaw, coriander and jalapeños

Note. Bolded words are added to the neutral description to highlight sensory, context, and health-positive features.

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[1] The subscript "raw" denotes that the descriptive information is based on the entire data set, without aggregating by participant first.

[2] When running the analyses without these participants, excluding them did not change the results.

positive descriptions would not differ from neutral descriptions. To test these hypotheses, we constructed two maximal models (for desire and simulations, respectively) that included description type as fixed effect (sum-to-zero coded), a random intercept for participants and foods, and random slopes varying across participant and food. The model predicting desire did not converge and yielded a warning for singular fit. We followed best practices to troubleshoot convergences issues in mixed-effects models (Barr et al., 2013): We increased the number of iterations; started from previous fit; and ran the model with different optimizers. Parameter estimates were not stable across optimizers, which is why we had to start simplifying the model. We began by removing correlations between random effects, followed by removing random intercepts and removing the random slope for foods. Neither of these steps helped with convergence (for numerical details, see OSF). We did not want to remove random slopes varying across participants because of a high risk of Type I error (Barr et al., 2013).

Instead, we ran a repeated-measures ANOVA. Contrary to our predictions, the main effect of description type was not significant, $F(3, 507) = 1.25$, $\eta^2_g = 0.003$, $p = .290$. There were only small differences between desire for foods with neutral ($M = 53$, $SD = 13$),[3] context ($M = 52$, $SD = 15$), sensory ($M = 54$, $SD = 15$), or health-positive descriptions ($M = 51$, $SD = 15$; see Fig. 4).

The mixed-effects model predicting simulations also ran into convergence problems. We followed the same troubleshooting steps as above. We had to remove the random slope varying across food for the model to stay within an acceptable level of tolerance for singular fit. The effect of description type was not significant (at $\alpha = 0.01$), $F(3, 242.1) = 2.98$, $p = .032$. Again, there were only small differences between simulations for foods with neutral ($M = 59$, $SD = 15$), context ($M = 61$, $SD = 15$), sensory ($M = 61$, $SD = 16$), or health-positive descriptions ($M = 58$, $SD = 15$; see Fig. 5).

The *r.squaredGLMM* function from the *MuMIn* package (version 1.43.6; Barton, 2019) yielded an effect size estimate of 0.002 for vari-
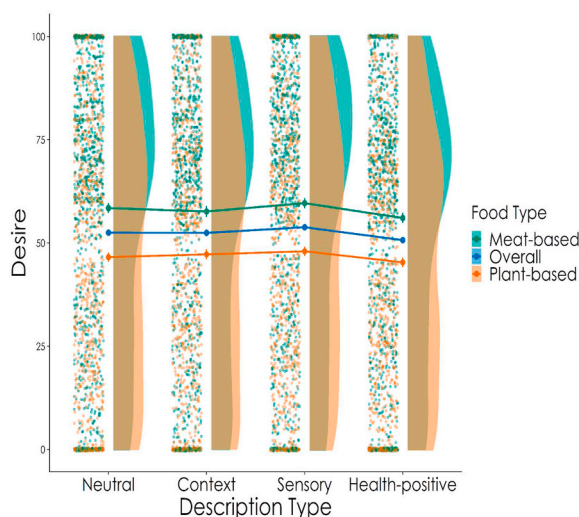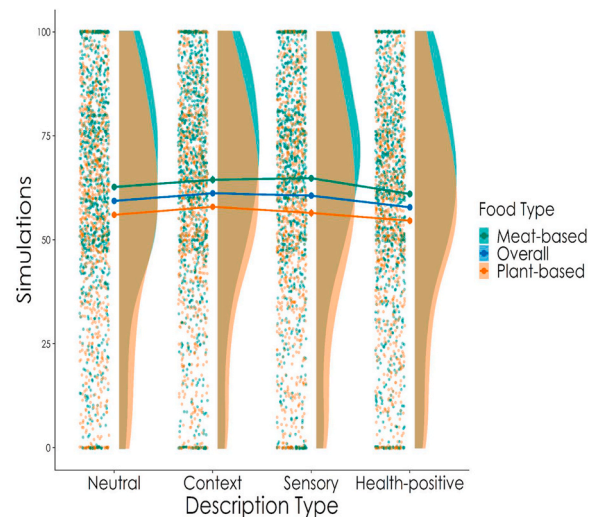

Fig. 5. Raincloud plots of the raw data associated with our analysis of the effects of description type on simulations. Points represent each raw data point; density plots represent the distribution. Connected points represent the group means. The overall group shows the main effect of description type (i.e., the average over both foods types). We display separate means for food types to be consistent with other figures.

ance explained by the fixed effect (R^2_m), and an estimate of 0.36 for variance explained by both fixed and random effects (R^2_c).

3.2.1.2. Exploratory. Despite the nonsignificant omnibus test, we were interested in possible differences between the conditions on desire. Pairwise comparisons with the *emtrends* command in the *emmeans* package (version 1.4.2; Lenth, 2019) showed that none of the contrasts were significant (all $p > .246$). For simulations, no contrast (after correction for multiple testing) was below our adjusted significance level (all $p > .015$). In addition, for the model predicting simulations, we identified outliers by inspecting Cook's distance and DFBETAs (Verkoeijen, Polak, & Bouwmeester, 2018). The effect of label descriptions did not change when excluding outliers, $F(3, 287.47) = 2.60$, $p = .052$.

