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Pleasure vs. identity: More eating simulation language in meat posts than plant-based posts on social media #foodtalk

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ABSTRACT

Current levels of meat consumption in Western societies are unsustainable and contribute to the climate emergency. However, most people are not reducing their intake. Here, we examine the language used on social media to describe meat and plant-based foods, since the ways people think and communicate about food could hinder the transition towards sustainable eating. In two pre-registered studies, we analysed the degree to which the language in food posts on Instagram reflects eating simulations, which have been found to be associated with desire for appetitive stimuli. Specifically, thinking about or presenting foods or drinks in terms of rewarding simulations (i.e., re-experiences of enjoying their consumption) has been found to increase their appeal. Here, we analysed the words used in Instagram hashtags ($N_{Study1} = 852$; $N_{Study2} = 3104$) and caption text ($N_{Study1} = 682$) to examine how much they refer to eating simulations (e.g., taste, texture, enjoyment, eating context) or to other food-related features (e.g., ingredients, preparation, health, category information). As hypothesized, meat posts contained more eating simulation hashtags than plant-based and vegetarian posts, which instead contained more eating-independent hashtags, for example referring to health or to vegan identity. Findings for the text words were generally in the same direction but much weaker. Thus, meat food posts contained hashtag language that is likely more appealing to mainstream consumers, because it refers to the enjoyable experience of eating the food, rather than the food being healthy or identity affirming. This pattern reflects polarisation surrounding sustainable foods, which may hinder the shift towards plant-based diets needed to curb climate change.

1. Introduction

Current levels of animal meat consumption in Western societies are unsustainable. Although meat products only provide 18% of the average calories consumed per day (Poore & Nemecek, 2018), the production of meat contributes to 14.5% of all human-induced greenhouse gas emissions (Gerber et al., 2013), and has a substantial negative impact on water pollution, agricultural land use, biodiversity loss and worldwide poverty (Hoegh-Guldberg et al., 2019; Springmann et al., 2018; Tilman & Clark, 2014). In fact, the increase in global temperature due to emissions from the food system alone would likely exceed the Paris Agreement 1.5° target between 2051 and 2063 (Clark et al., 2020). Additionally, health issues related to high meat consumption, such as diabetes, cancer and cardiovascular disease (Abete et al., 2014; Wolk, 2017) and associated moral concerns (Bastian et al., 2012; Rosenfeld et al., 2020), have also brought current Western meat eating habits into question.

Despite these concerns, just one in six meat-eaters intend to reduce their meat intake (Bryant, 2019). Why are sustainable food choices perceived as undesirable to the majority of consumers, even in the face of environmental, health and animal welfare pressures? Taste and reward expectations play a key role in food choices (Franchi, 2012), with vegetarian and vegan foods expected to be less tasty and enjoyable than meat (Corrin & Papadopoulos, 2017; Rosenfeld & Tomiyama, 2020). Here, we explored how individuals communicate about these foods on social media, in order to better understand socially shared perceptions of meat and plant-based foods, and help inform strategies aimed at promoting sustainable food choices among mainstream consumers.

The way we communicate about food reflects a wealth of information about our underlying attitudes and values (Stajcic, 2013). Daily behaviours such as eating habits are often guided by nonconscious processes (Graça et al., 2019; Roberto, 2020), which then impact our language surrounding food (Riley & Cavanaugh, 2017). Conversely, language can be used to change food perceptions and preferences. Using labelling that focuses on the eating experience, such as words referring

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to the taste, texture or eating context, has been found to increase the appeal of plant-based foods, especially among more habitual meat-eaters (Papies, Johannes, et al., 2020), boost healthy food selections, and enhance post-consumption ratings of vegetable deliciousness (Turnwald & Crum, 2019). Therefore, associating sustainable food choices with words that refer to the short-term enjoyment of eating a food, instead of long-term health benefits, can likely boost their appeal (Piqueras-Fiszman & Spence, 2015). At the same time, healthy and sustainable foods have been found to be described with less indulgent language than unhealthy or less sustainable foods on restaurant menus and ready meal packages (Papies, Johannes, et al., 2020; Turnwald et al., 2017), suggesting that this strategy is not consistently used in food marketing.

Why can language focused on the eating experience increase food attractiveness? According to the Grounded Cognition Theory of Desire, food cues, such as words or images, can trigger rewarding simulations, or re-experiences, of eating a food, which can lead to desire, especially for more attractive foods (Papies et al., 2020a, 2022). Indeed, viewing food words or images activates gustatory and reward areas in the brain, like when tasting a food, suggesting that food cues trigger re-experiences, or simulations, of eating (Chen et al., 2016; Simmons et al., 2005). Participants also spontaneously use more eating simulation words when describing 'attractive' foods such as crisps, than 'neutral' foods such as rice (Papies, 2013), suggesting that they simulate eating a food when describing it, especially if the food is attractive. These simulations predict desire to consume a food or drink, as well as intake, even when controlling for consumption habits (Papies et al., 2021). Further, such eating simulations can be enhanced by appropriate context cues (e.g., a setting where one would eat the food), suggesting that eating context plays an important role in food desire through its effects on eating simulations (Papies, Barsalou, et al., 2022). Together, these findings show that simulations of eating and enjoying a food can reflect and increase desire for it, and that language can be used to tap into and activate such simulations. In this paper, we examined the eating simulations in food language on social media, since this may reflect how users think about foods, and in turn influence the food perceptions of other users.

1.1. The present research

The current studies were designed to explore the language used when consumers communicate about meat, vegetarian, and vegan foods on Instagram, which hosts an abundance of online food discourse (Barre et al., 2016). Instagram is a popular photo-sharing platform which allows users to upload photos and videos alongside linguistic annotations in the form of text captions and searchable hashtags (Zappavigna, 2015). Hashtags describe the visual contents of the image (Giannoulakis & Tsapatsoulis, 2016), and express the affective stance of the user through a common set of text labels (Lee & Chau, 2018). Social media functions as interactive communication channels that are used to form and maintain social relationships (Blackwood, 2019), and have also been found to alter food preferences. For example, exposure to socially endorsed images of low energy-dense foods led to a greater consumption of healthy snacks by female students, and similarly, exposure to either health or taste framed Instagram feeds impacted future snack choice (Blundell & Forwood, 2021; Hawkins et al., 2021). Furthermore, engagement with food adverts on social media was associated with high intake of unhealthy foods (Gascoyne et al., 2021), and short videos typically posted on social media influenced food choice behaviour, liking and intentions to eat the foods portrayed (Ngqangashe & Backer, 2021). More generally, discursive psychological studies have found that online communication aids in establishing food identities (Sneijder & te Molder, 2006). However, research has yet to explore the language associated with different foods in an online setting.

