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Social influence effects on food valuation generalize based on conceptual similarity

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Abstract

Opinions of others influence behavior and decision-making, with important consequences for health. An unaddressed question is whether and how social influence can generalize across different situations or decisions. From a learning perspective, generalization is the transfer of previously acquired information to new stimuli and can be based on both perceptual and conceptual similarity. Here, we test whether social influence generalizes to new choices based on shared conceptual features, such as the healthiness and tastiness of different food items. We conducted three studies (total N = 468), in which healthy participants rated how much they would like to eat different food items and were subsequently presented with the ratings of several other people ('social ratings'). Unbeknownst to our participants, they were randomly assigned to social ratings that either reflected a mainly health-driven valuation of food items ('health group') or to social ratings that reflected a taste-driven valuation of food items ('taste group'). The results in all three studies showed that participants' food ratings became more influenced by healthiness in the 'health group' than in the 'taste group'. In one study, these effects further transferred to food choices in a naturalistic supermarket task. Our findings provide experimental evidence of generalization of social influence effects based on inferred social health norms. Futures studies could test conceptual generalization of other types of social and non-social learning and characterize the brain mechanism underlying these effects.

Keywords: *social influence, food valuation, dietary decision-making, generalization, learning*

Social influence effects on food valuation generalize based on conceptual similarity

Human behavior is strongly influenced by social and cultural context. A prominent example are food choices and eating behavior. Some of these social norms are relatively stable and strict. We are likely used to eat beef if we have grown up in Argentina or in Japan, but we would be repelled by the idea if we were Hindu. Other social norms may be more subtle, evolve over time, and vary between different subcultures or even smaller groups. For example, even if we usually like to eat steak with fries, we might choose something different if we go to the restaurant with a new group of friends that are health-conscious and/or concerned about climate change. Social norms can be defined as “the implicit or explicit rules a group has for the acceptable behaviors, values, and beliefs of its members” (Aronson et al., 2010, p. 258). Whereas explicit norms reflect conscious consideration of how the group norms, implicit norms develop through exposure to other people’s reactions or evaluations (Yoshida et al., 2012). This framework invites the question: How do humans learn about and adapt their behavior to implicit social norms?

Many experimental and observational studies show that food choices are influenced by the observed behavior of other people (Higgs, 2015; Robinson, 2015; Stok et al., 2016). For example, when people eat together with someone eating a large amount, people are more likely to consume more than when they eat alone (Cruwys et al., 2015; Vartanian et al., 2015). Food preferences are influenced by the ratings of even anonymous peers (Nook & Zaki, 2015), and even non-human primates have been shown to choose food in line with observed group norms (Van de Waal et al., 2013). Social influence effects are thus an important factor when making food choices and may interact with other factors known to be important, such as health and taste considerations (Rangel, 2013; Sobal et al., 2006; Steptoe et al., 1995). Epidemiological and social network studies have shown that a person's chance of becoming obese increases with the number of social contacts who are obese (Christakis & Fowler, 2007), and that social influence is the strongest driver of changes in diet (Eker et al., 2019). Observational studies have analyzed large-scale purchasing data to show that colleagues who eat together, choose similarly healthy food in workplace restaurant (Levy et al., 2021), and that over time, students and staff on university campuses are influenced in the healthiness of food and beverage purchases by the persons they regularly eat with (Gligorić et al., 2021). Using ecological momentary assessment, a recent study suggests that social cues influence eating behavior via changes in momentary social norms about the appropriateness of snacking behavior (Schüz et al., 2018), suggesting that perception of norms may change even on a relatively short time scale. Such effects are important, because, over time, even small social and cultural influences on food choices and other health-related behaviors such as exercising may have important consequences for health.

An important yet unaddressed question is whether and how social influence may generalize across different situations and across different foods that share common features. Previous studies have typically tested whether people’s behavior is influenced by specific observation of others’ behavior, such as whether they become more likely to choose the salad over the steak if others have chosen the salad. However, social and cultural influences likely operate in more general and abstract ways. For instance, we might not choose the same salad but something else that is also in line with the inferred values and norms of the group—such as an equally healthy vegetable soup. Here, we test the idea that social influence can generalize across food choices based on abstract conceptual dimensions such as healthiness and tastiness of food items.

From a learning perspective, generalization can be defined as the transfer of previously acquired information to new stimuli and situations, based on the similarity between the original and a new situation (Guttman & Kalish, 1956). Generalization was already noticed by Pavlov (1927) in his classic conditioning experiments with dogs where he associated food with the sound of a bell and noticed that the animal's reaction generalized to other similar sounds. Subsequently, other scientists have obtained empirical "stimulus generalization gradients", which relate the probability, speed, or strength of a learned response to the difference between the test and training stimuli (Guttman & Kalish, 1956; Shepard, 1987). Generalization does not necessarily reflect a lack of discrimination between learned and new stimuli. Instead, generalization can be seen as an active process of associating a stimulus to a more general underlying pattern or rule, which is adaptive in a world where situations are often similar but rarely identical (Shepard, 1987). Accordingly, generalization follows both perceptual similarity gradients as well as conceptual relationships (Dunsmoor & Murphy, 2015). Thus, generalization allows people to learn not only about specific stimuli but to infer more general norms and apply them to novel contexts to adapt (Behrens et al., 2018).

Here, we tested whether similar conceptual generalization mechanisms could apply to social influence effects. Recent brain imaging studies suggest parallels between social influence and reinforcement learning, demonstrating that agreeing with others evokes activity in reward-related brain areas (Campbell-Meiklejohn et al., 2010; Klucharev et al., 2009; Zaki et al., 2011). Disagreeing with others is associated with activity in brain areas related to error processing and cognitive conflict (Klucharev et al., 2009; Koban et al., 2014), leading to subsequent adjustments in behavior and decision-making to reduce this kind of social conflict (Klucharev et al., 2009). If social influence is based on partially similar mechanisms as reinforcement learning, then it may also generalize based on perceptual and conceptual features.

Food choices naturally lend themselves for testing this idea. As other types of decisions, valuation of food items can be described as a function of different attributes and the importance (measured as beta weights) of these attributes for any given individual. Two of the most important attributes when evaluating food are its tastiness and its healthiness (Rangel, 2013) and the importance of these attributes varies substantially across individuals and situations (Hare et al., 2011; Schmidt et al., 2018). We hypothesized that social influence on food choices can generalize by shifting how much people take into account health and taste attributes. Thus, we predicted that, during observation of other people's food ratings, people implicitly infer underlying social norms regarding the importance of health and taste, which then influence their own food choices. In other words, if we observe that other people prefer broccoli and plain yoghurt over chocolate bars and sodas, we could infer that they are influenced by the healthiness of food items, and we might also shift our preferences to more healthy food options, even if this concerns new food items (in this example here, other foods than broccoli or plain yoghurt).

For this purpose, we developed a novel social influence task in which participants rated how much they would like to eat different food items, first during a baseline phase without social information, then during a social influence phase (**Figure 1A**). During the social influence phase, they were presented with the ratings of several other people ('social ratings') after their own food rating. For each food item, two sets of social ratings were selected to create two different experimental groups (**Figure 1B**). One group of participants (the *Health* group) was presented with social ratings that reflected a preference for healthy food items (i.e., ratings were selected based on high weights of health and low weights of taste). The other group was presented with social ratings that reflected a low weighting of health and a

high weighting of taste aspects of the food (*Taste* group). If participants generalize from the social ratings, then participants in the *Health* group should increase the importance (or weight) of health attributes compared to the *Taste* group in the social influence phase (**Figure 1C**). Participants in the *Taste* group in contrast should increase the importance of taste attributes compared to the *Health* group. We tested these hypotheses in three different studies, with different food stimuli and across two different countries. Further, in order to investigate the possible transfer of generalized social influence to another task, we implemented an additional online supermarket task (Huang et al., 2006; Lai et al., 2020) in Study 2 and 3, providing a measure of participants' food preferences closer to how they make food choices in the real world (**Figure 1A**). We expected that participants in the *Health* group would still be more guided by food healthiness than the *Taste* group and thus buy healthier food products in the supermarket (**Figure 1C**).