3.2.2. Interaction of food type and meat-eating frequency

3.2.2.1. Confirmatory. Next, we tested the hypothesis that across description types, meat-based foods would be rated as more desirable than plant-based foods, especially for people who eat meat more often. We constructed a maximal mixed-effects model predicting desire that included an interaction of food type and meat-eating frequency (standardized) as fixed effect (sum-to-zero coded), with random intercepts for participant and food and a random slope for food type within participant. The model converged without problems. Both the main effect of food type, $F(1, 48.15) = 14.88$, $p < .001$, and its interaction with meat-eating frequency, $F(1, 166.99) = 38.50$, $p < .001$, were significant predictors of desire; the main effect of meat-eating frequency was not significantly related to desire, $F(1, 166.99) = 0.24$, $p = .625$, $R^2_m = 0.04$, $R^2_c = 0.26$. As predicted, meat-based foods elicited higher desire ($M = 58$, $SD = 13$) than plant-based foods ($M = 47$, $SD = 15$). This difference only emerged the more frequent participants eat meat. We proceeded to estimate simple slopes with the *emtrends* command in the *emmeans* package (version 1.4.2; Lenth, 2019). As illustrated in Fig. 6, a one standard deviation increase in meat-eating frequency was associated with a 3.25 increase in desire for meat-based foods, $SE = 1.00$, asymptotic CL[1.30, 5.21], but with a 4.13 decrease in desire for plant-based foods, $SE = 1.14$, asymptotic CL[-6.37, -1.88].

3.2.2.2. Exploratory. The exclusion of outliers did not change results

Fig. 4. Raincloud plots of the raw data associated with our analysis of the effects of description type and food type on desire. Points represent each raw data point; density plots represent the distribution. Connected points represent the group means. The overall group merely shows the main effect of description type (i.e., the average over both foods types).

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[3] We report the *SD* aggregated by participant, rather than *SD* based on all observations, to make our results comparable to other research and to make it easier to calculate effect sizes for meta-analyses.
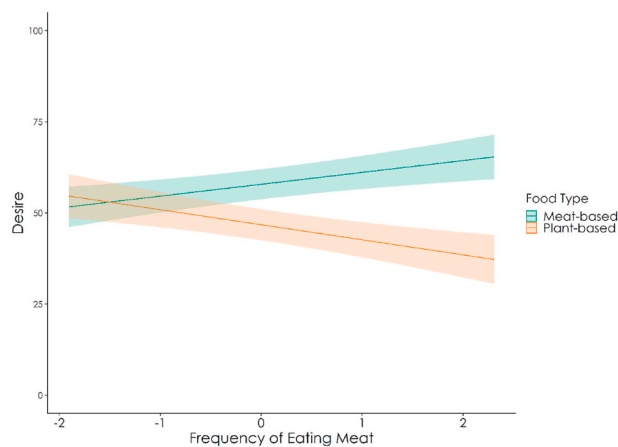
Fig. 6. Model-based slopes and CI for the relation between the frequency of eating meat (standardized 100-point visual analogue scale, such that one unit represents one SD) and desire ratings (on 100-point visual analogue scales) of meat-based and plant-based foods.

(significant effects remained at $p < .001$).

3.2.3. Interaction of description type and food type

3.2.3.1. Confirmatory. Next, we tested the hypothesis that the effect of description type would be stronger for plant-based compared to meat-based foods. We constructed a maximal model predicting desire with a fixed effect of the interaction of description type and food type (sum-to-zero coded), a random intercept for participant and food, a random slope for the interaction within participant, and a random slope for description type within food. The model yielded a singularity warning that was within acceptable levels of tolerance. There was a significant difference between food types, $F(1, 56.60) = 14.61$, $p < .001$, but neither description type, $F(3, 55.17) = 2.03$, $p = .121$, nor its interaction with food type, $F(3, 48.70) = 0.19$, $p = .901$, were significant predictors of desire, $R^2_m = 0.03$, $R^2_c = 0.29$.

3.2.3.2. Exploratory. We explored pairwise comparisons between description across food types. None of the contrasts were significant (all $p > .084$). Excluding outliers did not change the pattern of results.

3.2.4. Correlation between intention to reduce eating meat and desire

Last, we tested whether the intention to reduce eating meat would correlate with desire for plant-based foods. We aggregated desire ratings per participant. The intention to reduce eating meat was positively correlated with those ratings, $r = 34$, $p < .001$. There were no visual outliers influencing this relation.

3.3. Summary and discussion

This experiment provided no evidence that food descriptions which add either sensory, context, or health positive words increase desire or eating simulations of foods. While the pattern of means was in the expected direction, the differences between conditions were very small. In Study 3, we therefore combined features to produce stronger simulation-inducing labels.

4. Study 3

This experiment was designed to replicate Study 2 with a stronger manipulation that combined sensory, context, and hedonic words in food descriptions to induce eating simulations and desire. We did not include health positive words, because there was no evidence or expectation that these would increase desire. Finally, we ensured that

the neutral descriptions were equally long as the simulation-based descriptions to increase experimental control. We again predicted that simulation-based descriptions would increase eating simulations and attractiveness ratings, especially for plant-based foods. We further predicted that simulation ratings would predict attractiveness ratings. Finally, we predicted that the intention to reduce meat consumption would be positively associated with attractiveness ratings of plant-based foods and negatively with the attractiveness of meat-based foods.

4.1. Method

We preregistered hypotheses, sampling plan, exclusion criteria, and our confirmatory analysis plan. The preregistration, all study materials, data, and analysis code can be found on the OSF, https://osf.io/kygup/?view_only=22226a4824d145bab15bc7ce58097681.