We investigated whether different language is used to describe meat, vegetarian and plant-based foods. More specifically, we examined whether more eating simulation language is used for meat foods, which are part of the dominant Western eating culture and typically seen as more attractive than both vegetarian and vegan foods. We decided to distinguish between vegetarian and vegan dishes, as the language associated with foods that do not contain meat could differ from foods that do not contain any animal products. To analyse the language, we used a recently developed feature listing manual (Papies, Tatar, et al., 2020) which categorises food-related words into three main categories: consumption situation, non-consumption situation and situation-independent. In Study 1, we examined caption text and hashtag words for meat, vegetarian and plant-based food posts. In Study 2, we replicated this, looking at hashtag words in a larger dataset. We hypothesized that posts about meat dishes would contain more consumption situation words in hashtags (H1) and caption text (H3) than plant-based and vegetarian dishes, reflecting stronger eating simulations. Based on findings that sustainable foods are less likely to be described with indulgent language (Papies, Johannes, et al., 2020), we also hypothesized more situation-independent language in the hashtags (H2) and text (H4) of posts about plant-based and vegetarian dishes than meat dishes. Given the similarity in methodologies for Studies 1 and 2, we present the Methods and Results for both studies side by side to increase comparability.

2. Methods

2.1. Design and sample size

Both observational studies had food type as the independent variable, and consumption situation and situation-independent language proportions as the dependent variables. All variables, measures and exclusions are reported. Sample sizes were determined before data analysis. Both studies were pre-registered, with all materials available here: https://osf.io/uy45w/.

We used G*Power (version 3.1; Erdfelder et al., 1996) for power analyses. For Study 1, we ran a power analysis for a fixed-effects, one-way ANOVA, as we had initially planned to run linear models. Our goal was to obtain 0.95 power to detect a very small effect size of 0.10 (Sawilowsky, 2009) with an adjusted alpha of .0125 for our pairwise comparisons testing in H1–H4. This produced a minimum required sample size of 1548 posts total, or 516 per food type. For Study 2, we ran our power calculations based on a two independent proportions z-test for our pairwise comparisons testing in H1–H2. Our group proportion parameters were set at 0.33 and 0.28, based on the Study 1 meat and vegetarian consumption situation hashtag means, which had the smallest between-group proportional difference (0.34 vs 0.26, respectively). Our goal was to obtain 0.95 power to find a 5% difference in proportions (adjusted alpha = .025), which produced a minimum required sample size of 6603 posts total, or 2201 per food type.

2.2. Data collection

For Study 1, data was collected manually from the most recent search engine results on Instagram by TD in November 2019, using three searchable labels: '#plantbased', '#meat' and '#vegetarian'. We generated separate datasets for the post hashtags and caption text because a) hashtags are used to search for relevant content (Highfield & Leaver, 2015) and are therefore included in posts for different purposes than the text, and b) a maximum limit of 30 hashtags and 2200 characters for captions per post means there is a considerable difference between these two types of data in length and form. Although we only focused on language and not on the image content, we excluded posts that had no food-related image, to ensure that we included only language from food-related posts. We further excluded posts that were not written in English, contained videos, and commercial marketing posts from business accounts. We also excluded posts of non-savoury and dessert foods. 1200 posts for each food type were collected to ensure sufficient power after these planned exclusions. Using these criteria, and after removing posts with missing data, a total of 852 posts ($N_{meat} = 306$, $N_{plantbased} = 250$, $N_{vegetarian} = 296$) were included for analysis of hashtags, and 682 posts ($N_{meat} = 237$, $N_{plantbased} = 252$, $N_{vegetarian} = 193$) for analysis of caption text.

For Study 2, data was gathered manually from the most recent search engine results on Instagram by TD and a research assistant between August and September 2020. To avoid potential effects of the COVID-19 lockdowns on eating behaviour (Ammar et al., 2020), we decided to collect posts from February 2020. We could not use the same searchable labels as Study 1, as search results are ordered by most recent on the Instagram search engine, and the vast number of post results generated from our food type searchable labels made it impossible to scroll back far enough. Therefore, we decided to collect posts using 33 pre-registered dish searchable labels across 12 dish categories (see Table 1), that had a post results total of 120,000 or fewer, which made it possible to scroll back to posts from February 2020.

In addition to the Study 1 exclusion criteria, we excluded posts that did not include one of the three food type hashtags (#plantbased, #meat, #vegetarian) or a hashtag that clearly referred to a food type (e.g. #vegan, #carnivore, #veggie). Unlike Study 1, posts were excluded at the point of data collection. Using these criteria, and after removing posts with missing data, we collected a total of 3104 posts ($N_{meat} = 515$, $N_{plantbased} = 1946$, $N_{vegetarian} = 643$). We could not achieve our desired sample size due to the introduction of new automaticity measures by Instagram during our data collection period, which restricted our ability to manually scroll retrospectively to February 2020 posts (Instagram, 2020b).

In line with the Instagram Terms of Use Data Policy (Instagram, 2020a) we gathered publicly accessible data from each post. No personally identifiable information was collected.

2.3. Data coding

Data was coded according to a hierarchical coding scheme designed to categorise features of food and drink descriptions (Papies, Tatar, et al., 2020). This coding scheme categorises features into 5 main categories, and 42 sub-categories. Features are coded as 'consumption situation' language if they refer to aspects of situations where the food is consumed, such as the sensory aspects (e.g. "spicy, "thick", "warm"), consumption context (e.g. "evening", "café", "with a beer") or the immediate experiences of eating a food (e.g. "delicious", "comforting", "bloating"). Features are coded as 'non-consumption situation' language if they refer to aspects of situations in which the food is present but not consumed, such as the production (e.g. "recipe", "local", "cow"), purchasing (e.g. "cheap", "drive-thru", "supermarket"), preparation (e.g. "fridge", "sliced", "frozen") or the cultural aspects of a food (e.g. "italian, "popular", "christmas"). Features are coded as 'situation-independent' language if they refer to aspects that are independent of consumption or non-consumption situations, such as the health consequences (e.g., "healthy", "good for you", "fattening"), ingredients and content (e.g. "high protein", "broccoli", "gluten-free"), visual properties (e.g. "red", "beautiful", "round") or the overall evaluations of a food ("good", "bad", "favourite"). Features that could be equally coded in two or more main categories are coded as 'ambiguous' language, and features that cannot be identified as a food word in the study language (i.e. English) are coded as 'nonword'. Syncategorematic words, i.e. words that do not stand by themselves such as prepositions, logical connectives, articles and quantifiers (e.g. "at", "the", "in", "of") are also coded as 'nonword'. For further details and subcategories, see the Supplementary Online Materials (SOM).

During the coding process, we decided to add three novel categories to capture words specific to our data. First, considering that many identity-related words were found in the text and hashtags, and given that identity expression is a crucial motivation for social media use (Baym, 2015), we added an identity subcategory within the situation-independent main category to capture language referencing the group membership of the consumer in relation to the food they eat (e.g., "foodie", "carnivore", "vegancommunity"). Second, we also added a social and political context subcategory into the main situation-independent category to capture words that refer to general social norms or political ideas or movements (e.g., "climate", "movement", "yes2meat"), which are commonly used to communicate attitudes within online platforms (Lee et al., 2015). Finally, we added a social media main category for any feature that refers to the social media platform (e.g., "blog", "followers", "dailypost") rather than the food. Therefore, 6 main categories and 44 sub-categories in total were used for coding.

Features that consisted of several words were divided into the smallest meaningful units and coded separately, for example "#healthyfoodporn" became "healthy" (situation independent: long-term positive health consequences) and "foodporn" (situation independent: visual), and "dinner with friends" became "dinner" (consumption situation: time setting and frequency) and "with friends" (consumption situation: social setting). Further examples can be found in Table 2. We excluded food type searchable labels from Study 1 ('#plantbased', '#meat', '#vegetarian'), and food type and dish searchable labels from Study 2 (e.g. '#mushroomrisotto', '#chickenburrito', '#nutroast'; see Table 1), as these had been used to identify and select the posts for inclusion in the studies, and including them in our analyses could have influenced category means.

