Mechanisms underlying the effects of context on food decisions in humans

Doctoral thesis

to obtain a doctorate (PhD)

from the Faculty of Medicine

of the University of Bonn

Qëndresa Rramani Dervishi

from Struga, North Macedonia

2023

Written with authorization of

the Faculty of Medicine of the University of Bonn

First reviewer: Prof. Dr. Bernd Weber

Second reviewer: Prof. Dr. Ulrich Ettinger

Day of oral examination: 16.05.2023

From the Institute of Experimental Epileptology and Cognition Research

Director: Prof. Dr. Heinz Beck

Dedicated to my family, whose sacrifice has brought me closer to achieving my goals and dreams.

Table of Contents

List of abbreviations

ACC	Anterior cingulate cortex
AOI	Area of interest
BMI	Body Mass Index
BSCS	Brief Self Control Scale
CBG	Cyberball Game
CI	Confidence interval
cm	Centimeter
DEBQ	Dutch Eating Behavior Questionnaire
DG	Dictator Game
dlPFC	Dorsolateral prefrontal cortex
DV	Dependent variable
fMRI	Functional Magnetic Resonance Imaging
FNS	Food Neophobia Scale
FoV	Field of view
FWE	Familywise error
GDA	Guideline Daily Amount
GFM	Gradient field map
GLM	General linear model
h	Hours
k	Cluster size
kg	Kilogram
L	Left
M	Mean
m	Meter
MFG	Middle frontal gyrus
Min	Minute
mm	Millimeter
MNI	Montreal Neurological Institute
ms	Millisecond
NAcc	Nucleus accumbens
OFC	Orbitofrontal cortex

PPI	Psychophysiological Interaction
R	Right
ROI	Region of interest
RT	Reaction time
RTR	Reaction Time Ranking
SD	Standard deviation
SE	Standard error
sec	Second
SEM	Standard error of the mean
SPM	Statistical Parametric Mapping
SV	Subjective value
SVC	Small volume correction
T	Tesla
TE	Echo time
TFEQ	Three Factor Eating Questionnaire
TL	Traffic light
TOST	Two-One-Sided-Test
TR	Repetition time
vmPFC	Ventromedial prefrontal cortex
vS	Ventral striatum
WTP	Willingness to pay

1. Abstract

Food decisions are inevitable, frequent, and complex decisions with a high impact on our health. Understanding the mechanisms that underly food decisions has become a multi-disciplinary endeavor over the last decades, particularly due to the high and increasing rates of obesity worldwide. Employing an influential framework from neuroeconomics, I conducted behavioral, eye-tracking, and fMRI studies to investigate contextual effects on food decisions and possible mechanisms underlying these effects. I focused on contexts that are commonly associated with food decisions and can be addressed at a larger scale, such as social factors and food marketing strategies.

In Publication 1, I investigated whether common social contexts impact food choices and whether such influences are mediated by the emotions that these contexts evoke. I found that lab-induced social contexts do not impact food choices, despite inducing emotions of different valence. These behavioral findings suggest that either the role of social contexts on food choices is limited or it may be more complex than assessed.

In Publication 2, my collaborators and I conducted an eye-tracking study to investigate the interplay between visual saliency, attention, and food choice. We found that salient nutrition labels shift attention allocation in favor of healthy food items and increase preference for these foods. These results support the use of salient instead of purely numerical labels to promote healthy food choices.

In Publication 3, I investigated the effect of nutrition claims on expected and perceived food attributes both at the behavioral and at the neural level (using fMRI). At the behavioral level, I found that nutrition claims elicit expectations about different food attributes, but do not impact perceived pleasantness. At the neural level, I found that claims attenuate activity in reward-associated brain regions during tasting otherwise equal milk-mix drinks, but not during swallowing them. These findings suggest that exposure may be a good strategy to “update” expectations, and to even promote acceptance of healthier food.

In summary, these findings indicate that context affects food-related decision-making through different mechanisms. This knowledge not only advances our understanding of food decisions in humans but can also be applied to improve them at a larger scale.

2. Introduction

2.1. General introduction

Decisions guided by individual preferences are called value-based decisions (Fehr and Rangel, 2011). Food decisions are specific value-based decisions that are inevitable, very frequent, and have a high impact on our present and future well-being. Indeed, the World Health Organization (2017) lists nutrition and food choices among the most crucial determinants of health. Consequently, public health policies increasingly focus on improving food choices as a proxy for improving health (Gearhardt et al., 2012; Malik et al., 2013). Such efforts have increased especially in the last decades due to the growing rates of obesity worldwide (World Health Organization, 2021).

Identifying and implementing more effective prevention and intervention strategies requires a deeper understanding of the mechanisms underlying food-related decision-making. An important development in this regard has been the investigation of food decisions using a neuroeconomics approach, which integrates theories and methods from psychology, economics, neuroscience, and computational modeling to investigate how the brain performs value-based decisions (Fehr and Rangel, 2011). In the context of nutrition, prominent contributions of neuroeconomics research have been: (i) acknowledging that food decisions are value-based decisions and providing a framework to investigate them as such, and (ii) showing that food decisions in humans are determined and affected by interplays between homeostatic, psychological, cognitive, and contextual factors.

In the following sections, I first describe an influential neuroeconomics framework used to investigate food decisions (based on reviews by Rangel et al., 2008 and Rangel, 2013). I then summarize existing findings on the contextual effects on food decisions and state the objectives of my work. Following this description, I include three research articles relevant for this thesis. Additionally, I mention a review paper and an unpublished research article that I contributed to, given their overall relevance to this thesis. Finally, I provide an overall discussion and suggest directions for future research.

Please note that the introduction and discussion sections are concise on purpose and are not meant to provide an exhaustive review of the literature. The referenced literature and the publications included in this thesis provide more detailed descriptions and a more in-depth discussion of the findings.

2.2. A neuroeconomics framework for studying value-based decisions

According to an influential theoretical framework (Rangel et al., 2008; Rangel, 2013), five main computations take place when an individual performs a value-based decision (see Fig. 1). In the first step, the decision maker has to realize the decision context and the feasible options and actions (e.g., realizing that one is hungry and that there is food in the environment). Next, values to actions are assigned (e.g., eating food A or food B), and a course of action is chosen based on these values (e.g., deciding to eat food A). After the choice, the outcome of the decision is evaluated (e.g., how pleasurable eating food A was). Importantly, the decision maker *learns* which actions lead to which outcomes in order to "update" predictions relevant for future decisions. While all these computations take place, the decision maker also keeps track and updates the internal and external states (e.g., changes in perceived hunger while one eats). In my research, I focused on valuation, action selection, and outcome evaluation, which are introduced in greater detail below.

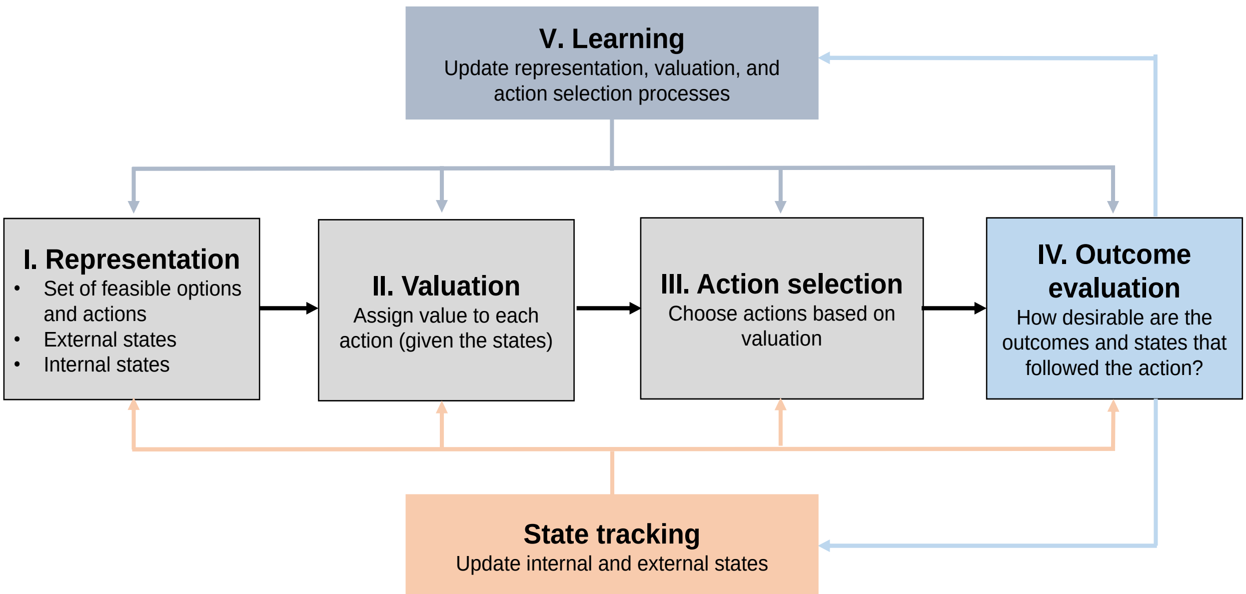

Fig. 1. Schematic representation of the computational steps that take place during value-based decision-making, according to a hypothetical framework proposed by Rangel et al. (2008). Figure adapted from Rangel et al. (2008) and Rangel (2013).

2.2.1. Valuation and action selection[1]

Valuation is the process in which the brain assigns values to specific stimuli [referred to as "stimulus value" or "subjective value" (SV)] and actions (referred to as "action cost") to guide choice (Rangel et al., 2008; Fehr and Rangel, 2011). Considering that in lab settings action costs are usually identical across options (e.g., pressing a button to select an item), in my research, I only focused on stimulus values, i.e., SV. For food decisions, values are assigned by three different but not completely independent hypothetical systems: (i) Pavlovian, (ii) habitual, and (iii) goal-directed. The Pavlovian and habitual systems are less flexible, more automatic, and can assign values only to a set of stimuli and behaviors, most likely known to serve an evolutionary purpose (Rangel et al., 2008; Rangel, 2013). The goal-directed system is the most flexible and assigns values to *action–outcome* associations. It is capable of computing, comparing, and updating values while considering internal states (e.g., hunger), external states (e.g., environmental cues), as well as short and long-term consequences for the decision maker. Furthermore, whenever a conflict between the different systems is detected, this system can inhibit the other two (Fehr and Rangel, 2011; Rangel, 2013). For instance, upon encountering indulgent food in the environment, Pavlovian systems may encourage its consumption, whereas the goal-directed system may assign a higher value to the long-term aspects of consuming such food and thereby discourage its consumption.

Valuation in the goal-directed system consists of integrating individual values assigned to multiple attributes that the decision maker associates with a certain stimulus to compute an overall stimulus value (Rangel et al., 2008; Rangel, 2013). While the exact attributes considered in valuation have not been identified yet, generally, these attributes seem to have different features. Attributes that refer to the qualities that can be assessed and experienced directly (examples shown in orange in Fig. 2) are called "basic" attributes. On the other hand, attributes that are not immediately experienced but have long-term consequences (examples shown in blue in Fig. 2), are called "abstract" attributes. Ideally, the value assigned to a specific attribute should be equal to the average reward to which it is

[1] In the discussed framework, action selection and valuation are considered to be two different steps. However, research has shown that these steps are not so clearly differentiated (see Rangel, 2013).

expected to lead (known as “expected utility”). According to this framework, for an optimal decision, the decision maker should integrate both basic and abstract attributes in valuation (Rangel et al., 2008; Rangel, 2013). This ability, however, has been shown to vary across individuals. In the context of food decisions, while basic attributes are shown to be considered by all decision makers, abstract attributes are shown to be considered only by successful dieters, i.e., people with higher dietary self-control (Hare et al., 2009). Interestingly, the integration of different attributes in valuation is also shown to vary with context (see section 2.3). Two meta-analyses of functional magnetic resonance imaging (fMRI) data have shown that SV signals are represented consistently in two main brain regions: the ventromedial Prefrontal Cortex (vmPFC) and the striatum (Bartra et al., 2013; Clithero and Rangel, 2014). Even though the dissociation between the roles of these two structures is still unclear, a common distinction is that the vmPFC serves as a hub that integrates value signals into an overall “common currency” of value (Levy and Glimcher, 2012; Lim et al., 2013; Abitbol et al., 2015), while the striatum is rather associated with the “desirability of reward” (Schmidt et al., 2017) and with outcome evaluation (Hollerman and Schultz, 1998; Hare et al., 2008; Clithero and Rangel, 2014; see section 2.2.2).

The overall integrated SVs are essential for action selection. The higher the SV of an option, the more likely for it is to be selected among the available options. The value comparisons that the brain performs before selecting an action can be simple or complex. Simple comparisons are those between options that do not involve a conflict between different goal values (e.g., choosing between an apple and an orange, example from Fehr and Rangel, 2011). Complex comparisons are those that involve a conflict between goal-values, for instance, choosing between a food item that is considered tasty but not healthy (e.g., a burger) and a food item that is less tasty but healthier (e.g., an apple). In my research I focused more on such complex comparisons.

2.2.2. Outcome evaluation

After an action has been selected (e.g., one chooses to eat a burger instead of an apple), the outcome of the decision is evaluated. During this process, the brain computes two different signals: one associated with the evaluation of the stimuli, termed “experienced utility”, and one associated with the difference between the expected and experienced utility, termed “prediction error” signal (Fehr and Rangel, 2011). The reward prediction error signal helps the decision maker keep track of the outcomes, learn associations, and "update" expectations, which consequently impact the future valuation of the same or similar stimuli (Schultz et al., 1997; Khaw et al., 2017). In this sense, the outcome of a decision serves as a "lesson" for future decisions. At the brain level, experienced utility is, consistently across different domains, related to activity in the nucleus accumbens (NAcc) and orbitofrontal cortex (OFC) (Blood and Zatorre, 2001; O'Doherty et al., 2001; de Araujo et al., 2003; Small et al., 2003; Kringelbach, 2015). Prediction errors, by contrast, are related to ventral striatal (including NAcc) activity (Hollerman and Schultz, 1998; Hare et al., 2008; Clithero and Rangel, 2014).

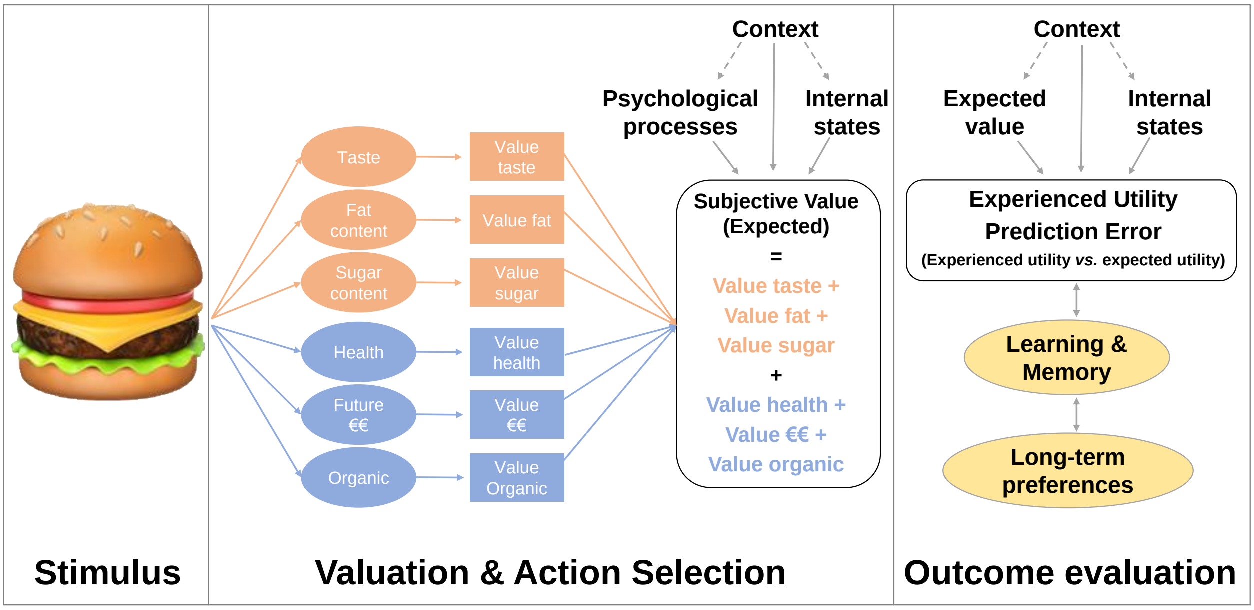

Fig. 2. Schematic representation of valuation, action selection, and outcome evaluation. Attributes in orange are examples of *basic* attributes, whereas attributes in blue are examples of *abstract* attributes. According to the framework proposed by Rangel et al. (2008), for an optimal decision, both types of attributes should be integrated in the computation of an overall subjective value. Context impacts the integration of these attributes, action selection, as well as outcome evaluation. The dashed lines indicate possible mechanisms by which context may affect the different stages of food-related decision-making. Figure adapted from Rangel (2013) and Enax and Weber (2015).

2.3. Contextual effects on food valuation and choice

As mentioned in section 2.2.1, not only individual heterogeneity in decision-making but also context influences value-based decisions, including food decisions (Fehr and Rangel, 2011; Engelmann and Hein, 2013; Enax and Weber, 2015; Konovalov and Krajbich, 2019). Based on the framework summarized in section 2.2, contexts that trigger automatic valuation systems and favor short-term rewards at the cost of long-term consequences would encourage suboptimal food choices. While such contexts may be many, scientific investigations have primarily focused on contexts that modulate stress and emotions, possibly due to their relevance. Stress and emotional discomfort are considered risk factors for obesity (Dallman et al., 2005; Singh, 2014), and obesity rates are shown to be higher in social groups experiencing higher amounts of stress and emotional discomfort (Malik et al., 2013; Loring and Robertson, 2014; Hoebel et al., 2019). When stressed or emotionally discomforted, the decision maker is thought to prioritize immediate concerns such as emotion regulation and the immediate rewarding aspects of food (e.g., taste) over long-term concerns (e.g., health) (Gardner et al., 2014). In line with this, exposure to stress-inducing contexts has been shown to decrease consideration for healthiness and to increase consideration for taste attributes. These effects have been associated with neural patterns seen in individuals with lower dietary self-control (Hare et al., 2009; Maier et al., 2015). Moreover, since high-caloric indulgent food is often more pleasurable, individuals may consume this type of food often as a means to alleviate emotional discomfort ("comfort food", Dallman et al., 2003). Importantly, by encouraging suboptimal food decisions, stress-inducing contexts may indirectly initiate a vicious cycle where consumption of indulgent food impacts the homeostatic and reward systems, which in turn decrease the probability of making optimal choices in the future (Rangel, 2013; Morris et al., 2015; Enax and Weber, 2016).

In contrast to contexts that may favor short-term rewards, contexts that "highlight" the long-term consequences of decisions would support optimal decision-making. Indeed, it has been shown that "highlighting" the healthiness aspects of food increases one's consideration for such attributes in valuation and improves food decisions. These effects have been associated with neural patterns observed in individuals with higher dietary self-control (Hare et al., 2009, 2011; Enax et al., 2015, 2016). Highlighting a particular attribute (e.g., healthiness) may also elicit certain expectations and thereby additionally impact experienced utility (Grabenhorst et al., 2008; Plassmann et al., 2008; Enax and Weber, 2015; Schmidt et al., 2017). Indeed, converging evidence supports that contextual information such as prices (Plassmann et al., 2008; Schmidt et al., 2017) or word-level descriptions (Grabenhorst et al., 2008) modulate expectations, thereby impacting behavioral and neural correlates of perceived pleasantness from otherwise equal items. In the context of food, however, it is challenging to modulate expectations such that they favor optimal decisions. In fact, marketing research has shown that in the food domain, context-induced expectations (e.g., via nutrition claims) may negatively impact the pleasantness perception of healthy food (Oostenbach et al., 2019), and may even favor overconsumption of food (Wansink and Chandon, 2006). Such marketing-induced “wrongful” expectations have even been argued to contribute to eating patterns associated with obesity (Chandon and Wansink, 2012; Cornil et al., 2022).

In today’s world, contexts that may favor suboptimal dietary choices like the availability of indulgent food, especially in developed countries, stress-inducing contexts, as well as different food marketing strategies, are omnipresent. In fact, it has even been argued that increased exposure to such contexts may partially explain high obesity rates around the world (Malik et al., 2013; Rangel, 2013). On the other hand, context is highly malleable, it can be addressed at a larger scale (e.g., at a population level), and as mentioned above, it can also encourage optimal dietary choices. These features make it an attractive tool that can be used to improve dietary choices at large (Enax and Weber, 2015). To date, the effectiveness of context as a tool remains limited, possibly because contextual effects on food decisions are complex and may be exerted through different mechanisms, which remain largely unknown (Enax and Weber, 2015).

Based on the literature reviewed above, context may impact several psychological states and processes ranging from internal states (e.g., expectations, emotions), to attentional processes (e.g., saliency effects). These processes and states may in turn affect valuation, action selection, and outcome evaluation (see Fig. 2). Understanding contextual effects on food-related decision-making and the underlying mechanisms may help in developing strategies that attenuate exposure to contexts that deteriorate these decisions and increase exposure to contexts that improve them.

2.4. Objectives of the thesis

Food decisions are inevitable, frequent, and complex value-based decisions with a high impact on our health (see section 2.1). Due to their characteristics, food-related decisions are not only subject to substantial interindividual differences but are also sensitive to contextual influences. Such influences are inevitable in today's world and are shown to contribute to both optimal and suboptimal food decisions (see section 2.3). During the qualification phase, I investigated contextual effects on food-related decision-making and possible mechanisms underlying these effects. I focused on contexts that are commonly associated with food decisions and can be addressed at a larger scale, such as social factors (Publication 1) and food marketing strategies (Publications 2 and 3).

In the project reported in Publication 1, my co-authors and I conducted behavioral experiments to investigate the association between social contexts, emotions, and food choices. More specifically, we assessed whether commonly experienced socially disadvantageous contexts impact food choices and whether such effects are mediated by the emotions that such contexts evoke. Based on previous research (see section 2.3), we hypothesized that disadvantageous social contexts would evoke negative emotions, which in turn will increase preference for unhealthy but tasty food. In the project reported in Publication 2, we conducted an eye-tracking study to assess the relation between visual saliency, attention, and choice. We hypothesized that salient nutrition labels would attract more visual attention, would induce shifts in attention allocation thereby increasing preference for healthy food. In the project reported in Publication 3, we conducted a behavioral and an fMRI study to investigate whether nutrition claims, commonly used in food marketing, influence expected and perceived food attributes. We hypothesized that nutrition claims would elicit several expectations about food attributes and would impact perceived pleasantness both at the behavioral and at the neural level.

2.5. References

Abitbol R, Lebreton M, Hollard G, Richmond BJ, Bouret S, Pessiglione M. Neural Mechanisms Underlying Contextual Dependency of Subjective Values: Converging Evidence from Monkeys and Humans. J Neurosci 2015; 35: 2308–2320. https://doi.org/10.1523/JNEUROSCI.1878-14.2015

Bartra O, McGuire JT, Kable JW. The valuation system: A coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. Neuroimage 2013; 76: 412–427. https://doi.org/10.1016/j.neuroimage.2013.02.063

Blood AJ, Zatorre RJ. Intensely pleasurable responses to music correlate with activity in brain regions implicated in reward and emotion. Proc Natl Acad Sci 2001; 98: 11818–11823. https://doi.org/10.1073/pnas.191355898

Chandon P, Wansink B. Does food marketing need to make us fat? A review and solutions. Nutr Rev 2012; 70: 571–593. https://doi.org/10.1111/j.1753-4887.2012.00518.x

Clithero JA, Rangel A. Informatic parcellation of the network involved in the computation of subjective value. Soc Cogn Affect Neurosci 2014; 9: 1289–1302. https://doi.org/10.1093/scan/nst106

Cornil Y, Plassmann H, Aron-Wisnewsky J, Poitou-Bernert C. Clément K, Chabert M, Chandon P. Obesity and Responsiveness to Food Marketing Before and After Bariatric Surgery. J Consum Psychol 2022; 32: 57–68. https://doi.org/10.1002/jcpy.1221

Dallman MF, Pecoraro N, Akana SF, la Fleur SE, Gomez F, Houshyar H, Bell ME, Bhatnagar S, Laugero KD, Manalo S. Chronic stress and obesity: A new view of “comfort food.” Proc Natl Acad Sci 2003; 100: 11696–11701. https://doi.org/10.1073/pnas.1934666100

Dallman MF, Pecoraro NC, la Fleur SE. Chronic stress and comfort foods: self-medication and abdominal obesity. Brain Behav Immun 2005; 19: 275–280. https://doi.org/10.1016/j.bbi.2004.11.004

de Araujo IET, Rolls ET, Kringelbach ML, McGlone F, Phillips N. Taste-olfactory convergence, and the representation of the pleasantness of flavour, in the human brain. Eur J Neurosci 2003; 18: 2059–2068. https://doi.org/10.1046/j.1460-9568.2003.02915.x

Enax L, Hu Y, Trautner P, Weber B. Nutrition labels influence value computation of food products in the ventromedial prefrontal cortex. Obesity 2015; 23: 786–792. https://doi.org/10.1002/oby.21027

Enax L, Krajbich I, Weber B. Salient nutrition labels increase the integration of health attributes in food decision-making. Judgm Decis Mak 2016; 11: 460–471. http://journal.sjdm.org/16/16620/jdm16620.html

Enax L, Weber B. Marketing Placebo Effects – From Behavioral Effects to Behavior Change? J Agric Food Ind Organ 2015; 13: 15–31. https://doi.org/10.1515/jafio-2015-0015

Enax L, Weber B. Neurobiology of food choices-between energy homeostasis, reward system, and neuroeconomics. e-Neuroforum 2016; 22: 13–21. https://doi.org/10.1515/s13295-015-0020-0

Engelmann JB, Hein G. Contextual and social influences on valuation and choice. In: V. S. C. Pammi and N. Srinivasan, eds. Progress in Brain Research. Elsevier, 2013: 215–237. https://doi.org/10.1016/B978-0-444-62604-2.00013-7

Fehr E, Rangel A. Neuroeconomic Foundations of Economic Choice—Recent Advances. J Econ Perspect 2011; 25: 3–30. https://doi.org/10.1257/jep.25.4.3

Gardner MP, Wansink B, Kim J, Park SB. Better moods for better eating?: How mood influences food choice. J Consum Psychol 2014; 24: 320–335. https://doi.org/10.1016/j.jcps.2014.01.002

Gearhardt AN, Bragg MA, Pearl RL, Schvey NA, Roberto CA, Brownell KD. Obesity and Public Policy. Annu Rev Clin Psychol 2012; 8: 405–430. https://doi.org/10.1146/annurev-clinpsy-032511-143129

Grabenhorst F, Rolls ET, Bilderbeck A. How Cognition Modulates Affective Responses to Taste and Flavor: Top-down Influences on the Orbitofrontal and Pregenual Cingulate Cortices. Cereb Cortex 2008; 18: 1549–1559. https://doi.org/10.1093/cercor/bhm185

Hare TA, Camerer CF, Rangel A. Self-Control in Decision-Making Involves Modulation of the vmPFC Valuation System. Science 2009; 324: 646–648. https://doi.org/10.1126/science.1168450

Hare TA, Malmaud J, Rangel A. Focusing Attention on the Health Aspects of Foods Changes Value Signals in vmPFC and Improves Dietary Choice. J Neurosci 2011; 31: 11077–11087. https://doi.org/10.1523/JNEUROSCI.6383-10.2011

Hare TA, O'Doherty J, Camerer CF, Schultz W, Rangel A. Dissociating the Role of the Orbitofrontal Cortex and the Striatum in the Computation of Goal Values and Prediction Errors. J Neurosci 2008; 28: 5623–5630. https://doi.org/10.1523/JNEUROSCI.1309-08.2008

Hoebel J, Kuntz B, Kroll LE, Schienkiewitz A, Finger JD, Lange C, Lampert T. Socioeconomic Inequalities in the Rise of Adult Obesity: A Time-Trend Analysis of National Examination Data from Germany, 1990–2011. Obes Facts 2019; 12: 344–356. https://doi.org/10.1159/000499718

Hollerman JR, Schultz W. Dopamine neurons report an error in the temporal prediction of reward during learning. Nat Neurosci 1998; 1: 304–309. https://doi.org/10.1038/1124

Khaw MW, Glimcher PW, Louie K. Normalized value coding explains dynamic adaptation in the human valuation process. Proc Natl Acad Sci 2017; 114: 12696–12701. https://doi.org/10.1073/pnas.1715293114

Konovalov A, Krajbich I. Over a Decade of Neuroeconomics: What Have We Learned? Organ Res Methods 2019; 22: 148–173. https://doi.org/10.1177/1094428116644502

Kringelbach ML. The pleasure of food: underlying brain mechanisms of eating and other pleasures. Flavour 2015; 4: 20. https://doi.org/10.1186/s13411-014-0029-2

Levy DJ, Glimcher P. W. The root of all value: a neural common currency for choice. Curr Opin Neurobiol 2012; 22: 1027–1038. https://doi.org/10.1016/j.conb.2012.06.001

Lim SL, O'Doherty JP, Rangel A. Stimulus Value Signals in Ventromedial PFC Reflect the Integration of Attribute Value Signals Computed in Fusiform Gyrus and Posterior Superior Temporal Gyrus. J Neurosci 2013; 33: 8729–8741. https://doi.org/10.1523/JNEURO-SCI.4809-12.2013

Loring B, Robertson A, 2014: Obesity and inequities. Guidance for addressing inequities in overweight and obesity. http://www.euro.who.int/__data/as-sets/pdf_file/0003/247638/obesity-090514.pdf (date accessed: 27.05.2022)

Maier SU, Makwana AB, Hare TA. Acute Stress Impairs Self-Control in Goal-Directed Choice by Altering Multiple Functional Connections within the Brain's Decision Circuits. Neuron 2015; 87: 621–631. https://doi.org/10.1016/j.neuron.2015.07.005

Malik VS, Willett WC, Hu FB. Global obesity: trends, risk factors and policy implications. Nat Rev Endocrinol 2013; 9: 13–27. https://doi.org/10.1038/nrendo.2012.199

Morris, M. J., Beilharz, J. E., Maniam, J., Reichelt, A. C., Westbrook, R. F. Why is obesity such a problem in the 21st century? The intersection of palatable food, cues and reward pathways, stress, and cognition. Neurosci Biobehav Rev 2015; 58: 36–45. https://doi.org/10.1016/j.neubiorev.2014.12.002