Methods

Participants

Study 1. We recruited 198 adult volunteers for Study 1, using an online participant pool in Germany (ClickWorker). Our target sample size of 100 participants per group was determined by an estimated small-to-moderate effect size (Cohen's d of 0.4-0.5), considering 80% power and a two-sided alpha of 0.05. The data of two participants were excluded due to no variance in ratings, leaving a final sample of 196 participants (73 females and 123 males, mean age= 36 years, range 18-60 years), 97 in the *Health* group and 99 in the *Taste* group. The groups were matched for age, BMI, gender, education, income, hunger level, and general dietary habits (all p -values > 0.12, see Supplementary Tables S1 and S2).

Study 2. We recruited 206 adult volunteers for Study 2, using an online participant pool in Paris, France from the INSEAD-Sorbonne University behavioral laboratory (the sample size was determined on the same assumed effect size as in Study 1). The data from one participant was excluded from all analyses because data for the supermarket task was not registered, leaving a final sample of 205 participants (140 females and 65 males, 103 in *Health* group and 102 in *Taste* group, mean age=24.5 years, range 18-35 years). The groups had comparable age, BMI, gender, education, income, hunger level, and general dietary habits (all p 's < 0.08, see Supplementary Tables S1 and S2).

Study 3. We recruited 66 adult volunteers for Study 3 from the participant pool of the BonnEconLab at the University of Bonn, Germany. The sample size for Study 3 was determined by practical constraints (time and participant availability). An *a posteriori* power analyses revealed that moderate-to-large effect sizes (Cohen's $d > 0.7$) could be detected with 80% power (assuming a two-sided alpha of 0.05) in this sample. Data from two participants was excluded from all analyses because the results for the supermarket task were not recorded, leaving a final sample of 64 participants (30 females and 34 males, 32 in *Health* group and 32 in *Taste* group, mean age= 24 years, range 18-35 years). The two groups were matched for age, BMI, and gender, education, income, hunger level, and general dietary habits (all p 's > 0.11, see Supplementary Tables S1 and S2).

In all three studies, participants provided informed consent and were paid for their time. The studies were conducted according to the Declaration of Helsinki and approved by the institutional review board of INSEAD (Studies 1-2, 2021-02A) and Bonn University (Study 3).

Experimental design

During the first 16 trials of the food rating task (baseline phase), all participants rated the same 16 food items (presented in randomized order) without any social information,

allowing us to control for participants' habitual weighting of health and taste considerations. Then, during the social influence phase (80 trials in Studies 1 and 3, 64 trials in Study 2), participants were presented with the ratings of several other participants following their own rating.

Participants were randomly assigned to one of two experimental groups using a pseudo-random number generator of Qualtrics. In the *Health* group, healthier but less tasty food items were associated with higher average preference ratings of others, whereas unhealthy but tasty items were associated with lower social ratings. In the *Taste* group, tastier but less healthy food items received higher preference ratings from others than healthier and less tasty items (see also Fig. 1B). See below for more details on the selection of social ratings for the different food stimuli.

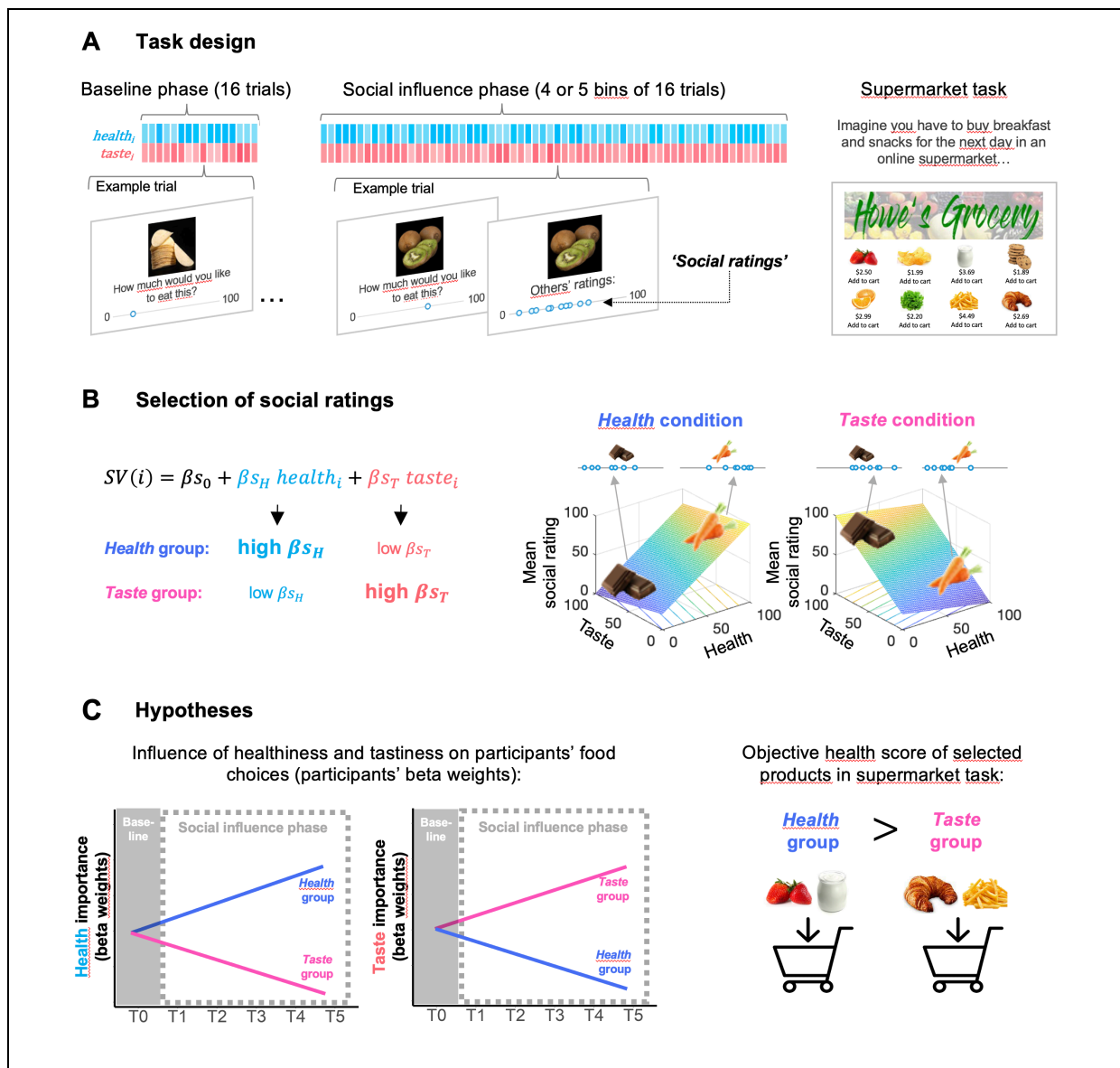


Figure 1. Experimental design and hypotheses. A) Task design. During the food choice task (left and middle), participants had to rate different food items, which varied on healthiness and tastiness ($health_i$ and $taste_i$), as rated by an independent sample of participants. Brighter versus darker colored bars illustrate less to more healthy (light to darker blue) and less versus more tasty (light to darker red) food items (randomized across participants). During the baseline phase (left), participants were presented with 16 food items in total without receiving any social feedback. During the social influence phase, participants were presented with 64-80 food items. For each food