TD coded all features for both studies, and secondary coding was completed by BT, who had previous experience using the feature listing coding scheme, to test for interrater reliability (McHugh, 2012). Secondary coding sample sizes for each study were calculated as 1% of the total unique words coded (i.e. single instances of words used, without counting repetitions). For Study 1, secondary coding of a random 50-word sample resulted in moderate agreement ($\kappa = 0.48$) at the main category level. After discussing coding discrepancies, TD recoded the dataset. An additional random 50-word sample was coded by BT. Results showed substantial agreement ($\kappa = 0.64$). For Study 2, a 75-word sample was double coded by BT, which resulted in moderate agreement ($\kappa =$

Table 1
Dish searchable labels by food type for study 2.

Dish Category	Meat	Plant-Based	Vegetarian
Breakfast	#fullenglishbreakfast	#plantbasedbreakfast	#vegetarianbreakfast
Brunch	#baconsandwich	–	#cheeseontoast
Burger	#lambburger	#veganburgers	#veggieburgers
Burrito	#chickenburrito	#veganburrito	#veggieburrito
Curry	#beefcurry	#vegetablecurry	#eggcurry
Pasta	#beeflasagna	#tomatopasta	#macaronicheese
Pizza	#chickenpizza	#plantbasedpizza	#veggiepizza
Ramen	#chickenramen	#veganramen	#veggieramen
Rice	#chickenfriedrice	#mushroomrisotto	#eggfriedrice
Roast	#roastlamb	#veganroast	#nutroast
Salad	#beefsalad	#vegetablesalad	–
Wrap	–	#veganwrap	#veggiewrap

Table 2
Example of text and hashtag data coding for a sample post.

Example	Features	Main Category	Subcategory
Text Data			
"loaded nachos for a cosy night in"	"loaded"	situation independent	ingredients and content
	"nachos"	situation independent	ingredients and content
	"for"	nonword	–
	"a"	nonword	–
	"cosy"	consumption situation	immediate positive emotional consequences
	"night in"	consumption situation	time setting and frequency
Hashtag Data			
"#food #foodporn #foodposts #delicious #meat"	"food"	situation independent	category information
	"foodporn"	situation independent	visual
	"foodposts"	social media	–
	"delicious"	consumption situation	immediate positive hedonic consequences
	"meat"	situation independent	ingredients and content

0.65), which was deemed satisfactory for our analyses.

2.4. Analysis plan

Although we had pre-registered to analyse category means in Study 1, we decided to analyse proportions instead, in order to control for the substantial variation in the overall number of words used in the hashtags and text captions. Proportions were calculated for each post by dividing the number of words coded per category (e.g. consumption situation features) by the total number of words coded across all categories, namely consumption situation, non-consumption situation and situation-independent features. For example, if a post had three consumption situation features out of ten coded features total, the consumption situation proportion for that post would be 0.30. Ambiguous, nonword and social media words were excluded from analysis, as these were considered separate to the food language of interest. As a robustness check, we re-ran our analyses with all categories included in our proportions denominator, and only found minor changes which did not change our overall conclusions (for further details, see the OSF).

All analyses were conducted in R (version 4.0.4; R Core Team, 2021) with data processing and visualisation generated using the tidyverse library and associated packages (version 1.3.1; Wickham et al., 2019). As we decided to analyse proportions, we could not use the linear modelling tests outlined in our Study 1 pre-registered analysis plan, which assumes a Gaussian distribution (Jaeger, 2008). Therefore, we instead fitted logistic binomial regression models with the *glm* function of the *lme4* package (Bates, Maechler, Bolker, & Walker, 2015) and ran pairwise comparisons with the *emmeans* package (version 1.6.0; Lenth, 2021). We obtained p-values using a chi-square test to compare our binomial models against a null model, as implemented in the *anova* function of the *stats* package (version 4.0.4; R Core Team, 2021). Across all our Study 1 models, we predicted proportions with a fixed effect for food type. To control for familywise error rate from multiple testing, we adjusted our alpha level in Study 1 to $p < .0125$ using the Bonferroni correction. Our effect sizes were estimated using the *r2_nagelkerke* function of the *performance* package (version 0.6.1; Lüdecke et al., 2021).

For Study 2, we followed the planned pre-registered binomial mixed-effect models using the *glmer* function of the *lme4* package, and running pairwise comparisons with the *emmeans* package. Across all binomial mixed-effects models, we used a maximal random effects structure (Barr et al., 2013), predicting proportions with a fixed effect for food type, and a random intercept and slope for dish type. We obtained p-values based on Likelihood Ratio Tests, as implemented in the *mixed* function of the *afex* package (version .28–1; Singmann et al., 2021). Again, to control for familywise error rate from multiple testing, we adjusted our alpha level to $p < .025$. Our effect sizes were estimated using the *r.squaredGLMM* function of the *MuMIn* package (version 1.43.17; Bartoń, 2020).

Post-hoc sensitivity analyses for both studies were conducted using G*Power (version 3.1; Erdfelder et al., 1996) based on the differences between two independent proportions z-test, one-tailed, set at 95% power and an adjusted alpha of 0.0125 for Study 1 and 0.025 for Study 2. Effect size thresholds were calculated using the smallest group proportion mean (e.g. 0.17 for plant-based posts), and group sample sizes (e.g. 250 for plant-based posts; 306 for meat posts). From this, output parameters generated a minimum proportion difference threshold between groups needed to obtain a reliable effect (e.g. a proportion of at least 0.31 for meat posts; a difference of 14% between plant-based and meat posts).

Following the results of our confirmatory analyses, we decided to run several exploratory analyses. Firstly, we ran three binomial mixed-effect models, with non-consumption situation proportions as our dependent variable for the hashtag data in Studies 1 and 2, and the text data in Study 1. Non-consumption situation is the third main category in the feature listing manual, which was used in our proportion calculations. Therefore, we also explored differences in non-consumption situation proportions. We further ran two binomial mixed-effect models comparing the frequency of hashtag words coded in the identity subcategory, between food types.

Data visualisation was produced using raincloud plots (Allen et al., 2019). Model diagnostics were assessed using the *DHARMa* package (version 0.3.3.0; Hartig, 2020). Although our models showed mild overdispersion ($\mathrm{Var}(\nu) \leq 2$), this often indicates more conservative results and is unlikely to influence Type 1 error rate, standard error or empirical power estimates (Xu et al., 2008). Considering this, we decided to run our binomial models without quasi, beta or observed-level random effect corrections.

3. Results

A total of 62,247 words, 10,036 (16%) unique, were coded across the three datasets. Table 3 shows the numbers of words coded in each study. The most frequently used features for each food type can be seen in Table 4. For further Descriptives, please see the SOM.

Table 3
Number of words coded for study 1 and 2.

	Total Words	Unique Words	Unique Words (%)	Mean Words per Post	SD Words per Post
Study 1					
Text	6775	2127	31%	9.93	10.29
Hashtag	12,072	3966	33%	14.17	8.03
Study 2					
Hashtag	43,400	11,483	26%	13.98	7.67

Table 4
Most frequent words by food type.