O'Doherty J, Rolls ET, Francis S, Bowtell R, McGlone F. Representation of Pleasant and Aversive Taste in the Human Brain. J Neurophysiol 2001; 85: 1315–1321. https://doi.org/10.1152/jn.2001.85.3.1315

Oostenbach LH, Slits E, Robinson E, Sacks G. Systematic review of the impact of nutrition claims related to fat, sugar and energy content on food choices and energy intake. BMC Public Health 2019; 19: 1296. https://doi.org/10.1186/s12889-019-7622-3

Plassmann H, O'Doherty J, Shiv B, Rangel A. Marketing actions can modulate neural representations of experienced pleasantness. Proc Natl Acad Sci 2008; 105: 1050–1054. https://doi.org/10.1073/pnas.0706929105

Rangel A. Regulation of dietary choice by the decision-making circuitry. Nat Neurosci 2013; 16: 1717–1724. https://doi.org/10.1038/nn.3561

Rangel A, Camerer C, Montague PR. A framework for studying the neurobiology of value-based decision making. Nat Rev Neurosci 2008; 9: 545–556. https://doi.org/10.1038/nrn2357

Schmidt L, Skvortsova V, Kullen C, Weber B, Plassmann H. How context alters value: The brain's valuation and affective regulation system link price cues to experienced taste pleasantness. Sci Rep 2017; 7: 8098. https://doi.org/10.1038/s41598-017-08080-0

Schultz W, Dayan P, Montague PR. A Neural Substrate of Prediction and Reward. Science 1997; 275: 1593–1599. https://doi.org/10.1126/science.275.5306.1593

Singh M. Mood, food, and obesity. Front Psychol 2014; 5: 925. https://doi.org/10.3389/fpsyg.2014.00925

Small DM, Gregory MD, Mak YE, Gitelman D, Mesulam MM, Parrish T. Dissociation of Neural Representation of Intensity and Affective Valuation in Human Gustation. Neuron 2003; 39: 701–711. https://doi.org/10.1016/S0896-6273(03)00467-7

Wansink B, Chandon P. Can “Low-Fat” Nutrition Labels Lead to Obesity? J Mark Res 2006; 43: 605–617. https://doi.org/10.1509/jmkr.43.4.605

World Health Organization, 2017: Determinants of health. https://www.who.int/news-room/questions-and-answers/item/determinants-of-health (date accessed: 27.05.2022)

World Health Organization, 2021: Obesity and overweight. https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight (date accessed: 27.05.2022)

3. Publications

3.1. Publication 1: "Do Disadvantageous Social Contexts Influence Food Choice? Evidence from Three Laboratory Experiments"

frontiers in Psychology

ORIGINAL RESEARCH
published: 06 November 2020
doi: 10.3389/fpsyg.2020.575170

Do Disadvantageous Social Contexts Influence Food Choice? Evidence From Three Laboratory Experiments

Qëndresa Rramani[1,2]*, *Holger Gerhardt*[1,3]†, *Xenia Grote*[1,2]†, *Weihua Zhao*[4], *Johannes Schultz*[1,2] *and Bernd Weber*[1,2]

[1] *Center for Economics and Neuroscience, University of Bonn, Bonn, Germany,* [2] *Institute of Experimental Epileptology and Cognition Research, University of Bonn Medical Center, Bonn, Germany,* [3] *Department of Economics, Institute for Applied Microeconomics, University of Bonn, Bonn, Germany,* [4] *Ministry of Education Key Laboratory for Neuroinformation, Clinical Hospital of Chengdu Brain Science Institute, University of Electronic Science and Technology of China, Chengdu, China*

OPEN ACCESS

Edited by:
*Jena Shaw Tronieri,
University of Pennsylvania,
United States*

Reviewed by:
*Anja Achtziger,
Zeppelin University, Germany
Ashleigh Haynes,
Cancer Council Victoria, Australia*

***Correspondence:**
*Qëndresa Rramani
rramani@uni-bonn.de*

† *These authors have contributed equally to this work*

Specialty section:
This article was submitted to Eating Behavior, a section of the journal Frontiers in Psychology

Received: 22 June 2020
Accepted: 02 September 2020
Published: 06 November 2020

Citation:
Rramani Q, Gerhardt H, Grote X, Zhao W, Schultz J and Weber B (2020) Do Disadvantageous Social Contexts Influence Food Choice? Evidence From Three Laboratory Experiments. Front. Psychol. 11:575170. doi: 10.3389/fpsyg.2020.575170

Increasing rates of obesity have fueled interest in the factors underlying food choice. While epidemiological studies report that disadvantaged social groups exhibit a higher incidence of obesity, causal evidence for an effect of social contexts on food choice remains scarce. To further our knowledge, we experimentally investigated the effect of disadvantageous social context on food choice in healthy, non-dieting participants. We used three established experimental methods to generate social contexts of different valence in controlled laboratory settings: (i) receiving varying amounts of money in a Dictator Game (DG; n = 40), (ii) being included or excluded in a Cyberball Game (CBG; n = 35), and (iii) performing well, average, or poorly in a response time ranking task (RTR; n = 81). Following exposure to a particular social context, participants made pairwise choices between food items that involved a conflict between perceived taste and health attributes. In line with previous research, stronger dispositional self-control (assessed via a questionnaire) was associated with healthier food choices. As expected, being treated unfairly in the DG, being excluded in the CBG, and performing poorly in the RTR led to negative emotions. However, we did not find an effect of the induced social context on food choice in any of the experiments, even when taking into account individual differences in participants' responses to the social context. Our results suggest that—at least in controlled laboratory environments—the influence of disadvantageous social contexts on food choice is limited.

Keywords: social contexts, food choice, Dictator Game, Cyberball Game, performance ranking task

INTRODUCTION

Increasing rates of obesity in many countries around the world and across age groups (World Health Organization, 2020) have sparked an exceptional interest in the factors underlying food choice. Psychological and neuroscientific research has shown that differences in food-related decision making such as heightened consideration of short-term rewards (e.g., taste) and a disregard or diminished consideration of longer-term abstract rewards (e.g., health) are associated with making food choices that contribute to being overweight or obese (Mela, 2001;

Volkow et al., 2008; Hare et al., 2009; Rangel, 2013; Sullivan et al., 2015). In line with this, promoting healthy eating and healthy food choices has become a common measure of public policies aiming to prevent obesity (Gearhardt et al., 2012). The measures taken to promote healthy eating are, however, not equally effective across different populations and contexts (Lyn et al., 2019). This is possibly due to the complexity of food decision making and its sensitivity to several environmental and psychosocial factors (Mela, 2001). A better understanding of the factors influencing food-related decision making is thus necessary for improving the efficacy of interventions promoting healthy eating.

In addition to being on the rise all over the world, studies have shown that obesity rates follow a socioeconomic gradient. More specifically, in industrialized Western societies, obesity rates have been found to be higher among people in disadvantageous social contexts (Malik et al., 2013; Loring and Robertson, 2014). Hoebel et al. (2019) report that in the years 1990–2011, obesity rates in Germany were highest among the lowest socioeconomic groups and lowest among the highest socioeconomic groups. Moreover, they found that during the examined time span, obesity incidence increased in the low socioeconomic groups (0.53 percentage points among men and 0.47 percentage points among women per year) but not in the high socioeconomic groups. Similarly, survey data from England and the United States also supports a negative correlation between socioeconomic variables (income and education levels) and obesity rates (Booth et al., 2017)[1]. This correlation has been argued to result from multiple factors including disparities in income in combination with low prices of unhealthy food, unequal healthcare access, and different levels of nutrition knowledge (McLaren, 2007; Robertson et al., 2007; Drewnowski, 2009; Harrison et al., 2010).

Importantly, being in a socially disadvantageous position often goes along with experiencing stress and negative emotions (Gallo and Matthews, 2003), which in turn can affect food intake and choice (Macht, 2008; Bublitz et al., 2010; Cardi et al., 2015; Maier et al., 2015) beyond the mentioned socioeconomic variables. More specifically, it has been shown that while there is heterogeneity in the effects of emotions on eating behavior, experiencing negative emotions generally goes along with increased intake of energy-dense and often unhealthy food (Macht, 2008; Bublitz et al., 2010; Konttinen et al., 2010). Support for these correlational findings comes from studies of social hierarchies and food consumption in animals. For instance, rodents in disadvantageous—that is, subordinate—social positions exhibit increased stress levels, altered dietary patterns, and a different fat distribution in the body. These findings have been argued to suggest a link between psychosocial stress and eating behavior that contributes to the etiology of obesity (Moles et al., 2006; Tamashiro et al., 2007; Coccurello et al., 2009). Similar effects have been found in house-hosted monkeys, with subordinate monkeys exhibiting increased levels of stress and anxiety, accompanied by elevated consumption of high-caloric foods (Wilson et al., 2008).

While these studies are informative, translating their results to human behavior has its limitations. The most obvious way in which food-related decision making differs between humans and animals is that humans can deliberate about their decisions and take higher-order objectives, like health considerations, into account. Humans can, moreover, plan—at least in developed countries—their food intake in advance. This means that for humans, one has to distinguish between at least two components of food-related decision making: food intake and food choice. By food choice we mean choice of a food item or of several items from a menu of options—which resembles, say, shopping for groceries at a supermarket. Food intake, by contrast, refers to eating behavior in a situation in which the type of food has already been decided upon—say, snacking in front of the TV.

To date, only a few experimental studies have explicitly investigated the effect of negative social contexts on eating behavior in humans. Laran and Salerno (2013) demonstrated that an "environmental harshness" priming increased the intake of high-caloric foods, probably by evoking perceptions of scarcity. This effect was attenuated when a $1 payment was given to the participants in the "harshness" condition. The findings of Laran and Salerno (2013) provide a potential explanation of the correlation between socioeconomic status and obesity reported above. Other studies have focused on the effects of lab-induced social comparisons on food intake: Cheon and Hong (2017) found that evoking comparisons with fellow citizens of higher socioeconomic status increased participants' intake of high-caloric snacks. Sim et al. (2018) corroborated this finding and furthermore suggest that the observed effect stems from perceived deprivation relative to the better-off comparison group. Along similar lines, lab-induced disadvantageous social contexts such as social exclusion have been found to increase the intake of unhealthy (high-caloric) snacks by adults (Baumeister et al., 2005), overweight adolescents (Salvy et al., 2011), and children (Senese et al., 2020). Crucially, these studies addressed *intake* of readily available food rather than food *choice*[2]. It is conceivable, however, that negative social contexts may influence food intake and food choice to different degrees.

While social exclusion and subjective feelings of deprivation are important phenomena commonly experienced by socially disadvantaged groups, there are several other relevant dimensions of being socially disadvantaged that may also have an impact on health, such as experiencing inequality, unfairness, and inferiority (Drewnowski, 2009; Lemaitre, 2016). It remains unexplored, thus far, whether these commonly experienced disadvantageous social contexts influence food

[1]One should keep in mind that the relation between socioeconomic status and obesity prevalence within a society depends on the country's economic development (for a review see Malik et al., 2013): In contrast to the developed countries, in developing and underdeveloped countries, obesity rates are likely to be higher among the higher socioeconomic groups. However, recent work by Templin et al. (2019) supports that these countries are quickly catching up, with obesity rates drastically increasing among the poor but remaining unchanged in the wealthy.

[2]Laran and Salerno (2013) also report the findings from two experiments ("Study 2" and "Study 3") that investigate the influence of priming on food *choice*. The food choice in these experiments was purely hypothetical, however, which may be more easily influenced by relatively subtle experimental manipulations than food choice that is incentivized.

choice of healthy individuals, and whether the emotional reaction to these contexts mediates their effect on food choice.

On this background, the objective of the present study was to investigate if disadvantageous social contexts affect food choice, and if these effects are mediated by the emotions evoked by the same. In pursuit of these objectives, we conducted three experiments each including an emotion-inducing social context and a food choice task. In the first experiment we induced unfairness using the Dictator Game (DG) (Hewig et al., 2011; Strang et al., 2016), in the second experiment we induced social exclusion using the Cyberball Game (CBG) (Williams et al., 2000; Bernstein and Claypool, 2012), and in the third experiment we induced inferiority using a performance (reaction time) ranking paradigm (RTR) (Zink et al., 2008; Gong and Sanfey, 2017). We hypothesized that in line with prior correlational findings, negative social contexts would influence participants' food choice in the direction of letting them choose tastier but unhealthier items more often, and that these effects would be mediated by emotions evoked by the respective social contexts.

MATERIALS AND METHODS

Participants

The experiments were approved by the ethics committee of the University of Bonn, and all participants gave written informed consent according to the Declaration of Helsinki. 156 healthy participants participated in the study: 40 in Experiment 1 (DG; 22 female, 18 male; age: M = 25.85, SD = 7.67 years), 35 in Experiment 2 (CBG; 19 female, 16 male; age: M = 25.94, SD = 3.10 years)[3], and 81 in Experiment 3 (RTR; 43 female, 38 male; age: M = 22.75, SD = 2.94 years). Given that there were no prior studies investigating the effects of disadvantageous social context on food choice, it is difficult to calculate a reasonable sample size—for instance, via power analysis—ex ante. Hence, we aimed at a number of observations that is comparable to the sample sizes reported in related studies (Baumeister et al., 2005; Salvy et al., 2011). For the first two experiments, participants were recruited via e-mail from the subject pool of the Life and Brain research center, while invitations for the third experiment were sent out via the hroot database (Bock et al., 2014) of the BonnEconLab. Registration in these databases is voluntary and open to anyone; the pools consist mostly of local university students but also include university staff and members of the general public. Participation was voluntary, and participants were paid a €10 per-hour flat fee and an additional amount of money depending on their performance and/or the experiment they completed. As a first step, participants had to fill in an online survey to ensure their eligibility for the study. Exclusion criteria were age below 18 years, Body Mass Index (BMI) below 18 or above 30 kg/m^2, psychological and/or psychiatric disorders, eating disorders, food allergies, non-consumption of snacks, dieting, or any other medical condition known to affect eating behavior.

[3]In Experiment 2, two additional participants (one female, one male) were recruited and showed up, but could not be included in the study. One participant had a higher BMI than the specified criteria allowed, and the other one started but did not complete the experiment.

Experimental Procedure

All data were collected before any analyses for the respective experiment were conducted. Below we disclose all data exclusions, all measures, and all variables acquired in the experiments.

One day before the experiment, participants were reminded to eat a snack not less than 3 h before the experiment (M = 4.8 h, $Median$ = 3 h, SD = 3.7 h), so that they would be neither very hungry nor very satiated during the experiment. To check this and other baseline levels, before the experiment we asked participants to rate their subjective hunger, hours of sleep, arousal, happiness, and time of the last meal consumption. The descriptive statistics of these baseline scores, as well as the scores acquired from the psychometric measurements, are summarized in **Supplementary Table 1**.

All three experiments followed a similar protocol, consisting of a food rating task, a social context followed by an emotion rating stage, a food choice task, and several questionnaires. The experiments were computer-based; they were implemented using an in-house software (Scenario Designer) in Experiments 1 and 2 and z-Tree (Fischbacher, 2007) in Experiment 3. In Experiments 1 and 2, in addition to the behavioral data, we acquired functional magnetic resonance imaging (fMRI) data. That is why these two experiments were conducted while participants were alone in a room inside an MRI scanner. In Experiment 3, participants completed the tasks in silence together with 9–14 other participants. Participants used a computer of their own and were sitting in cubicles separated by room-high walls and curtains.

Stage 1 of All Experiments

The food rating task was adapted from a previous study (Enax et al., 2016). In this task, participants had to individually rate 158 food items in terms of healthiness and taste (see **Figure 1**). To acquire more sensitive ratings, in the first experiment we used an 11-point Likert scale (1—very unhealthy/not tasty at all; 11—very healthy/very tasty). Based on previous findings (Dawes, 2002; Lewis and Erdinç, 2017), to save time and simplify the use of the scales, in the second and third experiment we used a 7-point Likert scale. Taste and healthiness ratings were completed in two blocks. The order of the blocks and the order of the items to be rated within each block were randomized. The subjective ratings of healthiness and taste were used to construct food pairs for the subsequent part of the experiment.

Following Stage 1, participants had to perform multiple repetitions of Stages 2 and 3: a game giving rise to a social context (Stage 2), followed by a food choice task (Stage 3). The games used to induce social contexts differed between experiments (see **Figure 1**).

Stage 2 of Experiment 1 (DG Experiment)

In the first experiment, participants were assigned the role of recipients in a DG. We used varying monetary splits in the DG in order to subject participants to situations in which they felt treated fairly or unfairly (Strang et al., 2016). In a DG, a dictator decides on how to split an endowment between her-/himself and a receiver, who then has to accept the dictator's

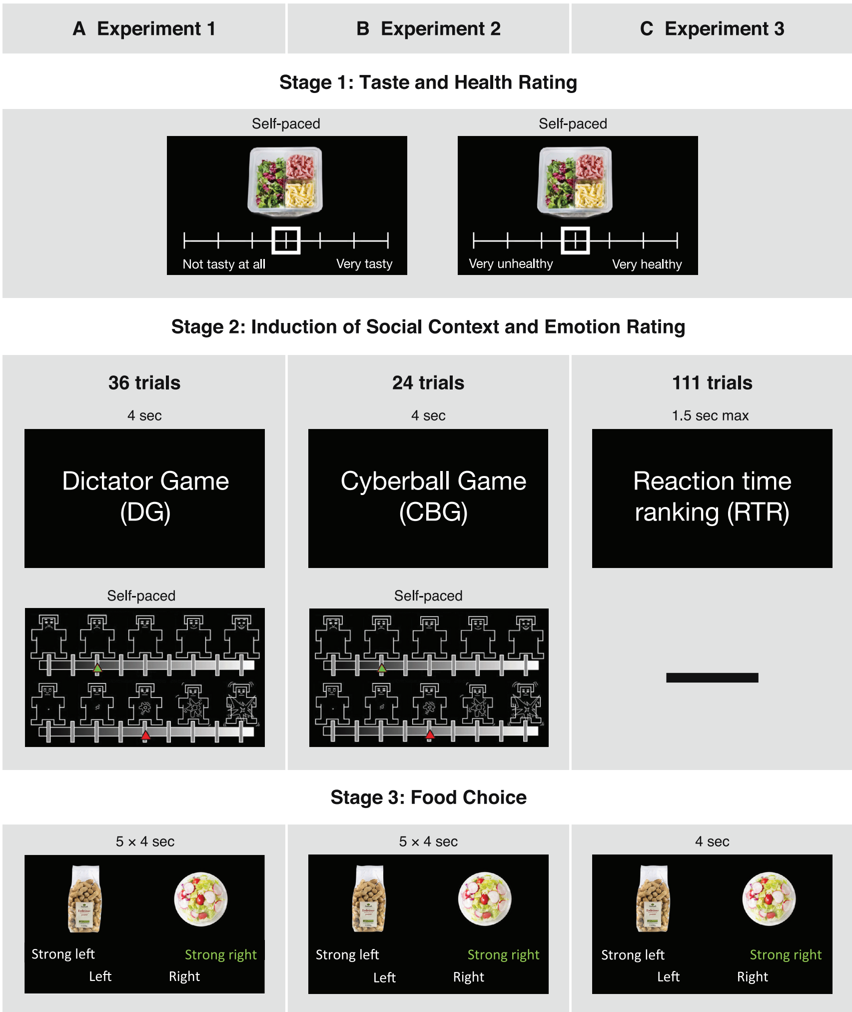

FIGURE 1 | Design and time courses of the three experiments. In all three experiments, participants initially had to rate food items in terms of taste and healthiness. After this they completed one of three tasks, depending on the experiment: **(A)** being the recipient in a Dictator Game (DG), **(B)** participating in a Cyberball Game (CBG), or **(C)** participating in a reaction time ranking task (RTR). An emotion rating stage followed the DG and the CBG, but not the RTR task. Lastly, in the food choice stage, participants chose between two food items (5 choices after each game in DG and CBG; 1 choice in RTR). The sequence was repeated 36 times in the DG, 24 times in the CBG, and 111 times in the RTR task

decision. Therefore, prior to the experiments, a separate session was run to acquire different money allocations decided upon by participants in the role of the dictator. These splits were then shown in our DG experiment to the participants in the role of the receiver. The stage consisted of three different money splits: unfair, neutral, and fair. In the "unfair split" condition, the participant was allocated an amount of money equal to 10, 13.3, 16.6, or 20% of the endowment, leaving the dictator with 90, 86.7, 83.4, or 80%, respectively. In the "neutral" condition, the participant was offered 30% of the endowment, while in the "fair" condition the participant was allocated 50, 46.66, 43.33, or 40% of the endowment. While the "fair" and "unfair" money splits were acquired from real people and were presented as such, the "neutral" condition consisted of one fixed value, presented to the participants as a split offered by the computer. Each condition was presented 12 times in a randomized order (thus, $3 \times 12 = 36$ rounds in total), and each trial lasted for 4 s. To ensure relevance of the money splits, participants were told that in the end they would get an additional amount of money based on a randomly selected round from those featuring "fair" and "unfair" splits. This means that the "neutral" condition was not relevant for the final payment, and participants knew about this. Given this knowledge, the "neutral" condition should indeed not have any influence and can thus be regarded as a baseline condition. After each money split, participants rated their emotional state in terms of valence and arousal, using the corresponding Self-Assessment Manikin subscales (Bradley and Lang, 1994). The affective space is considered to consist of these two dimensions: valence, referring to the quality (positive-negative), and arousal, referring to the intensity of the emotion (high-low) (Russell, 1979; Lang et al., 1993; Bradley and Lang, 1994; Bliss-Moreau et al., 2019). In line with previous findings, we hypothesized that unfairness in the DG as well as exclusion in the CBG would decrease valence ratings (Williams et al., 2000; Strang et al., 2016) and increase arousal ratings (Van't Wout et al., 2006; Kelly et al., 2012). The ratings were done on a scale of 9 states, with 1 indicating very negative valence/low arousal and 9 indicating very positive valence/high arousal. The emotion ratings were self-paced (see **Figure 1A**). Postexperimental questions were used to check how participants felt after the different conditions.

Stage 2 of Experiment 2 (CBG Experiment)

In the second experiment, we used a modified version of the CBG (Weik et al., 2010; Salvy et al., 2011; Kawamoto et al., 2012) to let participants experience social inclusion and exclusion. In the CBG experiment, participants played a ball-tossing game with two other virtual players. Before the start of the game, participants were told that the game would be played online and that the other two players were real. Unbeknownst to the participants, the game was played against a computer every time, and the other players were not real. The task was modified from the original as follows: The background color was black instead of white, IDs in form of numbers were used to indicate the players rather than showing names and/or pictures, the number of conditions was fixed to two game types (inclusion, exclusion), and the order of the conditions was randomized with the restriction that one game type could not be repeated more than two times in a row. In each game, the IDs of the other players changed to avoid feelings of intentional exclusion by a particular player. Participants played the game by pressing a button with either the left or right index finger to throw the ball to the player visualized on the respective side of the computer screen. Active participation in the game was incentivized such that if participants threw the ball back 75–100% of the times the ball was thrown to them, they would earn an additional amount of €5. This procedure ensured that participants actively played the game and felt part of it. Every game consisted of 12 ball tosses and lasted around 30 s. The stage consisted of two different conditions: Participants could be either "included" (receiving 50% of the ball tosses from the other players, i.e., being in possession of the ball exactly 1/3 of the time) in or "excluded" (getting only 25% of the ball tosses, i.e., being in possession of the ball only 1/6 of the time) from the game. In total, there were 12 inclusion and 12 exclusion games. Participants rated their state valence and arousal after every game using the same procedure as in the DG experiment (see **Figure 1B**). Postexperimental questions were used to check whether participants perceived the degree to which they were included in the two conditions differently and whether they felt different in each condition.

Stage 2 of Experiment 3 (RTR Experiment)

In the last experiment, we used a performance RTR task to let participants experience being at different positions in a social hierarchy based on performance. In the RTR task, participants were instructed to engage in a real-time reaction time task, which involved pressing a button whenever a circle in the middle of the screen changed its color. The circle was presented with a random duration between 0.5 and 1.5 s, and participants had to press the button during the presentation of the circle. Responses after 1.5 s were considered a missed trial, and responses before 0.5 s were considered false starts. To check whether the variation in reaction times between and within participants could provide a natural ranking, and thus alleviate the need for deceptive feedback, we conducted a pilot study before the experiment. As expected, our pilot data indicated that participants could naturally end first, second, third, fourth, or fifth in different rounds when matched with four competitors randomly drawn from the participants of the same session. Taking this into account, the experiment was conducted with at least 10 participants per session, such that every participant's performance could be compared to 4 other performances in real time. After each performance, the participants were shown a real ranking of themselves and 4 competitors; this way they were informed how well they performed relative to the others. False starts and missed trials were both assigned the last (5th) rank, and ties were resolved by a random draw. In total there were 111 reaction time task rounds, each followed by a ranking feedback presented for around 6 s. To make sure that recurring emotion ratings did not lead the participants to be aware or even regulate their emotions, and to keep the social context as close as possible to the food choices, in this experiment we did not acquire emotion ratings after each round (see **Figure 1C**). Additionally, the DG experiment showed that postexperimental valence ratings correlated strongly with the ratings acquired during the experiment (Spearman's rank correlation DG: $\rho = 0.84$, $p < 0.001$). Importantly, the postexperimental valence ratings were significantly different between conditions in the same manner as the immediate valence ratings (see **Supplementary Table 2**). Considering all these aspects, we decided to ask participants only postexperimentally how they felt during each ranking of the RTR task. More specifically, we asked them to indicate how proud, satisfied, annoyed, frustrated, and disappointed they felt after being ranked 1st, 3rd, and 5th. In line with previous findings, we hypothesized that inferiority experienced in the RTR would increase negative emotion ratings and decrease positive emotion ratings (Zink et al., 2008; Luo et al., 2018). Similar to the CBG experiment, we used postexperimental questions to assess whether participants perceived the ranks differently.

Stage 3 of All Experiments

The third stage of all three experiments was a food choice task. Each food choice trial was a four-alternative forced choice, and participants were asked to choose the food item that they preferred to eat at that very moment. However, the degree to which participants were prompted to consider healthiness during their choices differed across studies: In the DG and the CBG experiment, participants were prompted to consider healthiness while making their choices, whereas this cue was absent in the RTR experiment. (For the exact instructions provided to the participants see the **Supplementary Material**.) Participants had the opportunity to express the strength of each choice such that that one food item could be "preferred" or "strongly preferred" over the other food item (see **Figure 1**). One of all choices, from a randomly selected round was implemented at the end of each experiment; which choice would be implemented varied between participants was unknown to them so that they would treat each choice as equally important. The food pairs used in this phase were constructed based on the subjective ratings completed before the social context and emotion rating stage. Based on these previous ratings, the food choice trials were divided into congruent and incongruent trials. In congruent trials, health and taste aspects of the foods were aligned, with the healthier item being also tastier. In incongruent trials, health and taste attributes were not aligned, with the less healthy item being tastier than the other. Thus, by choosing the healthier item in the incongruent trials participants automatically forwent the tastier product and vice versa. The congruent trials were added as a sanity check to evaluate whether participants made reasonable decisions, that is, decisions that were aligned with their earlier health and taste ratings. The ratio of these trials (incongruent : congruent) was 3 : 2 in the DG, 4 : 1 in the CBG, and 10 : 1 in the RTR experiment. Each food pair was shown for 4 s, and the pairs were presented in random order. In the DG and in the CBG task, five food choice trials were presented after each emotion rating (see **Figures 1A,B**). In the RTR experiment, one food choice was presented after each ranking (see **Figure 1C**). Trials were counterbalanced across conditions in all three experiments.

Postexperimental Questionnaires

Finally, to control for the effect of possible differences in eating styles (van Strien et al., 2013; Blechert et al., 2014), and dispositional self-control (Hare et al., 2009; Stutzer and Meier, 2016), after each of the three experiments participants completed the following psychometric questionnaires: the Brief Self-Control Scale (BSCS; German: SCS-K-D) (Tangney et al., 2004; Bertrams and Dickhäuser, 2009), Dutch Eating Behavior Questionnaire (DEBQ) (van Strien et al., 1986; Grunert, 1989), Three Factor Eating Questionnaire (TFEQ; German: Fragebogen zum Essverhalten—FEV) (Stunkard and Messick, 1985; Pudel and Westenhöfer, 1989), and several questions designed to assess manipulation efficacy in every experiment. In the CBG experiment, we asked additional questions to assess the ostracism effect, as suggested in the literature (Williams et al., 2000). After the questionnaires were completed, participants were debriefed and reimbursed. In the CBG experiment, as part of the debriefing procedure, participants were told that the other players in the game were not real.

In addition to these measures, in the DG and CBG experiments, fMRI data were collected but are not reported in the current paper. Similarly, several additional questionnaires were included in the different experiments but are not reported in the current paper[4]. The questionnaires differed between the experiments because we had different analyses of subgroups in mind. In the current paper, we focus on possible subgroup effects present in the combined data from all the three experiments and hence only report results for the data that were collected in all of the experiments.

Statistical Analysis

General Information

Statistical analysis was performed using the R language (R Core Team, 2019). The following packages were used: *readxl, psych, dplyr, ggplot2, reshape2, lme4, lmerTest, MuMIn, sjstats, multcomp, mediation*, and *TOSTER*. A sensitivity power analysis was conducted using the G*Power software package (version 3.1.9.3) (Faul et al., 2009).