item, they rated how much they would like to eat it and were then presented with what we told them were the ratings of several other individuals. In Studies 2-3 and following the food rating task, participants performed a naturalistic online supermarket task. They were instructed to select several foods and drinks, as if they had to buy groceries for next days' breakfast and snacks. **B) Selection of social ratings in the two experimental conditions in all three studies.** Participants were randomly assigned to one of two experimental conditions of the food rating task. In the *health group*, the mean social value (SV) of each food item i was computed with a high beta weight for the item's healthiness ($health_i$) and a low weight for its tastiness ($taste_i$). In contrast, in the *taste group*, the mean social value (SV) of each food item i was computed with a high beta weight for the item's tastiness ($taste_i$) and a low weight for its healthiness ($health_i$). Several ratings were randomly drawn from a distribution around the mean SV to ensure plausible and variable social ratings. Thus, as illustrated on the right side, in the health group, healthy items such as vegetables or fruit would be followed by relatively high ratings, whereas unhealthy but tasty items such as chocolates or sweets would be followed by relatively low ratings. In the taste group, this relationship was the other way around. **C) Hypotheses.** We expected that participants in the health group would over time increase how much healthiness of food items influenced their food ratings as influenced by increased beta weights for $health_i$, whereas participants in the taste group would show lower influence of health considerations in their choices during the social influence phase. The opposite pattern was expected for the influence of taste on food ratings (beta weights of $taste_i$). We further expected that this effect would transfer to a second, independent supermarket task, such that participants in the health group would select healthier food items (as measured by a higher objective health star point score) than participants in the taste group.

Stimuli and materials

Food items. In each of the three studies, participants were presented with photos of 80 different snack food items, such as chips, nuts, fruits, and chocolate bars. All items were shown on a black background and selected from INSEAD's standardized picture databases (adapted from Schmidt et al., 2018) of German (in Study 1 and 3) or French supermarket products (in Study 2). Each item i had been previously rated by independent online participants (N=105 for the German food database, N=298 for the French food database) for its healthiness ($health_i$), 'How healthy is this product?', tastiness ($taste_i$), 'How tasty is this product?', willingness to pay (WTP) 'How much are you willing to pay for this product?' and familiarity ('How familiar are you with this product?'). The $health_i$ and $taste_i$ in $SocValue(i)$ were based on these health and taste ratings. Food cues were selected to systematically vary in healthiness and tastiness. Further, we divided the 80 food stimuli into five sets of 16 stimuli, such that each set contained an equal amount of food items spanning the whole 2-dimensional space of healthiness and tastiness. Thus, each bin contained four items rated high in tastiness and low in healthiness, four items high in tastiness and high in healthiness, four items low in tastiness and low in healthiness, and four items low in tastiness and high in healthiness, with each of this four ad-hoc categories being matched for familiarity, and such that each set of 16 times was matched for average healthiness, tastiness, and familiarity. This allowed us to present the five matched sets in random order and to investigate the time course of social generalization effects.

Social ratings. During the social influence phase, we presented the ratings of ten (Studies 1-2) or seven (Study 3) previous people after participants had submitted their own rating. The social ratings were displayed as small circles on a visual analog scale that matched the VAS that participants used for their own ratings (see **Figure 1A**). They were simulated (Studies 1-2) or selected (Study 3) as a function of the taste and health attributes of each food items. More specifically, for each food item i and each experimental condition, we used the following equation to simulate a mean social value (SV) for each food item i :

$$SV(i) = \beta_{s_0} + \beta_{s_H} health_i + \beta_{s_T} taste_i$$

Where β_{s_0} reflects a fixed intercept ($\beta_{s_0}=20$ in Studies 1-2, $\beta_{s_0}=1.2$ in Study 3, to avoid values below 0), β_{s_H} reflects the weighting of health in the social ratings, and β_{s_T} reflects the taste weighting in the social ratings, with $health_i$ describing the healthiness and $taste_i$ the tastiness

of each food item. Social weighting of health and taste differed between the two experimental groups in order to create two different social influence conditions. In the *Health* group, health had a high weight ($\beta_{SH}=0.8$ in Studies 1-2, $\beta_{SH}=0.7$ in Study 3) and taste had a low weight ($\beta_{ST}=-0.2$ in Studies 1-2, $\beta_{ST}=0.2$ in Study 3). The opposite was the case for *Taste* group ($\beta_{SH}=-0.2$ and $\beta_{ST}=0.8$ in Studies 1-2, $\beta_{SH}=0.2$ and $\beta_{ST}=0.7$ in Study 3).

For Studies 1-2, we used Matlab 2018b to simulate ten different ratings (reflecting the ratings of ten other individuals) for each food item and each condition. More specifically, we created Gaussian distributions with $SV(i)$ as the mean and a standard deviation of 15, from which we drew a random set of ten social ratings. For Study 3, we chose the seven WTP ratings in the INSEAD food database of German supermarket products that were closest to the simulated ratings. This approach added some variation around the simulated mean social values, thus leading to realistic and plausible values (cf. Koban & Wager, 2016; Zhang et al., 2024), as previous results have shown that people's food choices and brain valuation signals can be modeled based on individually different weighting of taste, health, and other attributes (Maier et al., 2015; Rangel, 2013; Schmidt et al., 2018).

Procedures

Studies 1-2 were conducted online and launched in the late afternoon to early evening. In Study 3, participants performed the tasks on computers in individual cubicles of the BonnEconLab, at the same time as several other participants in the late afternoon. This timing ensured that participants were moderately hungry (see Supplementary Table S1) and likely interested in the snack food items presented.

The food rating task, administered via Qualtrics, consisted of 96 trials (in Study 1 and 3) or 80 trials (Study 2) that were composed of several blocks of 16 trials each (**Figure 1A**). The first block constituted a baseline, in which participants were presented 16 different food items and rated how much they would like to eat the shown item at this moment ("How much would you like to eat this?", Study 1-2, see below) or how much they are willing to pay for this item (WTP, Study 3, see below), without any social ratings presented. This baseline block allowed us to verify that there were no group differences in food preferences before the social influence manipulation. The subsequent social influence phase was composed of five (Study 1 and 3) or four (Study 2) continuous blocks (see **Figure 1**). During the social influence phase, participants first rated the food item and were then presented (for at least 3s and until they continued per mouse click) with what we told them were the ratings of several other people for the same food item ('social ratings').

The first four blocks during the social influence phase (T1-T4) presented a total of 64 different food items (all different from each other and different from the items shown during the baseline phase). The order of food items was randomized within blocks and the order of blocks T1-T4 was counterbalanced across participants to obtain a similar composition of health and taste features in each block. The 5th block (Studies 1 and 3 only) was composed of the same 16 food items as during the baseline, allowing us to test the effects of social norm learning on both unseen and previously rated food items. However, due to limited statistical power, we do not compare bin-by-bin differences in our effects.

Food preference ratings (Study 1-2). In all trials of Studies 1 and 2, participants rated the food items ('How much would you like to consume this product at this moment?') on a visual analogue scale (VAS) from 0 (*not at all*) to 100 (*very much*) (self-paced and without time limit), which was displayed underneath the photo of the food item. Ten social ratings were subsequently presented on a similar VAS, again underneath the food picture (for at least 2s and a maximum of 8s, if participants did not click to advance the survey).

Willingness-to-pay (WTP) for food items (Study 3). Study 3 assessed WTP as an incentive-compatible measure of food craving. In each trial, participants indicated their WTP on a slider scale from 0-3 Euro (in 10-cent increments), which was displayed below the food item. WTP, as measured using a Becker-DeGroot-Mashak auction (Becker et al., 1964) is the gold standard to measure subjective valuation in behavioral economics and less susceptible to demand effects (Wertenbroch & Skiera, 2002). Participants were instructed as following: 'You will get an extra €3 for your participation in this study. During the experiment, you will be allowed to use this money to buy a snack from us. In fact, we would like you to think of us as your personal convenience store. Whatever money you do not spend is yours to keep and will be transferred to your bank account upon completion of the study. For your bids, you will receive €3, which you can either spend on your bid for one of the products or keep for yourself. At the end of the experiment, one of your bids from a random subset of products will be chosen. You do not have to worry about how you want to spread your budget on the different products, as only one bid will count. That means you can spend up to €3 for each product if you want.' As instructed, a random trial was selected at the end of the experiments and a price between 0-3 Euro was randomly generated by a computer algorithm. If the bid was as high or higher than the price generated by the computer, the participant had to pay the price and received the food item, otherwise they did not have to pay and did not receive any food item. After the WTP rating, participants were presented with the WTP of previous participants, again shown on the same scale below the picture of the food item (for at least 2s and a maximum of 8s, if participants did not click to advance the survey).