	Meat			Plant-Based			Vegetarian		
	Word	Freq.	% of posts	Word	Freq.	% of posts	Word	Freq.	% of posts
Study 1 Hashtag Words									
1	food	145	46%	veganfood	119	47%	food	105	33%
2	foodporn	126	39%	healthy	102	27%	healthy	99	26%
3	foodie	95	29%	whatveganseat	79	31%	recipes	80	18%
4	dinner	67	22%	foodporn	78	24%	foodporn	73	24%
5	bbq	66	18%	food	77	31%	foodie	68	22%
6	beef	65	20%	recipes	73	21%	healthyfood	66	22%
7	steak	56	15%	healthyfood	61	24%	breakfast	61	12%
8	lunch	54	17%	breakfast	51	15%	veggie	56	16%
9	yummy	54	17%	govegan	50	20%	lunch	49	14%
10	delicious	53	17%	veganlife	48	19%	homemade	44	13%
Study 2 Hashtag Words									
1	food	189	34%	veganfood	1099	50%	recipes	197	22%
2	foodporn	178	32%	whatveganseat	563	27%	food	168	23%
3	foodie	166	31%	recipes	535	22%	foodie	159	23%
4	dinner	142	20%	dinner	501	19%	healthy	155	20%
5	sunday	87	22%	foodporn	421	18%	foodporn	148	21%
6	delicious	79	15%	veganlife	327	16%	brunch	125	12%
7	yummy	75	14%	healthy	322	13%	dinner	114	13%
8	lunch	70	11%	meals	290	12%	slimmingworld	111	6%
9	slimmingworld	66	6%	plantbaseddiet	287	15%	healthyfood	106	15%
10	homemade	61	11%	lunch	284	10%	homemade	101	12%
Study 1 Text Words									
1	good	23	9%	delicious	37	15%	lunch	25	10%
2	beef	21	9%	day	32	10%	food	24	10%
3	chicken	21	8%	tofu	31	11%	made	21	10%
4	steak	21	7%	food	29	9%	good	19	8%
5	food	19	8%	breakfast	29	10%	delicious	18	9%
6	time	15	6%	good	23	8%	tomatoes	18	9%
7	cooked	14	6%	brunch	21	6%	sauce	18	7%
8	delicious	14	6%	salad	20	6%	eggs	18	8%
9	bbq	13	5%	spinach	20	8%	happy	17	8%
10	pork	13	5%	garlic	20	8%	potato	16	6%

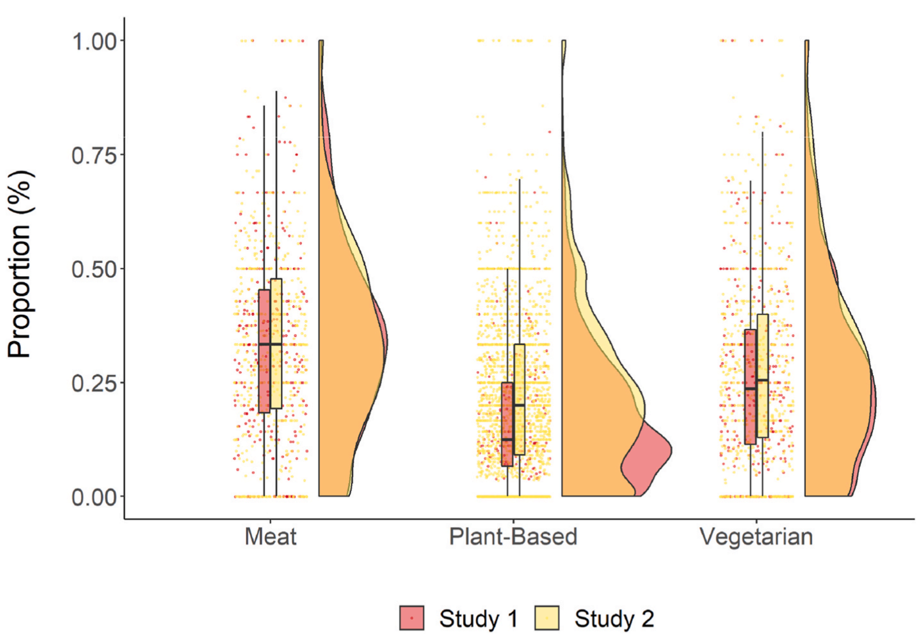

Fig. 1. Proportion of Consumption Situation Hashtag Words by Food Type
Note. Raincloud plot of the consumption situation category proportion means in hashtags on Instagram posts about meat foods, plant-based foods, and vegetarian foods in Study 1 and 2. The boxplots represent the proportion means and the scatterplots and violin plots represent the distribution of the proportions for all observations.

3.1. *Confirmatory analyses*

3.1.1. *Consumption situation words in hashtags*

We predicted that meat posts would contain a more consumption situation hashtag words than plant-based posts (H1). We also predicted that meat posts would contain more consumption situation hashtag words than vegetarian posts in Study 1, but did not predict this in Study 2. In line with these predictions, the overall effect of food type on the proportion of consumption situation hashtag words was significant in Study 1, $\chi^2(2) = 326.03$, $p < .001$, $R^2_{psuedo} = 0.16$, and Study 2, $\chi^2(2) = 34.16$, $p < .001$, $R^2_m = 0.15$, $R^2_c = 0.24$ (see Fig. 1). Pairwise comparison statistics are displayed in Table 5. Study 1 meat posts had a higher proportion of consumption situation hashtag words than plant-based posts, and vegetarian posts. Vegetarian posts also had a higher

Table 5
Pairwise comparisons of consumption situation words between food categories.

	Meat	Plant-based	Vegetarian	Meat vs.Plant-based	Meat vs. Vegetarian	Plant-based vs. Vegetarian
	M (SD)	*M (SD)*	*M (SD)*	*b (SE) p* *[95% CI]*	*b (SE) p* *[95% CI]*	*b (SE) p* *[95% CI]*
Study 1						
Text	0.35 (0.33)	0.32 (0.25)	0.33 (0.27)	0.03 (0.07) 0.49 [-0.10 – 0.16]	0.04 (0.07) 0.61 [-0.10 – 0.19]	0.01 (0.06) 0.18 [-0.11 – 0.14]
Hashtag	0.34 (0.21)	0.17 (0.15)	0.26 (0.21)	0.94 (0.05) **<0.001** [0.83 – 1.04]	0.28 (0.05) **<0.001** [0.19 – 0.38]	-0.66 (0.06) **<0.001** [-0.77 – -0.55]
Study 2						
Hashtag	0.34 (0.21)	0.23 (0.19)	0.29 (0.21)	0.55 (0.04) **<0.001** [0.47 – 0.62]	0.23 (0.08) **0.003** [0.08 – 0.39]	-0.32 (0.09) **<0.001** [-0.48 – -0.15]

proportion of consumption situation hashtag words than plant-based posts. Exactly the same pattern was found in Study 2.

Post-hoc sensitivity analyses were run to calculate the minimum proportional difference required to detect a reliable effect size of theoretical interest in our data. These showed that for the proportions of consumption situation words in hashtags, a minimum proportional difference between groups of at least 14% was required for Study 1, and at least 8% was required for Study 2. The observed difference between plant-based and meat posts was sufficiently powered for both studies, with a 17% difference in Study 1, and an 11% difference in Study 2. However, the observed differences between vegetarian and meat posts (Study 1: 8%; Study 2: 5%), and plant-based and vegetarian posts (Study 1: 9%; Study 2: 6%), were lower than the minimum proportional differences specified, suggesting under-powered results.