Assessing the Manipulation Efficacy

To check whether different social contexts lead to changes in the emotion ratings, we estimated linear mixed-effects models with emotion ratings as the dependent and condition as the explanatory variables. For the DG and CBG experiments, we estimated one model with valence and one with arousal ratings as the dependent variable (Eqs 1.1 and 1.2). For the RTR, we estimated one model with mean positive (sum of proud and satisfied ratings divided by two) and one with mean negative emotion ratings (sum of annoyed, frustrated, and disappointed ratings divided by three) as the dependent variable (Eqs 1.3 and 1.4):

$$\textit{Valence ratings}_{ij} = \beta_0 + \beta_1 \textit{Condition}_{ij} + u_j + \varepsilon_{ij}; \qquad (1.1)$$

$$\textit{Arousal ratings}_{ij} = \beta_0 + \beta_1 \textit{Condition}_{ij} + u_j + \varepsilon_{ij}; \qquad (1.2)$$

$$\textit{Mean positive emotion ratings}_{ij} = \beta_0 + \beta_1 \textit{Condition}_{ij} + u_j + \varepsilon_{ij}; \qquad (1.3)$$

$$\textit{Mean negative emotion ratings}_{ij} = \beta_0 + \beta_1 \textit{Condition}_{ij} + u_j + \varepsilon_{ij}. \qquad (1.4)$$

[4]In addition to the previously mentioned questionnaires, in the DG experiment, participants were asked to fill in Beck's Depression Inventory (BDI-II) (Beck et al., 1996; Hautzinger et al., 2006), the Toronto Alexithymia Scale-20 (TAS-20) (Bagby et al., 1994; Popp et al., 2008), the Neuroticism, Extraversion, and Openness to Experience Five Factor Inventory (NEO-FFI) (Costa and McCrae, 1992; Borkenau and Ostendorf, 1993), a measure of Social Value Orientation (SVO) (Murphy et al., 2011), Behavioral Activation System and Behavioral Inhibition System (BIS/BAS) (Carver and White, 1994; Strobel et al., 2001), the Positive and Negative Affect Schedule (PANAS; *today* version) (Watson et al., 1988; Krohne et al., 1996), the Barratt Impulsiveness Scale Version 11 (BIS-11) (Patton et al., 1995; Hartmann et al., 2011), and a questionnaire assessing the attitudes toward healthy eating (German: Einstellungen zu gesunder Ernährung—EGE) (Diehl, 2006). In the CBG experiment, participants had to fill in only the BDI-II, TAS-20, and PANAS (*today* version). Lastly, in the RTR experiment participants had to fill in only the PANAS (*last-two-weeks* version).

The subscript j indexes participants, while i indexes observations per subject. That is, u_j is a subject-specific random intercept, and ε_{ij} is the residual. An observation corresponds to one emotion rating. Condition is a factor (categorical) variable. For the DG, $Condition_{ij}$ had three levels, indicating whether the monetary split announced to subject j in trial i was fair, neutral, or unfair. For the CBG, $Condition_{ij}$ had two levels, indicating whether subject j was included or excluded in trial i. For the RTR, $Condition_{ij}$ had five levels, reflecting the rank that subject j attained in trial i.

Additionally, to check whether the participants perceived accurately that there were different conditions in the experiments, we performed paired-sample t-tests on the questions asked postexperimentally (CBG: how many times they got the ball in each condition; RTR: how many times they were ranked 1st and 5th). In the CBG experiment, to additionally assess the ostracism effect we performed mixed-effects linear regression analyses on the postexperimentally asked questions.

Assessing the Suitability of the Food Choice Task

The congruent trials served two purposes: First, we used them to check whether participants' food choices were reasonable. To do so, we conducted one-sample t-tests (for all three datasets separately) and compared the percentage of tastier–healthier choices in the congruent trials to chance level (50%). Second, we used the congruent trials to check for fatigue effects. To do so, we regressed reaction times (RT) on the trial number using a mixed-effects linear regression analysis with residual $\varepsilon_{ij} \sim N(0, \sigma_\varepsilon{}^2)$ and subject-specific random effects $u_j \sim N(0, \sigma_u{}^2)$ (see Eq. 2):

$$\log(RT_{ij}) = \beta_0 + \beta_1 \mathit{Trial\ number}_{ij} + u_j + \varepsilon_{ij}. \quad (2)$$

Here, similar to the previous model, the subscript j indexes participants, while i indexes observations per subject. RTs were log-transformed due to their skewed distribution.

Similarly, to investigate whether our food choice task worked as intended and that the food choices were reasonable in the incongruent trials as well, we checked the impact of taste and health ratings on food decisions. To achieve this, we performed a mixed-effects logistic regression; that is, the error term is assumed to follow the standard logistic distribution, $\varepsilon_{ij} \sim L(0, 1)$, and the subject-specific random effects are $u_j \sim N(0, \sigma_u{}^2)$ (see Eq. 3). In this model, the choice of the item on the left side (*Chose left*: 1 = Yes, 0 = No) was entered as the dependent variable, the z-scored difference in taste (TD) and health ratings (HD) between the simultaneously presented items (Left – Right) were entered as explanatory variables, and the random intercept term was added to account for between-subject heterogeneity:

$$\mathit{Chose\ left}_{ij} = 1 \text{ if } \beta_0 + \beta_1 TD_{ij} + \beta_2 HD_{ij} + u_j + \varepsilon_{ij} > 0, \text{ and } \mathit{Chose\ left}_{ij} = 0 \text{ otherwise.}$$

This gives rise to the regression equation:

$$\mathit{Chose\ left}_{ij} = F(\beta_0 + \beta_1 TD_{ij} + \beta_2 HD_{ij} + u_j), \quad (3)$$

where $F(x) = 1 / [1 + \exp(-x)]$ is the cumulative distribution function of the standard logistic distribution. This model was estimated for all three datasets.

Effect of Social Contexts on Food Choice

To assess the effect of social context on food choice, we analyzed the proportion of tastier food choices in the incongruent trials and tested whether the different conditions influenced this proportion systematically. To this end, we estimated mixed-effects models for the three datasets separately as a first step. In a second step, we aimed to further investigate whether the probability of choosing the tastier item in the incongruent trials varied with the condition and pooled the data of the three experiments so that we could analyze them jointly.

For the separate data analyses, we used mixed-effects logistic regression models with $\varepsilon_{ij} \sim L(0, 1)$ and $u_j \sim N(0, \sigma_u{}^2)$. In these models, the dependent variable was a binary variable indicating whether participants chose the tastier item in the trial (*Chose tastier*: 1 = Yes, 0 = No), and the explanatory variable was condition. Subject-specific random intercepts were added to account for between-subject heterogeneity:

$$\mathit{Chose\ tastier}_{ij} = F(\beta_0 + \beta_1 \mathit{Condition}_{ij} + u_j). \quad (4)$$

For the combined data analysis, we pooled the three datasets. Recall that $Condition_{ij}$ is a factor variable which originally has three levels in the DG, two levels in the CBG, and five levels in the RTR. To have the same number of levels for all three datasets, we discarded the neutral level from the DG and the 3rd-rank level from the RTR. Moreover, since in the RTR we had more levels, we pooled 2nd with 1st rank and 4th with 5th rank. This way we had two levels across all three experiments, one indicating a positive social context (fair, inclusion, 1st/2nd rank) and one indicating a negative social context (unfair, exclusion, 4th/5th rank). The food choice data remained the same.

We analyzed the combined data in two ways. First, we calculated the difference in the mean relative frequencies of tastier food choices between the two conditions (negative and positive social context) and analyzed these differences with a one-sample t-test. With this analysis we aimed to assess whether the difference between our conditions is significant in the most straightforward way.

Second, similar to the separate data analyses, we ran a mixed-effects logistic regression with *Chose tastier* as the dependent variable, condition and experiment as the explanatory variables, and a subject-specific intercept:

$$\mathit{Chose\ tastier}_{ij} = F(\beta_0 + \beta_1 \mathit{Condition}_{ij} + \beta_2 \mathit{Experiment}_j + u_j). \quad (5)$$

In this regression, we added a factor variable indicating the experiment (DG, CBG, RTR). We did so to capture potential differences between the three experiments resulting from the use of different subject pools, different locations, and different wording of the instructions. With this analysis we aimed to assess whether the difference between our conditions is significant if we control for the type of the manipulation (i.e., the *Experiment* variable) and are thereby able to explain additional variance.

Finally, we performed a sensitivity power analysis to assess the minimum effect size that could be detected in our most powerful analysis, that is, in the combined data analysis. For this, we used the one-sample t-test approach implemented in G*Power. We also performed an equivalence test by using the Two One-Sided Tests (TOST) procedure implemented in the *TOSTER* package in R (Lakens et al., 2018). With this analysis we assess whether the difference between food choices in the negative and positive social contexts is statistically equivalent to 0.

Mediation Analyses

To assess whether emotions mediate the association between social context and food choice, we ran mediation analyses on all three datasets. In all three experiments we had two measures of emotions: valence and arousal in DG and CBG, and positive and negative emotion ratings in the RTR. Thus, for each dataset, we ran two separate mediation analyses, each with one of the self-reported emotions as mediators.

We used a model-based causal mediation analysis (see **Figure 2**) as implemented in the *mediation* package for R (Tingley et al., 2014). Path c was estimated by regressing the proportion of tastier choices on condition (Eq. 6.1). Path a was estimated by regressing emotion ratings on condition (Eq. 6.2), and paths b and c' were estimated by regressing the proportion of tastier food choices on condition and z-scored emotion ratings (see Eq. 6.3). Given that in all our experiments, social context was experimentally manipulated and was followed by emotion ratings and food choice, we assume the paths in our mediation analyses to be causal and one-directional (with the direction indicated by the arrows in **Figure 2**). Direct, mediation, and total effects were estimated using a quasi-Bayesian Monte Carlo simulation method (number of simulations = 1,000) based on normal approximation:

$$\textit{Proportion of tastier choices}_{ij} = \beta_0 + c\ \textit{Condition}_{ij} + u_j + \varepsilon_{ij}; \qquad (6.1)$$

$$\textit{Emotion ratings}_{ij} = \beta_0 + a\ \textit{Condition}_{ij} + u_j + \varepsilon_{ij}; \qquad (6.2)$$

$$\textit{Proportion of tastier choices}_{ij} = \beta_0 + b\ \textit{Emotion ratings}_{ij} + c'\ \textit{Condition}_{ij} + u_j + \varepsilon_{ij}. \qquad (6.3)$$

For the DG and the CBG experiments, every social context condition was followed by emotion ratings, which were followed by 3 and 4 incongruent food choice trials, respectively. That is, for the DG we had 36 emotion ratings and around 108 food choices, and for the CBG we had 24 emotion ratings and 96 food choices per participant. Because of this, for these datasets, we calculated the proportion of tastier choices for every emotion rating trial. By contrast, in the RTR experiment, emotion ratings were collected after the experiment, and only for the 1st, 3rd, and 5th attained rank. Hence, for the mediation analyses, we excluded the trials were participants were ranked 2nd or 4th. Therefore, *Condition*

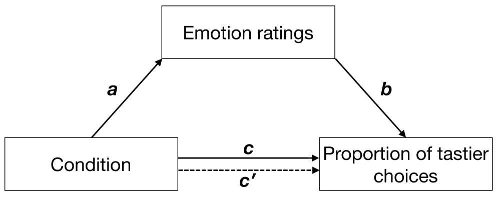

FIGURE 2 | Hypothetical mediation. Path c indicates the effect of condition (positive social context, negative social context) on the proportion of tastier food choices, path a indicates the effect of condition on emotions, path b indicates the effect of emotions on the proportion of tastier food choices when controlling for condition, and path c' indicates the effect of condition on the proportion of tastier food choices when considering emotions as mediators. Arrows indicate the direction of the hypothesized causal effects.

now is a factor variable with three levels in the DG, two levels in the CBG, and three levels in the RTR. Given that we had only one emotion rating per level of the factor variable *Condition*, for this dataset we calculated the proportion of tastier choices per level. This means that in the mediation analysis, an observation i does not correspond to a single food choice trial anymore but includes all trials covered by an emotion rating question.

Subgroup Effects

To evaluate whether condition has a different effect on the proportion of tastier choices in different subgroups, identified via questionnaire scores, we estimated interaction models with proportion of tastier choices as the dependent variable, condition, z-scored questionnaire scores (BSCS score, TFEQ subscale scores, DEBQ subscale scores), interaction between condition and questionnaire scores, and experiment as explanatory variables. Similar to the previous models, we added a random intercept u_j to account for between-subject effects (see Eq. 7). This model was calculated for each questionnaire score separately:

$$\textit{Proportion of tastier choices}_{ij} = \beta_0 + \beta_1\ \textit{Condition}_{ij} + \beta_2\ \textit{Questionnaire score}_j + \beta_3\ \textit{Questionnaire score}_j \times \textit{Condition}_{ij} + \beta_4\ \textit{Experiment}_j + u_j + \varepsilon_{ij} \qquad (7)$$

To have the same number of levels for all three datasets, we proceeded as described in the "Effect of Social Contexts on Food Choice" subsection above and discarded the neutral level from the DG and the median-rank level from the RTR. Moreover, since in the RTR we had a total of five levels, we pooled 2nd with 1st rank and 4th with 5th rank. This results in two levels across all three experiments, one indicating a positive social context (fair, inclusion, 1st/2nd rank) and one indicating a negative social context (unfair, exclusion, 4th/5th rank). With the dependent variable being the proportion of tastier food choices by subject j in condition i, we have two observations per subject, $i \in \{1, 2\}$, for this joint analysis of all three experiments. (It would be equally valid to treat each food choice trial as an independent observation and use *Chose tastier* as the dependent variable, as described above in the "Effect of Social Contexts on Food Choice" subsection. It turns out that our qualitative results do not depend on the specification of the regression.)

RESULTS

Overview

In this section, we first show the effect of social contexts on emotion ratings. Second, we show that participants made reasonable and systematic food choices in the congruent and incongruent trials. Third, we report the effect of social contexts on food choice. In addition to the main effect, we also report the effect of emotions as mediators between social context and the proportion of tastier food choices in the incongruent trials. Finally, we report subgroup effects of negative social contexts relative to positive social contexts on the proportion of tastier food choices.

Assessing the Manipulation Efficacy

Linear mixed-effects models indicated that in the DG experiment condition had a significant effect on the valence [$\chi^2_{(2)} = 712.77$, $p < 0.001$, marginal $R^2 = 0.26$] and arousal ratings [$\chi^2_{(2)} = 93.95$, $p < 0.001$, marginal $R^2 = 0.03$]. Tukey-adjusted comparisons revealed that valence ratings in the unfair condition were significantly lower than in the neutral and fair condition (Neutral − Unfair: $\beta = 1.11$, $SE = 0.07$, 95% CI [0.94, 1.28], $z = 15.18$, $p < 0.001$; Fair − Unfair: $\beta = 2.23$, $SE = 0.07$, 95% CI [2.06, 2.41], $z = 30.46$, $p < 0.001$; Fair − Neutral: $\beta = 1.12$, $SE = 0.07$, 95% CI [0.95, 1.29], $z = 15.29$, $p < 0.001$). In terms of arousal, the ratings were significantly different between the neutral and fair, and unfair and fair conditions (Neutral − Unfair: $\beta = -0.64$, $SE = 0.07$, 95% CI [−0.81, −0.48], $z = -9.07$, $p < 0.001$; Fair − Unfair: $\beta = -0.56$, $SE = 0.07$, 95% CI [−0.72, −0.39], $z = -7.86$, $p < 0.001$; Fair − Neutral: $\beta = 0.09$, $SE = 0.07$, 95% CI [−0.08, 0.25], $z = 1.21$, $p = 0.45$).

In the CBG experiment, valence ratings were significantly higher in the inclusion than in the exclusion condition [$\chi^2_{(1)} = 16.81$, $p < 0.001$, marginal $R^2 = 0.009$; Inclusion − Exclusion: $\beta = 0.33$, $SE = 0.08$, 95% CI [0.17, 0.49], $z = 4.12$, $p < 0.001$], while arousal ratings were not significantly different between the conditions [$\chi^2_{(1)} = 1.25$, $p = 0.26$, marginal $R^2 = 0.0005$; Inclusion − Exclusion: $\beta = -0.09$, $SE = 0.08$, 95% CI [−0.24, 0.06], $z = -1.12$, $p = 0.26$].

In the RTR experiment, condition had a significant effect on the positive [$\chi^2_{(2)} = 265.61$, $p < 0.001$, marginal $R^2 = 0.65$] and negative emotion ratings [$\chi^2_{(2)} = 133.79$, $p < 0.001$, marginal $R^2 = 0.37$]. Tukey-adjusted comparisons revealed that all pairwise comparisons were significant (Positive emotions: 3rd − 5th: $\beta = 1.76$, $SE = 0.21$, 95% CI [1.27, 2.25], $z = 8.45$, $p < 0.001$; 1st − 5th: $\beta = 5.01$, $SE = 0.21$, 95% CI [4.52, 5.50], $z = 23.90$, $p < 0.001$; 1st − 3rd: $\beta = 3.25$, $SE = 0.21$, 95% CI [2.76, 3.74], $z = 15.51$, $p < 0.001$; Negative emotions: 3rd − 5th: $\beta = -1.19$, $SE = 0.23$, 95% CI [−1.73, −0.64], $z = -5.12$, $p < 0.001$; 1st − 5th: $\beta = -3.32$, $SE = 0.23$, 95% CI [−3.87, −2.77], $z = -14.18$, $p < 0.001$; 1st − 3rd: $\beta = -2.13$, $SE = 0.23$, 95% CI [−2.68, −1.58], $z = -9.10$, $p < 0.001$). For an illustration of these effects (see **Supplementary Figure 1**).

Additional postexperimental questions indicated that in the CBG experiment, on average, participants thought that they got the ball around 42.69% in the inclusion condition and 32.4% in the exclusion condition. This difference was statistically significant [$t_{(34)} = 2.11$, $p = 0.04$, 95% CI [0.40, 20.18]], and the average stated frequencies are close to the actual frequencies (50% and 25%, respectively). Mixed-effects linear regressions on the postexperimentally asked questions indicate that in the exclusion condition, participants felt more ignored [$\chi^2_{(1)} = 27.00$, $p < 0.001$, marginal $R^2 = 0.32$], less wanted [$\chi^2_{(1)} = 24.03$, $p < 0.001$, marginal $R^2 = 0.24$], less invincible [$\chi^2_{(1)} = 6.30$, $p = 0.01$, marginal $R^2 = 0.05$] and less powerful [$\chi^2_{(1)} = 12.33$, $p < 0.001$, marginal $R^2 = 0.11$] than in the inclusion condition.

Similarly, postexperimental questions in the RTR experiment indicate that, on average, participants felt that they attained the first rank around 16.8% and the last rank around 15.8% of all rounds. Given that the average frequency of each attained rank is 20% by construction, participants seem to have been similarly reluctant to report having performed very well or very badly. Indeed, when testing whether the perceived frequency deviates from the actual frequency for the first and last rank, we find that it significantly does [1st rank: $t_{(80)} = 3.23$, $p = 0.002$, 95% CI [1.38, 5.78]; 5th rank: $t_{(80)} = 5.06$, $p < 0.001$, 95% CI [4.46, 10.23]]. However, the frequency for the last rank was not significantly different from the frequency for the first rank [$t_{(80)} = 0.31$, $p = 0.76$, 95% CI [−5.45, 7.45]], suggesting that participants were not underconfident or overconfident regarding their performance on average.

Assessing the Suitability of the Food Choice Task

Consistency of Food Choices in the Congruent Trials

In the congruent trials in all three experiments, participants chose the healthier food item—which in these trials also was at least as tasty as the other food item—significantly more often than chance level (50%). In all three experiments, the mean share is above 80% [DG: $M = 87.7\%$ of the congruent trials, $SD = 7.6\%$, $t_{(39)} = 31.4$, $p < 0.001$, 95% CI [85.31, 90.17]; CBG: $M = 84.1\%$ of the congruent trials, $SD = 11.14\%$, $t_{(34)} = 18.1$, $p < 0.001$, 95% CI [80.22, 87.87]; RTR: $M = 80.0\%$ of the congruent trials, $SD = 13.69\%$, $t_{(80)} = 19.72$, $p < 0.001$, 95% CI [76.97, 83.03]].

Mixed-effects linear regression analysis indicates that there were no fatigue effects (see Eq. 2), as time (trial number) had a significant effect on the RT such that the further an experimental session progressed, the shorter the reaction times became [DG: $\beta = -0.001$, $SE = 0.0001$, $t_{(2816)} = -13.5$, $p < 0.001$, 95% CI [−0.002, −0.001]; CBG: $\beta = -0.002$, $SE = 0.0003$, $t_{(789)} = -9.51$, $p < 0.001$, 95% CI [−0.003, −0.002]; RTR: $\beta = -0.001$, $SE = 0.0002$, $t_{(721)} = -5.22$, $p < 0.001$, 95% CI [−0.002, −0.001]].

Influence of Taste and Healthiness Ratings on Food Choices in the Incongruent Trials

As expected, in the incongruent trials of all experiments, taste significantly explained variation in choices (see Eq. 3) such that the tastier one item was in comparison to the other item, the higher was the probability of it being chosen (DG: β = 0.53, *SE* = 0.05, z = 11.5, $p < 0.001$, *OR* = 1.70, 95% CI [1.55, 1.86]; CBG: β = 1.08, *SE* = 0.06, z = 16.88, $p < 0.001$, *OR* = 2.96, 95% CI [2.61, 3.35]; RTR: β = 1.45, *SE* = 0.05, z = 27.93, $p < 0.001$, *OR* = 4.27, 95% CI [3.85, 4.73]). Similarly, in all three experiments, healthiness was positively related to food choice (see Eq. 3). Its impact, however, was significant only in the DG (β = 0.98, *SE* = 0.05, z = 19.37, $p < 0.001$, *OR* = 2.66, 95% CI [2.41, 2.94]) and in the CBG (β = 0.51, *SE* = 0.06, z = 8.85, $p < 0.001$, *OR* = 1.67, 95% CI [1.49, 1.87]), but not in the RTR experiment (β = 0.03, *SE* = 0.04, z = 0.66, p = 0.51, *OR* = 1.03, 95% CI [0.95, 1.12]). The relation between the probability of choosing left in the incongruent trials and attribute difference (Left − Right) between the food pairs is depicted in **Figure 3**.

Effect of Social Context on Food Choice

Separate Analyses of the Three Experiments

In the DG experiment, in line with the given instructions, in the incongruent trials participants chose the healthier item more often (*M* = 59.63% of the trials, *SD* = 23.92%) than the tastier item (*M* = 38.89% of trials, *SD* = 23.71%) (missed trials: *M* = 1.48% of the trials, *SD* = 2.49%). Without such an instruction, in the CBG and the RTR experiments, participants chose the tastier item more often (CBG: *M* = 60.80% of trials, *SD* = 20.75%; RTR: *M* = 75.51% of the trials, *SD* = 14.28%) than the healthier item (CBG: *M* = 37.44% of the trials, *SD* = 20.45; RTR: *M* = 23.52% of the trials, *SD* = 14.43%) (missed trials: CBG: 1.76% of the trials, *SD* = 3.61%; RTR: *M* = 0.98% of the trials, *SD* = 1.23%).

In none of the three experiments did condition have an effect on the proportion of tastier choices [DG: $\chi^2_{(2)} = 0.02$, marginal $R^2 = 0.00002$, $p = 0.99$; CBG: $\chi^2_{(1)} = 0.53$, $p = 0.47$, marginal $R^2 = 0.001$; RTR: $\chi^2_{(4)} = 0.81$, marginal $R^2 = 0.001$, $p = 0.94$] (see **Figure 4**). Similarly, mixed-effects logistic regression models estimated for the three datasets separately (see Eq. 4) indicated that condition could not significantly explain variance in choosing the tastier item (see **Table 1**).

Analysis of the Combined Data Set

When analyzing the data sets of all three experiments jointly, a one-sample t-test indicated that the difference in the mean frequencies of choosing the tastier item between the positive (*M* = 0.635, *SD* = 0.25) and the negative (*M* = 0.636, *SD* = 0.25) condition was not significantly different from 0 [β = −0.0004, $t_{(155)} = -0.046$, $p = 0.96$, 95% CI: [−0.017, 0.016]]. Similarly, mixed-effects logistic regression on the three data sets combined (see Eq. 5) also indicated that condition had no significant effect (β = −0.02, p = 0.65) on the probability of choosing the tastier item (Positive condition: *M* = 0.6416, *SD* = 0.479; Negative condition: *M* = 0.642, *SD* = 0.479; see **Table 2** and **Supplementary Figure 2**).

The sensitivity power analysis revealed that we have 80% power to detect an effect not smaller than Cohen's d = 0.2257 at a p-value of 0.05. This suggests that our design (with the combined data) is sensitive enough to capture a small effect if present. In other words, with our level of noise in the data (the *SD* of the differences in the mean frequencies of tastier choices between the two conditions is 0.1030), we would have been able to detect a 2.325% change ($d \times SD = 0.2257 \times 0.1030 = 0.02325$) between the conditions with 80% probability at α = 0.05.

The equivalence test using TOST was significant on the 5% level, given equivalence bounds of Cohen's $d = \pm 0.14$ [$t_{(155)} = 1.703$, $p = 0.0453$, 90% CI [−0.014, 0.013]].

Mediation Analyses

The results of the mediation analyses are reported in **Figure 5**. Overall our analyses indicated that while condition had a significant effect on self-reported emotions, the latter did not have a significant effect on the proportion of tastier choices. The direct, mediation, and total effects were not significant (see **Supplementary Table 3**).

Subgroup Effects

Interaction models (see Eq. 7) indicated that condition did not have a significant effect on the proportion of tastier choices in different subgroups (see **Supplementary Table 3**). We found that dispositional self-control as measured via the BSCS score [β = −0.06, *SE* = 0.02, $t_{(174.6)} = -4.11$, $p < 0.001$ [Bonferroni-corrected $p < 0.001$], 95% CI [−0.09, −0.03]] was related significantly to the proportion of tastier food choices. Cognitive Control score of the TFEQ [β = −0.04, *SE* = 0.02, $t_{(174.03)} = -2.4$, $p = 0.02$, 95% CI [−0.07, −0.01]], and the External Eating score of the DEBQ [β = 0.04, *SE* = 0.02, $t_{(173.5)} = 2.75$, $p = 0.007$, 95% CI [0.01, 0.08]] were also related to the proportion of tastier choices, however, these scores did not survive correction for multiple comparisons (Bonferroni-corrected p = 0.18 for Cognitive Control scale and Bonferroni-corrected p = 0.06 for External Eating score) (see **Supplementary Figure 3**). Other questionnaire scores did not have a significant relation to the proportion of tastier choices (see **Supplementary Table 4**). According to the models described in Eqs 5 and 7, the frequency of choosing the tastier option was significantly different across experiments, probably due to differences in the instructions.

DISCUSSION

Summary and Interpretation

Food choices are among the most frequent decisions that humans make. These decisions have a substantial influence on people's health and contribute to being overweight and the development of obesity. Given that correlational studies found social factors to be associated with both eating behavior and emotions, the objective of this study was to investigate the causal effect of social context on food choice, and whether this effect is mediated by emotions. Establishing the presence of such a causal link and its possible mediation by emotions would help identify social risk factors and design better intervention and prevention strategies against obesity and related conditions. This is important because social factors that contribute to obesity can be addressed more easily and at a large scale than other contributors like genetic, homeostatic, and biological factors.

Our results indicate that while lab-induced social contexts induced different emotions, they did not influence food choice.

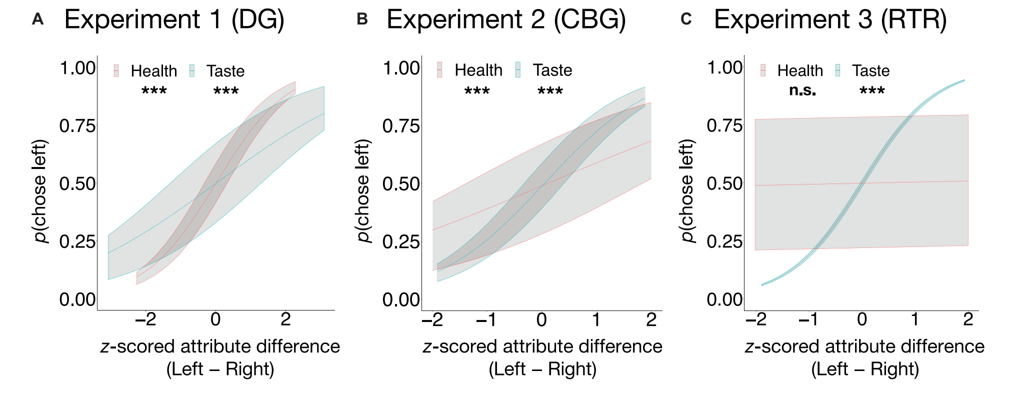

FIGURE 3 | Average predicted probabilities of food choice as a function of taste and health in the incongruent trials in the DG **(A)**, the CBG **(B)**, and the RTR **(C)**. In the DG experiment **(A)** and in the CBG experiment **(B)**, both taste and health were significant predictors of choice, whereas in the RTR experiment **(C)** only taste was. Predicted probabilities are shown with upper (75%) and lower (25%) quartiles. ***p < 0.001, n.s., not significant.

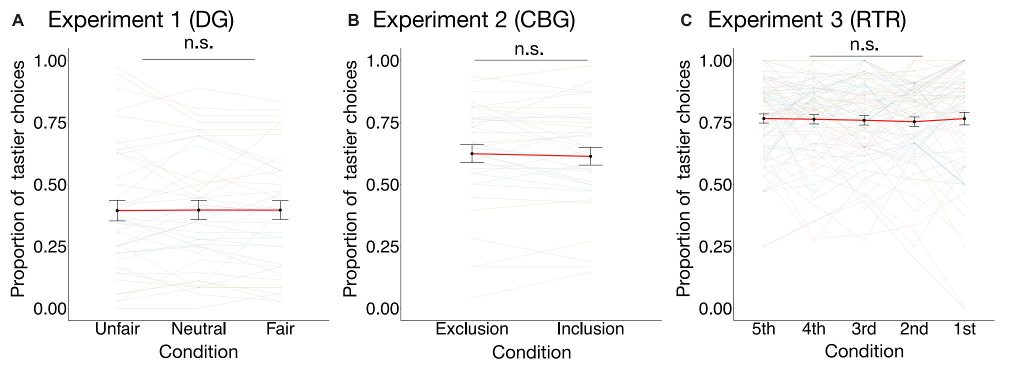

FIGURE 4 | Proportion of tastier choices per condition in the three experiments. The proportion of tastier choices was not significantly different between conditions in **(A)** the DG experiment [$\chi^2_{(2)}$ = 0.02, p = 0.99, marginal R^2 = 0.00002; n = 40], **(B)** the CBG experiment [$\chi^2_{(1)}$ = 0.53, p = 0.47, marginal R^2 = 0.001; n = 35], or **(C)** the RTR experiment [$\chi^2_{(4)}$ = 0.81, p = 0.94, marginal R^2 = 0.001; n = 81]. Colored dots are individual data points, and the black dots are mean values across participants. For better visualization of the differences between conditions, individual observations are connected with color-coded lines, whereas the mean values are connected with a red line. Error bars represent the standard error of the mean. Effects are estimated using mixed-effects linear models. n.s., not significant.