4.1.1. Design

We conducted an online experiment with a 2 (description type: control vs. simulation-based) by 2 (food type: plant-based vs. meat-based) within-participants design.

4.1.2. Sample

We employed mixed-effects models for our analysis, which rely on data simulations to estimate power (DeBruine & Barr, 2019). These simulations require knowledge of parameters, ideally based on available studies or pilot data. We did not have such information available. Instead, we opted to be able to detect a smallest effect size of interest of $d_z = 0.2$ in a one-tailed paired-samples t-test (Lakens et al., 2018), which represents an approximation of a priori power for our analyses. To achieve 80% power at $\alpha = 0.05$ for H_1, we needed to recruit 156 participants. To account for possible dropout and exclusions, we preregistered to collect a sample 10% larger, resulting in a target sample size of 172.

A total of 187 participants opened our survey on Prolific. Inclusion criteria were the same as in Study 2, and 12 participants did not fulfil them. We had two preregistered exclusion criteria: (1) We excluded one additional participant because they did not finish the survey; (2) no participant gave (almost) identical ratings on each trial. When inspecting the average time participants took for each trial, we discovered that several participants were rushing through the survey (e.g., average response times per trial of 1.5s). Because we did not have an objective cut-off for rushed responses, we relied on the Relative Speed Index (RSI), developed by Leiner (2013), which identifies meaningless responses by comparing individual page completion times to median completion times of the entire sample. Using this procedure, we excluded eight participants, leading to a final sample of $N = 166$ (age range = 18–69, $M_{age} = 31$, $SD_{age} = 10$, 48 men). Because we did not preregister the exclusion of rushed responses, we conducted all analyses with and without these eight cases (see OSF), and note when their exclusion changed the conclusions of the respective analysis. Participants received £ 1.39 for their participation.

4.1.3. Materials

We presented participants with 20 plant-based and 20 meat-based ready meals available in UK supermarkets, spanning a wide range of dishes (e.g., pasta dishes, wraps, burgers, stir-fries). Rather than designing descriptions ourselves, we adapted the foods' descriptions that were presented on the package or on the website of the supermarket. Control descriptions only contained words referring to ingredients (e.g., mushroom, vegetables), food categories (burger patty, roast), or composition of the food (added, assorted), whereas simulation-based descriptions also contained sensory words (e.g., fragrant, spiced), hedonic words (e.g., indulgent, tasty), and context words (Japanese lunch-style, Sunday lunch). Both description types were equally long and contained 12–21 words (see Table 3). The descriptions of plant-based foods did not state that the food was vegetarian, plant-based, or vegan.

Table 3
Examples of Food Descriptions used in Study 3.

	Control descriptions	Simulation-based descriptions
Plant-based foods	Mushroom burrito wrap with assorted beans, different vegetables, and added tomato sauce.	**Indulgent** *lunch* burrito with <u>fragrant</u> mushrooms, **flavourful** beans, and **generously** <u>spiced</u> tomato sauce.
Meat-based foods	Pizza base topped with tomato sauce, grated Mozzarella cheese and pepperoni sausage with added spices	*Family-style* pizza topped with **rich** and **tasty** tomato sauce, <u>soft</u> Mozzarella cheese, and <u>spiced</u> pepperoni

Note. Sensory words are underlined. Hedonic words are bolded. Context words are italicised.

In our analysis, we aimed to generalize from the foods in our study to foods more generally. Therefore, we counterbalanced the assignment of control and simulation-based descriptions to foods. Participants were randomly assigned to these two counterbalanced conditions, such that half of the plant-based and meat-based foods were assigned simulation-based descriptions for one counterbalanced condition and the other half were assigned control descriptions. This order was reversed for the other counterbalanced condition. This way, we could rule out food-specific effects and generalize to other foods in the analysis.

4.1.4. Procedure

The experiment was programmed in Qualtrics. The procedure was similar to that of Study 2. Participants first read a study information sheet, indicated whether they fulfilled the inclusion criteria, provided informed consent, and rated current levels of hunger/thirst as in Study 2 (M_{hunger} = 29, SD_{hunger} = 24 and M_{thirst} = 46, SD_{thirst} = 25). Next, we informed participants that they would rate how attractive they found 40 different ready meals for sale in supermarkets. The foods were presented in random order. We instructed them to follow their intuition when rating the foods, and to rate them on a visual analogue scale (VAS), ranging from 0 (*not attractive at all*) to 100 (*very attractive*), on the question "How attractive does this meal sound to you?" (M_{raw} = 55, SD_{raw} = 29). Next, to assess eating simulations, we told participants that we were interested in their experience as they read the food descriptions. We asked them to indicate on a VAS, ranging from 0 (*not at all*) to 100 (*very much*) to what extent they agreed with the statement "When I read this label, I imagine what the food would taste and feel like" (M_{raw} = 59, SD_{raw} = 27).