Overall, in line with our hypotheses in both studies, posts about meat dishes contained more hashtags referencing consumption situations than posts about plant-based dishes. Meat posts also contained more consumption situation hashtags than vegetarian posts, although our sensitivity analyses suggest this effect may be unreliable.

3.1.2. Situation-independent words in hashtags

We predicted that the proportion of situation-independent hashtag words would be higher for plant-based posts and vegetarian posts than meat posts in Study 1, and higher for plant-based posts than meat posts in Study 2 (H2). In line with these predictions, we found an overall effect of food type on situation-independent hashtag word proportions in Study 1, $\chi^2(2) = 362.84$, $p < .001$, $R^2_{psuedo} = 0.22$. and in Study 2, $\chi^2(2) = 20.45$, $p < .001$, $R^2_m = 0.13$, $R^2_c = 0.21$ (see Fig. 2). Pairwise comparison results (see Table 6) showed that in Study 1, plant-based posts had higher situation-independent hashtag word proportions than meat posts and vegetarian posts. Vegetarian posts also had a higher proportion of situation-independent hashtag word proportions than meat posts. The same results were found for Study 2.

Again, post-hoc sensitivity analyses were run. A minimum proportional difference between groups of at least 16% was required for Study 1, and at least 9% was required for Study 2. The observed difference in situation independent proportions between meat and plant-based posts was sufficiently powered for Study 1, with a 19% difference, and Study 2, with an 13% difference. However, the differences between meat and vegetarian posts (Study 1: 8%; Study 2: 6%), and vegetarian and plant-based posts (Study 1: 11%; Study 2: 7%), were below the specified minimum for an effect of theoretical interest.

Overall, in line with our hypotheses, posts about plant-based dishes contained more situation-independent hashtags than posts about meat and vegetarian dishes across both studies, although our sensitivity analyses suggest the effects between plant-based and vegetarian posts were under-powered.

3.1.3. Consumption situation words in text (study 1 only)

In Study 1, we predicted that there would be a higher proportion of

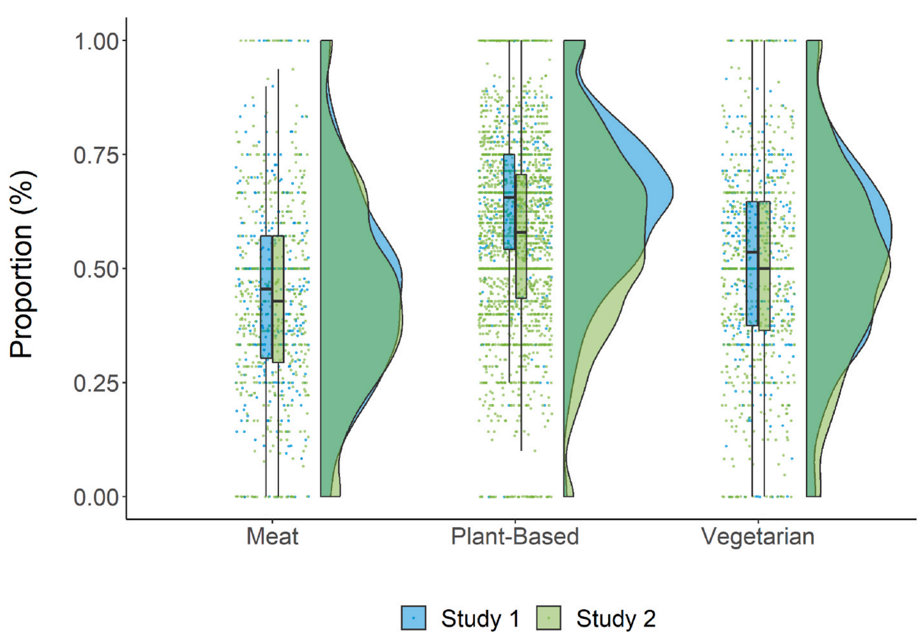

Fig. 2. Proportion of situation-independent hashtag words by food type.

Table 6
Pairwise comparisons of situation independent words between food categories.

	Meat	Plant-based	Vegetarian	Meat vs.Plant-based	Meat vs. Vegetarian	Plant-based vs. Vegetarian
	M (SD)	*M (SD)*	*M (SD)*	*b (SE)* *p* *[95% CI]*	*b (SE)* *p* *[95% CI]*	*b (SE)* *p* *[95% CI]*
Study 1						
Text	0.43 (0.31)	0.55 (0.24)	0.52 (0.25)	-0.34 (0.06) **<0.001** [-0.46 – -0.22]	-0.30 (0.07) **<0.001** [-0.42 – -0.17]	0.04 (0.06) 0.47 [-0.07 – 0.16]
Hashtag	0.45 (0.21)	0.64 (0.17)	0.53 (0.21)	-0.85 (0.05) **<0.001** [-0.94 – -0.76]	-0.31 (0.05) **<0.001** [-0.40 – -0.23]	0.53 (0.05) **<0.001** [0.45 – 0.62]
Study 2						
Hashtag	0.44 (0.22)	0.57 (0.21)	0.50 (0.23)	-0.48 (0.07) **<0.001** [-0.61 – -0.35]	-0.15 (0.06) **0.02** [-0.27 – -0.03]	0.33 (0.06) **<0.001** [0.22 – 0.45]

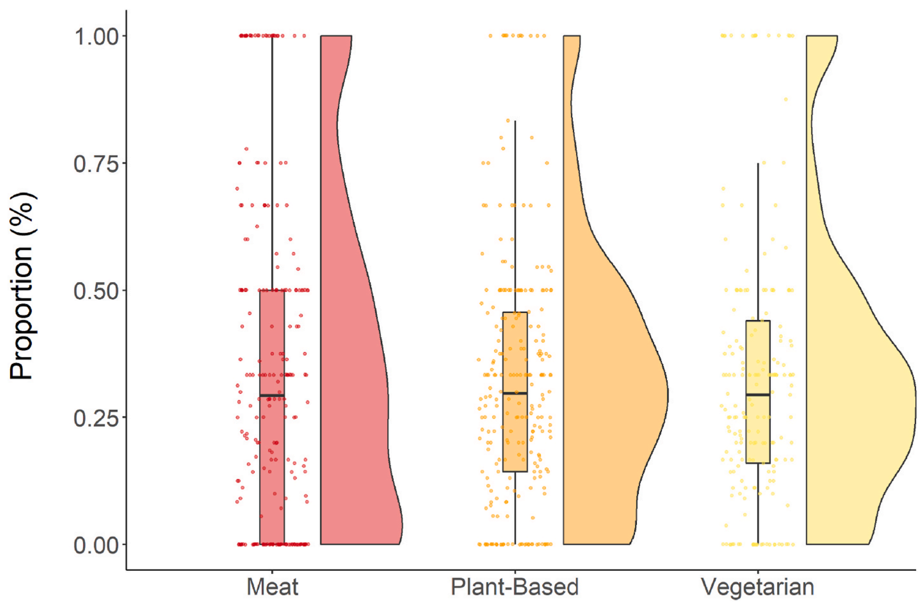

Fig. 3. Proportion of consumption situation text words by food type.