Crucially, there was a significantly positive relation (Bonferroni-corrected) between healthy food choices and dispositional self-control as measured via the BSCS. Apart from this, cognitive restraint of eating as measured via the Cognitive Control subscale of the TFEQ and external eating as measured via the External Eating subscale of the DEBQ correlated with healthy food choices in our experiment, but significantly so only without Bonferroni correction. These findings are in line with previous studies that have associated healthy eating with higher dispositional self-control (Hare et al., 2009; Will Crescioni et al., 2011; Keller and Hartmann, 2016), higher cognitive control of eating behavior, and lower external eating (Elfhag et al., 2007; Keller and Siegrist, 2015). On the basis of these findings, we believe that the food choice task employed in our study captures relevant aspects of participants' food choices outside the lab.

Importantly, not only external but also internal validity of the food choice task seems to be satisfied: Across all three experiments, in the congruent food choice trials, participants chose the tastier and healthier option significantly more often than the less tasty, less healthy option, indicating that participants made deliberate choices. Further evidence comes from the fact that in the incongruent trials of all three experiments, food choice was predicted by both taste and health attributes (see **Figure 3**). While the effect of taste was significant in all three data sets, the effect of healthiness was significant in the DG and CBG

TABLE 1 | Mixed-effects logistic regression results with choosing the tastier item as the dependent variable. In all three experiments, condition did not significantly explain variance in choosing the tastier food item.

Fixed effects	Estimate (*SE*)	*p*-value	*OR*	CI (95%)
DG: Chose tastier (1 = Yes, 0 = No)				
Intercept	−0.58 (0.2)	0.005	0.56	[0.37, 0.84]
Unfair vs. Neutral	0.01 (0.1)	0.91	1.01	[0.85, 1.20]
Unfair vs. Fair	0.01 (0.1)	0.91	1.01	[0.85, 1.20]
Random effects	σ_u^2	*SD*		
Intercept (Subject ID)	3.29	1.24		
Model				
Marginal R^2/Conditional R^2	0.000/0.320			
Fixed effects	**Estimate (*SE*)**	***p*-value**	***OR***	**CI (95%)**
CBG: Chose tastier (1 = Yes, 0 = No)				
Intercept	0.58 (0.18)	0.001	1.78	[1.26, 2.52]
Exclusion vs. Inclusion	−0.05 (0.08)	0.50	0.95	[0.81, 1.11]
Random effects	σ_u^2	*SD*		
Intercept (Subject ID)	3.29	0.99		
Model				
Marginal R^2/Conditional R^2	0.000/0.230			
Fixed effects	**Estimate (*SE*)**	***p*-value**	***OR***	**CI (95%)**
RTR: Chose tastier (1 = Yes, 0 = No)				
Intercept	1.32 (0.11)	<0.001	3.74	[3.02, 4.63]
Rank 5 vs. Rank 4	0.01 (0.1)	0.93	1.01	[0.85, 1.19]
Rank 5 vs. Rank 3	−0.02 (0.1)	0.79	0.98	[0.82, 1.16]
Rank 5 vs. Rank 2	−0.07 (0.1)	0.42	0.93	[0.78, 1.11]
Rank 5 vs. Rank 1	0.10 (0.1)	0.29	1.11	[0.92, 1.34]
Random effects	σ_u^2	*SD*		
Intercept (Subject ID)	3.29	0.80		
Model				
Marginal R^2/Conditional R^2	0.001/0.163			

n = 40 for the DG, n = 35 for the CBG, and n = 81 for the RTR. SE, Standard error; OR, Odds ratio; CI, Confidence interval. CIs are shown for ORs.

TABLE 2 | Mixed-effects logistic regression results with condition and experiment as explanatory and choosing the tastier item as the dependent variable.

Fixed effects	Estimate (*SE*)	*p*-value	*OR*	CI (95%)
Combined data: Choosing the tastier item (1 = Yes, 0 = No)				
(Intercept)	0.56 (0.17)	0.001	1.75	[1.25, 2.45]
Condition	−0.02 (0.04)	0.65	0.98	[0.90, 1.07]
CBG vs. DG	−1.10 (0.23)	<0.001	0.33	[0.21, 0.52]
CBG vs. RTR	0.79 (0.20)	<0.001	2.20	[1.47, 3.28]
Random effects	σ_u^2	*SD*		
Subject ID (Intercept)	3.29	0.97		
Model				
Marginal R^2/Conditional R^2	0.118/0.316			

Three data sets were combined (n = 156). Even when controlling for the type of experiment, condition had no effect on the probability of choosing the tastier item. n = 156. SE, Standard error; OR, Odds ratio; CI, Confidence interval. CIs are shown for ORs. Condition: 0 = Negative, 1 = Positive.

experiments. All these findings suggest that the food choice task worked and that both taste and health are integrated in the choice, in line with previous findings (Enax et al., 2016).

Our results indicate that the lab-induced negative social contexts did not influence food choice. This is in contrast to previous research which found that the mere perception of a lower socioeconomic status (Cheon and Hong, 2017; Sim et al., 2018) and social exclusion affect food *intake* (Baumeister et al., 2005; Salvy et al., 2011; Senese et al., 2020). This apparent incompatibility of our results with the previous findings may be due to several factors.

First, while our results on the effect of social exclusion on food choice are to some degree comparable to previous research, our results on the effect of unfairness and inferiority are less so due to methodological differences. Previous research on the effects of experiencing unfairness and inferiority has used different methods to induce social disadvantages. For example, Sim et al. (2018) induced the experience of (hypothetical) unfairness through a vignette about being deprived of a deserved outcome: receiving a smaller bonus relative to one's colleagues. While this represents unfairness, it is different from the unfairness induced by the DG in our study. In the DG, participants are allocated money independent of their past actions, whereas in the study by Sim et al. (2018), the money allocated to the participant according to the vignette is a bonus awarded by the company for which the participant is working. It is conceivable that participants perceive money awarded for some prior performance (even though hypothetical) as more "deserved" than receiving money from an anonymous other participant. Moreover, the management awarding the bonus does not directly gain anything from awarding unequal bonuses. By contrast, in the DG, the dictator's payoff depends on the amount of money allocated to the recipient; hence, the dictator has an incentive to be selfish. Consequently, it may be easier to regulate the emotional response toward a selfish person than toward an unfair party that does not have a clear benefit from the unfair behavior. Similarly, the explicit framing of the vignette that one's hypothetical colleagues get more money for the same job may trigger relatively strong social comparison. Regarding lab-induced inferiority, previous studies have relied on asking participants to compare themselves (in writing) to people that they consider better off (Cardel et al., 2016; Cheon and Hong, 2017; Sim et al., 2018). Thus, while the objective is the same (i.e., to induce inferiority through comparison) as in our study, the means through which the comparison was achieved may have triggered different processes, related to more general self-evaluation, than our manipulation. These differences in the triggered processes and the intensity of the emotional responses may account for the different findings.

Second, in these previous studies, food preference was quantified by the amount of food participants ate after social exclusion or after an emotion induction. By contrast, we asked participants to make decisions between food items to be consumed later. Making choices regarding food items to be

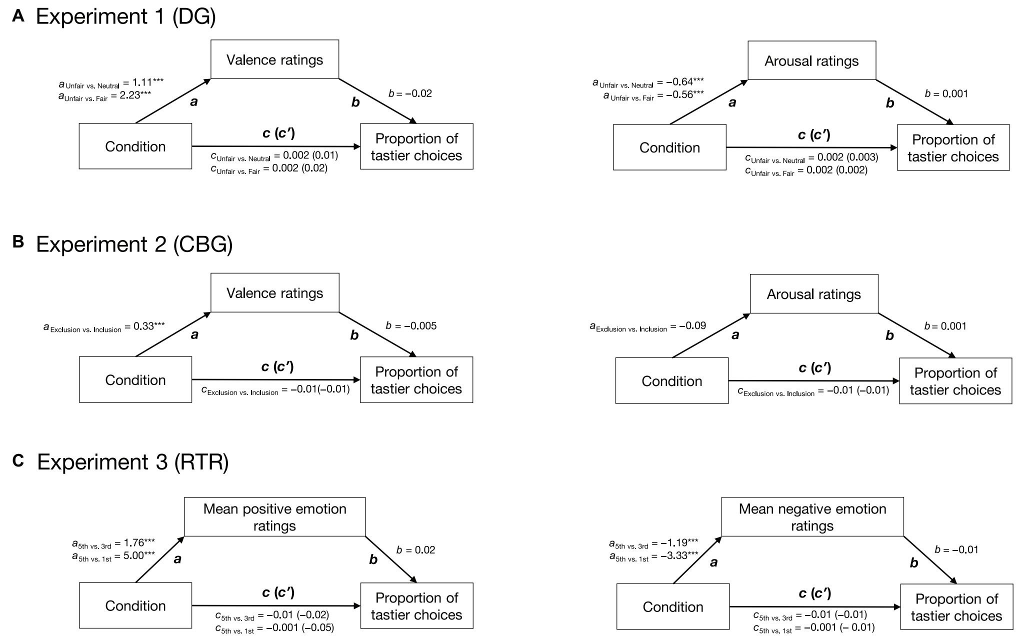

FIGURE 5 | Results of the mediation analyses. For all three experiments, two mediation analyses were run separately: for the DG **(A)** and CBG **(B)**, one with valence and one with arousal as mediators; for the RTR **(C)**, one with mean positive and one with mean negative emotions as mediators. In all experiments, condition had a significant effect on self-reported emotions (path *a*). Emotions did not have an effect on the proportion of tastier food choices (path *b*). Condition did not have an effect on the proportion of tastier food choices (path *c*) neither when including self-reported emotions as mediators (path *c′*). Arrows indicate the assumed direction of the effects. $^{***}p < 0.001$.

consumed later (Hare et al., 2009; Maier et al., 2015) results in different neural activity than actually consuming food (de Araujo and Simon, 2009), which suggests that decisions about future consumption and actual consumption of food draw on different processes (Higgs, 2016). While negative social contexts like social exclusion and lab-induced emotions have been found to have an effect on *immediate* food intake, it may be the case that the same do not influence food decisions about *future* food intake.

Future studies should consider directly comparing the effects of negative social contexts and emotions on food decisions about *future* food intake in contrast to *immediate* food intake.

Given that we did not find an effect of the experimental manipulation on observed food choices, it is important to note that in all three experiments, social contexts had a significant effect on the emotion ratings. In the DG experiment, we found that the unfair condition resulted in significantly lower valence ratings in line with the literature (Hewig et al., 2011; Rilling and Sanfey, 2011; Strang et al., 2016) and in higher arousal ratings compared to the neutral and fair conditions. In the CBG experiment, exclusion significantly decreased valence ratings (however, it did not significantly affect arousal ratings). Additionally, analysis of the self-report questions administered after the CBG experiment indicated that, as expected (Williams et al., 2000), participants felt significantly more ignored, less wanted, less invincible, and less powerful after the exclusion condition. Similarly, in the RTR experiment, analysis of the postexperimentally acquired emotion ratings indicated that in line with previous research (Zink et al., 2008), the attained rank (1st, 3rd, 5th) had a significant effect on the emotion ratings, such that being ranked first was associated with higher positive and lower negative emotions, while the reverse was true for when being ranked last. Even so, these induced emotions did not have an effect on food choice.

These findings may, at first glance, differ from the results of previous studies that have shown that both positive and negative lab-induced emotions affect food intake (Baucom and Aiken, 1981; Bongers et al., 2013, 2016; Cardi et al., 2015). More specifically, it has been shown that when under stress and/or in a negative emotional state, individuals prefer energy-dense foods (comfort foods) and often consume more of the same (Leigh Gibson, 2006; Macht, 2008; Bublitz et al., 2010; Konttinen et al., 2010; Cardi et al., 2015). It is worth mentioning, however, that the effects of emotions on food intake are heterogenous, and for specific populations, also *positive* emotions can increase preference for energy-dense foods (Bongers et al., 2016; Ashurst et al., 2018; Evers et al., 2018).

Our null finding may thus reflect the inconclusiveness of the previous findings.

More importantly, however, to our knowledge no study has investigated the effects of emotions on food *choice* by using a task similar to ours. The closest to our study is recent work by Privitera et al. (2019) which showed that lab-induced negative emotions increased the number of choices of high-caloric food items "in a buffet-style setting." Our null finding regarding a potential relationship between emotions and food choice may stem from the fact that in our study, intake of the chosen items was less immediate than in the study by Privitera et al. (2019): Our choice environment more resembled choice in a supermarket than a "buffet-style" choice. That is, while in their study, participants consumed the chosen items almost immediately, while still in the lab, our participants consumed the chosen items only later; and while their participants picked up the items physically from the buffet, our participants merely saw the items displayed on a computer screen.

Another characteristic that makes a direct comparison of our results with those of previous studies difficult is the emotion induction procedure. In these studies, the focus was on emotional eating, such that the emotion induction procedures were more traditional ones, including means such as movies (Bongers et al., 2013; van Strien et al., 2013), vodcasts, perceptual tasks (Kenardy et al., 2003; Cardi et al., 2015), or vignettes (Privitera et al., 2019). By contrast, in our study, the focus is on the effects of negative social contexts on food choice, with emotions as mediators of this possible relation. Even though our methods are comparable to the methods used in other studies in terms of emotion induction strength, assessed via effect sizes (Bongers et al., 2013, 2016; Evers et al., 2013; Cardi et al., 2015), this does not exclude the possibility that different methods induced different kinds of emotions. In line with this, while studies on emotional eating often are based on the induction of emotions such as sadness, happiness, joy, and satisfaction (van Strien et al., 2013; Cardi et al., 2015), the social contexts used in our study have previously been found to evoke feelings of being ignored, feeling powerless, less wanted (Williams et al., 2000; Williams, 2007), feeling of being treated unfairly (Xiao and Houser, 2005). It might be the case that these different emotions evoked by commonly experienced social contexts have no effect or a weaker effect on food choice.

Limitations and Suggestions for Future Research

Since our objective was to investigate the effect of social context in food choice, and its possible mediation by emotions, in the DG and the CBG we included emotion ratings between each induction and food-choice task. These emotion rating stages may have led participants to be aware of their emotional states, regulate them, and thereby reduce the effect of the negative context. It is important to note that, however, even in the RTR experiments, in which we did not acquire emotion ratings after each trial, we did not find a significant change in participants' behavior in response to the experimental manipulation. One alternative to address this and assess the emotional state on a trial-by-trial basis for future studies, would consist in collecting emotion-related biomarkers such as measuring skin conductance. Such markers avoid that participants verbalize their state, thereby making it conscious.

The sample size considered in each individual experiment is relatively small. We would like to point out, however, that in all three experiments we employed a within-subject design, which avoids confusing the treatment effect with between-subject variability and is, hence, comparatively powerful. Moreover, sample size was sufficiently large to clearly establish effects of the manipulation on emotions ($p < 0.001$ for all three experiments). We reasoned that if this change in emotions translated to a change in behavior in a similar way in all participants, then the sample size would be sufficient. Furthermore, to increase power, we combined the data from the three experiments and analyzed them jointly. The results of this combined analysis confirmed the results from the separate analyses and suggest that if an effect is present at all, it is relatively small.

For all three studies, we invited healthy participants who occasionally consume snacks. Crucially, across all experiments, the instructions included the statement that participants should choose what they would like to eat in the immediate future, because one of their choices would be implemented at the end of the experiment. However, the degree to which participants were prompted to consider healthiness during their choices differed across studies: In both the DG and the CBG experiment, participants were prompted to consider healthiness while making their choices, whereas this cue was absent in the RTR experiment. While we do observe that the different instructions influenced the *level* of participants' inclination to make healthy choices, there is no indication of an *interaction* of the instructions with the social context. Crucially, the lack of this interaction is not due to ceiling or floor effects, because there is sufficient room in both directions for the conditions to have an effect (see **Figure 4**). This is why it is possible to analyze the three experiments jointly. The different instructions even add information and corroborate our null finding: The fact that the different strengths of the health cues influenced participants' inclination to make healthy choices demonstrates that their decision making was indeed malleable—but the lab-induced social contexts nevertheless failed to have an effect.

Our sample consisted by design of non-dieting, healthy individuals. On this background, a possible explanation of our null result is that food decisions and food-related goals in healthy participants may not be as easily influenced by negative social contexts and emotions as they are in individuals with obesity, binge and restrained eaters (Ganley, 1989; Kenardy et al., 2003; Cardi et al., 2015; Privitera et al., 2019). Furthermore, it is important to mention that our sample consisted mostly of university students, who are not representative of the general population so that also their food-related decisions may diverge from the population's average. It is possible that subgroups of participants of different socio-demographic background, and of different health status, may be more sensitive to negative social contexts and may be more susceptible to the manipulation of their emotional state than the average subject in our study. Future studies should consider comparing the effects of social context on food choices in different populations. Our study is nevertheless informative by showing that food-related decisions of healthy participants do not seem to be particularly susceptible to negative emotions that result from (acute, non-chronic) disadvantageous social contexts.

Our null finding raises the question whether other types of emotions or more potent negative social contexts might be able to influence food choice. Unfortunately, this points to a fundamental limitation of this line of research: One cannot induce arbitrarily strong, and lasting, negative emotions in an ethically acceptable way. Consequently, there are limits to using negative social contexts—say, sustained, severe exclusion over several weeks—as a tool in research. This, of course, limits our ability to establish a causal effect of social contexts on food choice.

CONCLUSION

In this study, we found that experimentally induced social context did not significantly influence food choices of healthy participants. Our data reveal, however, that, in contrast to the emotion-inducing social contexts, dispositional self-control, a more stable characteristic, was significantly related to food choice. More precisely, weaker self-control was associated with a higher number of tastier choices (and, thus, a lower number of healthy choices).

Our work contributes to the literature in several ways. First, we investigated the effects of commonly experienced social contexts on food choice. This is an approach that has not been used in this line of research before, even though social contexts and emotions resulting from social interactions are probably highly relevant for health-related behavior and the disorders associated with it. Second, our approach raises new research questions regarding the nature of emotions that do or do not influence food choices, and whether these influences differ across populations. Third, this study contributes to the literature on the effect of negative social contexts and emotions on food choice and raises the question whether food *intake* and *choice* are influenced to a different degree by social contexts and emotions. Directly comparing the effects of social contexts on food choice and food intake could provide a better understanding of how and when social-context–dependent influences on eating behavior arise. Last but not least, the results of our equivalence test indicate that the effect of different social contexts on food choice is equivalent to 0, and that considering our design, effect sizes of Cohen's $d \geq 0.14$ can be excluded. This comes with the caveat, of course, that conducting an equivalence test relies on choosing suitable "equivalence bounds." The equivalence bounds are supposed to be based on a "smallest effect size of interest" (SESOI). When objective justifications of a SESOI are impossible, a suggestion (Lakens et al., 2018) for picking a SESOI is to derive it from earlier, related studies. This, however, is impossible for a lab experiment with a novel design. We therefore simply report which effect sizes we can rule out based on our data (i.e., Cohen's $d \geq 0.14$), and we would like to leave it to our readers to judge whether the minimum effect size is "of interest."

Overall, this study offers a first attempt to better understand the effects of negative social contexts on food choice in healthy individuals. Knowledge about the presence of an effect—or its *absence*, as in our study—in the healthy population may contribute to a better understanding of the causes and consequences of pathological behavior. We believe that our research will inform the experimental investigation of the link between social disadvantage and food-related decision making. Understanding how social disadvantage does or does not contribute to unhealthy food decisions will help in designing and implementing policies against obesity and eating-related disorders.

DATA AVAILABILITY STATEMENT

All datasets generated for this study are available online as **Supplementary Material**.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Ethics committee of the University of Bonn, Germany. The participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

QR: conceptualization, methodology, software, investigation, formal analysis, visualization, writing—original draft, writing—review and editing. HG: methodology, software, investigation, formal analysis, writing—review and editing. XG: conceptualization, methodology, software, investigation, formal analysis, writing—review and editing. WZ: conceptualization, methodology, investigation. JS: writing—review and editing, supervision. BW: conceptualization, writing—review and editing, supervision. All authors contributed to the article and approved the submitted version.

FUNDING

This work was supported by the BMBF grant DietBB (01E1809B).

ACKNOWLEDGMENTS

We are grateful to Peter Trautner for helping with programming, Bettina Mahlow for helping with participant recruitment, and Leonhard Grabe, Alexander Grote, Sofia Konrad, Aenne Läufer, Lena Michaelis, Clemens Overkott, Jana Paus, Evert Reins, Laura Schinabeck, Ilinca Serbanescu, Dominik Suri, and Kenan Suljic for excellent research assistance, in particular regarding data collection and the preparation of documents for the ethics proposal, and Michael J. Böhm and David N. Danz for helpful comments on the statistical analysis. Moreover, we would like to thank the reviewers for their critical evaluation of our manuscript and their constructive comments.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2020.575170/full#supplementary-material

REFERENCES

Ashurst, J., van Woerden, I., Dunton, G., Todd, M., Ohri-Vachaspati, P., Swan, P., et al. (2018). The association among emotions and food choices in first-year college students using mobile-ecological momentary assessments. *BMC Public Health* 18:573. doi: 10.1186/s12889-018-5447-0

Bagby, R. M., Parker, J. D. A., and Taylor, G. J. (1994). The twenty-item Toronto Alexithymia scale—I. Item selection and cross-validation of the factor structure. *J. Psychosom. Res.* 38, 23–32. doi: 10.1016/0022-3999(94)90005-1

Baucom, D. H., and Aiken, P. A. (1981). Effect of depressed mood on eating among obese and nonobese dieting and nondieting persons. *J. Pers. Soc. Psychol.* 41, 577–585. doi: 10.1037/0022-3514.41.3.577

Baumeister, R. F., DeWall, C. N., Ciarocco, N. J., and Twenge, J. M. (2005). Social exclusion impairs self-regulation. *J. Pers. Soc. Psychol.* 88, 589–604. doi: 10.1037/0022-3514.88.4.589

Beck, A., Brown, G., and Steer, R. (1996). *Manual for the Beck Depression Inventory-II*. San Antonio, TX: Psychological Corporation.

Bernstein, M. J., and Claypool, H. M. (2012). Not all social exclusions are created equal: emotional distress following social exclusion is moderated by exclusion paradigm. *Soc. Influ.* 7, 113–130. doi: 10.1080/15534510.2012.664326

Bertrams, A., and Dickhäuser, O. (2009). Messung dispositioneller Selbstkontroll-Kapazität. *Diagnostica* 55, 2–10. doi: 10.1026/0012-1924.55.1.2

Blechert, J., Goltsche, J. E., Herbert, B. M., and Wilhelm, F. H. (2014). Eat your troubles away: electrocortical and experiential correlates of food image processing are related to emotional eating style and emotional state. *Biol. Psychol.* 96, 94–101. doi: 10.1016/j.biopsycho.2013.12.007

Bliss-Moreau, E., Williams, L. A., and Santistevan, A. C. (2019). The immutability of valence and arousal in the foundation of emotion. *Emotion* 20, 993–1004. doi: 10.1037/emo0000606

Bock, O., Baetge, I., and Nicklisch, A. (2014). hroot: hamburg registration and organization online tool. *Eur. Econ. Rev.* 71, 117–120. doi: 10.1016/j.euroecorev.2014.07.003

Bongers, P., de Graaff, A., and Jansen, A. (2016). 'Emotional' does not even start to cover it: generalization of overeating in emotional eaters. *Appetite* 96, 611–616. doi: 10.1016/j.appet.2015.11.004

Bongers, P., Jansen, A., Havermans, R., Roefs, A., and Nederkoorn, C. (2013). Happy eating. The underestimated role of overeating in a positive mood. *Appetite* 67, 74–80. doi: 10.1016/j.appet.2013.03.017

Booth, H. P., Charlton, J., and Gulliford, M. C. (2017). Socioeconomic inequality in morbid obesity with body mass index more than 40 kg/m2 in the United States and England. *SSM Popul. Heal.* 3, 172–178. doi: 10.1016/j.ssmph.2016.12.012

Borkenau, P., and Ostendorf, F. (1993). *NEO-FFI: NEO-Fünf-Faktoren-Inventar nach Costa und McCrae*. Göttingen: Hogrefe.

Bradley, M. M., and Lang, P. J. (1994). Measuring emotion: the self-assessment manikin and the semantic differential. *J. Behav. Ther. Exp. Psychiatry* 25, 49–59. doi: 10.1016/0005-7916(94)90063-9

Bublitz, M. G., Peracchio, L. A., and Block, L. G. (2010). Why did I eat that? Perspectives on food decision making and dietary restraint. *J. Consum. Psychol.* 20, 239–258. doi: 10.1016/j.jcps.2010.06.008

Cardel, M. I., Johnson, S. L., Beck, J., Dhurandhar, E., Keita, A. D., Tomczik, A. C., et al. (2016). The effects of experimentally manipulated social status on acute eating behavior: a randomized, crossover pilot study. *Physiol. Behav.* 162, 93–101. doi: 10.1016/j.physbeh.2016.04.024

Cardi, V., Leppanen, J., and Treasure, J. (2015). The effects of negative and positive mood induction on eating behaviour: a meta-analysis of laboratory studies in the healthy population and eating and weight disorders. *Neurosci. Biobehav. Rev.* 57, 299–309. doi: 10.1016/j.neubiorev.2015.08.011

Carver, C. S., and White, T. L. (1994). Behavioral inhibition, behavioral activation, and affective responses to impending reward and punishment: the BIS/BAS scales. *J. Pers. Soc. Psychol.* 67, 319–333. doi: 10.1037/0022-3514.67.2.319

Cheon, B. K., and Hong, Y.-Y. (2017). Mere experience of low subjective socioeconomic status stimulates appetite and food intake. *Proc. Natl. Acad. Sci. U.S.A.* 114, 72–77. doi: 10.1073/pnas.1607330114

Coccurello, R., D'Amato, F. R., and Moles, A. (2009). Chronic social stress, hedonism and vulnerability to obesity: lessons from rodents. *Neurosci. Biobehav. Rev.* 33, 537–550. doi: 10.1016/j.neubiorev.2008.05.018

Costa, P. T., and McCrae, R. R. (1992). *Revised NEO Personality Inventory (NEO-PI-R) and NEO Five Factor Model (NEO-FFI) Professional Manual*. Odessa, FL: Psychological Assessment Resources.

Dawes, J. (2002). Five point vs. eleven point scales: does it make a difference to data characteristics? *Austral. J. Mark. Res.* 10, 39–47.

de Araujo, I. E., and Simon, S. A. (2009). The gustatory cortex and multisensory integration. *Int. J. Obes.* 33, S34–S43. doi: 10.1038/ijo.2009.70

Diehl, J. M. (2006). *Fragebögen zur Erfassung ernährungs- und gewichtsbezogener Einstellungen und Verhaltensweisen*. Available online at: https://docplayer.org/27800523-Joerg-m-diehl-fachbereich-psychologie-justus-liebig-universitaet-giessen-diagnostik-von-essgewohnheiten-und-essstoerungen.html (accessed September 14, 2020).

Drewnowski, A. (2009). Obesity, diets, and social inequalities. *Nutr. Rev.* 67, S36–S39. doi: 10.1111/j.1753-4887.2009.00157.x

Elfhag, K., Tynelius, P., and Rasmussen, F. (2007). Sugar-sweetened and artificially sweetened soft drinks in association to restrained, external and emotional eating. *Physiol. Behav.* 91, 191–195. doi: 10.1016/j.physbeh.2007.02.005

Enax, L., Krajbich, I., and Weber, B. (2016). Salient nutrition labels increase the integration of health attributes in food decision-making. *Judgm. Decis. Mak.* 11, 460–471.

Evers, C., Adriaanse, M., de Ridder, D. T. D., and de Witt Huberts, J. C. (2013). Good mood food. Positive emotion as a neglected trigger for food intake. *Appetite* 68, 1–7. doi: 10.1016/j.appet.2013.04.007

Evers, C., Dingemans, A., Junghans, A. F., and Boevé, A. (2018). Feeling bad or feeling good, does emotion affect your consumption of food? A meta-analysis of the experimental evidence. *Neurosci. Biobehav. Rev.* 92, 195–208. doi: 10.1016/j.neubiorev.2018.05.028

Faul, F., Erdfelder, E., Buchner, A., and Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: tests for correlation and regression analyses. *Behav. Res. Methods* 41, 1149–1160. doi: 10.3758/BRM.41.4.1149

Fischbacher, U. (2007). z-Tree: zurich toolbox for ready-made economic experiments. *Exp. Econ.* 10, 171–178. doi: 10.1007/s10683-006-9159-4

Gallo, L. C., and Matthews, K. A. (2003). Understanding the association between socioeconomic status and physical health: do negative emotions play a role? *Psychol. Bull.* 129, 10–51. doi: 10.1037/0033-2909.129.1.10

Ganley, R. M. (1989). Emotion and eating in obesity: a review of the literature. *Int. J. Eat. Disord.* 8, 343–361.

Gearhardt, A. N., Bragg, M. A., Pearl, R. L., Schvey, N. A., Roberto, C. A., and Brownell, K. D. (2012). Obesity and public policy. *Annu. Rev. Clin. Psychol.* 8, 405–430. doi: 10.1146/annurev-clinpsy-032511-143129

Gong, X., and Sanfey, A. G. (2017). Social rank and social cooperation: impact of social comparison processes on cooperative decision-making. *PLoS One* 12:e0175472. doi: 10.1371/journal.pone.0175472

Grunert, S. C. (1989). Ein Inventar zur Erfassung von Selbstaussagen zum Ernährungsverhalten. *Diagnostica* 35, 67–179.

Hare, T. A., Camerer, C. F., and Rangel, A. (2009). Self-control in decision-making involves modulation of the vmPFC valuation system. *Science* 324, 646–648. doi: 10.1126/science.1168450

Harrison, M., Lee, A., Findlay, M., Nicholls, R., Leonard, D., and Martin, C. (2010). The increasing cost of healthy food. *Aust. N. Z. J. Public Health* 34, 179–186. doi: 10.1111/j.1753-6405.2010.00504.x

Hartmann, A. S., Rief, W., and Hilbert, A. (2011). Psychometric properties of the german version of the barratt impulsiveness scale, version 11 (BIS–11) for adolescents. *Percept. Mot. Skills* 112, 353–368. doi: 10.2466/08.09.10.PMS.112.2.353-368

Hautzinger, M., Keller, F., and Kühner, C. (2006). *Das Beck Depressions-Inventar II. Deutsche Bearbeitung und Handbuch zum BDI-II*. Frankfurt: Harcourt Test Services.