Supermarket task. In Studies 2 and 3, participants performed an online supermarket task following the food choice task. We used Howe's Grocery (<https://openscience-onlinegrocery.com/>), an online supermarket developed for research purposes (Howe et al., 2022) which allows to investigate food decision-making in a naturalistic setting very similar to many real online grocery shops (Fig. 1D). Participants were asked to select several food items in the online supermarket with the following instructions: 'Imagine that you move to the US for a 3-month internship. When you arrive in your apartment you need to get some groceries for tomorrow's breakfast and some snacks for the day. Buy what you would like from the online supermarket below. Keep in mind that in total, you should spend any amount between 40-60 US Dollar.'. The participants were aware that this was a hypothetical purchasing task and that they would not pay for or receive any food ordered in Howe's Grocery Store.

Other measures. Before and after the task, participants rated how hungry they felt (see Supplementary Table S1). After the task, they provided basic demographic measures, self-reported height and weight (allowing us to compute their body mass index / BMI), as well as general dietary habits using custom items (see Supplementary Table S2). At the end of Studies 1 and 2, participants also answered a question about the perceived purpose of the study (results detailed in Supplementary Table S3). In total, participation in the study took approximately 30-45 minutes.

Statistical analysis

Food rating task. Participants' individual health (β_H) and taste beta weights (β_T) were computed by fitting a multilevel general linear model (GLM) to participants' food wanting ratings (Studies 1-2) or WTP (Study 3) $V(i)$ as a function of the healthiness and tastiness of each food item i , separately for the baseline and the social influence phase:

$$V(i) = \beta_0 + \beta_H \text{health}_i + \beta_T \text{taste}_i$$

For statistical analyses of group differences, we performed a GLM to test the effect of group on individual health and taste weights (β_H and β_T) during the social influence phase (see

Fig. 2B), controlling for baseline weights. All statistical tests used a significance threshold of $p < 0.05$ (two-sided). Shapiro-Wilk normality test was used to examine the normality distribution of each variable. Data were analyzed using Matlab version R2020b, R version 3.6.1 (R Core Team, 2020), and RStudio version 1.2.5001.

Supermarket task. We analyzed the healthiness of products selected in the participants' shopping basket at check-out, by computing the average health star points of all the food items in participants' online basket at the time of check-out ('health star points'). Howe's Grocery store includes detailed information regarding the nutritional composition of each food item, including calories, fat, carbohydrates, fiber, sugar, protein, and other measures. Based on its nutritional composition, each food is associated with an aggregate health measure, the so-called 'health star points'. The health star points ranged from minus ten to ten, with greater values indicating more healthiness (see details in Howe et al., 2022). Food items high in vitamins, minerals, fiber, whole grains, and omega-3 have higher number of health star points, whereas foods with saturated and trans fatty acids, added sodium, added sugar and artificial colors have a lower number of health star points.

Results

Study 1 (online study)

The first experiment tested the generalization of social influences on self-reported food preference ratings in 196 adult participants of an online study. **Figure 2A** illustrates the time course of participants' individual health and taste weights (i.e., beta estimates) during baseline (T0) and the five bins of trials during the social influence phase (T1-T5). Each bin consisted of 16 trials that were balanced regarding the healthiness and tastiness of the 16 food items. This allowed us to assess how participants weighted health and taste in their food ratings in each bin and in each phase (over multiple bins), by fitting a multilevel general linear model (GLM) with healthiness and tastiness of food items as predictors and food preference ratings as the outcome variable. This multi-level model yielded beta-weights for the taste and the health regressors for each participant, with larger beta-weights indicating greater importance of the regressor in predicting food preference ratings.

While the two groups had similar health weights during the baseline phase, they diverged during the social influence phase (see **Figure 2A-B**). In line with our prediction, during the social influence phase and controlling for baseline weights, the *Health* group ($N_H=97$, $M=0.04$, $STD=0.40$) placed significantly more weight on health than the *Taste* group ($N_T=99$, $M=-0.08$, $STD=0.38$), $t(193)=4.12$, $p<0.001$, Cohen's $d=0.30$. This suggests that participants adapted their food ratings to implicit social norms regarding the importance of health considerations, depending on their experimental group. In contrast, there was no significant difference in taste weights between the *Taste* ($M=0.74$, $STD=0.50$) and *Health* ($M=0.90$, $STD=0.59$) groups during the social influence phase, controlling for baseline, $t(193)=-1.25$, $p=0.21$, Cohen's $d=0.30$ (see **Figure 3A-B**). This suggests that social influence may generalize less based on the tastiness dimension.

Study 2 (online study)

The second online experiment aimed to replicate the results of Study 1 in a different data set from a different country (France, $N=205$) and using a different set of food items. The time courses of healthiness beta weights for the two groups are shown in **Figure 2C**. Paralleling the findings of Study 1, the *Health* group ($N_H=103$, $M=5.03$, $STD=8.23$) had significant higher healthiness weights during the social influence phase than the *Taste* group ($N_T=102$, $M=2.32$, $STD=8.69$), controlling for baseline weights, $t(202)=-2.00$, $p=0.047$,

Cohen's $d=0.32$ (see **Figure 2D**). As in Study 1, there was no significant difference between the *Taste* ($M=12.20$, $STD=7.17$) and *Health* ($M=10.71$, $STD=6.58$) groups for the tastiness weights during the social influence phase, $t(202)=1.08$, $p=0.28$, Cohen's $d=0.22$ (see **Figure 3C-D**).

Study 2 further tested whether the generalization of social influence would transfer to food choices in an ecological online grocery store task (Howe's Grocery <https://openscience-onlinegrocery.com/>), in which participants were instructed to select foods for next day's breakfast and some snacks. To measure the healthiness of participants food choices in the supermarket task, we computed the average 'health star points' (an objectively defined measure of food healthiness, as implemented in the experimental online grocery store) of selected products in participants' basket. We first tested whether participants' health preferences in the food rating task was consistent with their food choices the supermarket task. Indeed, we found a positive and significant correlation between the healthiness beta weights during the social phase and objective health score of the selected products in the online supermarket ($r(203)=0.34$, $p<.001$, see **Figure 4A**). Thus, participants whose food ratings were more driven by the healthiness of food items during the social learning task also made healthier food choices in the online supermarket task, supporting the consistency of both measures. However, in contrast to our hypothesis, the *Health* group ($M=0.43$) did not select significantly healthier food items (i.e., items with higher health star points) in the supermarket task compared to the *Taste* group ($M=0.49$), $t(203)=-0.11$, $p=0.913$, Cohen's $d=0.02$ (see **Figure 4B**). Thus, in Study 2, the learning from the main task did not significantly transfer to this second, supermarket task.

Study 3 (lab study)

The aim of the third study was to replicate the generalization of social influence effects in an in-person laboratory study ($N=64$ participants). This allowed us to use willingness-to-pay (WTP) as an incentive-compatible measure of how much participants valued the food items, by using a second price auction to actually implement one of their food choices (see Methods and Plassmann et al., 2007 for details), thus reducing the influence of demand effects on changes in food preferences.

Time courses of health weights are shown in **Figure 2E**. As in the two previous studies, during the social influence phase (controlling for baseline), the *Health* group ($N_H=32$, $M=0.19$, $STD=0.16$) put significantly greater weights on the healthiness of food items than the *Taste* group ($N_T=32$, $M=0.10$, $STD=0.16$): $t(61)=-2.22$, $p=0.030$, Cohen's $d=0.58$ (see **Figure 2F**). As previously, the weights for food tastiness did not significantly differ between the *Health* ($M=0.11$, $STD=0.11$) and the *Taste* group ($M=0.10$, $STD=0.11$), $t(61)=0.10$, $p=0.92$, Cohen's $d=0.09$ (see **Figure 3E-F**).