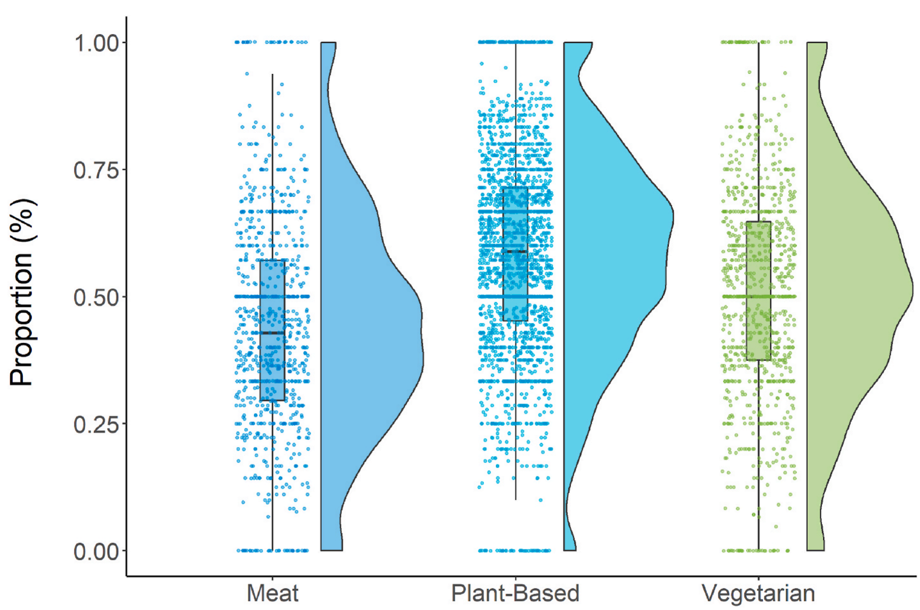

Fig. 4. Proportion of situation-independent text words by food type.

consumption situation text words in meat posts versus plant-based and vegetarian posts (H3). Unlike our hashtag results, we did not find an overall effect of food type on consumption situation proportions in the text, $\chi^2(2) = 0.40$, $p = .82$ (see Fig. 3). Pairwise comparisons showed no differences between the consumption situation proportions of meat posts, plant-based posts or vegetarian posts (see Table 5).

3.1.4. Situation-independent words in text (study 1 only)

In Study 1, we hypothesized that the text words used in vegetarian and plant-based posts would have a higher proportion of situation-independent language than meat posts (H4). Results showed a significant overall effect of food type on situation-independent word proportions in the text, $\chi^2(2) = 33.72$, $p < .001$, $R^2_{psuedo} = 0.03$ (see Fig. 4). Pairwise comparisons (see Table 6) revealed that plant-based posts had a higher proportion of situation-independent text words than meat posts. Vegetarian posts also had a higher proportion of situation-independent text words than meat posts. There was no difference in the proportion of situation-independent text words between plant-based posts and vegetarian posts.

A post-hoc sensitivity analysis suggested a minimum proportional difference of at least 16% was required. Both the observed difference in situation independent proportions between meat and plant-based posts (12%), and between meat and vegetarian posts (9%), were below the minimum detectable effect size threshold.

Overall, in line with our hypothesis, posts about plant-based dishes contained more situation-independent text words than posts about meat, but not vegetarian, dishes. However, results from our sensitivity analysis suggest our results were under-powered.

3.2. Exploratory analyses

3.2.1. Non-consumption situation words in hashtags

We explored differences between food types in non-consumption situation proportion means for both hashtag and text words in Studies 1 and 2, again using binomial mixed-effects models. For hashtag words, we found an effect of food type in Study 1, $\chi^2(2) = 18.95$, $p < .001$, $R^2_{psuedo} = 0.01$, but not in Study 2, $\chi^2(2) = 2.10$, $p = .35$ (see Fig. 5). In Study 1, meat posts had a higher proportion of non-consumption situation hashtag words than plant-based posts, and vegetarian posts had a higher proportion than plant-based posts (see Table 7). When correcting for multiple comparisons ($p = .025$), no significant difference was found between vegetarian posts and meat posts. In Study 2, there was no effect of food type on non-consumption situation hashtag words.

3.2.2. Non-consumption situation words in text (study 1 only)

For text words, which we only collected in Study 1, there was an overall effect of food type on non-consumption situation proportions, $\chi^2(2) = 44.50$, $p < .001$, $R^2_{psuedo} = 0.05$ (see Fig. 6). Meat posts had a higher proportion of non-consumption situation text words than plant-based posts, and vegetarian posts. There were no differences in non-consumption situation text words between vegetarian and plant-based posts (see Table 7).

3.2.3. Analyses of additional categories

We explored the effects of food type on the novel identity and social and political context subcategories, which we added within the situation-independent main category to accommodate some of the language specific to the social media data we had collected. 6838 identity words (20% unique), and 1529 social and political context words (29% unique) were coded across the three datasets. We ran two binomial effects models to test the differences in identity features with the Study 1 and 2 hashtag data. There was a small number of identity text words, and there were few social and political context hashtags and text words overall. Therefore, we did not analyse these.

There was an overall effect of food type on Identity proportions in Study 1, $\chi^2(2) = 51.71$, $p < .001$, $R^2_{psuedo} = 0.04$, and Study 2, $\chi^2(2) = 15.75$, $p < .001$, $R^2_m = 0.18$, $R^2_c = 0.46$ (see Table 8). Plant-based posts had a higher proportion of identity hashtag words than meat posts, and vegetarian posts. In Study 1, meat posts also had a greater proportion of Identity language than vegetarian posts, but this was not found in Study 2 when correcting for multiple comparisons ($p = .025$).

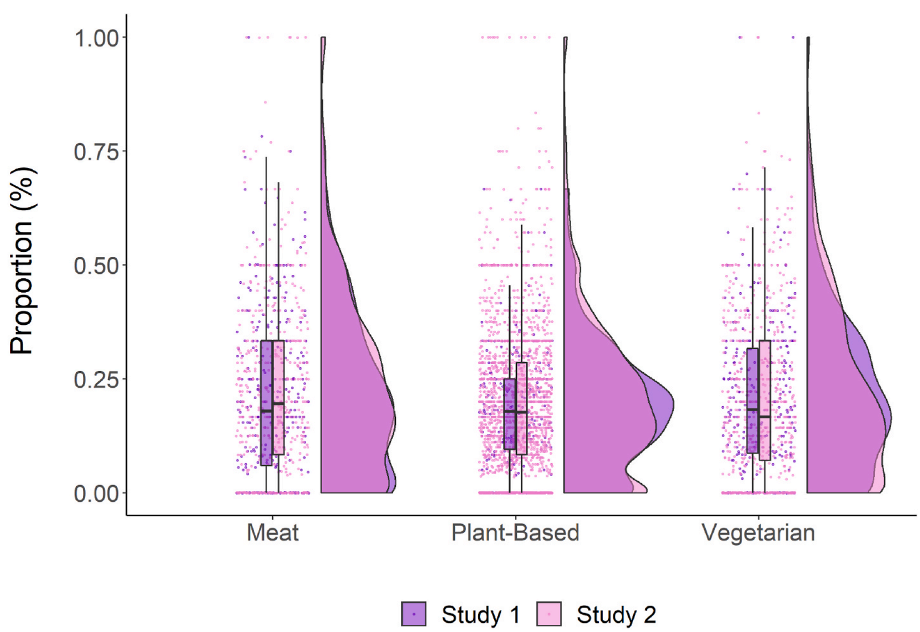

Fig. 5. Proportion of non-consumption situation hashtag words by food type.