Then, participants provided additional demographic information, including their age and sex, and height (M_{cm} = 169, SD_{cm} = 9) and weight (M_{kg} = 73, SD_{kg} = 16). All but two participants indicated to follow an omnivore diet; two participants indicated to be vegetarian. These two indicated to be omnivores at the beginning of the survey (i.e., one of our exclusion criteria) and one of them reported to occasionally eat meat; thus, we did not exclude these cases, as they might occasionally consume meat.[4] We assessed meat eating frequency by asking participants to report the number of their meals that contain meat per week (M = 7.10, SD = 3.81). Using 100-point VAS, we then assessed the following variables: intentions to reduce meat consumption ("Are you currently trying to change your diet to reduce your meat consumption?" not at all trying – certainly trying; M = 45, SD = 34); attitude toward eating meat ("What do you think about eating meat?" I don't like it at all – I like it very much; M = 75, SD = 26); attitudes toward vegan food ("What do you think about vegan food? I don't like it at all – I like it very much; M = 54, SD = 27); and attitudes toward plant-based food ("What do you think about plant-based food? I don't like it at all – I like it very much; M = 59, SD = 25). In addition, participants reported any food allergies, language comprehension difficulties during the study, what

food preferences may have influenced their responses, what they thought the study was about, and any technical issues during the study. Finally, we debriefed and thanked participants. The median duration of the study was about 14 min.

4.2. Results

Following our preregistration, we constructed mixed-effects models with a maximal effects structure for all hypotheses (Barr et al., 2013). For all models, we obtained *p*-values based on *F*-tests with Satterthwaite approximation for degrees of freedom for Type III Sums of Squares (Luke, 2017). Like in Study 2, the two main outcomes, attractiveness and simulations, were conceptually similar and empirically related (r = 0.51), warranting correction for multiple testing. In total, we conducted seven confirmatory tests with either simulations or attractiveness as outcome. To control our familywise error rate, we therefore applied a Bonferroni correction, such that we only considered effects to be significant at α = 0.05/7 = 0.007.

4.2.1. Main effect of description type

4.2.1.1. Confirmatory analyses. To test the hypothesis that simulation-based descriptions would increase simulation and attractiveness ratings, we constructed two maximal models, one for simulations and one for attractiveness. The models included a fixed effect of description type (treatment coded), a random intercept for participant and food stimulus, and random slopes varying across participant and food.[5] Both models converged without problems.

As predicted, participants reported stronger eating simulations when foods had simulation-based (M = 63, SD = 13) compared to control descriptions (M = 55, SD = 15), $F(1, 95.13)$ = 37.51, p < .001, R^2_m = 0.02, R^2_c = 0.32, see Fig. 7.

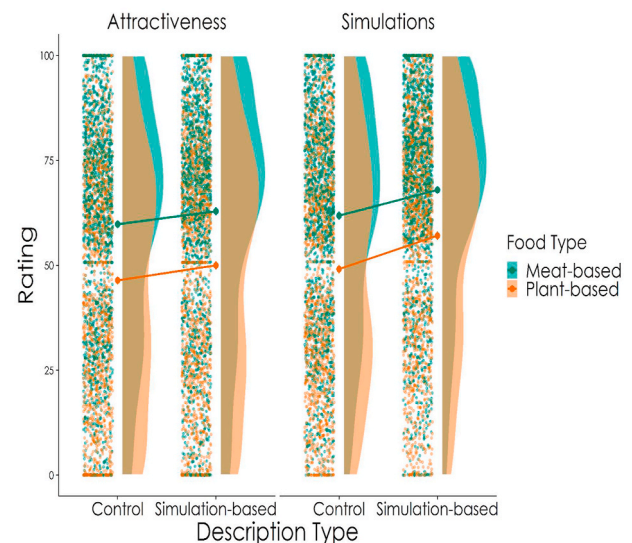A similar effect emerged for attractiveness. Again as predicted, par-

Fig. 7. Raincloud plots of the raw data associated with our analysis of the effects of description type and food type on attractiveness and simulations. Points represent each raw data point; density plots represent the distribution. Connected points represent the group means.

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[4] We re-ran all preregistered analyses without these two participants. Their exclusion did not affect the results.

[5] Note that we were imprecise in the preregistration, where we specified to predict each outcome from label type and food type. We meant random intercepts and random slopes for food stimuli, rather than including a fixed effect of food type.

ticipants rated foods more attractive if they had simulation-based descriptions ($M = 56$, $SD = 13$) compared to control descriptions ($M = 53$, $SD = 12$), $F(1, 47.57) = 10.74$, $p = .002$, $R^2_m = 0.003$, $R^2_c = 0.26$; see Fig. 7. The mean attractiveness rating per food in each condition, averaged across participants, can be found in the Online Supplemental Materials.

4.2.1.2. Exploratory. We tested whether the effects were robust to (1) the inclusion of the eight participants with a high relative speed index, (2) the exclusion of potential outliers, and (3) the inclusion of covariates. All effects were robust. Details on these analyses can be found in the supplemental materials. We also inspected whether the effect of description type on attractiveness was different for men or women. Neither the main effect of gender nor its interaction with description type was significant (both $p > .215$).

4.2.2. Interaction with food type

4.2.2.1. Confirmatory analyses. To test whether the effect of simulation-based descriptions was especially pronounced for plant-based foods, we constructed a maximal model for simulations and attractiveness, with a fixed effect of the interaction of food type and description type (sum-to-zero coded), a random intercept for participant and food stimulus, a random slope for the interaction within participant, and a random slope for description type within food stimulus. Both models yielded a convergence error. We followed the same troubleshooting steps as in Study 2 (Barr et al., 2013). Both fixed and random effects were stable across all troubleshooting steps (in particular across optimizers), suggesting that we could trust the model estimates (for numerical details, see OSF).