Hewig, J., Kretschmer, N., Trippe, R. H., Hecht, H., Coles, M. G. H., Holroyd, C. B., et al. (2011). Why humans deviate from rational choice. *Psychophysiology* 48, 507–514. doi: 10.1111/j.1469-8986.2010.01081.x

Higgs, S. (2016). Cognitive processing of food rewards. *Appetite* 104, 10–17. doi: 10.1016/j.appet.2015.10.003

Hoebel, J., Kuntz, B., Kroll, L. E., Schienkiewitz, A., Finger, J. D., Lange, C., et al. (2019). Socioeconomic inequalities in the rise of adult obesity: a time-trend analysis of national examination data from Germany, 1990–2011. *Obes. Facts* 12, 344–356. doi: 10.1159/000499718

Kawamoto, T., Onoda, K., Nakashima, K., Nittono, H., Yamaguchi, S., and Ura, M. (2012). Is dorsal anterior cingulate cortex activation in response to social exclusion due to expectancy violation? An fMRI study. *Front. Evol. Neurosci.* 4:11. doi: 10.3389/fnevo.2012.00011

Keller, C., and Hartmann, C. (2016). Not merely a question of self-control: the longitudinal effects of overeating behaviors, diet quality and physical activity on dieters' perceived diet success. *Appetite* 107, 213–221. doi: 10.1016/j.appet.2016.08.007

Keller, C., and Siegrist, M. (2015). Does personality influence eating styles and food choices? Direct and indirect effects. *Appetite* 84, 128–138. doi: 10.1016/j.appet.2014.10.003

Kelly, M., McDonald, S., and Rushby, J. (2012). All alone with sweaty palms — Physiological arousal and ostracism. *Int. J. Psychophysiol.* 83, 309–314. doi: 10.1016/j.ijpsycho.2011.11.008

Kenardy, J., Butler, A., Carter, C., and Moor, S. (2003). Eating, mood, and gender in a noneating disorder population. *Eat. Behav.* 4, 149–158. doi: 10.1016/S1471-0153(03)00019-9

Konttinen, H., Männistö, S., Sarlio-Lähteenkorva, S., Silventoinen, K., and Haukkala, A. (2010). Emotional eating, depressive symptoms and self-reported food consumption. A population-based study. *Appetite* 54, 473–479. doi: 10.1016/j.appet.2010.01.014

Krohne, H. W., Egloff, B., Kohlmann, C.-W., and Tausch, A. (1996). Untersuchungen mit einer deutschen version der positive and negative affect schedule" (PANAS). *Diagnostica* 2, 139–156.

Lakens, D., Scheel, A. M., and Isager, P. M. (2018). Equivalence testing for psychological research: a tutorial. *Adv. Methods Pract. Psychol. Sci.* 251524591877096. doi: 10.1177/2515245918770963

Lang, P. J., Greenwald, M. K., Bradley, M. M., and Hamm, A. O. (1993). Looking at pictures: affective, facial, visceral, and behavioral reactions. *Psychophysiology* 30, 261–273. doi: 10.1111/j.1469-8986.1993.tb03352.x

Laran, J., and Salerno, A. (2013). Life-history strategy, food choice, and caloric consumption. *Psychol. Sci.* 24, 167–173. doi: 10.1177/0956797612450033

Leigh Gibson, E. (2006). Emotional influences on food choice: sensory, physiological and psychological pathways. *Physiol. Behav.* 89, 53–61. doi: 10.1016/j.physbeh.2006.01.024

Lemaitre, B. (2016). Connecting the obesity and the narcissism epidemics. *Med. Hypotheses* 95, 10–19. doi: 10.1016/j.mehy.2016.08.001

Lewis, J., and Erdinç, O. (2017). User experience rating scales with 7, 11, or 101 points: does it matter? *J. Usabil. Stud.* 12, 73–91.

Loring, B., and Robertson, A. (2014). *Obesity and Inequities. Guidance for Addressing Inequities in Overweight and Obesity*. Geneva: WHO.

Luo, Y., Eickhoff, S. B., Hétu, S., and Feng, C. (2018). Social comparison in the brain: a coordinate-based meta-analysis of functional brain imaging studies on the downward and upward comparisons. *Hum. Brain Mapp.* 39, 440–458. doi: 10.1002/hbm.23854

Lyn, R., Heath, E., and Dubhashi, J. (2019). Global implementation of obesity prevention policies: a review of progress, politics, and the path forward. *Curr. Obes. Rep.* 8, 504–516. doi: 10.1007/s13679-019-00358-w

Macht, M. (2008). How emotions affect eating: a five-way model. *Appetite* 50, 1–11. doi: 10.1016/j.appet.2007.07.002

Maier, S. U., Makwana, A. B., and Hare, T. A. (2015). Acute stress impairs self-control in goal-directed choice by altering multiple functional connections within the brain's decision circuits. *Neuron* 87, 621–631. doi: 10.1016/j.neuron.2015.07.005

Malik, V. S., Willett, W. C., and Hu, F. B. (2013). Global obesity: trends, risk factors and policy implications. *Nat. Rev. Endocrinol.* 9, 13–27. doi: 10.1038/nrendo.2012.199

McLaren, L. (2007). Socioeconomic status and obesity. *Epidemiol. Rev.* 29, 29–48. doi: 10.1093/epirev/mxm001

Mela, D. J. (2001). Determinants of food choice: relationships with obesity and weight control. *Obes. Res.* 9, 249S–255S. doi: 10.1038/oby.2001.127

Moles, A., Bartolomucci, A., Garbugino, L., Conti, R., Caprioli, A., Coccurello, R., et al. (2006). Psychosocial stress affects energy balance in mice: modulation by social status. *Psychoneuroendocrinology* 31, 623–633. doi: 10.1016/j.psyneuen.2006.01.004

Murphy, R. O., Ackermann, K. A., and Handgraaf, M. (2011). Measuring social value orientation. *Judgm. Decis. Mak.* 6, 771–781. doi: 10.2139/ssrn.1804189

Patton, J. H., Stanford, M. S., and Barratt, E. S. (1995). Factor structure of the Barratt impulsiveness scale. *J. Clin. Psychol.* 51, 768–774.

Popp, K., Schäfer, R., Schneider, C., Brähler, E., Decker, O., Hardt, J., et al. (2008). Faktorstruktur und reliabilität der toronto-alexithymie-skala (TAS-20) in der deutschen bevölkerung. *PPmP Psychother. Psychosom. Medizinische Psychol.* 58, 208–214. doi: 10.1055/s-2007-986196

Privitera, G. J., King-Shepard, Q. W., Cuifolo, K. N., and Doraiswamy, P. M. (2019). Differential food intake and food choice by depression and body mass index levels following a mood manipulation in a buffet-style setting. *J. Health Psychol.* 24, 199–208. doi: 10.1177/1359105316650508

Pudel, V., and Westenhöfer, J. (1989). *Fragebogen zum Eßverhalten (FEV)*. Göttingen: Hogrefe.

R Core Team (2019). *R: A Language and Environment for Statistical Computing*. Available online at: https://www.r-project.org/ (accessed September 14, 2020).

Rangel, A. (2013). Regulation of dietary choice by the decision-making circuitry. *Nat. Neurosci.* 16, 1717–1724. doi: 10.1038/nn.3561

Rilling, J. K., and Sanfey, A. G. (2011). The neuroscience of social decision-making. *Annu. Rev. Psychol.* 62, 23–48. doi: 10.1146/annurev.psych.121208.131647

Robertson, A., Lobstein, T., and Knai, C. (2007). *Obesity and Socio-Economic Groups in Europe: Evidence Review and Implications for Action*. Available online at: http://ec.europa.eu/health/ph_determinants/life_style/nutrition/documents/ev20081028_rep_en.pdf (accessed September 14, 2020).

Russell, J. A. (1979). Affective space is bipolar. *J. Pers. Soc. Psychol.* 37, 345–356. doi: 10.1037/0022-3514.37.3.345

Salvy, S., Bowker, J. C., Nitecki, L. A., Kluczynski, M. A., Germeroth, L. J., and Roemmich, J. N. (2011). Impact of simulated ostracism on overweight and normal-weight youths' motivation to eat and food intake. *Appetite* 56, 39–45. doi: 10.1016/j.appet.2010.11.140

Senese, V. P., Pezzella, M., Pasquariello, L., Ali, S., and Rohner, R. P. (2020). Effects of social exclusion and maternal rejection on Children's high-caloric food consumption. *Appetite* 145:104494. doi: 10.1016/j.appet.2019.104494

Sim, A. Y., Lim, E. X., Forde, C. G., and Cheon, B. K. (2018). Personal relative deprivation increases self-selected portion sizes and food intake. *Appetite* 121, 268–274. doi: 10.1016/j.appet.2017.11.100

Strang, S., Grote, X., Kuss, K., Park, S. Q., and Weber, B. (2016). Generalized negative reciprocity in the dictator game – how to interrupt the chain of unfairness. *Sci. Rep.* 6:22316. doi: 10.1038/srep22316

Strobel, A., Beauducel, A., Debener, S., and Brocke, B. (2001). Eine deutschsprachige version des BIS/BAS-Fragebogens von Carver und White. *Z. Diff. Diagnostische Psychol.* 22, 216–227.

Stunkard, A. J., and Messick, S. (1985). The three-factor eating questionnaire to measure dietary restraint, disinhibition and hunger. *J. Psychosom. Res.* 29, 71–83. doi: 10.1016/0022-3999(85)90010-8

Stutzer, A., and Meier, A. N. (2016). Limited self-control, obesity, and the loss of happiness. *Health Econ.* 25, 1409–1424. doi: 10.1002/hec.3227

Sullivan, N., Hutcherson, C., Harris, A., and Rangel, A. (2015). Dietary self-control is related to the speed with which attributes of healthfulness and tastiness are processed. *Psychol. Sci.* 26, 122–134. doi: 10.1177/0956797614559543

Tamashiro, K. L. K., Hegeman, M. A., Nguyen, M. M. N., Melhorn, S. J., Ma, L. Y., Woods, S. C., et al. (2007). Dynamic body weight and body composition changes in response to subordination stress. *Physiol. Behav.* 91, 440–448. doi: 10.1016/j.physbeh.2007.04.004

Tangney, J. P., Baumeister, R. F., and Boone, A. L. (2004). High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *J. Pers.* 72, 271–324. doi: 10.1111/j.0022-3506.2004.00263.x

Templin, T., Cravo Oliveira Hashiguchi, T., Thomson, B., Dieleman, J., and Bendavid, E. (2019). The overweight and obesity transition from the wealthy to the poor in low- and middle-income countries: a survey of household data from 103 countries. *PLoS Med.* 16:e1002968. doi: 10.1371/journal.pmed.1002968

Tingley, D., Yamamoto, T., Hirose, K., Keele, L., and Imai, K. (2014). mediation: R package for causal mediation analysis. *J. Stat. Softw.* 59, 1–38. doi: 10.18637/jss.v059.i05

van Strien, T., Cebolla, A., Etchemendy, E., Gutiérrez-Maldonado, J., Ferrer-García, M., Botella, C., et al. (2013). Emotional eating and food intake after sadness and joy. *Appetite* 66, 20–25. doi: 10.1016/j.appet.2013.02.016

van Strien, T., Frijters, J. E. R., Bergers, G. P. A., and Defares, P. B. (1986). The dutch eating behavior questionnaire (DEBQ) for assessment of restrained, emotional, and external eating behavior. *Int. J. Eat. Disord.* 5, 295–315.

Van't Wout, M., Kahn, R. S., Sanfey, A. G., and Aleman, A. (2006). Affective state and decision-making in the ultimatum game. *Exp. Brain Res.* 169, 564–568. doi: 10.1007/s00221-006-0346-5

Volkow, N. D., Wang, G.-J., Fowler, J. S., and Telang, F. (2008). Overlapping neuronal circuits in addiction and obesity: evidence of systems pathology. *Philos. Trans. R. Soc. B Biol. Sci.* 363, 3191–3200. doi: 10.1098/rstb.2008.0107

Watson, D., Clark, L. A., and Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. *J. Pers. Soc. Psychol.* 54, 1063–1070. doi: 10.1037/0022-3514.54.6.1063

Weik, U., Maroof, P., Zöller, C., and Deinzer, R. (2010). Pre-experience of social exclusion suppresses cortisol response to psychosocial stress in women but not in men. *Horm. Behav.* 58, 891–897. doi: 10.1016/j.yhbeh.2010.08.018

Will Crescioni, A., Ehrlinger, J., Alquist, J. L., Conlon, K. E., Baumeister, R. F., Schatschneider, C., et al. (2011). High trait self-control predicts positive health behaviors and success in weight loss. *J. Health Psychol.* 16, 750–759. doi: 10.1177/1359105310390247

Williams, K. D. (2007). Ostracism. *Annu. Rev. Psychol.* 58, 425–452. doi: 10.1146/annurev.psych.58.110405.085641

Williams, K. D., Cheung, C. K. T., and Choi, W. (2000). Cyberostracism: effects of being ignored over the Internet. *J. Pers. Soc. Psychol.* 79, 748–762. doi: 10.1037/0022-3514.79.5.748

Wilson, M. E., Fisher, J., Fischer, A., Lee, V., Harris, R. B., and Bartness, T. J. (2008). Quantifying food intake in socially housed monkeys: social status effects on caloric consumption. *Physiol. Behav.* 94, 586–594. doi: 10.1016/j.physbeh.2008.03.019

World Health Organization (2020). *Obesity and overweight*. Available online at: https://www.who.int/en/news-room/fact-sheets/detail/obesity-and-overweight (accessed May 27, 2020).

Xiao, E., and Houser, D. (2005). Emotion expression in human punishment behavior. *Proc. Natl. Acad. Sci. U.S.A.* 102, 7398–7401. doi: 10.1073/pnas.0502399102

Zink, C. F., Tong, Y., Chen, Q., Bassett, D. S., Stein, J. L., and Meyer-Lindenberg, A. (2008). Know your place: neural processing of social hierarchy in humans. *Neuron* 58, 273–283. doi: 10.1016/j.neuron.2008.01.025

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

3.2. Publication 2: "Salient nutrition labels shift peoples' attention to healthy food and exert more influence on their choices"

NUTRITION RESEARCH 80 (2020) 106–116

Available online at www.sciencedirect.com

ScienceDirect

www.nrjournal.com

Salient nutrition labels shift peoples' attention to healthy foods and exert more influence on their choices

Qëndresa Rramani[a,b], Ian Krajbich[c,d], Laura Enax[a], Lisa Brustkern[e], Bernd Weber[a,b,*]

[a] Center for Economics and Neuroscience, University of Bonn, Nachtigallenweg 86, 53127 Bonn, Germany
[b] Institute of Experimental Epileptology and Cognition Research, University of Bonn, Venusberg-Campus 1, 53127 Bonn, Germany
[c] Department of Psychology, The Ohio State University, Columbus, OH, 43210, USA
[d] Department of Economics, The Ohio State University, Columbus, OH, 43210, USA
[e] Department of Psychology I, Differential Psychology, Personality Psychology, and Psychological Diagnostics, Julius Maximilians University Würzburg, Würzburg, Germany

ARTICLE INFO

Article history:
Received 15 October 2019
Revised 30 April 2020
Accepted 17 June 2020

ABSTRACT

Nutrition labels are the most commonly used tools to promote healthy choices. Research has shown that color-coded traffic light (TL) labels are more effective than purely numerical Guideline Daily Amount (GDA) labels at promoting healthy eating. While these effects of TL labels on food choice are hypothesized to rely on attention, how this occurs remains unknown. Based on previous eye-tracking research we hypothesized that TL labels compared to GDA labels will attract more attention, will induce shifts in attention allocation to healthy food items, and will increase the influence of attention to the labels on food choice. To test our hypotheses, we conducted an eye-tracking experiment where participants chose between healthy and unhealthy food items accompanied either by TL or GDA labels. We found that TL labels biased choices towards healthier items because their presence caused participants to allocate more attention to healthy items and less to unhealthy items. Moreover, our data indicated that TL labels were more likely to be looked at, and had a larger effect on choice, despite attracting less dwell time. These results reveal that TL labels increase healthy food choice, relative to GDA labels, by shifting attention and the effects of attention on choice.

1. Introduction

In a world with high rates of obesity accompanied by tremendous consequences and costs, understanding the mechanisms underlying food choice is crucial [1,2]. Deciding if, what, when, and how much to eat involves an interplay between the internal homeostatic balance and cognitive capacity–which encapsulates the ability to behave in line with one's goals [2,3]. Even though being healthy and living healthy seem like straightforward goals to have, research shows that the ability to behave in line with these goals seems to depend not only on interindividual differences in decision-making processes, but also on external cues that may promote different goals [4-7]. Among these external cues are nutrition labels which have become the most commonly used tool to promote healthy food choices [8].

Abbreviations: AOI, area of interest; DV, dependent variable; GDA, guideline daily amount; *M*, mean; RT, reaction time; *SE*, standard error of the estimate; *SD*, standard deviation; TL, traffic light; WTP, willingness to pay.

* *Corresponding author at:* Center for Economics and Neuroscience, University of Bonn, Nachtigallenweg 86, 53127 Bonn, Germany.
E-mail address: Bernd.Weber@ukbonn.de (B. Weber).

https://doi.org/10.1016/j.nutres.2020.06.013

While overall the presence of nutrition labels seems to have an impact on food choices, not all label formats are equally effective. Several studies have shown that compared to numerical labels (eg, monochrome Guideline of Daily Amount–GDA), labels that provide nutrition information in a more salient and easy to interpret way are more effective in helping consumers identify and choose healthier foods [9-18]. One type of salient label, which uses color codes to indicate nutrient levels, is the traffic light (TL) label. These labels have been shown to be effective in promoting healthy choice [18] but the exact mechanisms underlying their effects remain unknown.

Many studies have shown that when attended to, TL labels increase health awareness [19,20], which is an important factor associated with healthy food choice [2,5]. In line with this, Enax et al [21] showed that TL labels increase the weight on health attributes in the decision-making process. These effects of salient nutrition labels on food choice have been hypothesized to rely on attention [7, 21]. Supporting this idea, eye-tracking research has shown that while front-of-package labels attract visual attention [22], some formats attract more attention than others. More specifically, it has been shown that color coded labels, like TL labels, attract more attention than monochromatic, numerical labels [12,14,22]. Interestingly, these effects have been reported even in more naturalistic shopping environments such as canteens, where participants can see different food items with different label formats on their packaging [23]. However, what these studies do not answer is how attention more specifically relates to subsequent food choice [12,23,24].

In recent years, research has shown that attention plays an important role in the choice process, amplifying the value of attended items and attributes, and so increasing their impact on choice outcomes (for a review see [25]). These studies provide a framework for understanding how salient nutrition labels might encourage healthy food choice. The first possibility is that more salient labels simply attract more gaze, leading to more weight on nutritional information in participants' choices. A second possibility is that more salient labels divert attention away from unhealthy items towards healthy items, giving healthy items an advantage in the comparison process. Finally, a third possibility is that more salient labels more effectively convey nutrition information, thereby increasing the influence of attention paid to the label on the food choice.

The aim of this study is to explore these possibilities by examining the relationship between visual attention and food choice in the presence of different nutrition labels. Based on the findings from previous eye-tracking studies [12,25], we hypothesized that: (**H1**) more salient labels will attract more attention and will increase the weight of health in the decision process; (**H2**) more salient labels will increase the proportion of time that participants dwell on the healthier item; (**H3**) more salient labels will increase the correlation between attention and food choice. To test these hypotheses, we conducted an eye-tracking experiment where we assessed visual attention while participants performed a binary food choice task between healthy and unhealthy food items in either the presence of purely numerical labels (GDA labels) or in the presence of color-coded and thus more salient labels (TL labels).

2. Methods and materials

2.1. *Participants*

The study was conducted at the Life & Brain center in Bonn, Germany. The study was approved by the local ethics committee of the Medical Faculty of the University of Bonn, and all participants gave written informed consent according to the Declaration of Helsinki. The study protocol, and the potential risks were explained to the participants before they gave their written consent. The study was not registered at ClinicalTrial.gov. We recruited 51 participants (11 male), between the ages of 18 and 60 years old (mean [*M*] = 26.24 years old, standard deviation [*SD*] = 6.4 years old). All participants were German speakers and had either normal or corrected-to-normal vision with contact lenses on. All participants were tested for red-green deficiency to enable accurate testing during eye-tracking. Participation in the study was voluntary and participants were reimbursed with 10€ per hour and with a randomly chosen food product encountered in the experiment. One participant's data had to be excluded due to a software-malfunction. For a visualization of the criteria and the selection of the participants for the study refer to Fig. 1.

2.2. *Stimuli*

The stimulus set used in this study consisted of 100 packaged products that were chosen from the internet. All products were categorized as either healthy or unhealthy according to the TL color classification scheme label (as described in [7]). The products that were accompanied by a minimum of one green light, and no red lights were categorized as healthy. By contrast, products that were accompanied with at least one red light and at most one green light were categorized as unhealthy. We did not include products with one red and multiple green lights. The labels and values for GDA and TL were retrieved from the producer's nutrition information and the EU Food and Drink Confederation [26], as well as the Food Standards Agency's website [27], respectively. We used the same procedure as described in [21]. The label's notation and categorization were normalized to a portion size of 100 g and can be seen in Tables 1 and 2. The labels accompanying the food products were based on the products' nutrition facts and were presented below the food product (Fig. 2). The reason to separate the food images and their nutrition labels was so that we could clearly distinguish between attention paid to the nutrition labels and attention paid to the food items.

2.3. *Procedure*

Participants were asked to refrain from eating any food for 4 hours prior to the start of the experiment. The experimental procedure consisted of three parts. In the first part, participants rated each of the 100 products based on how much they

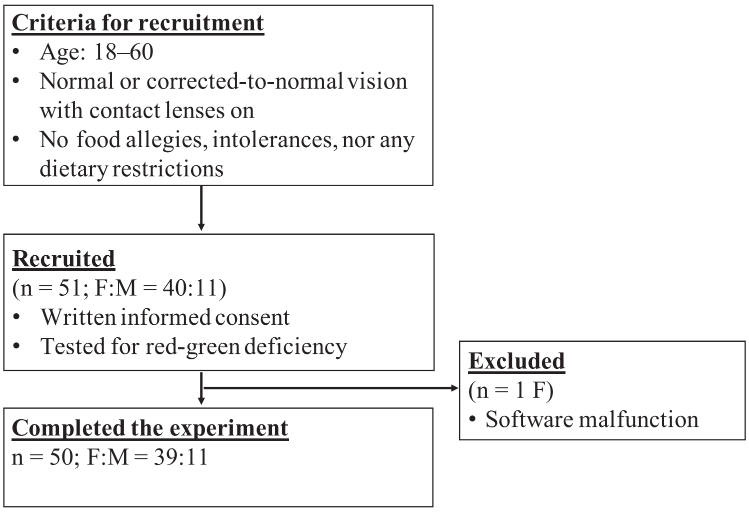

Fig. 1 – Flow diagram of the study participants from recruitment criteria to completion of the experiment. F: female; M: male.

liked their taste (subjective liking ratings) on a nine-point scale from –4 (not at all) to 4 (very much). The pictures of the products were displayed in the center of a black screen. Between each rating there was a fixation-cross that appeared for 50 ms. Participants could proceed with the task only after rating each food. In this part of the experiment, the products were shown without any nutrition labels.

In the second part of the experiment, participants had to make choices between two food products. Participants completed 480 trials in total, from which 240 were "normal" trials and 240 were trials with scrambled/unintelligible nutrition labels. The scrambled trials were included for another set of analysis for a different project. In this paper we restrict all analyses to the "normal" trials. In half of these "normal" trials, both foods were presented with GDA nutrition labels, while in the other half both foods were presented with TL nutrition labels. In total, there were five blocks of 48 trials each, and GDA/TL trials were randomly intermixed throughout these blocks. Participants indicated their choice by pressing computer keys with their corresponding index fingers. If a participant did not make a choice within 20 s, the experiment proceeded automatically to the next trial. Pictures of the two products and nutrition labels were presented on a black background (Fig. 2). To avoid possible effects of the brand information [22,28], the brand names on the products were covered up. Trials were separated by a fixation cross shown on a black background for 1000 ms.

In the third and final part of the experiment we assessed participants' willingness to pay (WTP) for each product. To do so, participants were asked to indicate the price they would pay for each food if they saw it in a supermarket. Like in the first part of the experiment, in this task the food products were presented in the middle of a black screen without any nutrition label. We ended up not using these WTP ratings in our analyses because they were potentially contaminated by the earlier choice trials; for a discussion on these issues see [29].

In addition to these measurements, we also assessed participants' weight, height, waist to hip ratio, and their attitudes towards eating behavior (assessed *via* questionnaires). These measures were acquired as part of a different project and are not included in our analysis.

All parts, except the questionnaires and the assessment of the anthropometric variables, were computer-based. However,

Table 1 – Guideline daily amount for an average adult

Ingredient	Value	Example values per 100 g	
Caloric requirement	2000 kcal	334 kcal	17% of GDA
Sugar	90 g	1.5 g	2% of GDA
Fat	70 g	2.0 g	3% of GDA
Saturated fatty acids	20 g	0.4 g	2% of GDA
Sodium	2.4 g	0.3 g	13% of GDA

GDA, guideline daily amount; g, gram; kcal, kilocalorie. In the GDA labels values for a portion of 100 g are displayed.

Table 2 – Guidelines for traffic light labels

Ingredient	Green (low content)	Yellow (middle content)	Red (high content)
Sugar	<5 g	5-12.5 g	>12.5 g
Fat	<3 g	3-20 g	>20 g
Saturated fatty acid	<1.5 g	1.5-5 g	>5 g
Sodium	<0.12 g	0.12-0.7 g	>0.7 g

The values are calculated for a portion size of 100 g. Color coding does not apply to energy information.

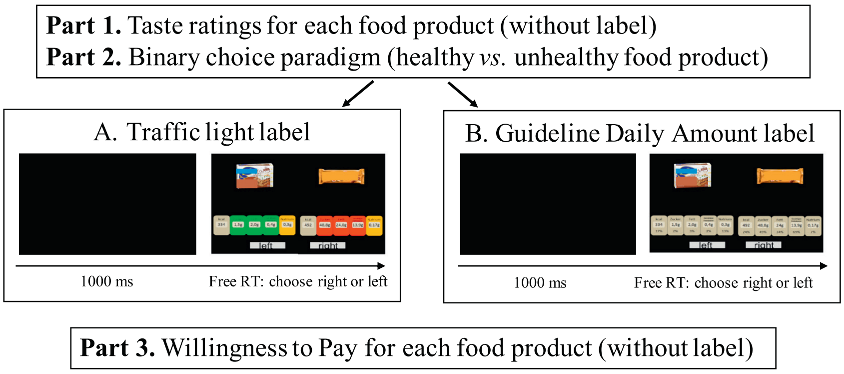

Fig. 2 – Experimental paradigm. **In the first part participants had to rate every food item in terms of how much they liked the taste of that food item. In the second part participants had to make a binary food choice between a healthy and an unhealthy item. This task consisted of trials where the food products were shown with a TL label (TL trials) and trials where the food products were shown with a GDA label (GDA trials). The brand names were covered up. In the third part participants were asked to indicate how much they were willing to pay for every food product. GDA: guideline daily amount; TL: traffic light; RT: reaction time.**

we collected eye-tracking data only in the second part (binary choice task). For this, we used the EyeLink 1000 (SR research Ltd, Mississauga, Ontario, Canada) eye-tracker with a sampling rate of 1000 Hz, and average accuracy lower than 0.5°. Calibration was done using a standard 13-point calibration task provided by the manufacturer (white dots, black background). Participants were seated at an approximately 50–55 centimeter distance from the EyeLink camera, which was positioned centrally and immediately under the 27 × 35-cm screen. Their head was placed on a forehead- and chin rest (the "tower"), to stabilize the participants and avoid movement during testing. The settings were adjusted to each participant, regarding the cornea-reflex, calibration and validation. Following every 20th trial, the eye tracker was recalibrated to ensure accurate measurement. The food rating, food choice, and WTP tasks were created and displayed using Experiment Builder software (SR Research Ltd., version 2.1.140).

Because we were interested in the attention paid to the food items, and the attention paid to the labels, our areas of interest (AOI) included the images of the food items, and the nutrition labels (see **Supplemental Fig. S1**). We analyzed the individual dwell times and the total dwell times on the food items (*item dwell time*, *total item dwell time*) and on the nutrition labels (*label dwell time*, *total label dwell time*). Individual dwell times refer to the amount of time spent looking at an AOI before moving on to another AOI, whereas total dwell times refer to the amount of time spent looking at a given AOI over the course of the whole trial.

2.4. *Statistical analyses*

Statistical analysis was performed using R (version 3.6.1) [30] and R Studio (version 1.2.1335) [31]. The following packages were used: *lme4* (version 1.1–21), *lmerTest* (version 3.1–0), *ggplot2* (version 3.2.1), *plyr* (version 1.8.4), *grid* (version 3.6.1). The data was analyzed using full mixed-effects regressions (either linear or logistic, depending on the type of the dependent variable) to account for repeated measures within subjects. In cases where these mixed-effects models did not successfully converge, we report the results from regression models with clustered standard errors (cluster-corrected models). Additionally, paired *t*-tests were used to compare mean percentages, and Pearson correlation analysis was used to test for associations between the time participants spent looking at the labels and the probability of choosing healthy items. Variables that were not normally distributed, were log transformed. The detailed analyses of the behavioral and eye-tracking data are explained below.

2.4.1. *Behavioral data analyses*

Using the behavioral data, we first sought to replicate previous findings on the effect of subjective liking ratings on reaction times (RTs) and choice, and further investigate whether these effects depend on the type of the label with which the food items were presented (either TL or GDA). Second, we sought to establish the effect of TL labels on choosing the healthier food items. For these analyses we estimated mixed-effects regression models, and alternatively cluster-corrected regression models, where our behavioral dependent variables (*RTs*, *left choice*, *healthy choice*) were regressed against the difference in subjective rating between the two food items shown in a pair, interacted with the *TL label* dummy (1 = Yes, 0 = No).

2.4.2. *Eye-tracking data analyses*

Similar to the behavioral data, with the eye-tracking data, we first aimed to replicate previous findings on the relation between attention, value, and choice, and further investigate whether these relations change depending on the label format with which the food items were presented.