As in Study 2, participants performed the online supermarket task following the food rating task. We again found a positive and significant correlation between individual weights for food healthiness during the social influence phase and average objective health score during the supermarket task (health 'star points'), $r(62)=0.44$, $p<.001$ (see **Figure 4C**). Further and in line with our hypothesis, the *Health* group bought significantly healthier food items on average (i.e., items with higher objective health scores) than the *Taste* group, $t(58)=2.43$, $p=0.018$, Cohen's $d=0.61$ (see **Figure 4D**). This suggests that the generalization of social influence effects on food choices transferred to a second, independent and more ecologically valid task in Study 3.

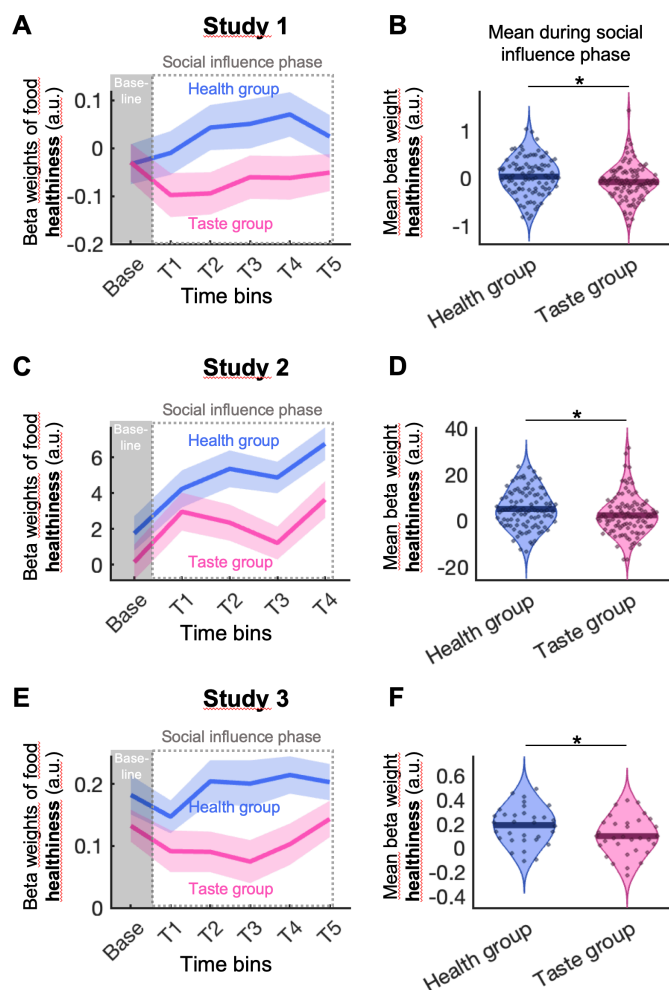
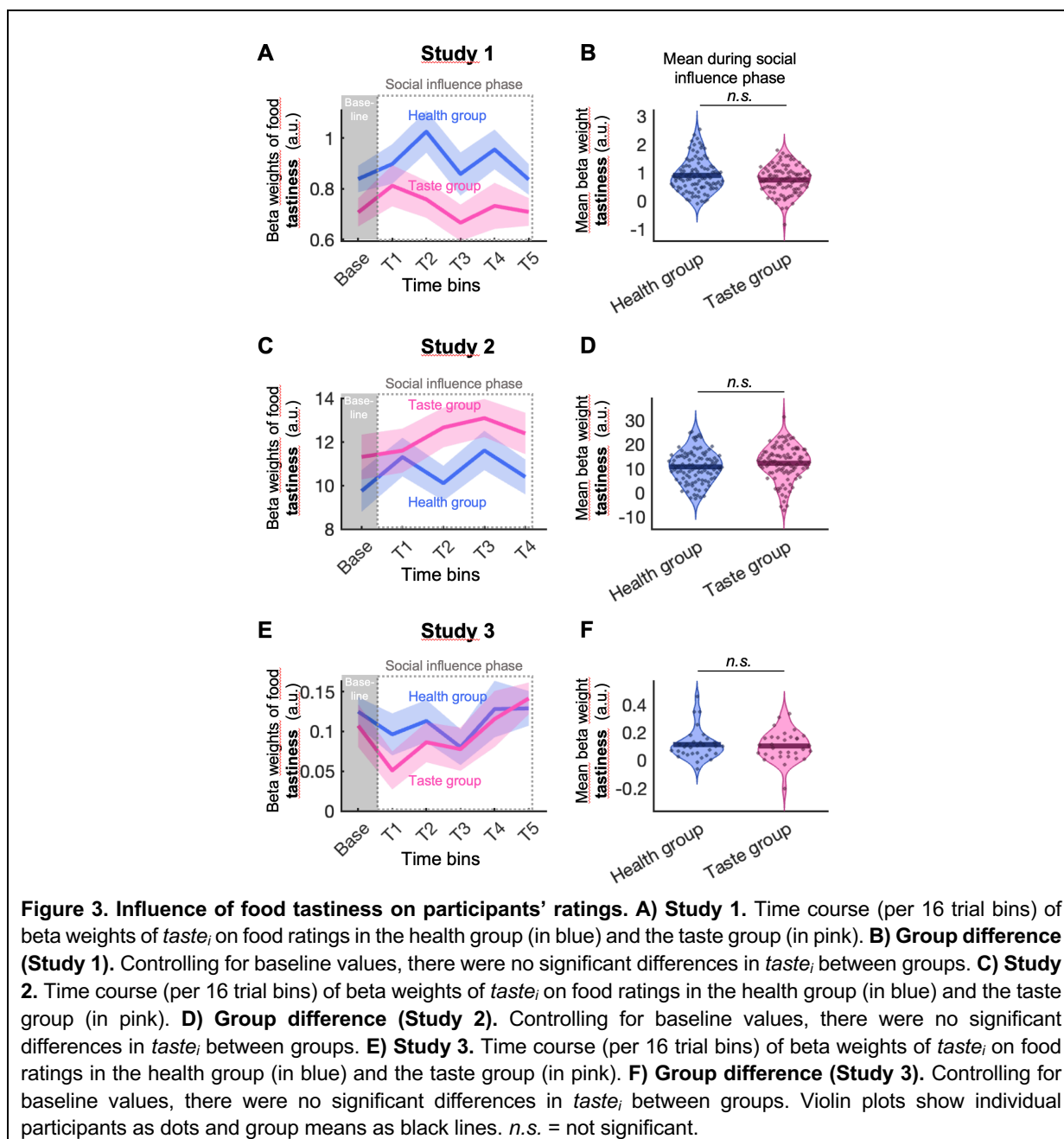