We did not find that the effects of description types were more pronounced for plant-based than for meat-based foods. In the model predicting simulations, both description type, $F(1, 96.81) = 37.42$, $p < .001$, and food type, $F(1, 62.30) = 37.49$, $p < .001$, had significant main effects, but their interaction was not significant, $F(1, 36.31) = 1.28$, $p = .265$; $R^2_m = 0.06$, $R^2_c = 0.37$. Similarly, predicting attractiveness, both description type, $F(1, 48.82) = 10.26$, $p = .002$, and food type, $F(1, 60.11) = 30.64$, $p < .001$, had significant main effects, but their interaction was not significant, $F(1, 37.45) = 0.07$, $p = .800$; $R^2_m = 0.05$, $R^2_c = 0.32$; see Fig. 7. Thus, contrary to our hypothesis, we did not find evidence that simulation-based descriptions would increase simulations and attractiveness more for plant-based compared to meat-based foods. These results did show, however, that both attractiveness and simulations were rated higher for meat-based foods ($M = 61$, $SD = 28$ and $M = 65$, $SD = 26$, resp.) than for plant-based foods ($M = 49$, $SD = 29$ and $M = 53$, $SD = 28$, resp.). In other words, participants indicated to find meat-based meals more attractive, and to think more about what it would be like to eat them when reading the food descriptions (see Fig. 7), compared to plant-based foods. Exploratory analyses showed that the two main effects remained robust for the simulation and the attractiveness model (all $ps < .003$). Likewise, excluding outliers did not change the pattern of results (all $ps < .003$).

4.2.3. Simulations predicting attractiveness

4.2.3.1. Confirmatory analyses. To test the hypothesis that eating simulations predict attractiveness, we ran a maximal model, with a fixed effect for simulations (standardized), as well as description type and food type (sum-to-zero coded), random intercepts for participant and food stimulus, random slopes for the three predictors within participant, and random slopes for simulations and description type within food stimulus. The model yielded a convergence error. We followed the same steps as above and estimates were identical across optimizers, allowing us to proceed and interpret the model estimates.

As predicted, simulations predicted attractiveness, such that an increase of one standard deviation in simulations was related to a 12.37 ($SE = 0.60$) increase in attractiveness, $F(1, 130.55) = 429.14$, $p < .001$.

After including simulations as a predictor, description type did not significantly affect attractiveness anymore, $F(1, 47.33) = 0.23$, $p = .64$. This pattern suggests that the some of the variance created by the different food descriptions which increased attractiveness was captured by eating simulations.

Consistent with the high correlation between simulations and attractiveness, the overall model explained a large amount of the variation in attractiveness, $R^2_m = 0.23$, $R^2_c = 0.43$.

4.2.3.2. Exploratory analyses. The effects of simulations and food type were robust to the inclusion of participants with a high RSI (both $p < .001$) and to the exclusion of outliers (both $p < .001$). In addition, we explored whether simulations interacted with either of the manipulations. Neither the interaction with description type, $F(1, 43.97) = 1.12$, $p = .396$, nor the interaction with food type, $F(1, 60.61) = 1.55$, $p = .218$, were significant.

We were interested in following up the finding that including simulations as a predictor of attractiveness reduced the effect of description type to such a degree that the effect became insignificant. This pattern is often indicative of mediation. Although the measurement of attractiveness occurred before the measurement of simulations, the Hyman-Tate conceptual timing criterion states that a mediator should precede the outcome in conceptual rather than in actual time (Tate, 2015). According the grounded cognition theory of desire, simulations indeed precede attractiveness conceptually: Food cues activate situated conceptualizations, which then trigger simulations. These simulations increase the attractiveness of food. Therefore, we wanted to test the statistical mediation model *description type → simulations → attractiveness*.

We conducted the test of the mediation model with the *mediate* command (*mediation* package; version 4.5.0; Tingley, Yamamoto, Hirose, Keele, & Imai, 2014). The command decomposes the total effect of description time on attractiveness into a direct effect and an indirect effect via simulations. We passed two mixed-effects models to the *mediate* command: One model predicting the mediator (i.e., unstandardized simulations) with description type, and one model predicting the outcome (i.e., unstandardized attractiveness) with the mediator and description type. Description type was sum-to-zero coded in both models. We fitted models with maximal effects structure for the participant grouping. As of this writing, the *mediation* package cannot accommodate designs with fully crossed levels (i.e., both description types were present for all participants for all foods). We retained the participant grouping because it had more associated variance than the food grouping.

In line with the grounded cognition theory of desire, the data were compatible with the statistical model *description type → simulations → attractiveness*. The average causal mediation effect was large and significant, $b = 3.63$, 95% CI[2.44, 4.90], $p < .001$. The direct effect of description type on attractiveness was negligible in size, $b = -0.20$, 95% CI[-1.89, 1.50], $p = .810$. The total effect was mostly driven by the indirect effect, $b = 3.43$, 95%CI[1.42, 5.35], $p < .001$. Therefore, the effects of description type on simulations and simulations on attractiveness were strong enough to account for the effect of description type on attractiveness. This pattern is consistent with, but not exclusive to our proposed mediation model (Fiedler, Harris, & Schott, 2018).

4.2.4. Effects of the intention to reduce meat consumption

4.2.4.1. Confirmatory analyses. To test the hypothesis that the intention to reduce meat consumption would be associated positively with attractiveness ratings for the plant-based foods, and negatively with attractiveness for meat-based foods, we ran a maximal model predicting

attractiveness. The model included the interaction of the intention to reduce eating meat (standardized) and food type as fixed effect (sum-to-zero coded), with random intercepts for participant and food stimulus, and a random slope for food type within participant.