Second, we assessed whether TL labels attract more attention (**H1**), and whether their presence causes differences in attention allocation to the food items (**H2**). To do this, we regressed attention measures (*item dwell time*, *label dwell time*) against type of item/label (healthy 1 = Yes, 0 = No), and *item rating difference,* both interacted with *TL label* (1 = Yes, 0 = No).

Third, to test our **H3** hypothesis we assessed whether the relative contribution of attention (paid to the labels, paid to the food items) and subjective liking ratings on making a healthy food choice was different with TL labels. For this we estimated regression models with *healthy choice* (1 = Yes, 0 = No) as the dependent variable, and *item rating difference* (rating of the healthy food item– rating of the unhealthy food item), *total item dwell time difference* (total time spent looking at the healthy food item–total time spent looking at the unhealthy food item), *total label dwell time difference* (total time spent looking at the healthy label–total time spent looking at unhealthy label), all interacted with *TL label* (1 = Yes, 0 = No) as fixed effects. Finally, to capture these effects at the subject level, we examined the across-subject correlations between the average fraction of dwell time on the labels and the probability of choosing healthy items.

3. Results

In summary, we first show the behavioral effect of subjective liking ratings on food choice and RTs, and the effect of nutrition labels on making healthy food choices. Second, we show the effect of nutrition labels on the relation between gaze, value, and choice. Third, we show the effect of nutrition labels on attention allocation (**H1** and **H2**) and how this relates to food choice (**H3**).

3.1. *Behavioral data results*

To establish that participants' choices are responsive to their subjective liking ratings, we regressed *left choice* (1 = Yes, 0 = No), on *item rating difference* (rating of the food item on the left – rating of the food item on the right), *TL label* (1 = Yes, 0 = No), and their interaction. This mixed-effects logistic regression indicated that *item rating difference* significantly predicted food choice ($\beta = 0.54$, $z = 12.94$, $P < 10^{-16}$). However, there was a significant negative interaction between *TL label* and *item rating difference*, indicating that taste ratings were significantly less predictive of choice in the TL trials compared to the GDA trials ($\beta = -0.07$, $z = -1.98$, $P = .047$).

To assess whether TL labels increased the bias for choosing the healthier item, we performed cluster-corrected logistic regression with *healthy choice* (1 = Yes, 0 = No) as the dependent variable, *TL label* (1 = Yes, 0 = No), *item rating difference* (rating of the healthy food item – rating of the unhealthy food item), and their interaction as fixed effects. This analysis revealed a significant positive intercept ($\beta = 0.26$, $z = 2.25$, $P = .025$), which indicates a bias to choose the healthy item on GDA trials with a rating difference of zero (when the two items were liked same). The *TL label* coefficient was also significantly positive ($\beta = 0.40$, $z = 4.06$, $P = 10^{-5}$), indicating an increased bias to choose healthy food items when presented with TL labels. Interestingly, there was no significant interaction effect between *TL label* and *item rating difference* ($\beta = -0.017$, $z = -0.50$, $P = .62$), suggesting that subjective liking ratings had a similar effect on healthy choice in both the TL and the GDA trials (see Fig. 3a). When not controlling for subjective liking ratings, the bias to choose healthy was significant only in the presence of TL labels (Mixed-effects logistic regression results: $\beta_{\text{TL label}} = 0.3$, $z = 3.18$, $P = .001$; $\beta_{\text{intercept}} = -0.04$, $z = -0.37$, $P = .71$).

To assess whether participants were faster in the easy trials (trials that involved food items with larger difference in subjective ratings) and whether this was dependent on the type of the labels that were presented, we ran a mixed-effects regression with *log(RT)* as the dependent variable, *absolute item rating difference*, *TL label* (1 = Yes, 0 = No), and their interaction as fixed effects. This analysis revealed that, as seen in previous work, there was a significant negative effect of the *absolute item rating difference* on RTs ($\beta = -0.06$, $t = -9.12$, $P = 10^{-10}$), which means that easier choices were made significantly faster. The effect of *TL label* was also significant ($\beta = -0.052$, $z = -2.49$, $P = .016$), indicating that in the TL trials participants were significantly faster for a rating difference of zero. A significant interaction between *absolute item rating difference* and *TL label*, indicated that the effect of the liking ratings on RTs was reduced for the TL-labeled food items ($\beta = 0.013$, $t = 2.256$, $P = .031$). This suggests that taste was having less of an effect on the decision process in the presence of TL labels.

Looking again at RTs, one can see that the inverse-U-shaped curve, as a function of item rating difference, is shifted to the left for the TL trials (Fig. 3b). The peaks of these curves reveal participants' indifference points [32]. For the GDA labels the peak of the curve occurred at −1, indicating that the healthy item essentially gained 1 rating point for its healthiness. For the TL labels the peak occurred at −2 instead, doubling the advantage for the healthy item compared to the health advantage with GDA labels.

3.2. *Eye-tracking data results*

3.2.1. *Relationship between value, attention, and choice*

Our data indicated that as seen in previous studies [25], there was no tendency for participants to look at higher-rated food items first, nor was there a tendency to look at them longer. However, there was a tendency to choose the food items that were looked at last. These effects did not depend on the TL label (see **Supplemental Tables S1, S2 and S3** and **Supplemental Fig. S2**). Similarly, there was a significant tendency to choose the food items that were looked at more, independent of the label. Interestingly, while there was a tendency to choose the food items whose labels were looked at more, this effect was stronger in the presence of TL labels (see **Supplemental Table S4** and **Supplemental Fig. S3**).

3.2.2. *The effect of nutrition labels on attention (H1 & H2)*

To test our **H1** and **H2** hypotheses, we assessed the effect of TL label on the total dwells and on the individual dwells. Below we report the results on the individual dwells (excluding the final dwell in each trial), whereas the results on the total dwell times can be seen in **Supplemental Table S5** and **Supplemental Fig. S4**.

To test our **H1** hypothesis, we first counted the trials where the labels were looked at and the trials where labels were not looked at. Paired *t*-tests indicated that participants were more likely to look at TL labels compared to GDA labels (see **Supplemental Fig. S5**). More specifically, they did not look at

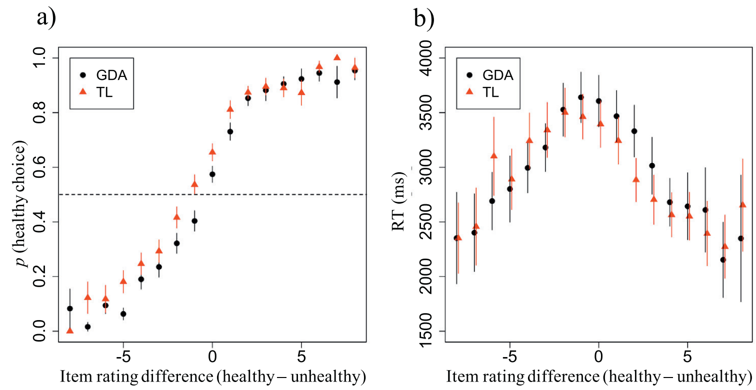

Fig. 3 – Effect of labels and subjective liking ratings on choices (a) and RTs (b). Data points are mean values with standard errors clustered by subject (*n* = 50). (a) Participants generally chose in line with their subjective liking ratings, choosing the healthier item when it was rated higher than the unhealthy item, and *vice-versa*. Across the rating-difference bins participants were consistently more likely to choose the healthy item with the TL labels and showed a healthy-choice bias of ~15% when otherwise indifferent between the items ($\beta_{\text{TL label}}$ = 0.40, z = 4.06, P = 10^{-5}). Effects are estimated using cluster-corrected logistic regression analyses. (b) Participants' indifference points were different for the two trial types. While for the GDA trials this point was at –1, for the TL trials this was at –2; indicating a doubled bias in favor of the healthy item in the TL trials compared to the GDA trials. GDA: guideline daily amount; TL: traffic light; RT: reaction time.

both labels (because they looked at no labels or they looked at only one label) in 54% of the GDA trials *vs.* 50% of the TL trials ($t_{(49)}$ = 2.31, P = .025), and looked at no labels in 43% of the GDA *vs.* 38% of TL trials ($t_{(49)}$ = 3.86, P = .0003). In the trials where participants did not look at the labels, RTs were significantly shorter (*M* = 1.71 s, *SD* = 1.01 s) than in the trials where the labels were looked at (*M* = 4.2 s, *SD* = 2.09 s; mixed-effects regression results: $\beta_{\text{label looked at}}$ = 0.73, t = 18.77, P < .0001). Additionally, in the trials where the labels were not looked at, there was a larger absolute item rating difference (see **Supplemental Fig. S6**). These findings suggest that participants generally relied first on the item ratings and only in close situations turned to the nutrition labels.

When considering the individual dwells to the labels, we saw that on average participants looked at TL labels (*M* = 412 ms, *SD* = 168 ms) less than GDA labels (*M* = 506 ms, *SD* = 199 ms). To assess whether these differences depended on the healthiness of the label (healthy label *vs.* unhealthy label), we regressed individual dwells to the labels (*log[label dwell time]*) on the healthiness of the label (*healthy label,* 1 = Yes, 0 = No), *TL label* (1 = Yes, 0 = No) and their interaction. These mixed-effects regression analyses indicated that there was no significant effect of the healthiness of the label (β = –0.023, z = –7.43, P = .16); this means that in the GDA trials there was no significant difference in dwell time between healthy and unhealthy labels (GDA unhealthy labels: *M* = 504 ms, *SD* = 214 ms; GDA healthy labels: *M* = 522 ms, *SD* = 208 ms). On the other hand, the effect of *TL label* was significant (β = –0.24, z = –7.54, P = 10^{-9}), indicating that participants spent less time looking at unhealthy TL labels. The same model revealed no significant interaction between *TL label* and *healthy label*, indicating no difference between healthy and unhealthy TL labels (β = 0.0006, z = 0.028, P = .98; TL-labeled unhealthy labels: *M* = 417 ms, *SD* = 183 ms; TL-labeled healthy labels: *M* = 410 ms, *SD* = 156 ms) (Fig. 4). An additional model with regressors for *current item rating*, *other item rating*, and *absolute item rating difference* yielded very similar results (see **Supplemental Table S6**).

When looking at the individual dwells to the food items, we saw that on average participants spent less time looking at the unhealthy food items (*M* = 512 ms, *SD* = 137 ms), than healthy food items (*M* = 523 ms, *SD* = 142 ms). To assess whether these differences depend on the presence of TL label (as stated in our **H2** hypothesis), we regressed the individual dwells to the food items (*log[item dwell item]*) on the healthiness of the food item (*healthy food*, 1 = Yes, 0 = No), *TL label* (1 = Yes, 0 = No) and their interaction. Mixed-effects regression analyses revealed a non-significant effect of the healthiness of the food item on the *log(item dwell time)* (β = 0.0085, z = 0.68, P = .5). This indicates that in the GDA trials, there was no significant difference between how much participants looked at the healthy *vs.* unhealthy food items (GDA labeled healthy items: *M* = 519 ms, *SD* = 145 ms; GDA labeled unhealthy items: *M* = 520 ms, *SD* = 143 ms). The same analyses revealed that the effect of *TL label* was significant, indicating that in the TL trials, participants spent less time looking at the unhealthy food items (β = –0.033, z = –2.58, P = .01). There was a significant interaction between *TL label* and *healthy food* (β = 0.047, z = 2.77, P = .008; TL-labeled healthy items: *M* = 526 ms, *SD* = 143 ms; TL-labeled unhealthy items: *M* = 504 ms, *SD* = 135 ms) (see Fig. 4). An additional model with regressors for *current item rating*, *other item rating*, and *absolute item rating difference*, yielded very similar results (see **Supplemental Table S6**). Altogether, these results indicate that in the presence of TL labels, participants dwelled less on the unhealthy items.

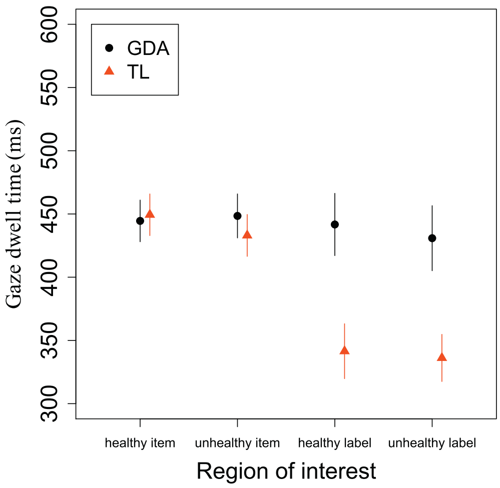

Fig. 4 – Effects of nutrition labels on the attention paid to the food items and the labels. Data points represent median individual gaze dwell times with standard errors clustered by subject (n = 50). In this figure the final fixation of each trial is excluded. Participants spent significantly more time looking at the healthy food items in the TL trials ($\beta_{TL\ label\ x\ healthy\ food}$ = 0.047, z = 2.77, P = .008). Similarly, participants spent substantially less time looking at the TL labels relative to the GDA labels ($\beta_{TL\ label}$ = −0.24, z = −7.54, P = 10^{-9}). Effects are estimated using mixed-effects regression analyses. GDA: guideline daily amount; TL: traffic light.

Table 3 – Relative contribution of subjective value and attention on the probability of making a healthy choice

DV: Healthy choice (1 = Yes, 0 = No)		
	Estimate (SE)	*Estimate (SE)*
Intercept	**0.25** *(0.12)**	−0.13 *(0.13)*
TL label	**0.35** *(0.10)****	0.15 *(0.11)*
Item rating difference	**0.51** *(0.03)****	**0.52** *(0.03)****
Total item dwell time difference	**1.40** *(0.13)****	**1.38** *(0.14)****
Total label dwell time difference	**0.71** *(0.19)****	**0.48** *(0.14)****
Look at healthy label		**1.95** *(0.33)****
Look at unhealthy label		**−1.20** *(0.33)****
TL label × Item rating difference	**−0.037** *(0.03)****	−0.01 *(0.04)*
TL label × Total item dwell time difference	**−0.32** *(0.14)**	**−0.36** *(0.15)**
TL label × Total label dwell time difference	**0.42** *(0.19)**	**0.38** *(0.18)**
TL label × Look at healthy label		0.11 *(0.28)*
TL label × Look at unhealthy label		0.27 *(0.31)*

DV, dependent variable; *SE*, standard error of the estimate; TL, traffic light.
Values represent estimates with their corresponding standard errors (n = 50). The estimates were calculated using logistic regression with cluster corrected standard errors. Significant effects are presented in bold. Significance is assessed using z-test of coefficients. Differences in ratings are calculated by subtracting the rating of the unhealthy food item from the rating of the healthy food item. Similarly, dwell time differences are calculated by subtracting the time spent looking at the unhealthy food item/label, from the time spent looking at the healthy food item/label. ***P < .001, *P < .05.

3.2.3. The effect of nutrition labels on the relation between attention and healthy food choice (H3)

To test our **H3** hypothesis, and to tease apart the effect of attention paid to the items, attention paid to the labels, and subjective liking ratings on food choice, we regressed *healthy choice* (1 = Yes, 0 = No) on *total item dwell time difference* (total time spent looking at the healthy food item – total time spent looking at the unhealthy food item), *total label dwell time difference* (time spent looking at the healthy label – time spent looking at the unhealthy label), *item rating difference* (rating of the healthy food item – rating of the unhealthy food item), *TL label* (1 = Yes, 0 = No), and its interaction with the other variables. This cluster-corrected regression analyses revealed that there was a significant bias for choosing the healthy item, as indicated by a significant positive intercept (β = 0.25, z = 2.13, P = .03). A significant effect of *TL label* indicated that this bias was higher in the presence of TL labels (β = 0.35, z = 3.44, P = .0006; for the full model results see Table 3). The interaction between *TL label* and *total item dwell time difference* was significant (β = −0.32, z = −2.23, P = .026), indicating that in the presence of TL labels the effect of dwell time on food choice is reduced. The interaction between *TL label* and *total label dwell time difference* was also significant (β = 0.42, z = 2.17, P = .03), indicating that TL labels increase the effect of dwell time on the labels on choice. Looking at the correlation between fraction dwell time on the labels and the probability of making a healthy choice also supports this finding (Fig. 5). The effect of *TL label*, and its interaction with *total item dwell time difference* was still significant even when controlling for the last fixation location (see **Supplemental Table S7**).

To check whether the effect of TL labels on healthy food choice might come solely from them being more likely to be seen, we ran the same regression analysis as above, with additional dummy variables for whether a nutrition label was looked at or not. More specifically, we included *healthy label looked at* (1 = Yes, 0 = No), and *unhealthy label looked at* (1 = Yes, 0 = No), in addition to the attention measures and subjective liking ratings. This analysis indicated that indeed, when accounting for whether a label is looked at or not, the effect of *TL label* was no longer significant (β = 0.15, z = 1.38, P = .17). However, the interaction between *TL label* and *total label dwell time difference* (β = 0.38, z = 2.14, P = .03), as well the interaction between *TL label* and *total item dwell difference* (β = −0.36, z = −2.43, P = .02) were again significant (for the full model results see Table 3). Overall, these analyses reveal that TL labels exert their influence by increasing the effect of attention to labels and decreasing the effect of attention to foods, on choice. Furthermore, in this study, we did not observe any differences between males and females in how much they looked at the labels or how much they were influenced by the labels in their choices (**Supplemental Fig. S7** and **Supplemental Table S8**).

4. Discussion

In this study, we aimed to assess possible mechanisms of how TL labels encourage healthy food choice. We found that TL

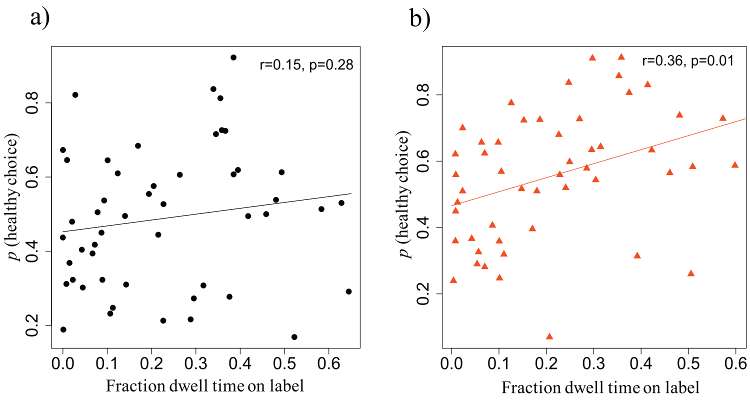

Fig. 5 – Probability of making a healthy choice as a function of the fraction dwell time on the (a) GDA and (b) TL nutrition labels. Each dot is the data from one participant (*n* = 50). Pearson correlation analyses were used to assess the strength of the correlations. GDA: guideline daily amount; TL: traffic light.

labels induce more attention to healthy food products and increase the choice effect of attention paid to the labels while decreasing the choice effect of attention paid to the foods. These findings support our **H2** and **H3** hypotheses. Surprisingly, our results do not support the hypothesis that TL labels will attract more gaze (**H1**); to the contrary they suggest that even though TL labels are more likely to be looked at, they attract shorter dwells.

As shown in previous studies, we find that participants' food choices are explained by subjective ratings of taste [2,21,33]. Interestingly, when considering the labels with which the food items were presented, we find that the effect of subjective ratings on food choice is significantly reduced when the items are presented with the TL labels compared to GDA labels. While decreasing the effects of subjective liking ratings and decreasing the RTs, the presence of TL labels induced a significantly higher bias to choose the healthier food item compared with GDA labels. This is in line with previous studies that have shown that salient labels increase the frequency of healthy choices in the lab [11,12,21], and also increase the sales of healthy food products in different populations [15,19,34].

As hypothesized before [21], our results show that indeed, salient labels induce shifts in attention allocation. More specifically, we found that in the presence of TL labels, participants looked at healthy items significantly more than at the unhealthy items, while this difference was not apparent in the presence of GDA labels. This shift in attention allocation was associated with an increased bias to choose healthy in the TL trials but not in the GDA trials. Together these findings support the hypothesis that in the presence of TL labels, healthy food items get an advantage in the evidence gathering and value comparison process.

In addition to the effects of nutrition labels on the attention paid to the food items, the presence of the labels attracts attention to the nutrition information related to the respective foods. In line with previous studies, our results support that TL labels are more likely to be looked at, possibly due to their physical features, including colors in addition to numerical information [22,35]. However, even though they were more likely to be looked at, compared to the GDA labels TL labels attracted less dwell time overall. Even though attending to a stimulus indicates that participants are gathering evidence on that particular option, it does not necessarily mean that this gathered evidence is utilized correctly in the value computation processes. It could just as well reflect the fact that due to their numeric features, extracting information from the GDA labels requires more cognitive effort [36,37]. Indeed, when looking at how attention paid to the labels relates to choice, we found that in the GDA trials the attention paid to the label and the attention paid to the food item had a similar effect on the food choice. On the other hand, in the TL trials, the attention paid to the label had a higher impact on the food choice, compared to the attention paid to the food item. This indicates that the effect of the TL labels was to boost the effect of dwell time on the labels but shrink the effect of dwell time on the items. Furthermore, when looking at across-subject correlations between the dwell time on the label and the probability of making a healthy choice, we saw that for the TL labels this correlation was stronger than for the GDA labels, supporting the idea that the information acquired from the TL labels influenced the choices more.

Interestingly, when accounting for whether a label was looked at all, in addition to the other attention measures (item and label dwell times), and the subjective liking ratings, the main effect of the TL labels on the probability of choosing healthy disappeared, but the significant interactions of TL label with label dwell time and item dwell time remained. Altogether, these results suggest that TL labels operate by increasing the likelihood of the nutrition information to be looked at, by increasing the effect of dwell times on the labels, and by decreasing the effect of dwell times on the items.

There are some limitations to the present study. First, in this study, the nutrition labels were shown separately from the food items (below) and were larger than the ones usually found in packaging. We designed the study this way so that we could clearly distinguish between the consideration given to the food items and labels. While this presentation resembles online shopping using digital displays/touchscreens where nutrition labels can be magnified, it may not completely reflect the allocation of attention to food items and nutrition labels in brick-and-mortar shops. In these shopping environments, nutrition labels are smaller and are located on the actual packaging of the food products—which can make them less salient. While this might cause one to question whether TL labels would have the same effect in the field, we do know that lab experiments using more realistic stimuli also provide evidence that color-coded labels are more effective than purely numerical labels in promoting healthy food choices [12,16]. It is possible that by increasing the size of the labels in our study we may have in fact underestimated the advantage of TL labels over GDA labels, since TL labels have the advantage of standing out on the package and also being easier to decipher for those who have trouble reading small print. Thus, TL labels may have an even bigger advantage in brick-and-mortar shops. On the one hand, there is indeed evidence from field studies that these color-coded labels are effective [10,13,15,19,20,34]. On the other hand, bigger nutrition labels would be more salient [35], and likely more effective. Increasing the size of nutrition labels is thus an interesting direction to pursue in future research. To further increase the generalizability of these findings, future studies might also consider investigating these effects when combining eye-tracking with virtual reality setups, which might produce a more realistic shopping environment [38].

Second, since the aim of the study was to investigate the effects of TL labels on attention, the two label formats were not pitted against each other in any trials; participants had to always choose between food items with the same label format. There were no choices between a food item with a TL label and a food item with a GDA label. It would be interesting to know how subjects treat a GDA labeled food when compared directly against a TL-labeled food.

Third, by design, in this study the food items shown in a pair included one healthy (no red lights, and minimum one green light), and one unhealthy (minimum one red light, maximum one green light) item. We did not use a continuous measure of the healthiness difference between the food products in a pair. Future work could additionally try to model how attention and label type interact with the relative degree of healthiness, rather than using our rough healthy *vs.* unhealthy dichotomy. On a similar note, while we included a semi-continuous WTP task to assess participants' preferences for the presented food items, we did not use this measure in our analyses as it was likely contaminated by the preceding binary food choice task [29]. This aspect of the design makes it difficult to investigate the downstream effects of nutrition labels on WTP. While this was not the aim of our study, future research aspiring to study such influences should avoid eliciting WTP after a choice task.

Fourth, while our sample consisted of both male and females, the number of female participants was much higher (n = 39) than that of the male participants (n = 11). This could be important to note especially since previous studies have shown that there are differences between males and females in how much nutrition labels are considered when making food choices [8,39,40]. In this study, we did not observe any differences between males and females in how much they looked at the labels or how much they were influenced by the labels in their choices as presented in the results. However, these results should be considered with caution, given the small number of male participants. In particular, our various coefficient estimates are likely closer to the female values than to the male values, if there are differences between them. To assess possible gender differences, future studies should consider recruiting similar numbers of male and female participants.

Last, while we assessed participants' subjective ratings of the food products used in the binary choice task, we did not assess several other factors that could have influenced their food choice behavior and their attitude towards the nutrition labels, including participants' individual characteristics, as well as interindividual differences in self-control, and eating styles [41-44]. These are interesting avenues for future research.

Overall, our findings provide novel insights on the mechanisms underlying the effect of nutrition labels on food choice, which have practical implications. The usage of nutrition labels is among the most promising public policy strategies to promote healthy choices [8,33]. Advancing knowledge about how these labels influence food choices will hopefully lead to more efficient labels. In this context, our study supports the use of more salient labels instead of purely numerical labels, since they are more likely to be looked at, increase the use of the nutritional information provided on the label, and consequently affect food choice.

Supplemental materials

Supplemental materials to this article can be found online at https://doi.org/10.1016/j.nutres.2020.06.013.

Acknowledgment

The authors would like to thank all the participants that participated in the study, Wolf Harmening and Ulrich Ettinger for their technical support, and Jana Paus for research assistance. This work was supported by the BMBF grant DietBB (01EA1410B and 01E1809B) and NSF grant 1554837 to IK. The authors declare no conflicts of interest.

REFERENCES

[1] World Health Organization. Obesity and overweight. http://www.who.int/mediacentre/factsheets/fs311/en/; 2020. [Accessed 25 April 2020].
[2] Rangel A. Regulation of dietary choice by the decision-making circuitry. Nat Neurosci. 2013;16:1717–24https://doi.org/10.1038/nn.3561.
[3] Rangel A, Camerer C, Montague PR. A framework for studying the neurobiology of value-based decision making. Nat Rev Neurosci. 2008;9:545–56. https://doi.org/10.1038/nrn2357.
[4] Enax L, Krapp V, Piehl A, Weber B. Effects of social sustainability signaling on neural valuation signals and

taste-experience of food products. Front Behav Neurosci. 2015;9:247. https://doi.org/10.3389/fnbeh.2015.00247.
[5] Hare TA, Malmaud J, Rangel A. Focusing attention on the health aspects of foods changes value signals in vmPFC and improves dietary choice. J Neurosci. 2011;31:11077–87. https://doi.org/10.1523/JNEUROSCI.6383-10.2011.
[6] Hare TA, Camerer CF, Rangel A. Self-control in decision-making involves modulation of the vmPFC valuation system. Science. 2009;324:646–8. https://doi.org/10.1126/science.1168450.
[7] Enax L, Hu Y, Trautner P, Weber B. Nutrition labels influence value computation of food products in the ventromedial prefrontal cortex. Obesity. 2015;23:786–92. https://doi.org/10.1002/oby.21027.
[8] Campos S, Doxey J, Hammond D. Nutrition labels on pre-packaged foods: a systematic review. Public Health Nutr. 2011;14:1496–506. https://doi.org/10.1017/S1368980010003290.
[9] Borgmeier I, Westenhoefer J. Impact of different food label formats on healthiness evaluation and food choice of consumers: a randomized-controlled study. BMC Public Health. 2009;9:184. https://doi.org/10.1186/1471-2458-9-184.
[10] Gorton D, Ni Mhurchu C, Chen MH, Dixon R. Nutrition labels: a survey of use, understanding and preferences among ethnically diverse shoppers in New Zealand. Public Health Nutr. 2009;12:1359–65. https://doi.org/10.1017/S1368980008004059.
[11] Bauer JM, Reisch LA. Behavioural insights and (un)healthy dietary choices: a review of current evidence. J Consum Policy. 2019;42:3–45. https://doi.org/10.1007/s10603-018-9387-y.
[12] Bialkova S, Grunert KG, Juhl HJ, Wasowicz-Kirylo G, Stysko-Kunkowska M, van Trijp HCM. Attention mediates the effect of nutrition label information on consumers' choice. Evidence from a choice experiment involving eye-tracking. Appetite. 2014;76:66–75. https://doi.org/10.1016/j.appet.2013.11.021.
[13] Hawley KL, Roberto CA, Bragg MA, Liu PJ, Schwartz MB, Brownell KD. The science on front-of-package food labels. Public Health Nutr. 2013;16:430–9. https://doi.org/10.1017/S1368980012000754.
[14] Jones G, Richardson M. An objective examination of consumer perception of nutrition information based on healthiness ratings and eye movements. Public Health Nutr. 2007;10:238–44. https://doi.org/10.1017/S1368980007258513.
[15] Thorndike AN, Sonnenberg L, Riis J, Barraclough S, Levy DE. A 2-phase labeling and choice architecture intervention to improve healthy food and beverage choices. Am J Public Health. 2012;102:527–33. https://doi.org/10.2105/AJPH.2011.300391.
[16] van Herpen E, van Trijp HCM. Front-of-pack nutrition labels. Their effect on attention and choices when consumers have varying goals and time constraints. Appetite. 2011;57:148–60. https://doi.org/10.1016/j.appet.2011.04.011.
[17] Hersey JC, Wohlgenant KC, Arsenault JE, Kosa KM, Muth MK. Effects of front-of-package and shelf nutrition labeling systems on consumers. Nutr Rev. 2013;71:1–14. https://doi.org/10.1111/nure.12000.
[18] Cecchini M, Warin L. Impact of food labelling systems on food choices and eating behaviours: a systematic review and meta-analysis of randomized studies. Obes Rev. 2016;17:201–10. https://doi.org/10.1111/obr.12364.
[19] Sonnenberg L, Gelsomin E, Levy DE, Riis J, Barraclough S, Thorndike AN. A traffic light food labeling intervention increases consumer awareness of health and healthy choices at the point-of-purchase. Prev Med. 2013;57:253–7. https://doi.org/10.1016/j.ypmed.2013.07.001.
[20] Trudel R, Murray KB, Kim S, Chen S. The impact of traffic light color-coding on food health perceptions and choice. J Exp Psychol Appl. 2015;21:255–75. https://doi.org/10.1037/xap0000049.
[21] Enax L, Krajbich I, Weber B. Salient nutrition labels increase the integration of health attributes in food decision-making. Judgm Decis Mak. 2016;11:460–71.
[22] Graham DJ, Orquin JL, Visschers VHM. Eye tracking and nutrition label use: a review of the literature and recommendations for label enhancement. Food Policy. 2012;37:378–82. https://doi.org/10.1016/j.foodpol.2012.03.004.
[23] Fenko A, Nicolaas I, Galetzka M. Does attention to health labels predict a healthy food choice? An eye-tracking study. Food Qual Prefer. 2018;69:57–65. https://doi.org/10.1016/j.foodqual.2018.05.012.
[24] Graham DJ, Jeffery RW. Predictors of nutrition label viewing during food purchase decision making: an eye tracking investigation. Public Health Nutr. 2012;15:189–97. https://doi.org/10.1017/S1368980011001303.
[25] Krajbich I. Accounting for attention in sequential sampling models of decision making. Curr Opin Psychol. 2019;29:6–11. https://doi.org/10.1016/j.copsyc.2018.10.008.
[26] CIAA (EU Food and Drink Confederation). GDAs: Guideline Daily Amounts, https://www.fooddrinkeurope.eu/S=0/publication/gdas-guideline-daily-amounts-the-facts-your-choice/; 2009 [accessed 20 September 2019].
[27] Department of Health, Food Standards Agency (FSA). Guide to creating a front of pack (FoP) nutrition label for pre-packed products sold through retail outlets, https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/566251/FoP_Nutrition_labelling_UK_guidance.pdf; 2016 [accessed 20 September 2019].
[28] Spinelli S, Masi C, Zoboli GPP, Prescott J, Monteleone E. Emotional responses to branded and unbranded foods. Food Qual Prefer. 2015;42:1–11. https://doi.org/10.1016/j.foodqual.2014.12.009.
[29] Chen MK, Risen JL. How choice affects and reflects preferences: revisiting the free-choice paradigm. J Pers Soc Psychol. 2010;99:573–94. https://doi.org/10.1037/a0020217.
[30] R Core Team. R: A language and environment for statistical computing. Version 3.6.1[software]. R Foundation for Statistical Computing. 2019 [cited September 2019]. Available from: http://www.R-project.org/.
[31] R Studio Team. RStudio: Integrated Development for R. Version 1.2.1335 [software]. RStudio Inc. 2019 [cited September 2019]. Available from: https://rstudio.com.
[32] Konovalov A, Krajbich I. Revealed strength of preference: inference from response times. Judgm Decis Mak. 2019;14:381–94.
[33] Hawkes C, Smith TG, Jewell J, Wardle J, Hammond RA, Friel S, et al. Smart food policies for obesity prevention. Lancet. 2015;385:2410–21. https://doi.org/10.1016/S0140-6736(14)61745-1.
[34] Levy DE, Riis J, Sonnenberg LM, Barraclough SJ, Thorndike AN. Food choices of minority and low-income employees: a cafeteria intervention. Am J Prev Med. 2012;43:240–8. https://doi.org/10.1016/j.amepre.2012.05.004.
[35] Bialkova S, van Trijp H. What determines consumer attention to nutrition labels? Food Qual Prefer. 2010;21:1042–51. https://doi.org/10.1016/j.foodqual.2010.07.001.
[36] Muller L, Prevost M. What cognitive sciences have to say about the impacts of nutritional labelling formats. J Econ Psychol. 2016;55:17–29. https://doi.org/10.1016/j.joep.2016.01.005.
[37] Bialkova S, van Trijp HCM. An efficient methodology for assessing attention to and effect of nutrition information displayed front-of-pack. Food Qual Prefer. 2011;22:592–601. https://doi.org/10.1016/j.foodqual.2011.03.010.
[38] Meißner M, Pfeiffer J, Pfeiffer T, Oppewal H. Combining virtual reality and mobile eye tracking to provide a naturalistic experimental environment for shopper research. J Bus Res. 2019;100:445–58. https://doi.org/10.1016/j.jbusres.2017.09.028.