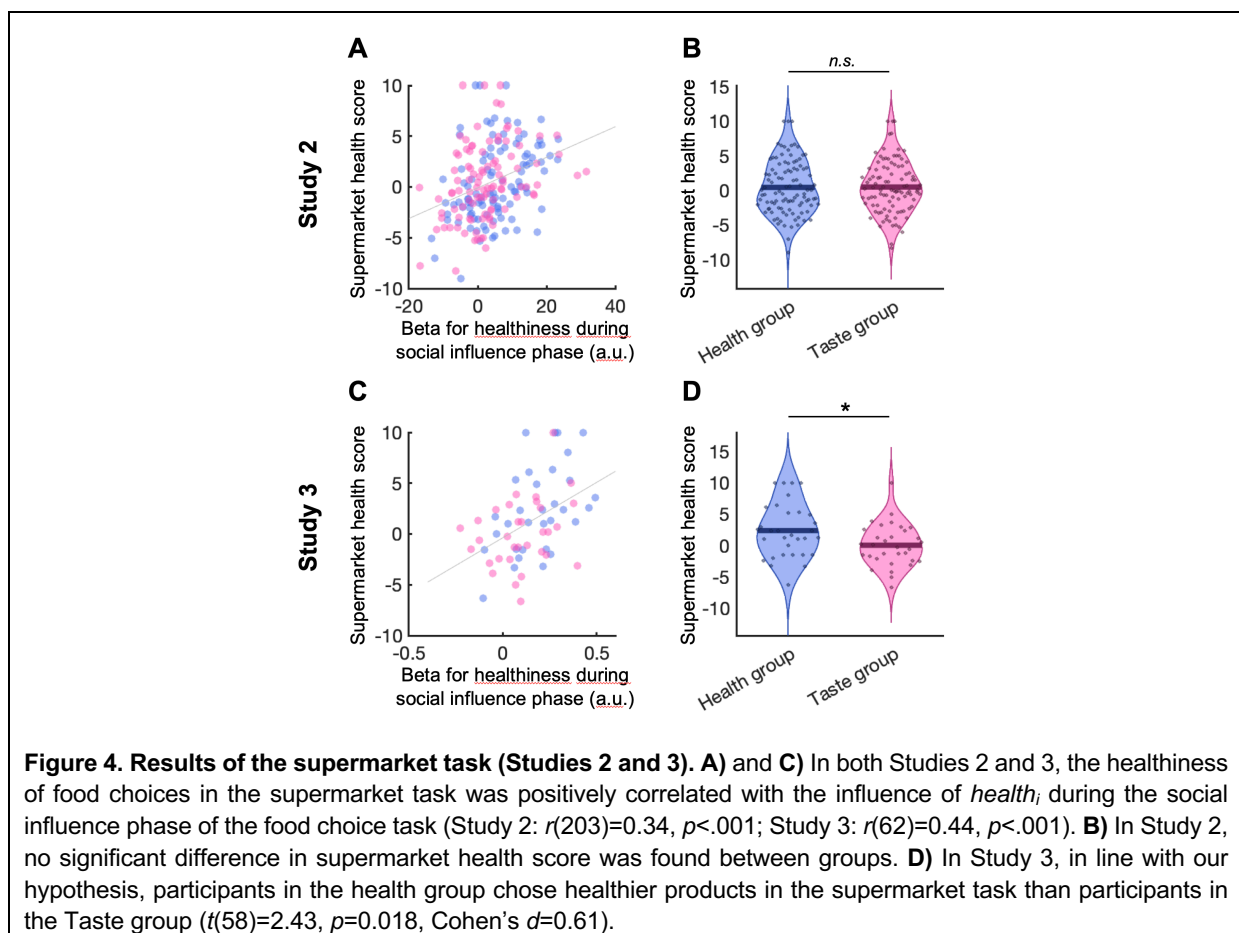
Figure 2. Influence of food healthiness on participants' ratings. **A) Study 1.** Time course (per 16 trial bins) of beta weights of healthiness on food ratings in the health group (in blue) and the taste group (in pink). **B) Group difference (Study 1).** Controlling for baseline values, the Health group showed significantly higher health beta weights than the Taste group during the social influence phase. **C) Study 2.** Time course (per 16 trial bins) of beta weights of healthiness on food ratings in the health group (in blue) and the taste group (in pink). **D) Group difference (Study 2).** Controlling for baseline values, the Health group showed significantly higher health beta weights than the Taste group during the social influence phase. **E) Study 3.** Time course (per 16 trial bins) of beta weights of healthiness on food ratings in the health group (in blue) and the taste group (in pink). **F) Group difference (Study 3).** Controlling for baseline values, the Health group showed significantly higher health beta weights than the Taste group during the social influence phase. Asterisks (*) indicate a significant difference between the two groups ($p < 0.05$). Violin plots show individual participants as dots and group means as black lines. Pooled across all three studies, the average effect size for the group difference in health weighting was Cohen's $d = 0.35$.



Discussion

People's behavior is influenced by how other people behave. A well-established and health-relevant example is eating behavior: Observation of other people's food choices influences both the type and amount of food we eat (Higgs, 2015), and such social context effects may translate into important effects on health and well-being in the long-term. Social influence is typically shown for specific observations of behavior (e.g., choosing specific food items). Less is known on how humans infer more general social norms and how this influences their behavior. Here, we tested the idea that social influence may generalize based on inferred conceptual dimensions. More specifically, we studied whether the effects of other people's food ratings can generalize based on two common conceptual attributes of food items: tastiness and healthiness. In line with our hypothesis, the results of three different experiments consistently showed such conceptual generalization of social influence, namely a change in

how people's food preferences were driven by health aspects. In other words, by observation how peers rated different food items, participants inferred how much importance their peers assigned to food healthiness. This inferred importance of the healthiness of the food item for others then influenced participants' subsequent food preferences, leading to a higher or lower preference for healthy food items. We did not observe a significant change in how people weighted tastiness of foods and were only partially successful in extending this social generalization of health weighting to an independent online supermarket food choice task (discussed further below). Taken together, these experimental findings suggest that people implicitly infer the more general social norms driving other people's opinions and adjust their own preferences accordingly—at least for knowledge-related conceptual attributes such as healthiness, but potentially less for more subjective attributes such as tastiness of foods.



Our findings build on and further inform recent frameworks of how humans learn, generalize, and represent conceptual relationships (Behrens et al., 2018; Constantinescu et al., 2016; Dunsmoor & Murphy, 2015; Koban et al., 2021). A long history of work has investigated the generalization of conditioned cue-stimulus association along perceptual similarity gradients (Guttman & Kalish, 1956; Shepard, 1987) and perceptual generalization also guides social decision-making (FeldmanHall et al., 2018; FeldmanHall & Dunsmoor, 2019; van Baar et al., 2021). Moreover, humans also generalize learned associations based on conceptual relationships (Dunsmoor & Murphy, 2015; Tenenbaum & Griffiths, 2001). For instance, humans also use categories and abstract representations to generalize learnt fear responses (Dunsmoor & Murphy, 2015) and pain modulation (Koban et al., 2018). In the context of food choices, a recent study has used an evaluative conditioning paradigm to show

that pairing a few unhealthy food items with unpleasant words or pictures leads to a lower preference for other unhealthy compared to healthy food items (Bui & Fazio, 2016).

Our results suggest that such conceptual learning and inference processes could also be at play during social interactions and social influence. They resonate with a study that used social influence together with a hidden detection covariation design (Lewicki, 1986) to implicitly shift attractiveness ratings of faces based on one perceptual features of the rated images (namely hair length) (Ivanchei et al., 2019). Recent work has also used computational learning models to understand how people infer other agents' mental states (e.g., beliefs and desires) based on their observable actions (Baker et al., 2017; Jara-Ettinger, 2019). For instance, theory of mind problems could be described with inverse reinforcement learning models, which allow to recover latent world models and reward functions given observed policy execution (Jara-Ettinger, 2019). In the present study, in which ratings of others were observed for different food items, a possible underlying cognitive mechanism is the identification of the latent reward function (or higher-order social norms) that best explain the variability in social ratings. Identifying the higher-order social norms and reward functions that drive other people's decision-making then allows the observer to be influenced by them and to not only conform to specific behaviors but to social norms more globally.

This perspective also aligns well with recent findings and models in neuroscience. Several studies have suggested that humans use grid-like code to navigate not only spatial, but also perceptual and conceptual relationships between objects, allowing them to make decisions about situations and object that they have never encountered in the same configuration before (Constantinescu et al., 2016). Grid-like fMRI activity has been observed in hippocampal and parahippocampal areas (Doeller et al., 2010), as well as ventromedial prefrontal cortex (vmPFC) (Constantinescu et al., 2016; Park et al., 2020, 2021; Schafer & Schiller, 2018) known to be involved in abstract cognition, memory, and spatial orientation. VmPFC in particular has been suggested to guide behavior and decision-making by extracting abstract situational features and conceptual models (Koban et al., 2021; Schuck et al., 2016) and has also been associated with social and non-social reward processing (Hiser & Koenigs, 2018; Smith & Delgado, 2015), modulation of valuation by health-concerns (Hare et al., 2011; Schmidt et al., 2018), and by social influence on food preferences (Nook & Zaki, 2015). The vmPFC would thus be a candidate region for mediating conceptual generalization processes, including generalization of social normative influence. The present study cannot provide any insight into the neurobiological mechanisms underlying generalization of social influences on decision-making, we therefore call for future studies to use brain imaging and test these hypotheses more directly.