The intention to reduce meat consumption did not affect the evaluation of meat-based dishes, but was positively associated with ratings of plant-based dishes. Specifically, there was a significant main effect of food type, $F(1, 57.36) = 31.46$, $p < .001$, and a main effect of the intention to reduce meat consumption, $F(1, 164.00) = 7.99$, $p = .005$, such that an increase of one standard deviation in the intention to reduce eating meat, averaged across food type, was associated with a 2.59 ($SE = 0.92$) increase in attractiveness. As predicted, the interaction term was significant, $F(1, 164.00) = 16.65$, $p < .001$. As illustrated in Fig. 8, the intention to reduce meat consumption was not significantly associated with evaluations of meat-based foods, $b = 0.14$, $SE = 1.09$, asymptotic CL[-1.99, 2.27], but was positively associated with the evaluations of plant-based foods, $b = 5.03$, $SE = 1.10$, asymptotic CL[2.88, 7.19].

Exploratory analyses showed that including participants with a high RSI did not change the results (all $p < .003$); neither did the exclusion of outliers (all $p < .005$).

4.2.5. Further exploratory analyses

To explore whether eating meat more frequently would be positively associated with attractiveness ratings of meat and negatively associated with plant-based food, we ran a maximal model with a fixed effect for the interaction of frequency of eating meat and food type, random intercepts for participant and food stimulus, and a random slope for food type within participant. We found a main effect of food type on attractiveness, $F(1, 55.80) = 31.93$, $p < .001$, no main effect of frequency of eating meat, $F(1, 164.01) = 0.80$, $p = .372$, and a significant interaction effect, $F(1, 163.99) = 27.52$, $p < .001$, $R^2_m = 0.06$, $R^2_c = 0.31$. Illustrated in Fig. 9, an increase of one standard deviation in frequency of eating meat was significantly associated with an increase in attractiveness for meat-based foods, $b = 2.22$, $SE = 1.07$, asymptotic CL[0.11, 4.32], but with a significant decrease for plant-based foods, $b = -3.89$, $SE = 1.13$, asymptotic CL[-6.10, -1.68]. Thus, the more meat people ate, the more attractive they found meat-based foods, and the less attractive they found plant-based foods, replicating the results from Study 2.

Finally, we tested whether simulation-based food descriptions help frequent meat eaters in finding plant-based foods more attractive. To that end, we constructed a maximal model to predict the attractiveness of plant-based foods only, with a fixed effect for the interaction of frequency of eating meat and description type, a random intercept per participant and food stimulus, and random slopes for food type within
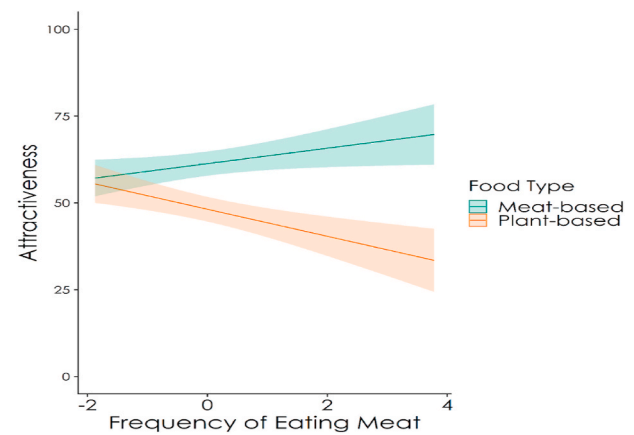
Fig. 9. Model-based slopes and CI for the relation between the frequency of eating meat (standardized 100-point visual analogue scale, such that one unit represents one *SD*) and attractiveness ratings (on 100-point visual analogue scales) of meat-based and plant-based foods.

participant and food stimulus.

Meat eating frequency negatively predicted attractiveness ratings of plant-based foods, $F(1, 163.88) = 11.96$, $p < .001$. There was no main effect of description type, $F(1, 19.12) = 4.39$, $p = .050$. There was a significant interaction, however, such that the effect of meat eating frequency was moderated by the description type, $F(1, 163.12) = 8.18$, $p = .005$, $R^2_m = 0.02$, $R^2_c = 0.31$. Simple slopes analyses, illustrated in Fig. 10, showed that in the control condition, meat eating frequency was negatively associated with attractiveness ratings of plant-based foods, $b = -5.16$, $SE = 1.17$, asymptotic CL[-7.45, -2.87], but this effect was less pronounced when the foods were presented with simulation-based descriptions, $b = -2.64$, $SE = 1.25$, asymptotic CL[-5.09, -0.18]. Thus, frequent meat eaters found plant-based foods less appealing, but this effect was attenuated by simulation-inducing food descriptions.