[39] Cannoosamy K, Jeewon R. A critical assessment of nutrition labelling and determinants of its use and understandng. J Nutr Educ Behav. 2014;46:334–40. https://doi.org/10.1016/j.jneb.2014.03.010.

[40] Kim SY, Nayga RM, Capps O. Food label use, self-selectivity, and diet quality. J Consum Aff. 2001;35:346–63. https://doi.org/10.1111/j.1745-6606.2001.tb00118.x.

[41] Keller C, Siegrist M. Successful and unsuccessful restrained eating. Does dispositional self-control matter? Appetite. 2014;74:101–6. https://doi.org/10.1016/j.appet.2013.11.019.

[42] Keller C, Siegrist M. Does personality influence eating styles and food choices? Direct and indirect effects. Appetite. 2015;84:128–38. https://doi.org/10.1016/j.appet.2014.10.003.

[43] Blechert J, Goltsche JE, Herbert BM, Wilhelm FH. Eat your troubles away: Electrocortical and experiential correlates of food image processing are related to emotional eating style and emotional state. Biol Psychol. 2014;96:94–101. https://doi.org/10.1016/j.biopsycho.2013.12.007.

[44] Miller LMS, Cassady DL. The effects of nutrition knowledge on food label use. A review of the literature. Appetite. 2015;92:207–16. https://doi.org/10.1016/j.appet.2015.05.029.

3.3. Publication 3: "Nutrition claims influence expectations about food attributes, attenuate activity in reward-associated brain regions during tasting, but do not impact pleasantness"

Check for updates

Received: 15 June 2022 | Revised: 15 September 2022 | Accepted: 3 November 2022

DOI: 10.1002/brb3.2828

Brain and Behavior Open Access WILEY

ORIGINAL ARTICLE

Nutrition claims influence expectations about food attributes, attenuate activity in reward-associated brain regions during tasting, but do not impact pleasantness

Qëndresa Rramani[1,2] | Youssef Barakat[1,2] | George Jacob[1,2] | Kathrin Ohla[3,4] | Shirley Xue Li Lim[3,5] | Doris Schicker[6,7] | Jessica Freiherr[6,7] | Elodie Saruco[8] | Burkhard Pleger[8] | Bernd Weber[1,2] | Johannes Schultz[1,2]

[1]Center for Economics and Neuroscience (CENs), University of Bonn, Bonn, Germany

[2]Institute of Experimental Epileptology and Cognition Research (IEECR), University of Bonn, Bonn, Germany

[3]NutriAct-Competence Cluster Nutrition Research Berlin-Potsdam, Nuthetal, Germany

[4]Firmenich SA, Satigny, Switzerland

[5]Cognitive Neuroscience (INM-3), Institute of Neuroscience and Medicine, Research Center, Jülich, Germany

[6]Sensory Analytics & Technologies, Fraunhofer Institute for Process Engineering and Packaging IVV, Freising, Germany

[7]Department of Psychiatry and Psychotherapy, Friedrich-Alexander-Universität Erlangen-Nürnberg, Erlangen, Germany

[8]Department of Neurology, BG University Clinic Bergmannsheil, Ruhr-University Bochum, Bochum, Germany

Correspondence
Qëndresa Rramani, Center for Economics and Neuroscience (CENs), University of Bonn, Bonn, Germany.
Email: rramani@uni-bonn.de

Bernd Weber and Johannes Schultz share last authorship.

This work was supported by the Federal Ministry of Education and Research (BMBF) grant DietBB (01E1809B). DS and JF were partially supported by the BMBF grant enable (01EA1807G); BP and ES were partially supported by the BMBF grant nutriCARD (01E01001). BP was further supported by the IFB Adiposity Diseases and the German Research Foundation (DFG), within the framework of the CRC 1052 Obesity Mechanisms, project TP 6 and the CRC 874 Integration and Representation of Sensory Processes, project TP10.

Abstract

Introduction: Nutrition claims are one of the most common tools used to improve food decisions. Previous research has shown that nutrition claims impact expectations; however, their effects on perceived pleasantness, valuation, and their neural correlates are not well understood. These claims may have both intended and unintended effects on food perception and valuation, which may compromise their effect on food decisions.

Methods: We investigated the effects of nutrition claims on expectations, perceptions, and valuation of milk-mix drinks in a behavioral ($n = 110$) and an fMRI ($n = 39$) study. In the behavioral study, we assessed the effects of a "fat-reduced" and a "protein-rich" nutrition claim on expected and perceived food attributes of otherwise equal food products. In the fMRI study, we investigated the effect of a "protein-rich" claim on taste pleasantness perception and valuation, and on their neural correlates during tasting and swallowing.

Results: We found that both nutrition claims increased expected and perceived healthiness and decreased expected but not perceived taste pleasantness. The "protein-rich" claim increased expected but not perceived satiating quality ratings, while the "fat-reduced" claim decreased both expected and perceived satiating quality ratings. In the absence *vs.* presence of the "protein-rich" claim, we observed an increased activity in a cluster extending to the left nucleus accumbens during tasting and an increased functional connectivity between this cluster and a cluster in right middle frontal gyrus during swallowing.

Conclusion: Altogether, we found that nutrition claims impacted expectations and attenuated reward-related responses during tasting but did not negatively affect perceived pleasantness. Our findings support highlighting the presence of nutrients with positive associations and exposure to foods with nutrition claims to increase their acceptance. Our study offers insights that may be valuable in designing and optimizing the use of nutrition claims.

KEYWORDS
expectations, fMRI, food attributes, nutrition claims, taste pleasantness perception, valuation

1 | INTRODUCTION

Increasing rates of obesity across all age groups and all around the world have deemed the understanding of eating behavior and more particularly food-related decisions to be an important global health issue (World Health Organization, 2021). Considering the complexity and the burden of obesity and related conditions, public health policies have become increasingly invested in prevention strategies (Gearhardt et al., 2012; Gortmaker et al., 2011; Lyn et al., 2019; Malik et al., 2013). Among the most common strategies in this regard is promoting healthy eating by providing more accessible information on the nutritional and health value of foods in the form of nutrition labels and claims. On one hand, the presence of nutrition labels has been shown to help consumers identify and choose healthier alternatives (Cecchini & Warin, 2016; Hawkes et al., 2015; Hersey et al., 2013; Williams, 2005). On the other hand, different nutrition and health claims have also been shown to have unintended effects on expectations, perceptions, and consumption experience—which has raised the concern that such marketing strategies may often perpetuate unhealthy eating patterns (Chandon & Wansink, 2012; Cornil et al., 2022). Understanding the effects and the mechanisms through which these effects are exerted is thus crucial in optimizing the use of nutrition labels and claims as marketing strategies for food items.

Nutrition claims indicate the presence, absence, and/or level of a certain nutrient in a food product. These claims are particularly interesting when used in novel foods, where marketing strategies may have an exceptionally important impact on consumers' acceptance of these products. The effects of nutrition claims on food preference and choice are not completely understood, although it is supported that they in general increase the expected and perceived healthiness of food products (Nobrega et al., 2020; Oostenbach et al., 2019; Prada et al., 2021; van Trijp & van der Lans, 2007; Williams, 2005). In this context, nutrition claims are unique in the sense that they provide information about the contents of a food product, *i.e.*, basic attributes, and also elicit expectations about more abstract attributes, such as the healthiness of a food product (Rangel, 2013). While an enhanced healthiness awareness may motivate consumers to make healthier choices (Chan et al., 2005; Hare et al., 2011; Sonnenberg et al., 2013), it may also compromise expectations of other attribute qualities (known as "health halo" effects[1]). For instance, it has been shown that participants consume more of the same food when labeled as "low-fat" (*vs.* conventional), possibly due to modulated expectations and perception of healthiness and satiating quality (Belei et al., 2012; Chan et al., 2005; Wansink & Chandon, 2006). Similar effects have been reported regarding taste pleasantness, where the presence of a claim indicating lower fat content has been shown to decrease the expected, and even, although not always, perceived taste pleasantness (Levin & Gaeth, 1988; Ng et al., 2011; Norton et al., 2013; Okamoto & Dan, 2013; Piqueras-Fiszman & Spence, 2015). This is especially important since experienced taste pleasantness is among the most important determinants of future decisions upon encounter with the same or similar food products (Mela, 2001; Piqueras-Fiszman & Spence, 2015; Rangel, 2013).

Taste pleasantness has been shown to be affected by several external contexts (Grabenhorst et al., 2008; Piqueras-Fiszman & Spence, 2015; Plassmann et al., 2008; Schmidt et al., 2017; Spence, 2015). Such contexts have been shown to modulate not only behavioral preference but also activity in brain regions associated with taste processing and taste pleasantness perception (Grabenhorst et al., 2008; Ng et al., 2011; Piqueras-Fiszman & Spence, 2015). For instance, Grabenhorst et al. (2008) found that perceived taste pleasantness of the same solution differed depending on whether that solution was presented as "monosodium-glutamate," "rich and delicious taste," "rich and delicious flavor," or "boiled vegetable water." These cognitive-level manipulations modulated activity in regions associated with taste and reward processing such as the pregenual cingulate cortex, ventral striatum (vS), and orbitofrontal cortex (OFC) (Grabenhorst et al.,

[1] "Health halo" effects occur when the perceived and/or expected healthiness of a product generalizes to the other qualities of that product and discourages consumers to seek further information about these other qualities or characteristics. For instance, a low-fat product may be considered as healthier but also as having less calories by default, even though this may not always be the case.

2008). Similarly, perceived taste pleasantness and its neural representation can be enhanced by cues such as price (Plassmann et al., 2008; Schmidt et al., 2017), familiar brands (McClure et al., 2004), and labeling (Enax et al., 2015b; Sörqvist et al., 2013). Such effects on perceived pleasantness are argued to rely on the expectations that these cues elicit (Okamoto & Dan, 2013; Plassmann & Weber, 2015). In this context, Schmidt et al. (2017) found that activity in the brain valuation system (vS, ventromedial prefrontal cortex–vmPFC) was higher when anticipating the same wine presented as more expensive than when presented as less expensive; these differences in the activity of the brain valuation system during anticipation were related to differences in brain activity during taste valuation of the same wines.

Whether and how expectations relate to perception in the context of nutrition claims remains to be investigated. Nutrition claims may elicit different expectations about several attributes, which may, in turn, have different impacts on perceived taste pleasantness, valuation, and choice. For instance, highlighting the healthiness of a food product may negatively impact expected and perceived taste pleasantness; *i.e.*, tasty food is often considered to be less healthy and vice versa (so-called unhealthy-tasty intuition; see Raghunathan et al., 2006). In line with this, we have previously shown that highlighting healthiness aspects of food via salient labeling increases the weight of healthiness and decreases the weight of taste pleasantness in the decision process via attentional shifts (Enax et al., 2016; Rramani et al., 2020). Moreover, it has been shown that directing attention to healthiness of food via overt instructions (Hare et al., 2011) or via salient labeling (Enax et al., 2015a) increases the behavioral and neural correlates of healthy food items' value. These effects were linked to an increased connectivity between vmPFC and dorsolateral prefrontal cortex (dlPFC), which may reflect the integration of healthiness in the valuation process. However, whether healthiness expectations about a food product modulate perceived taste pleasantness, valuation, and their neural correlates remains unclear.

Considering that cues may direct attention to aspects of foods such as healthiness (Enax et al., 2016; Rramani et al., 2020), which may impact valuation (Enax et al., 2015a; Hare et al., 2011) and perceived taste pleasantness (Grabenhorst & Rolls, 2008; van Rijn et al., 2018), we hypothesized that nutrition claims may (i) influence expectations about food attributes, (ii) modulate perceived taste pleasantness, and (iii) impact valuation of food. We tested these hypotheses in a behavioral (Study 1) and an fMRI study (Study 2). In Study 1, we assessed how nutrition claims affect expectations and perceptions of taste pleasantness, healthiness, and satiating quality. Moreover, we compared the effects of a claim that emphasizes reduction of a negative attribute ("fat-reduced") with those of a claim emphasizing the increase of a positive attribute ("protein-rich"). In Study 2, we tested whether nutrition claims modulate perceived taste pleasantness and valuation at the behavioral and at the neural level. Specifically, we tested whether activity in brain regions associated with taste pleasantness and valuation (vmPFC, vS, dlPFC, OFC) during tasting and swallowing is modulated by the presence of nutrition claims. Since in Study 1 we did not find different effects of both claims on pleasantness, in Study 2 we only tested one claim. More specifically, we only tested the "protein-rich" claim, considering the scarcity of research on protein-related claims despite an increase in demand, production, and consumption of protein-enriched foods in the last decades (Wilson, 2019).

2 | STUDY 1 (BEHAVIORAL STUDY)

2.1 | Material and methods

2.1.1 | Participants

Participation in the study was voluntary, and participants were paid a €10 flat fee for their participation. For this study, we invited 113 participants of which three were excluded due to technical problems. Participants were invited via the hroot database (Bock et al., 2014) of the BonnEconLab. Registration in this database is voluntary and open to anyone. The final sample consisted of 110 participants (M_{age} = 23.66, SD_{age} = 3.25 years old; 67 women). Participants were asked to get around 6–8 h sleep the night before the experiment (indicated sleep hours M = 7.56, SD = 0.78 h) and to not eat 3 h before the experiment (indicated hours before the last meal M = 5.12, SD = 3.71 h; perceived hunger level on a 10-point scale M = 5.42, SD = 2.31). We recruited only participants who liked milk-mix drinks, had no neurological/psychiatric/psychological/metabolic conditions, no current upper-respiratory infection, no food allergies, no intolerances, no conditions known to affect metabolism, and with a Body Mass Index (BMI) between 17.5 and 30 kg/m^2 (M_{BMI} = 24.08, SD_{BMI} = 2.39 kg/m^2, calculated by self-reported weight and height).

2.1.2 | Study design

Data collection took place at the BonnEconLab at the University of Bonn, Germany. Upon arrival in the lab, participants were randomly assigned to either the fat-claim or protein-claim conditions. In total, 57 participants were assigned to the protein-claim condition and 53 were assigned to the fat-claim condition. The experiment comprised four main parts. In the first part, participants completed a survey containing questions assessing task comprehension, sociodemographic questions, and questions assessing baseline levels of hunger (on a 10-point scale scale; 1 = not at all, 10 = very much), hours of sleep on the night before the experiment, and emotional valence and arousal (using the corresponding Self-Assessment Manikin subscales from Bradley and Lang, 1994). There were no significant differences between groups in terms of age, BMI, baseline hunger, indicated hours of sleep, and emotional arousal and valence. There were also similar number of men and women assigned to each condition (see Supplementary Table S1).

Next, they were given information[2] about the meaning of "fat-reduced"/"protein-rich" claims and were asked to rate their expecta-

[2] This information was given in written form as part of the instructions, and was taken from the "Regulation on nutrition and health claims made on foods" adopted by the EU in December 2006 (European Union Parliament, 2006; regulation [EC] No 1924/2006). According to this

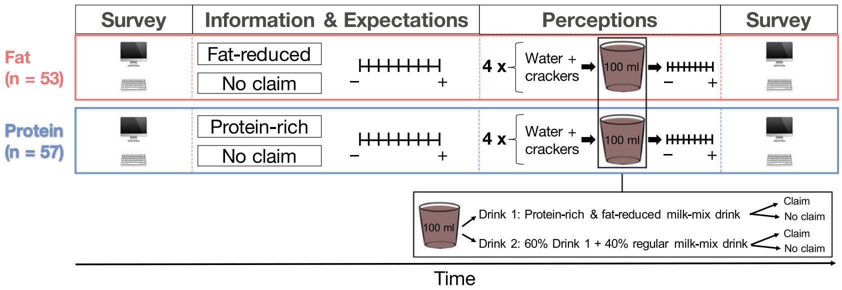

FIGURE 1 Behavioral study design. Each participant rated expected and perceived attributes about a milk-mix drink with and without a nutrition claim on a 9-point scale. Claims were "fat-reduced" (red, $n = 53$ participants) or "protein-rich" (blue, $n = 57$ participants). Each participant sampled two drinks, each presented once with and once without a nutrition claim. Drink order was fixed: Drink 1 was presented in the first and fourth round, and Drink 2 in the second and third round. Order of nutrition claim presence was counterbalanced across participants.

tions regarding a conventional milk-mix drink and a milk-mix drink with a "fat-reduced"/"protein-rich" claim depending on the assigned condition. Participants rated expectations in terms of healthiness, taste pleasantness, satiating quality, needed amount of consumption to feel full, and wanting on a 9-point scale (1 = not at all, 9 = very much).

In the third part, participants sampled two different drinks, once presented with a nutrition claim ("fat-reduced milk-mix drink"/"protein-rich milk-mix drink") and once without any nutrition claim ("milk-mix drink"). In both conditions participants sampled the same drinks so that any observed difference in ratings between conditions could be attributed to the type of the claim. The drinks used in the study were chocolate-flavored milk-mix drinks found in the German market. One drink was a protein-rich and fat-reduced chocolate milk drink from Arla (Drink 1), and the other was a mixture of Drink 1 and a conventional chocolate milk drink from Müller (Drink 2). To avoid deception of participants, we prepared Drink 2 as a mixture such that it could be claimed to be "protein-rich" and "fat-reduced" (European Union Parliament, 2006). Participants were instructed how to swirl each drink in their mouth for ~10 s and to concentrate on the taste of the drinks. Sampling was done in four rounds; in each round, 100 ml of one drink was presented to the participants ad libitum. Drink 1 was presented in the first and fourth round, whereas Drink 2 was presented in the second and third round; the order of the nutrition claim presentation was counterbalanced across participants. Before sampling each drink, participants ate saltine crackers and drank some still water to cleanse their palate and reduce taste spillover effects between trials. After each sampling, participants rated the perceived taste pleasantness, healthiness, satiating quality, needed amount of consumption to feel full, and wanting; all ratings were assessed on a 9-point scale (1 = not at all, 9 = very much; see Figure 1 for a representation of the design).

regulation, foods containing the "protein-rich" claim (or any other protein claim likely to have the same meaning for the consumer) must contain at least 30% more protein than a comparable regular reference product, and at least 20% of the energy value of these foods must come from proteins; foods containing the "fat-reduced"/"low-fat" claim must contain at least 30% less fat than a comparable regular reference product (<3g/100g).

In the fourth part, participants completed a survey with questions about their general attitude toward food with nutrition claims and nutrition labels/claims and indicated which of the sampled drinks they preferred.

2.2 | Statistical analyses

All behavioral data analyses were performed with R programming language (R Core Team, 2020) and RStudio version 4.0.3 (RStudio Team, 2019) using *lme4* (Bates et al., 2015), *nlme* (Pinheiro et al., 2020), *ggplot2* (Wickham, 2016), *GGally* (Schloerke et al., 2021), *lsmeans* (Lenth, 2016), *reshape2* (Wickham, 2007), *readxl* (Wickham & Bryan, 2019), *sjPlot* (Lüdecke, 2021), *dplyr* (Wickham et al., 2021), and *TOSTER* (Lakens, 2017).

First, to assess the effect of the presence (Yes/No) and type (Protein/Fat) of the nutrition claim, we estimated mixed-effects regression models with expectation and perception ratings as dependent variables, nutrition claim presence (1 = Yes, 0 = No), nutrition claim type (1 = Protein, 0 = Fat), their interaction, and drink type (1 = Drink 2, −1 = Drink 1; to assess claim effects across drinks) as explanatory variables. In all models, we added an intercept per participant to control for interindividual differences in average ratings. To supplement our findings, for null results we also conducted equivalence tests by using the Two One-Sided Test (TOST) procedure implemented in the *TOSTER* package in R (Lakens, 2017).

Second, we explored the association between claim effects and gender. To this end, we performed linear regression analyses where we included Gender (1 = Man, 0 = Woman) and Condition (1 = Protein, 0 = Fat) as explanatory variables, and claim effects as the dependent variable. We calculated claim effects for every attribute of interest by subtracting the ratings for the drinks without claims from the ratings for drinks with claims ($X_{claim} - X_{no\ claim}$). Regression analyses were performed separately for each attribute.

Third, we assessed whether the presence and type of the nutrition claim have an effect on the overall preference for the drinks. To this end, we compared the percentage of participants that preferred the drinks presented with a nutrition claim with the percentage of participants that preferred the drinks presented without a nutrition claim using a binomial test.

Fourth, we calculated claim prediction errors, that is, the differences in perceived and expected claim effect regarding all the assessed qualities as follows:

$$[Perceived\,X\,claim - Perceived\,X\,no\,claim]$$

$$- [Expected\,X\,claim - Expected\,X\,no\,claim],$$

where X is substituted with the ratings for the assessed qualities, namely taste pleasantness, healthiness, and satiating quality. We tested these prediction errors against zero using one-sample *t*-tests.

Finally, we assessed whether differences in expectation, perception ratings, or prediction errors could explain preference for drinks with a nutrition claim (assessed post-sampling). To this end, we estimated a logistic model where we included preference for the drink with the claim (1 = Yes, 0 = No) as the dependent variable, and the type of claim (Protein = 1, Fat = 0), difference in expected and perceived taste pleasantness, healthiness, and satiating quality, as well as differences in prediction errors as explanatory variables. Differences were calculated by subtracting the ratings for the drink presented without a nutrition claim from the ratings for the drinks presented with a nutrition claim ($X_{claim} - X_{no\,claim}$, where X is substituted for the average ratings for the respective attribute for each participant).

2.3 | Results

2.3.1 | Effect of nutrition claims on expected and perceived food attributes

Mixed-effects regressions revealed that nutrition claims decreased taste pleasantness expectations ($\chi^2_{claim\,(1)} = 33.45, p < .001$), increased healthiness expectations ($\chi^2_{claim\,(1)} = 7.86, p = .005$) and more so in the protein-claim condition ($\chi^2_{claim\,x\,type\,of\,claim\,(1)} = 17.001, p < .001$), and changed expected satiating quality ratings depending on the type of the claim ($\chi^2_{claim\,(1)} = 28.61, p < .001; \chi^2_{claim\,x\,type\,of\,claim\,(1)} = 119.04, p < .001$; see Figure 2 and Table 1). Nutrition claims did not have an effect on perceived taste pleasantness ($\chi^2_{claim\,(1)} = 0.51, p = .47$) but significantly increased perceived healthiness ($\chi^2_{claim\,(1)} = 9.05, p = .003$). Nutrition claims influenced perceived satiating quality ratings, but differently depending on the type of the claim ($\chi^2_{claim\,(1)} = 6.98, p = .008; \chi^2_{claim\,x\,type\,of\,claim\,(1)} = 8.68, p = .003$) (see Figure 2 and Table 1).

Equivalence testing revealed that the difference in perceived taste pleasantness ratings for drinks presented with and without a nutrition claim is statistically equivalent to zero given equivalence bounds of Cohen's $d = \pm 0.23$, at 5% alpha level ($t_{(109)} = -1.77$, 90% CI [−0.137, 0.309], $p = .04$; data pooled across claims).

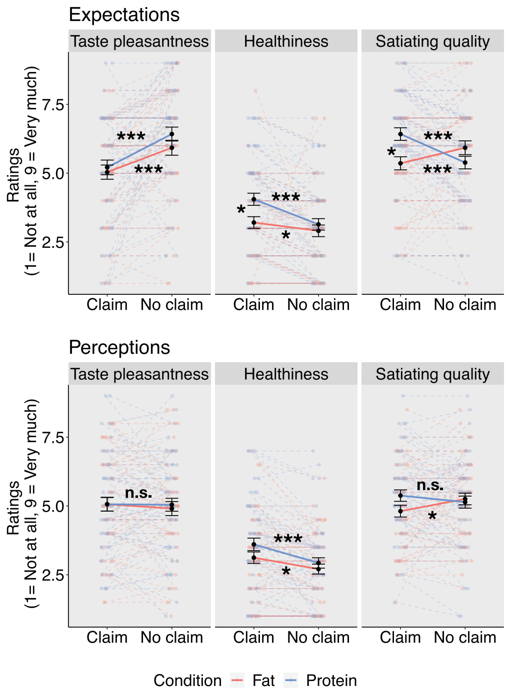

FIGURE 2 Effect of nutrition claims on expected (upper panel) and perceived (lower panel) attribute ratings. Black dots indicate means across participants, red and blue dots are mean ratings per participant. Error bars represent the standard error of the mean. Tukey's tests were used for pairwise comparisons. $n_{Protein} = 57$, $n_{Fat} = 53$; ***$p < .001$, **$p < .01$, *$p < .05$, n.s.: not significant.

Linear regression analyses revealed an association between gender and claim effects on expected satiating quality ($F_{Gender\,x\,Condition\,(1)} = 4.24, p = .04$). More specifically, the difference in claim effects between the protein and the fat condition was significantly higher in women than in men ($B_{Gender\,x\,Claim} = -1.08$, $SE = 0.52$, 95% CI [−2.11, −0.04], $p = .04$). Further pairwise comparisons also indicated that the effect of the "protein-rich" claim on expected satiation was significantly higher in women than in men (Tukey-adjusted comparison: $t_{(106)} = 2.83, p = .03$). There were no associations between gender and other expectation and perception ratings (see Supplementary Table S2 and Supplementary Figure S1 for full model results).