While social influence generalized based on the importance of healthiness of food items in all three experiments, no significant difference between the two groups was found for the importance given to tastiness. Several reasons may explain this absence of effect for taste weighting. First, perceived tastiness of food items is more idiosyncratic than perceived healthiness (Puputti et al., 2019). It may therefore have been more difficult for participants to accurately detect the social weighting of tastiness, therefore limiting its possible generalization. However, previous evidence also suggests that importance of healthiness is more easily modifiable than weighting of tastiness. For example, observational studies (Gligorić et al., 2021; Levy et al., 2021) or studies with different social norm interventions (Mollen et al., 2013) in real-life settings have found more impact for healthiness than tastiness. While taste preferences are difficult to change, there are many studies showing that social modeling of healthy food choices is a robust phenomenon in different contexts, including lab experiments

(Higgs et al., 2019; Robinson et al., 2013, 2014), agent-based models (Li et al., 2016), and in real-life settings (Higgs et al., 2019; Thomas et al., 2017).

This is consistent with a recent meta-analysis (Melnyk et al., 2021) showing that social norms have an especially large effect on socially responsible behavior in general. Purely tastiness-driven eating is not perceived as a positive social norm which could explain why participants were less influenced by taste-related norms (Higgs et al., 2019). The timing of taste and health perception might also contribute to this difference. On average, people estimate a food's tastiness more than 450 ms before its healthiness (Sullivan & Huettel, 2021). Together, these findings are in line with the idea that health considerations are a more controlled, 'top-down' process, which may be more readily modulated by social norms than more bottom-up appetitive processes such as food preferences based on tastiness.

In the last two studies, we also tested whether generalization of social influence in our experimental task could transfer to an ecological online supermarket task. Our results in Study 3, but not in Study 2, showed such a transfer, by demonstrating healthier food choices in the online supermarket by participants in the Health-norm compared to participants in the Taste-norm group. These findings build on other recent studies that have shown transfer of learned strategies to regulate food craving across different food images and to real-life eating behavior (Boswell et al., 2018). Other studies have also found maintenance over time directly after the experiment (Higgs et al., 2019; Thomas et al., 2017) or five months after (Garcia et al., 2021). However, Study 2 did not show a significant group difference in the supermarket task and showed smaller effect size for the main social influence task as well. Several differences between Studies 2 and 3 may explain this absence of effect. Study 2 was conducted online in France and assessed food preference ('would like to eat') ratings, while Study 3 was conducted in the laboratory in Germany and measured non-hypothetical willingness-to-pay (WTP) for food items. The incentive compatible measure of WTP and the more interactive and more controlled lab setting likely lead to higher engagement in the task and may also increase sensitivity to social norms. Further, differences between participant populations (Paris, France versus Bonn, a smaller city in Germany) and food products shown may also contribute to the different results. Demographic factors such as proportion of female versus male participants, BMI, income, and education differed slightly between the two studies. However, these factors were not correlated with the objective health score and are thus unlikely to substantially alter the results.

We note several other limitations of our study. First, the study participants were relatively young and highly educated adults. Social influence, especially towards healthy foods, may have a greater impact in this population (Higgs, 2015; Li et al., 2016), potentially due to differences in beliefs and concerns about healthy diets (Wardle et al., 2004). Future studies should test whether these effects are also observed in more representative samples. Second, we used normative health and taste ratings from a large sample of different participants to select the health- or taste-driven social ratings of wanting or willingness-to-pay, in order to not evoke these two dimensions (healthiness and tastiness) prior to our experimental manipulation and to reduce the time spent in the online surveys. This may have reduced the size of the generalization effects, due to idiosyncratic differences in health and especially in taste perception. Future studies could acquire participant's idiosyncratic health and taste ratings or display normative health and taste ratings to obtain better representations of this two-dimensional conceptual space. Third, we did not use a cover story to avoid deception of participants. This has led a small proportion of participants to guess the overall topic of these the studies (social influence), raising the question of demand effects (the idea that participants try to behave in line with the experimenter's hypothesis). However, we think

that it is unlikely that our findings can be explained by participants' motivation to comply with experimenter demands, for the following reasons. First, we instructed participants that we were interested in their genuine and subjective rating, which should motivate participants (if they want to indeed comply with the experimenter as suggested by the concept of 'demand effects') to provide accurate ratings based on their own preferences. Second, our results also held when using WTP as an outcome measure, which is incentive compatible and thus less likely to be driven by demand effects. Third, we used a between-subject experimental design and participants neither knew about the different groups, about the rather subtle experimental manipulation of the social ratings, nor the hypothesis regarding the learning of healthiness and tastiness preferences, with these two conceptual dimensions never mentioned during the study. Given that, for each food item, social ratings were only shown after the participant's own rating, it would be very hard for the participants to infer how exactly they should behave if they wanted to please the experimenter. Last but not least, we notice that, while demand effects are ubiquitous in introductory psychology textbooks, the actual evidence for such effects is rather small (McCambridge et al., 2012; Mummolo & Peterson, 2019), except for cases when an hypothesis is explicitly stated and when participants are in direct contact with an experimenter, as in the case of laboratory experiments (Nichols & Maner, 2008).

The present study used social ratings, which are omnipresent on social media and online shops, where they are known to influence customer behavior (e.g., Gavilan et al., 2018; Moe & Trusov, 2011). Social influence in non-digital settings likely operates via the transmission of a combination of more complex and different social cues, including language and facial or bodily expressions of emotion and of social approval versus disapproval. Future studies could investigate social cues such as facial expressions in in-person social interactions to test how social influence generalizes based on different aspects of food choices. They could also test more gradual social norms or how people adjust to social norms that evolve and change over time.

In conclusion, the results of our three studies showed that people infer social norms regarding the importance of healthiness when observing other people's food ratings and these implicit norms shift their own food preferences. Taste might be less susceptible to social influence due to idiosyncratic perceptions of tastiness and more automatic processing of taste, compared to health attributes. Future studies with large sample sizes could further assess how weighting of taste might be altered by social influence effects. Future studies could also test generalization of social influence effects in other domains and characterize the brain mechanisms underlying these effects. Given that social norms are one of the most efficient ways to change behavior and decision-making (Zhao et al., 2022), better understanding how social norms are inferred and how social influence can generalize across different instances and contexts opens new possibilities for interventions to encourage healthier eating and other health-related behaviors in everyday life. More broadly, our experimental findings suggest a new mechanism of how human behavior can be influenced by unspoken social norms even in new instances, thus providing new insight in how human learn about and adapt to group norms and culture.

Code and data availability

The lead author (LK) has full access to the data reported in the manuscript. Code for analysis is available at <https://github.com/ldmk> and <https://github.com/canlab>. Deidentified data is available at https://github.com/ldmk/2025_SocInfl_Generalization/.

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Author contributions

OC: Investigation, formal analyses, visualization, writing of original draft. PF: Resources and review of the manuscript. BW: Resources, review of the manuscript, project administration. HP: Supervision, conceptualization, review of the manuscript, funding acquisition, project administration. LK: Conceptualization, methodology, formal analysis, investigation, visualization, supervision, funding acquisition, writing and editing of the original draft.