5. General discussion

5.1. Summary

We report three studies to understand how plant-based foods can best be labelled and described to support more sustainable consumer food choices. In Study 1, we analysed the descriptions of meat-based, vegetarian, and plant-based ready-meals in UK supermarkets. We found that meat-based foods were more likely to be described with
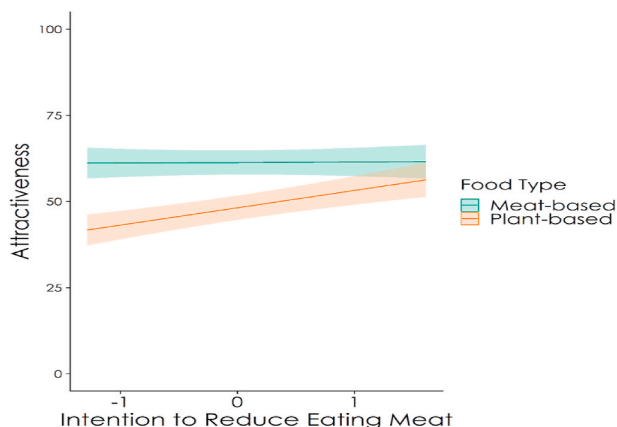
Fig. 8. Model-based slopes and CI for the relation between the intention to reduce eating meat (standardized 100-point visual analogue scale, such that one unit represents one *SD*) and attractiveness (on 100-point visual analogue scales), separately for food type. All line graphs visualized based on the output from the *effects* package (Fox, 2003).
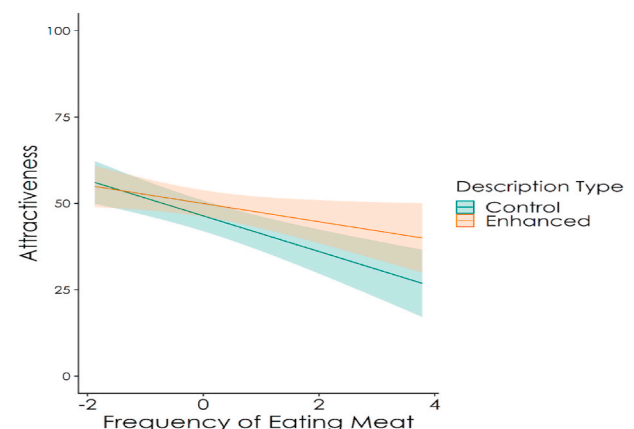
Fig. 10. Model-based slopes and CI for the relation between the frequency of eating meat (standardized 100-point visual analogue scale, such that one unit represents one *SD*) and attractiveness ratings (on 100-point visual analogue scales) of plant-based foods only, separately for description type.

sensory and action words than vegetarian foods and, to a lesser degree, than plant-based foods. Vegetarian and plant-based food were more likely to be described in terms of words unrelated to eating experiences, such as food categories and ingredients, compared to meat-based foods. This suggests that current food descriptions use language that might increase rewarding eating simulations and attractiveness for meat-based foods, but use less appealing language for foods without meat.

In Studies 2 and 3, we assessed whether such differences in language would indeed affect the appeal of foods. In Study 2, we tested whether the appeal of plant-based foods can be increased by simulation-based food descriptions, which included words related to either sensory experiences or eating context. Contrary to our predictions, we found no evidence that adding these words to the food descriptions increased self-reported likelihood of ordering the foods in a restaurant. As predicted, descriptions with added positive health words also did not increase desire.

In Study 3, we therefore created simulation-based food descriptions that combined sensory, context, and hedonic words. Using this stronger manipulation, we found that in line with our predictions, simulation-based descriptions increased the appeal of both plant-based and meat-based foods, compared to equally long control descriptions merely listing ingredients. Simulation-based descriptions further increased the degree to which participants thought about eating the food when reading food descriptions. Exploratory analyses further suggested that eating simulations might mediate the effect of simulation-based descriptions on food attractiveness. In line with the grounded cognition theory of desire, the data supported a mediation model that expects simulation-based labels to increase the foods' appeal through increasing eating simulations. However, although our model was compatible with the Hyman-Tate criterion of mediation (Tate, 2015), we must view conclusions about mediation with caution. There may be alternative mediation models that account for a significant proportion of variance in our outcome (Fiedler et al., 2018). Finally, while more frequently eating meat was associated with liking plant-based foods less, an exploratory analysis showed that simulation-based descriptions attenuated this effect. Thus, simulation-based food descriptions can be used to increase the appeal of plant-based foods, including among frequent meat eaters, who otherwise like this food less.

Our findings are consistent with recent research on the language used for healthy foods in restaurants, and on taste-focused language to increase choices for vegetable-based dishes (Turnwald, Boles, & Crum, 2017; Turnwald & Crum, 2019; see also; Cadario & Chandon, 2019). The results of Study 3 indicate that rich simulation-based descriptions which add several simulation words covering sensory, context, and hedonic features can indeed increase the attractiveness of plant-based foods, possibly through eating simulations, and that they can attenuate habitual meat eaters' aversion to plant-based foods. Crucially, Study 3 improved upon Study 2 and upon previous research by comparing simulation-based food descriptions to control descriptions which are equally long, and which are neutral, rather than to focusing on foods being healthy. Many consumers expect healthy foods to be less tasty (Raghunathan, Naylor, & Hoyer, 2006), and health-focused labels reduce the appeal of foods (e.g., Liem, Miremadi, Zandstra, & Keast, 2012; Liem, Toraman Aydin, & Zandstra, 2012; Turnwald, Boles, & Crum, 2017). Therefore, they cannot be regarded as a neutral control condition. Study 3 therefore compared simulation-based descriptions to control descriptions that simply listed ingredients without emphasizing health, whilst making sure that the descriptions in both conditions contained the same number of words on average. The difference between the simulation-based descriptions and these neutral control descriptions clearly shows that simulation-based descriptions are effective at increasing attractiveness of plant-based foods.