Table 7
Pairwise comparisons of non-consumption situation words between food categories.

	Meat	Plant-based	Vegetarian	Meat vs. Plant-based	Meat vs. Vegetarian	Plant-based vs. Vegetarian
	M (SD)	*M (SD)*	*M (SD)*	*b (SE)* *p* *[95% CI]*	*b (SE)* *p* *[95% CI]*	*b (SE)* *p* *[95% CI]*
Study 1						
Text	0.22 (0.25)	0.13 (0.14)	0.14 (0.16)	0.49 (0.07) **<0.001** [0.34 – 0.64]	0.40 (0.08) **<0.001** [0.24 – 0.56]	-0.09 (0.08) 0.24 [-0.24 – 0.06]
Hashtag	0.21 (0.18)	0.19 (0.14)	0.21 (0.17)	0.24 (0.05) **<0.001** [0.13 – 0.34]	0.11 (0.05) 0.04 [<0.01 – 0.22]	-0.13 (0.06) 0.02 [-0.24 – -0.02]
Study 2						
Hashtag	0.23 (0.20)	0.20 (0.17)	0.21 (0.19)	0.04 (0.10) 0.67 [-0.15 – 0.24]	-0.08 (0.11) 0.48 [-0.30 – 0.14]	-0.12 (0.08) 0.14 [-0.28 – 0.04]

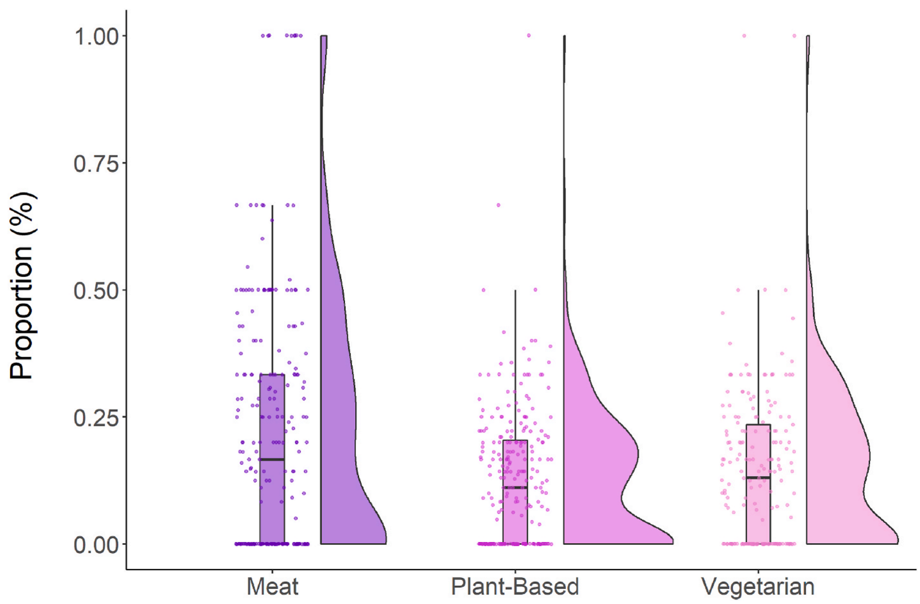

Fig. 6. Proportion of non-consumption situation text words by food type.

Table 8
Pairwise comparisons of identity words between food categories.

	Meat	Plant-based	Vegetarian	Meat vs.Plant-based	Meat vs. Vegetarian	Plant-based vs. Vegetarian
	M (SD)	*M (SD)*	*M (SD)*	*b (SE)* *p* *[95% CI]*	*b (SE)* *p* *[95% CI]*	*b (SE)* *p* *[95% CI]*
Study 1						
Hashtag	0.09(0.11)	0.11 (0.11)	0.07 (0.12)	-0.24 (0.07) **<0.001** [-0.38 – -0.10]	0.31 (0.08) **<0.001** [0.15 – 0.47]	0.55 (0.08) **<0.001** [0.40 – 0.70]
Study 2						
Hashtag	0.09 (0.11)	0.15 (0.15)	0.08 (0.11)	-0.46 (0.14) **<0.001** [-0.72 – -0.19]	0.20 (0.09) 0.03 [0.02 – 0.38]	0.66 (0.12) **<0.001** [0.43 – 0.88]

4. Discussion

In two observational studies, we examined whether social media posts about meat dishes use more language reflecting eating simulations than posts about vegetarian and plant-based dishes. In line with our hypotheses, results consistently showed that hashtags in meat posts contained more eating simulation language than plant-based posts, whereas plant-based posts had more situation-independent language than meat posts.

We also found that vegetarian posts had more eating simulation and fewer situation-independent hashtags than plant-based posts, and had fewer eating simulation and more situation-independent hashtags than meat posts. However, these results were under-powered and therefore warrant replication in a well-powered study. Considering the associations found between simulation language and perceived attractiveness (Papies et al., 2020b, 2021), our findings suggest that meat dishes are framed as more appealing than vegetarian dishes, and vegetarian dishes are framed as more appealing than plant-based dishes.

In contrast to the hashtags, results from the text data in Study 1 showed no significant differences in eating simulation language use across meat, plant-based and vegetarian dish posts, although effects were in the predicted direction. Specifically, the caption text in posts about plant-based and vegetarian dishes included more situation-independent language than meat dishes, but this was a much weaker, under-powered effect than in the hashtags. The difference in results between our hashtag and text data may be due to processing the caption text with a feature listing coding scheme intended to categorise one-word descriptions or small phrases of a particular product. Therefore, our methodological approach seems suitable for hashtags, but less so for captions. Reducing free text into the smallest meaningful units may have resulted in a loss of important semantic context, meaning intended by the users, and statistical power. Thus, different qualitative analysis methods may be more suitable for text caption data. In addition, the variability and inconsistency of feature frequencies in the text data, in comparison to the hashtag data, may have contributed to the small effects seen. Nonetheless, these results add to our understanding of how the language used to caption content on image-centric social media platforms varies from the 'searchable talk' of hashtags (Zappavigna, 2015), and thus differ in function.

From our exploratory analyses, we discovered that meat posts in Study 1 had higher proportions of non-consumption situation language than plant-based posts. This may mean that food origins and production, in addition to cultural elements, are potentially more salient with meat foods than plant-based foods. This is not surprising, as meat dishes have high status and traditional importance across a majority of cultures (Fiddes, 2004), and the authenticity of a meat dish is often derived from its provenance (Monahan et al., 2018). Importantly, we also found that plant-based posts had a greater proportion of identity focused language than meat posts, which suggests the salience of food identity within descriptions of sustainable foods.