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Supplementary materials**Social influence effects on food valuation generalize based on conceptual similarity**

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Supplementary Table S1.*Demographic variables and hunger ratings by experimental group in Studies 1-3.*

Study	Health group		Taste group		W-statistic	df	p-value		
	Mean	SD	Mean	SD					
Age (years)									
Study 1	35.4	9.32	36.7	9.16	4344	194	0.25		
Study 2	24.4	3.17	24.6	3.90	4529	203	0.86		
Study 3	23.7	3.62	24.3	4.21	484	62	0.71		
BMI (kg/m²)									
Study 1	25.0	4.80	24.6	4.56	5230	194	0.28		
Study 2	22.5	4.38	22.7	3.84	4858	203	0.35		
Study 3	23.7	3.47	23.8	3.63	501	62	0.88		
Pre-task hunger (from 0 to 100)									
Study 1	45.00	26.88	50.38	28.45	4276	194	0.19		
Study 2	48.94	30.23	49.97	30.01	5211	203	0.92		
Study 3	55.34	23.72	62.90	22.95	420	62	0.22		
Post-task hunger (from 0 to 100)									
Study 1	52.99	27.77	58.11	28.96	4181	194	0.12		
Study 2	56.00	28.17	63.47	24.85	4519	203	0.08		
Study 3	62.03	25.26	72.25	16.99	395	62	0.11		
Number of participants									
Annual income (€)	0 to 20,000€		20,000 - 39,999€		More than 40,000€		No answer		p-value
	Health group	Taste group	Health group	Taste group	Health group	Taste group	Health group	Taste group	
Study 1	35	33	16	22	29	33	17	11	0.47
Study 2	66	75	12	13	5	4	20	11	0.36
Study 3	29	27	1	2	1	1	1	2	0.85
Education									
	With higher education				Without higher education				
	Health group		Taste group		Health group		Taste group		
Study 1	41		43		56		56		0.98
Study 2	91		88		12		12		0.91
Study 3	8		14		24		18		0.18
Gender									
	Female				Male				
	Health group		Taste group		Health group		Taste group		
Study 1	39		34		58		65		0.48
Study 2	74		66		29		36		0.34
Study 3	15		15		17		17		1

Note. Df=degree of freedom, SD=Standard Deviation. Wilcoxon-Mann-Whitney test were performed for age, BMI, and hunger. Chi-square or Fisher tests were performed for gender ratio income and education.

Supplementary Table S2.

General dietary habits by experimental group in Studies 1-3.

Study	Health group		Taste group		W-statistic	p-value	df
	Mean	SD	Mean	SD			
Control on Eating (from 0 to 100) (How much do you typically control how much and what you are eating?)							
Study 1	56.41	24.01	59.81	25.32	4288	0.20	194
Study 2	56.73	26.86	57.16	24.58	5234	0.97	203
Study 3	62.44	24.93	62.31	24.11	507	0.95	62
Influence Bodily Signals (from 0 to 100) (How much do the following factors typically influence your eating behavior? - Bodily signals (e.g., feeling hungry or full))							
Study 1	71.68	20.64	70.95	20.33	4889	0.83	194
Study 2	73.46	22.30	75.31	16.86	5244	0.98	203
Study 3	72.78	19.64	71.62	23.18	531	0.80	62
Influence Habit (from 0 to 100) (How much do the following factors typically influence your eating behavior? - Habit (e.g., eating at specific times))							
Study 1	51.41	28.05	54.58	26.70	4550	0.53	194
Study 2	55.97	29.83	54.35	26.44	5495	0.57	203
Study 3	58.38	30.22	54.97	33.43	525	0.86	62
Influence Seeing Others Eating (from 0 to 100) (How much do the following factors typically influence your eating behavior? - Seeing others eating)							
Study 1	36.58	25.42	41.13	27.32	4357	0.26	194
Study 2	50.41	30.54	45.49	25.42	5800	0.20	203
Study 3	39.78	24.03	40.56	24.49	506	0.95	62
Influence Health Considerations (from 0 to 100) (How much do the following factors typically influence your eating behavior? - Health considerations)							
Study 1	46.00	27.89	49.75	28.72	4455	0.38	194
Study 2	57.83	27.92	54.44	27.64	5632	0.37	203
Study 3	54.78	29.82	54.44	31.00	503	0.91	62
Influence Weight Considerations (from 0 to 100) (How much do the following factors typically influence your eating behavior? - Weight considerations (e.g., lose or maintain weight))							
Study 1	47.45	28.75	48.78	30.32	4681	0.76	194
Study 2	45.74	31.29	52.17	30.05	4607	0.13	203
Study 3	45.91	26.64	49.03	28.08	461	0.50	62
Influence Taste (from 0 to 100) (How much do the following factors typically influence your eating behavior? - Taste and attractiveness of food)							
Study 1	73.85	19.74	74.31	21.70	4581	0.58	194
Study 2	77.56	18.19	77.75	17.30	5322	0.87	203
Study 3	78.12	20.47	77.94	17.52	538	0.73	62
Influence Doctor Recommendations (from 0 to 100) (How much do the following factors typically influence your eating behavior? - Recommendations of doctors and health professionals)							
Study 1	25.26	25.14	25.93	24.39	4772	0.94	194
Study 2	41.40	29.20	38.57	27.37	5516	0.54	203
Study 3	23.62	27.95	23.50	21.42	464	0.53	62
Influence Other People (from 0 to 100) (How much do the following factors typically influence your eating behavior? - What others (friends, family) tell me to eat)							
Study 1	30.24	24.82	35.42	25.33	4232	0.15	194
Study 2	28.79	23.10	25.16	23.81	5777	0.22	203
Study 3	33.81	29.31	28.97	20.00	532	0.79	62
Frequency Diet (from 0 to 100) (How often do you follow a diet in order to lose weight? - Dieting)							
Study 1	28.35	26.53	23.42	27.16	5496	0.08	194
Study 2	18.88	24.34	22.70	26.29	4762	0.24	203
Study 3	13.22	19.23	17.34	23.33	497	0.84	62
Frequency Snacking (from 0 to 100) (How often do you snack in between meals? - Snacking)							
Study 1	65.09	21.12	63.96	23.32	4816	0.97	194
Study 2	54.22	28.52	54.53	27.69	5203	0.91	203
Study 3	70.66	20.68	68.56	19.14	556	0.56	62

Note. Df=degree of freedom, SD=Standard Deviation. Wilcoxon-Mann-Whitney test were performed.

Supplementary Table S3.

Purpose of the study according to participants for study 1 and 2. Participants gave free-text answers to the question: “What do you think is the purpose of this study?”, and the answers were then classified.

Guessed study purpose	Number of participants (%)		
	Study 1	Study 2	Total
Hunger	34 (17.3%)	36 (17.6%)	70 (17.5%)
Eating habits	23 (11.7%)	39 (19.0%)	62 (15.5%)
Eating behaviors	36 (18.4%)	23 (11.2%)	59 (14.7%)
Social influence	35 (17.9%)	19 (9.3%)	54 (13.5%)
Don't know	10 (5.1%)	14 (6.8%)	24 (6.0%)
Food presentation	10 (5.1%)	16 (7.8%)	26 (6.5%)
Eating influence	1 (0.5%)	13 (6.3%)	14 (3.5%)
Healthy nutrition	14 (7.1%)	4 (2.0%)	18 (4.5%)
Packaging	2 (1.0%)	16 (7.8%)	18 (4.5%)
Food preferences	13 (6.6%)	7 (3.4%)	20 (5.0%)
Craving	3 (1.5%)	3 (1.5%)	6 (1.5%)
Purchasing	8 (4.1%)	1 (0.5%)	9 (2.2%)
Other topics	4 (2.0%)	4 (2.0%)	8 (2.0%)
Hourly consumption	0 (0%)	6 (2.9%)	6 (1.5%)
Advertising	3 (1.5%)	1 (0.5%)	4 (1.0%)
Financial aspects	0 (0%)	2 (1.0%)	2 (0.5%)
Impact of COVID-19	0 (0%)	1 (0.5%)	1 (0.2%)
Total	196	205	401