5.2. Limitations

Our work has some important limitations that futures studies should

address. First of all, we analysed only a sample of ready meals from four UK supermarkets in Study 1. While the selected supermarkets cover a wide price range and offer a lot of convenience food that was of interest to our analysis, future studies could include a more comprehensive analysis of the convenience meals available in the biggest supermarkets in the UK and other countries. Second, in Studies 2 and 3 we only used self-reported choice and attractiveness ratings, rather than actual food ordering or grocery shopping behaviour as an outcome variable. However, a large-scale manipulation of food descriptions is not feasible in a commercial setting. Previous field trials (Bacon, Wise, Attwood, & Vennard, 2018; Turnwald & Crum, 2019; Turnwald et al., 2019) show that sensory-focused labels increase choices of vegetable-dishes in cafeteria settings over an extended period of time. By extension, these findings suggest that simulation-based labels may also be effective to increase choices of plant-based foods in restaurant and grocery settings. Finally, the grounded cognition theory of desire predicts that rewarding eating simulations are the mechanism through which food labels can increase attractiveness. We explored this possibility in Study 3 and indeed found results that are consistent with a mediation model, such that food descriptions with simulation words increase desire through increasing eating simulations. However, experimentally manipulating, rather than measuring, simulations would provide a stronger test of this possible causal mechanism and might be examined in future research.

Another potential limitation is that we assessed intentions to reduce meat intake by asking participants whether they were currently trying to reduce their meat consumption. This likely captures both ongoing and planned attempts at behaviour change, and may therefore be an imperfect measure of intentions per se. Future research might examine whether participants who are not yet engaging in meat reduction attempts, i.e., are in the preparation rather than the action phase of behaviour change (DiClemente & Prochaska, 1998), also view plant-based foods increasingly positive.

5.3. Implications

Our work has both theoretical and applied implications. Our findings are in line with key predictions of the grounded cognition theory of desire. The theory predicts that people spontaneously simulate eating food when exposed to food cues, especially of attractive food, and that these simulations can in turn increase attractiveness and desire. Indeed, we saw that simulation ratings were higher for meat-based foods, which participants found more attractive overall than the plant-based foods. Consistent with the theory, Study 3 showed that labels that increased simulations also increased attractiveness, for both types of food. Thus, while previous work has shown that instructing participants to imagine eating a food increases desire (Keesman et al., 2016; Muñoz-Vilches, van Trijp, & Piqueras-Fiszman, 2019), this work shows that such effects can also be achieved more incidentally through rich, simulation-inducing language, if this uses several simulation features. Critically, simulation labels increased simulations also for plant-based foods, which participants were less familiar with and did not find highly attractive to begin with (i.e., they were rated below the midpoint of the scale). This suggests that sensory, hedonic and context features that have been associated with rewarding experiences in other situations (e.g., when eating a familiar food) can be transferred to novel experiences (e.g., expectations about an unfamiliar food) in order to increase their appeal.

Our findings have implications for strategies to increase choices of healthy and sustainable foods. Again, our analysis of the language used to label and describe plant-based ready meals shows that there is room for improvement. Specifically, meat-free meals were described with more situation-independent words and less sensory, hedonic, and context words than meat-based meals, while our work demonstrated that using such simulation language can increase the appeal of foods. Clearly, simulation language, referring to several rewarding aspects of a consumer's previous eating experiences, should be used more to label and describe healthy and sustainable foods. This strategy can be

conceptualised as a cueing intervention (Best & Papies, 2017; Papies, 2017) because it activates different, more rewarding representations, and should replace health-focused labelling of foods, which are not likely to induce rewarding consumption simulations.

When designing simulation-based labels, variability among foods and consumers should be considered in attempts to trigger the most rewarding consumption simulations. The grounded cognition theory of desire suggests that people's representations of food items, and therefore the simulations that are triggered by these foods, are the result of highly individual learning histories, and will therefore vary strongly between individuals. As an example, while for some people, and for some of the foods they eat, context features are most likely to trigger desire, for other people and other foods, it will be sensory features that matter most. In addition, the specific features within each category that most strongly trigger rewarding simulations will also differ. Future research may attempt to establish useful regularities in these representations, for example which features are linked to desire among certain demographics or for certain foods, so that they can be used most effectively. In any case, simulation labels should contain several simulation features and should be carefully derived and pilot-tested for specific products and target groups, before applying them on a large scale.

While the size of the effect of simulation-based labels on attractiveness (Study 3) was not large (averaging 3 points on a 100-point scale), if even part of this effect were translated into plant-based choices, it would lead to a meaningful increase in plant-based choices in the population. In addition, simulation-based labels were more effective at influencing highly regular meat-eaters, among whom behaviour change would be most important, for both health and sustainability reasons. Furthermore, even small numbers of sustainable food choices can have beneficial downstream effects by allowing healthier habits to develop if a product is later chosen for repeat consumption, and by influencing the behaviour of others through changing social norms. Thus, small but systematic effects of theory-based interventions to increase healthy and sustainable choices can have meaningful effects given the millions of food choices that people make in supermarkets each day (see Funder & Ozer, 2019).

Ultimately, such strategies should be combined with other interventions, such as increasing the ease, salience, and availability of plant-based foods (Bianchi, Garnett, et al., 2018; Garnett et al., 2019; Hollands et al., 2017; Marteau, 2017). Specifically, to maximise the choices of plant-based foods, they should be placed in central positions to increase their salience and accessibility, they should constitute a large proportion of the foods on offer, and they should be labelled in ways that increase their attractiveness. This way, more people are likely to assume that plant-based foods are a mainstream, attractive choice. In future research, large-scale field trials could examine which of these intervention strategies or combinations thereof are most effective for replacing meat-based with plant-based foods.

Ethics statement

The study was approved by the Ethics Committee of the College of Science and Engineering at the University of Glasgow.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.appet.2020.104812.

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