4.1. Theoretical implications and future research

These findings are largely consistent with our predictions derived from the grounded cognition theory of desire and motivated behaviour, and with previous research showing language differences between food categorise in food service settings. Papies and colleagues found that descriptions for meat supermarket ready-meals tended to use more eating simulation language than those for sustainable, plant-based alternatives (Papies, Johannes, et al., 2020), and Turnwald et al. (2017) found that restaurants described healthy items with less appealing terms than unhealthy items. These language differences matter, because they have the potential to influence food choices and the development of food preferences over time (Papies, Johannes, et al., 2020; Turnwald & Crum, 2019; Turnwald et al., 2017). Indeed, using taste-focused labelling instead increased the purchasing of healthy foods by 38% (Turnwald & Crum, 2019). In line with the grounded cognition theory, these findings suggest that simulation-focused language taps into mechanisms that lead to desire (Papies et al., 2022).

The findings reported here extend research on language differences between more and less appealing foods to the increasingly important domain of food communication on social media. Notably, this language bias appears even when users are assumed to "advocate" for certain foods, i.e., on Instagram. While the grounded cognition theory of desire and previous research suggest that people describe liked foods in terms of consumption simulations, the current findings suggest that this may be less the case for foods where eating motives other than taste and enjoyment play a major role, for example social identity (Judge et al., 2022). Future research should examine the interplay between social identity and the degree to which consumption simulations play a role in food representations and communication.

We assume that the patterns of language found in our research across different dishes on social media reflect an attempt by users to connect and interact with others in their food identity communities (Potnis & Tahamtan, 2021). Previous research has found that language on social media is generated strategically to construct knowledge and share experiences (Lewis, 2009). Our results suggest that consumers use language to display food attitudes, which seemed more enjoyment oriented for meat foods, and more health and identity-oriented for plant-based foods. These attitudes in turn are likely to be reinforced over time from repeated exposure to users' social media feeds and habitual platform usage (Ohme, 2021). These attitudes displayed by members of the same online food in-group can then influence users' eating motivations (Blundell & Forwood, 2021), which may motivate some users to change their eating behaviour, for example by replacing meat with more sustainable alternatives (Pop et al., 2020). Thus, we assume that the language strategically used to describe food posts in our study reflects attitudes and may affect subsequent behaviour.

In addition, our results have implications for research on food-related identities. Plant-based posts had a larger proportion of identity language, making up 17% of all situation-independent language in Study 1, and 26% in Study 2, in comparison to meat posts, suggesting that emphasising shared values and identities in the descriptions of plant-based foods is crucial to vegan communication. This may be due to the fact that vegans are a minority group, who use social media as a way to tap into their 'identity bubble' (Kaakinen et al., 2020), create a sense of group membership and community, and defend their consumption practices against the status quo (Costa et al., 2019; Wehbe et al., 2021). For example, 47% of Study 1 and 50% of Study 2 plant-based posts included the hashtag '#veganfood', which demonstrates the homogeneous identity language used frequently to describe plant-based foods online in order to connect with other vegan users. Although vegan and vegetarian communities have been typically grouped together in psychological research to date (Rosenfeld, 2018; Rosenfeld et al., 2020), the differences found in identity-focused language for vegetarian and plant-based foods suggest that clear distinctions between these food types exist, and therefore should be treated separately in future studies.

The identity language in plant-based food posts may contribute towards the polarisation between meat-eating and vegan communities (Buddle et al., 2018), who adopt different linguistic strategies that may not appeal to the "food out-group" (De Groeve et al., 2019). Such polarisation may not be helpful for realising the global transition to more sustainable diets that is required to keep the planet inhabitable (Fielding & Hornsey, 2016). Future studies should investigate whether these results are consistent across social media platforms, and whether these different language strategies affect the attitudes and eating intentions of other users that see their posts. An interesting theoretical question is whether emphasising shared identities can increase the appeal of foods to certain groups of consumers (see also Hackel et al., 2018), and again how the mechanisms of driving such an effect would relate to the eating simulations proposed by the Grounded Cognition Theory of Desire (Papies, Barsalou, & Rusz, 2020). Understanding how food posts are seen and received by varying food identity groups may help to understand the gatekeeping culture of online meat-eater and vegan communities (Malinen & Koivula, 2020).

4.2. Strengths and limitations

A key strength of our studies is the collection of real-world data in a natural setting. Furthermore, the use of a comprehensive food language coding scheme provides a more detailed understanding of the semantic differences between meat, vegetarian and plant-based food descriptions than traditional valence ratings, where words are rated as positive or negative. Another strength is the very close replication of results across Study 1 and 2, which used datasets collected four months apart, indicating the robustness of our findings (Francis, 2012). This suggests that these differences in online language use are stable across time and samples (Jebb et al., 2015). Our mixed-effects models also showed a similar distribution of proportions across datasets when controlling for multiple dish types, suggesting that the type of food is a greater predictor of eating simulation language than the dish, such as burger, pizza or salad.

One limitation of this research is that we did not reach our planned sample sizes, due to underestimating the posts excluded from our criteria in Study 1, and data accessibility issues in Study 2. Despite this, our models generated on average medium effect sizes, and post-hoc sensitivity analyses reported that the differences found between meat and plant-based post hashtag proportions were sufficiently powered, which supports the explanatory power of our findings (Funder & Ozer, 2019). Nonetheless, our under-powered and inconclusive vegetarian results need to be replicated with a larger sample to determine whether the proportional differences seen between vegetarian and plant-based posts, and vegetarian and meat posts, display a true effect.

Another potential issue with our data is that we only included English-language posts. However, considering the dominance of English language use in internet settings, and the subsequent development of 'internet English', which includes linguistic features specific to an online environment (Seargeant & Tagg, 2011), measuring an English-only sample may capture a majority of the discourse and nuance found across social media communities. In addition, another limitation is that we did not collect information about the identity of the post creators, due to the observational nature of our data collection. However, considering the amount of identity language included across meat, plant-based and vegetarian food posts, we assume that the food type of the post aligned with the users' own food identity and in-group attitudes.

5. Conclusion

We found that more eating simulation language was used for meat than for plant-based foods on social media, while more situation-independent language was used for plant-based foods, particularly identity language. Thus, communication about meat foods was characterised by a focus on short-term enjoyment, while communication about more sustainable foods reflected the salience of long-term shared values and identities. Food marketing teams should be conscious of these language trends when describing plant-based foods, and the potential effects that using situation-independent language might have on their appeal and subsequent purchasing likelihood by main-stream consumers. Policymakers should aim to prevent polarisation between meat-eaters and vegans by focusing on food attractiveness and shared eating experiences, in order to break down food identity barriers and encourage the global shift towards sustainable diets that is needed to maintain the planet inhabitable for humans.

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Credit taxonomy

EKP was involved in the Conceptualisation, Funding Acquisition, Methodology, Project Administration, Supervision, Validation and both the Original Draft Writing and Review and Editing Writing of the study. TD was involved in the Conceptualisation, Data Curation, Formal Analysis, Investigation, Methodology, Project Administration, Validation, Visualisation and both the Original Draft Writing and Review and Editing Writing of the study.

Ethical statement

In line with the Instagram Terms of Use Data Policy, we gathered publicly accessible data from each post (Instagram, 2020). No personally identifiable information was collected. Although observation social media research is not considered to be non-standard human subjects research, and is considered exempt from institutional review board and consent requirements (Sloan & Quan-Haase, 2017), we emailed the School of Psychology Research Ethics Committee regarding the need to submit an ethics application for this study. We were told no ethics approval was required, as no personal data was collected and the data was openly available.

Declaration of competing interest

We declare that there is no known conflict of interest or competing interests.

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