2.3.2 | Prediction errors (perception *vs.* expectation)

As effects of the claims on expectations and perception differed, we subtracted expectation ratings from perception ratings (*i.e.*, prediction errors) and tested the difference against zero (see Section 2.2). Prediction errors for taste pleasantness were positive for both claims

TABLE 1 Effect of nutrition claims on expected and perceived food attributes

	DV: Expected taste pleasantness			DV: Expected healthiness			DV: Expected satiating quality		
Fixed effects	***B* (*SE*)**	**95% CI**	***p***	***B* (*SE*)**	**95% CI**	***p***	***B* (*SE*)**	**95% CI**	***p***
Intercept	5.92 (*0.24*)	[5.45, 6.40]	< .001	2.91 (*0.20*)	[2.51, 3.30]	<.001	5.92 (*0.23*)	[5.47, 6.37]	<.001
Claim (1 = Yes, 0 = No)	−0.89 (*0.15*)	[−1.19, −0.59]	< .001	0.30 (*0.11*)	[0.09, 0.51]	.005	−0.57 (*0.11*)	[−0.77, −0.36]	<.001
Condition (1 = Protein, 0 = Fat)	0.49 (*0.34*)	[−0.17, 1.16]	.148	0.23 (*0.28*)	[−0.33, 0.78]	.421	−0.55 (*0.32*)	[−1.17, 0.08]	.087
Claim × Condition	−0.32 (*0.21*)	[−0.74, 0.10]	.134	0.62 (*0.15*)	[0.32, 0.91]	<.001	1.61 (*0.15*)	[1.32, 1.89]	<.001
Random effects	σ^2	τ_{00}	**ICC**	σ^2	τ_{00}	**ICC**	σ^2	τ_{00}	**ICC**
Intercept (ID)	1.25	2.52	.67	0.61	1.87	.75	0.59	2.48	.81
Model									
Marginal R^2/Conditional R^2	.076/.695			.072/.771			.060/.819		
	DV: Perceived taste pleasantness			**DV: Perceived healthiness**			**DV: Perceived satiating quality**		
Fixed effects	***B* (*SE*)**	**95% CI**	***p***	***B* (*SE*)**	**95% CI**	***p***	***B* (*SE*)**	**95% CI**	***p***
Intercept	4.91 (*0.26*)	[4.40, 5.41]	< .001	2.71 (*0.20*)	[2.31, 3.11]	<.001	5.25 (*0.21*)	[4.83, 5.68]	<.001
Claim (1 = Yes, 0 = No)	0.16 (*0.22*)	[−0.28, 0.60]	.475	0.42 (*0.14*)	[0.14, 0.69]	.003	−0.44 (*0.17*)	[−0.77, −0.11]	.009
Condition (1 = Protein, 0 = Fat)	0.13 (*0.36*)	[−0.57, 0.83]	.713	0.21 (*0.28*)	[−0.34, 0.77]	.452	−0.12 (*0.30*)	[−0.71, 0.47]	.690
Claim × Condition	−0.13 (*0.31*)	[−0.74, 0.48]	.678	0.27 (*0.19*)	[−0.11, 0.65]	.160	0.69 (*0.23*)	[0.23, 1.15]	.003
Drink (1 = Drink 2, −1 = Drink 1)	0.29 (*0.08*)	[0.14, 0.44]	< .001	−0.06 (*0.05*)	[−0.15, 0.03]	.212	0.23 (*0.06*)	[0.11, 0.34]	<.001
Random effects	σ^2	τ_{00}	**ICC**	σ^2	τ_{00}	**ICC**	σ^2	τ_{00}	**ICC**
Intercept (ID)	2.66	2.17	.45	1.01	1.71	.63	1.49	1.70	.53
Model									
Marginal R^2/Conditional R^2	.018/.459			.041/.645			.029/.546		

Notes: Effects are estimated using mixed effects regression models. *p*-values are calculated based on the *t*-statistics using the normal distribution function. τ_{00} denotes the variance in intercepts, σ^2 denotes the residual variance. $n_{Protein} = 57$, $n_{Fat} = 53$.
ID: participant ID; DV: dependent variable; *B*: unstandardized estimate; *SE*: standard error of the estimate; CI: confidence interval; ICC: intraclass correlation coefficient.

("protein-rich" claim taste pleasantness prediction error: $t_{(56)}$ = 3.86, p = .0003; "fat-reduced" claim taste pleasantness prediction error $t_{(52)}$ = 3.69, p = .0005) and did not significantly differ between them (group comparison $t_{(108)}$ = −0.42, p = .674). In other words, participants expected drinks with the claim to taste worse than they actually did. Prediction errors for healthiness were not significant for either claim ("protein-rich" claim $t_{(56)}$ = −1.46, p = .149; "fat-reduced" claim $t_{(52)}$ = 0.48, p = .633), whereas prediction errors for satiating quality were only significant for the "protein-rich" claim ($t_{(56)}$ = −3.61, p = .001; "fat-reduced" claim: $t_{(52)}$ = 0.42, p = .679; see Supplementary Figure S2).

2.3.3 | Preference for drinks

55.45% of participants preferred a drink with a claim (independent of the type) and 38.18% preferred a drink without a claim (6.36% indicated no preference). This was not different from chance level (proportion preferring drink with claim = 0.59, 95% CI [0.49, 0.69], p = .076; binomial test). Preference for drinks with a claim was explained by the perceived pleasantness difference (OR = 3.30, SE = 0.87, 95% CI [2.07, 5.87], p < .001) and pleasantness prediction errors (OR = 1.30, SE = 0.14, 95% CI [1.07, 1.62], p = .012), but not by expected pleasantness differences (OR = 1.09, SE = 0.11, 95% CI [0.89, 1.34], p = .410; see Supplementary Table S3).

3 | STUDY 2 (FMRI STUDY)

3.1 | Material and methods

3.1.1 | Participants

Participation in the study was voluntary, and participants were paid a fee of €15 per hour for their participation. Additionally, they received one of the milk-mix drinks they encountered in the experiment. The participants for this study were recruited via e-mail from the participant pool of the Life and Brain research center (a database where anyone can sign up) and flyers posted online on social media. The exclusion criteria were: not liking milk-mix drinks, being underweight or having obesity (BMI below 18 or above 30 kg/m^2), standard MRI exclusion criteria (metal/medical implants, claustrophobia), having neurological/psychiatric/psychological or being on medication for neurological/psychiatric/psychological/metabolic conditions, having a current upper-respiratory infection, and having food allergies, intolerances, diabetes or any condition known to affect taste perception and/or metabolism. In total, 42 participants participated in Study 2. From those, three were excluded from the behavioral data analyses and another six (nine in total) from the fMRI data analyses. Reasons for exclusions were: incomplete experiment, excessive movement (>3 mm), anatomical alterations discovered during data analyses, and technical problems during the experiment. The final sample of Study 2 consisted of 39 participants (M_{age} = 26.41, SD_{age} = 10.68 years old; M_{BMI} = 23.41, SD_{BMI} = 2.83 kg/m^2, calculated by assessed weight and height; 19 women) for the behavioral and 33 participants (14 women) for the fMRI data analyses. A sensitivity power analysis performed using the G*Power software (Faul et al., 2009) revealed that this sample size would allow us to detect an effect size of $dz \geq 0.503$ with α = 5% and 1 − β = 0.8 (80% power), in a two-tailed paired t-test.

Participants were asked to get a good night's sleep (approximately 6–8 h) before the experiment day (indicated sleep hours M = 7.27, SD = 1.31 h) and were asked to eat no later than 2 h before the experiment, so that they would be somewhat hungry during the experiment (indicated hours before the last meal M = 2.72, SD = 1.26 h; perceived hunger level on an 11-point scale M = 5.97, SD = 1.33).

3.1.2 | Study design

Data collection took place at the Life and Brain Research Center in Bonn, Germany. The study consisted of four parts. Like in Study 1, the first part of Study 2 consisted of a survey that included questions assessing task comprehension, sociodemographic questions, and questions assessing baseline levels of hunger (on an 11-point scale; 1 = not at all, 11 = very much), perceived stress (on a 9-point scale; 0 = not at all, 9 = very much), hours of sleep on the night before the experiment, emotional valence and arousal (using the corresponding Self-Assessment Manikin subscales from Bradley & Lang, 1994).

Since in Study 1 we did not find a difference in expected and perceived pleasantness between the "fat-reduced" and "protein-rich" claims, in Study 2 we did not compare the neural effects on pleasantness and valuation of both claims. Instead, in this study we only used the "protein-rich" claim. Like in Study 1, we gave participants information about the meaning of the claim and asked them to indicate their expectations about the taste pleasantness, healthiness, and satiating quality of protein-rich and conventional milk-mix drinks (on a 9-point scale; same scale as in Study 1). Considering that in Study 1 we found that nutrition claims affect some attributes and not others, in Study 2 we additionally assessed their effect on valuation. To this end, we asked participants to indicate their hypothetical willingness to pay (WTP) for protein-rich and conventional milk-mix drinks; they could indicate any amount ranging from 0 to €3 (€3 is approximately 30% more than the retail price for milk-mix drinks).

The second part of Study 2 was the fMRI experiment, which consisted of a taste-rating task, whereby participants were delivered different drinks while lying inside the MRI scanner and were asked to taste and rate the pleasantness of each delivered drink. The drinks were delivered using an in-house-built electronic syringe pump system used in a previous study by Schmidt et al. (2017). Participants were delivered two protein-rich drinks from Arla: one with chocolate (same as in Study 1) and one with vanilla flavor. Each drink was presented 12 times with and without the "protein-rich" claim (see Figure 3). In total, participants completed 48 trials (2 flavors × 2 conditions × 12 repetitions). The flavor of the drinks as well as the order of the claim presentation was randomized for each participant with the restriction

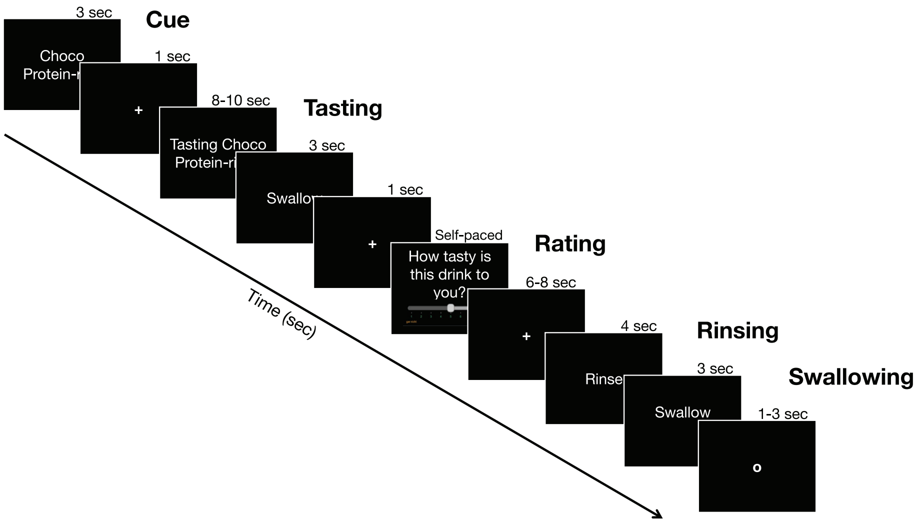

FIGURE 3 Timeline of a trial in the fMRI task. Each participant completed 48 trials in total, 12 for each *flavor+ claim presence* combination (12 claim chocolate, 12 no claim chocolate, 12 claim vanilla, 12 no claim vanilla). The flavor of the drinks as well as the order of the claim presentation was randomized for each participant with the restriction that the same combination of *flavor* + *claim* presence could not be presented two times in a row. Taste pleasantness ratings for each trial were self-paced and participants were told to rate the drinks as fast as they could.

that the same combination of *flavor* + *claim* presence could not be presented two times in a row.

Each trial started with a cue representation that indicated which drink was going to be delivered. The trial continued with the delivery of 1 ml (delivered in 2.67 s) of the cued drink and a tasting period where participants were asked to concentrate on the taste of the drink. Next, participants were instructed to swallow the drink and rate its pleasantness (on a 9-point scale, like in Study 1). Participants were told to rate the drinks as fast as possible so that their ratings reflect the momentarily perceived pleasantness (across participants average rating per trial ranged from Min = 1.65 s to Max = 5.33 s; M_{Rating} = 3.15 s, $Median_{Rating}$ = 2.84 s, SD = 0.94 s). At the end of the trial, participants were delivered a tasteless rinsing solution (for details on the rinsing solution preparation see Supplementary Material Section 2.1.1), which they were then instructed to swallow (see Figure 3); participants were reminded to strictly follow the instructions presented on the screen, and only swallow when told to do so. The rinsing solution was used to avoid spillover over trials, and to provide a baseline condition later used to assess taste responses at the neural level. To make sure that participants understood the task and were comfortable with it, we ran a few test trials prior to starting scanning.

The third part, similar to the first part, was completed outside the scanner and consisted of another survey. This post-fMRI survey contained questions concerning the drinks that participants sampled during the fMRI task and their attitudes toward labels and claims (like in Study 1). Moreover, in this part, participants were asked to complete the Dutch Eating Behaviour Questionnaire (DEBQ; Grunert, 1989; van Strien et al., 1986), Food Neophobia Scale (FNS; Pliner & Hobden, 1992), and the Brief Self-Control Scale (BSCS; Bertrams & Dickhäuser, 2009; Tangney et al., 2004). In this study, we only report descriptive statistics for the DEBQ questionnaire, as the other questionnaires were collected for a different project. DEBQ was included only for better characterization of the eating styles of our sample.

The fourth and final part was a sweet taste sensitivity test, used to assess participants' ability to taste sweetness. For this, we estimated sucrose recognition thresholds using an adaptive procedure based on QUEST+ (Watson, 2017), which is an extension of an established protocol using a yes–no task (Höchenberger & Ohla, 2017, 2019) (for details on the procedure, see Supplementary Material Section 2.1.2). This test was also included only for better sample characterization.

3.1.3 | fMRI data acquisition

The MRI data were acquired on a 3T Siemens Trio scanner with a 32-channel head coil. Participants were shown the fMRI task via a mirror that was mounted on the head coil and adjusted so that the participants could correctly see the screen positioned behind their heads. Responses were indicated using controllers in both hands. The scanning sequence consisted of a gradient field map (GFM), a functional scan, and T1-weighted structural images at the end. The GFM sequence was acquired using a double echo sequence with the first echo time (TE) = 4.92 ms and second TE = 7.38 ms, repetition time (TR) = 392 ms, field of view (FoV) = 92 mm, and flip angle = 60°.

Functional images were acquired using an echoplanar imaging (EPI) sequence with the following parameters: TR = 2500 ms, TE = 30 ms, flip angle = 90°, FoV = 192 mm, voxel size (*x*, *y*, *z*) = 2 mm × 2 mm × 3 mm^3, number of slices = 37. The slices were acquired on an axial orientation in an ascending order. The number of acquired images differed across participants (as certain stages of the fMRI task were self-paced), ranging from 678 to 763 images with M = 712.71 images. Structural images were acquired with the following parameters: TR = 1660 ms, TE = 2.54 ms, flip angle = 9°, voxel size (*x*, *y*, *z*) = 0.8 mm × 0.8 mm × 0.8 mm, FoV = 256 mm. The images were acquired on a sagittal orientation and a total of 208 images were acquired per participant.

3.1.4 | fMRI data preprocessing

All MRI data preprocessing was conducted using the SPM12 software package (Wellcome Department of Imaging Neuroscience, Institute of Neurology, London, UK) based on MATLAB R2020b. Preprocessing was done as follows: First, the images were slice-time corrected with the first image as the reference. Second, the data were corrected for motion. The realignment parameters were visually inspected, and all the participants that at any point during the session moved more than the voxel size (>3 mm) from their initial position (first functional scan) were excluded. Next, the images were unwarped using the GFMs acquired prior to the functional scans, coregistered to the individual high-resolution T1-weighted structural images, transformed into the Montreal Neurological Institute (MNI) template space, and resampled to 3 × 3 × 3 mm^3 voxel size. To account for interindividual anatomical differences and reduce the thermal noise, the images were smoothed with a Gaussian kernel with full width at half maximum (FWHM) of 8 mm. To filter out the low-frequency noise, a high-pass temporal filter of 128 s was used. The quality of the functional and structural data was checked using the Check Reg function in SPM12, the SPM CAT12 toolbox (r1184, http://www.neuro.uni-jena.de/cat/), and the MRI Quality Control (MRIqc) tool to extract objective quality metrics (Esteban et al., 2017).

3.2 | Statistical analyses

Consistent with Study 1, behavioral data analyses were performed using R and RStudio version 4.0.3 (RStudio Team, 2019). fMRI data were analyzed using SPM12 and SPM8 (Wellcome Department of Imaging Neuroscience, Institute of Neurology, London, UK) under MATLAB R2020b. We used MarsBar (Brett et al., 2002), AAL3 (Rolls et al., 2020), Anatomy (Eickhoff et al., 2005), WFU Pickatlas (RRID:SCR_007378; https://www.nitrc.org/projects/wfu_pickatlas/) (Maldjian et al., 2003), and gPPI (McLaren et al., 2012) SPM toolboxes.

3.2.1 | Behavioral analyses

Like in Study 1, we first assessed the effect of the "protein-rich" claim on expectations and perceived taste pleasantness. To this end, we estimated separate mixed-effects linear regression models with the respective ratings as the dependent variable, claim presence (1 = Yes, 0 = No) as the explanatory variable, and a random intercept term per participant to account for interindividual differences in average ratings. In the model assessing the effect of claim on perceived pleasantness, we additionally included flavor (1 = Chocolate, −1 = Vanilla; to assess claim effects across flavors), and trial number as explanatory variables. Like in Study 1, to supplement our findings, for null results we also conducted equivalence tests using the TOST procedure.

Second, we assessed the effect of the "protein-rich" claim on subjective value (as assessed via the WTP measure). To this end, we estimated a mixed-effects regression model with WTP ratings as the dependent variable, claim presence (1 = Yes, 0 = No) as the explanatory variable, and a random intercept term per participant to account for interindividual differences in average WTP. To assess which attributes related to valuation, and whether this changed depending on the claim, we estimated linear regression models with mean WTP ratings as dependent variable and mean expectation ratings as explanatory variables.

Third, like in Study 1, we explored the association between gender and claim effects on each attribute of interest (expectations, perceived taste pleasantness, WTP) using linear regression analyses. In these analyses we included Gender (1 = Man, 0 = Woman) as the explanatory variable, and claim effects as the dependent variable.

Fourth, we assessed whether claim effects on expectations explained claim effects on perceived taste pleasantness. To this end, we estimated a linear regression model with average perceived differences in taste pleasantness as the dependent variable, and the average expected differences in taste pleasantness, healthiness, and expected satiating quality as explanatory variables.

Fifth, similarly to Study 1, we calculated taste pleasantness prediction errors, and assessed whether they are different from zero using a one-sample *t*-test.

Finally, as in Study 1, we assessed the effect of claim on preference for drinks (assessed post-fMRI). To this end, we counted and compared the frequency of preferring a drink with the claim and preferring a drink without the claim, using a binomial test. Furthermore, we assessed whether preference for drinks with a claim could be explained by expectations and perceived taste pleasantness ratings. To this end, we estimated a logistic regression with preference for a drink with the "protein-rich" claim (1 = Yes, 0 = No) as the dependent variable, and the differences in expectations (taste pleasantness, healthiness, satiating quality), perceived taste pleasantness, and taste pleasantness prediction errors as explanatory variables.

3.2.2 | fMRI analyses

Analysis strategy

We used the following strategy. First, we checked whether our paradigm evoked the expected responses in brain regions associated with taste and flavor processing. Second, we tested whether the "protein-rich" claim modulated activity in brain regions associated with valuation. These regions were identified based on previous work (vS/Nucleus accumbens [NAcc], vmPFC, dlPFC, lateral OFC). Finally, we assessed the impact of the claim on functional connectivity. To assess effects of interest on the above-mentioned ROIs, we performed small-volume-correction (SVC) analyses. We consider activations as significant if they survive $p < .05$ with family-wise (FWE) correction for multiple comparisons; for whole-brain analyses, this correction was applied at the cluster level, based on a threshold of $p = .001$ uncorrected at the voxel level (cluster-forming threshold); for SVC analyses, this correction was applied at the peak level.

GLM definition and contrasts of interest

To assess the effect of claims on neural activity during tasting and swallowing of the drinks, we estimated a GLM including regressors for: cue claim, cue no claim, tasting drinks presented with a claim, tasting drinks presented without a claim, swallowing drinks presented with a claim, swallowing drinks presented without a claim, rinsing, swallowing rinsing solution, rating, and movement (three for translation, three for rotation). Every regressor modeled responses from event onset until event offset. We estimated this model for every participant and for each we calculated eight contrasts: tasting drinks *vs.* rinsing, swallowing drinks *vs.* swallowing rinsing solution, viewing cue for drinks with *vs.* without the claim and vice versa, tasting drinks with *vs.* without the claim and vice versa, and swallowing drinks with *vs.* without the claim and vice versa. These calculated contrasts were subjected to one-sample *t*-tests (2nd-level analyses).

Assessing taste and flavor response in brain regions of interest (ROIs)

Several regions including the OFC, insula, frontal and rolandic operculum, ACC, amygdala, caudate, putamen, pallidum, and thalamus have been associated with taste and flavor processing (Lundström et al., 2011; Veldhuizen et al., 2011). To assess whether our task evoked taste and flavor responses in these regions, we applied SVC to the whole-brain contrasts tasting *vs.* rinsing and swallowing drinks *vs.* swallowing rinsing solution. To restrict the number of independent tests and thus reduce the probability of type I errors, we constructed a common mask of these anatomical ROIs using the WFU Pickatlas tool (Maldjian et al., 2003) and applied SVC over the mask volume (see Supplementary Figure S3a); this approach has also been used in previous studies (e.g., van Rijn et al., 2018).

Assessing the effect of the "protein-rich" claim in brain ROIs

We applied SVC to the whole-brain results of our GLM to restrict analyses in a priori defined regions associated with valuation, including bilateral vS/NAcc ([x, y, z] = [−12, 10, −2], and [x, y, z] = [12, 10, −2], both 10 mm as in Knutson et al., 2008; Linder et al., 2010), vmPFC ([x, y, z] = [2, 46, −8], 10 mm as in Bartra et al., 2013), left dlPFC (Hare et al., 2009, 2011; [x, y, z] = [−48, 15, 24], 10 mm as in Enax et al., 2015a), and left lateral OFC ([x, y, z] = [−22, 34, −8], 10 mm as in Kringelbach et al., 2003). As for taste and flavor ROIs, to restrict the number of independent tests, we constructed a common mask of these valuation-associated ROIs (see Supplementary Figure S3b) and applied SVC over the mask volume. All ROIs were built in MarsBar as spheres and were combined using the ImCalc function in SPM.

Assessing the effect of the "protein-rich" claim on functional connectivity

To test if the "protein-rich" claim impacts functional connectivity patterns in the brain, we conducted Psycho Physiological Interaction (PPI) analyses using the *gPPI* toolbox (McLaren et al., 2012). In these analyses, we used regions that were more active in response to claim *vs.* no claim (and vice versa) as seed regions and searched for functional connectivity changes across the whole brain. For details on the PPI analyses, see Supplementary Material (Section 2.1.3).

3.3 | Results

3.3.1 | Behavioral results

Eating behavior and sweet taste sensitivity

The acquired baseline ratings, the DEBQ questionnaire subscores, and the sweet taste thresholds are summarized in Supplementary Table S4. Mean DEBQ subscores fell within ±3 SD of the published norms for the German population (Nagl et al., 2016), and therefore indicated that our sample exhibited an eating behavior within the norm. Sweet taste thresholds were numerically lower, indicating a higher sensitivity than in previous reports that used a similar procedure based on QUEST (Hardikar et al., 2017; Höchenberger & Ohla, 2017, 2019). Nevertheless, the results indicated that participants were able to recognize sweet taste (for a discussion on the taste test results, see Supplementary Material Section 2.2.2).

Effect of nutrition claim on expectations, perceived taste pleasantness, and valuation

Our mixed effects linear models revealed that, consistent with Study 1 results, participants expected a protein-rich drink to be less tasty ($\chi^2_{(1)}$= 11.94, p = .0005; B_{claim} = −0.83, SE = 0.24, 95% CI [−1.31, −0.35], p = .001), more healthy ($\chi^2_{(1)}$= 41.75, $p < .001$; B_{claim} = 1.00, SE = 0.15, 95% CI [0.69, 1.31], $p < .001$), and more satiating than a conventional drink ($\chi^2_{(1)}$= 11.149, p = .001; B_{Claim} = 0.55, SE = 0.17, 95% CI [0.22, 0.88], p = .001) (Figure 4a).

Participants rated the perceived pleasantness of the drink similarly when it was presented with and without the "protein-rich" claim ($\chi^2_{(1)}$ = 0.225, p = .636; see Figure 4b), corroborating the findings from Study 1 (see Table 2). Equivalence testing revealed that the difference in perceived taste pleasantness ratings for drinks presented with and without the "protein-rich" claim is statistically equivalent to

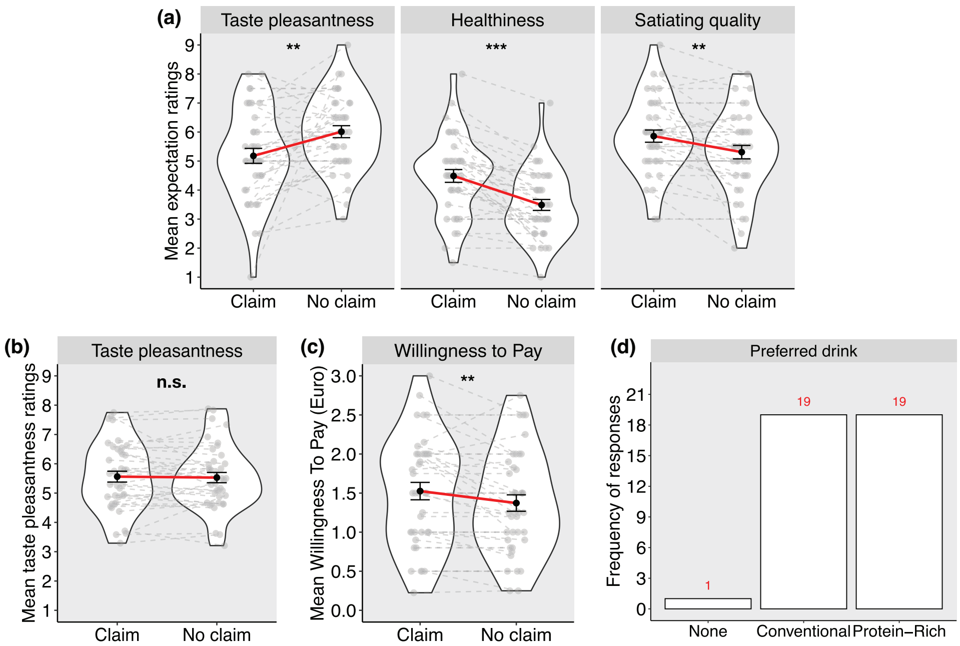

FIGURE 4 Effect of the "protein-rich" nutrition claim on expectations (a), perceived pleasantness (b), willingness to pay (c), and overall preference (d). Black dots are mean values across participants, whereas gray dots are individual mean values. The red line connects the mean ratings in both conditions, whereas dashed gray lines connect the mean ratings of each participant. Ratings and frequencies are pooled across both flavors (chocolate, vanilla). Error bars represent the standard error of the mean . $n = 39$; $^{***}p < .001$; $^{**}p < .01$; n.s.: not significant.

TABLE 2 Effects of a "protein-rich" nutrition claim on perceived taste pleasantness ratings

	DV: Perceived taste pleasantness					
Fixed effects	***B* (*SE*)**	**95% CI**	***p***	***B* (*SE*)**	**95% CI**	***p***
Intercept	5.65 (0.19)	[5.28, 6.01]	<.001	5.65 (0.19)	[5.28, 6.01]	<.001
Claim (1 = Yes, 0 = No)	−0.03 (0.06)	[−0.16, 0.09]	.636	−0.03 (0.06)	[−0.16, 0.09]	.636
Trial number	−0.004 (0.002)	[−0.01, 0.001]	.127	−0.003 (0.002)	[−0.01, 0.001]	.130
Flavor (1 = Chocolate, −1 = Vanilla)	0.30 (0.03)	[0.24, 0.36]	<.001	0.29 (0.05)	[0.20, 0.37]	<.001
Claim × Flavor				0.03 (0.06)	[−0.09, 0.16]	.591
Random effects						
	σ^2	τ_{00}	ICC	σ^2	τ_{00}	ICC
Intercept (ID)	1.90	1.16	.38	1.90	1.16	.38
Model						
Marginal R^2/Conditional R^2	.030/.399			.030/.399		

Notes: Effects are estimated using mixed-effects linear regression models. *p*-values are calculated based on the *t*-statistics using the normal distribution function. τ_{00} denotes the variance in intercepts, σ^2 denotes the residual variance; $n = 39$.
ID: participant ID; DV: dependent variable; *B*: unstandardized estimate; *SE*: standard error of the estimate; CI: confidence interval; ICC: intraclass correlation coefficient.

TABLE 3 Relation between the "protein-rich" claim effect on expectations with the claim effect on perceived taste pleasantness

	DV: Effect of claim on perceived taste pleasantness		
Fixed effects	***B* (*SE*)**	**95% CI**	***p***
Intercept	−0.03 (0.08)	[−0.20, 0.14]	.707
Effect of claim on expected taste pleasantness	0.12 (0.09)	[−0.05, 0.30]	.158
Effect of claim on expected healthiness	0.09 (0.09)	[−0.10, 0.27]	.363
Effect of claim on expected satiating quality	−0.02 (0.09)	[−0.21, 0.17]	.843
Model			
R^2/adjusted R^2	.082/.003		

Notes: Effects are estimated using a linear regression model. Differences in expectation ratings are *z*-scored; $n = 39$.
DV: dependent variable; *B*: unstandardized estimate; *SE*: standard error of the estimate; CI: confidence interval.

zero given equivalence bounds of Cohen's $d = \pm 0.34$ and alpha of 5% ($t_{(38)} = 1.746$, 90% CI [−0.175, 0.111], $p = .044$).

Participants were willing to pay significantly more for a protein-rich drink than a conventional drink ($\chi^2_{(1)} = 7.903$, $p = .005$; $B_{claim} = 0.15$, $SE = 0.05$, 95% CI [0.05, 0.26], $p = .006$; see Figure 4c). Linear regression analyses indicated that for protein-rich drinks, WTP was explained only by satiating quality ratings ($B = 0.44$, $SE = 0.11$, 95% CI [0.20, 0.67], $p = .001$), whereas for conventional drinks WTP was explained by expected taste pleasantness ratings ($B = 0.21$, $SE = 0.10$, 95% CI [0.004, 0.42], $p = .046$; see Supplementary Table S5).

Different than in Study 1, linear regression analyses revealed no significant associations between claim effects on attributes of interest (expectations, perceived pleasantness, WTP) and gender (see Supplementary Table S6).

Effect of expectations on perceived taste pleasantness

Linear regression results revealed that claim effects on expectations did not explain claim effects on perceived taste pleasantness (see Table 3).

Prediction errors and preference for drinks

Consistent with Study 1, we found that taste pleasantness prediction errors were significantly larger than zero ($t_{(38)} = 3.40$, $p = .002$; see Supplementary Figure S4), suggesting that the "protein-rich" claim reduced taste pleasantness less than expected.

We found that 48.72% of participants preferred a drink presented with the "protein-rich" claim and 48.72% preferred a drink without a claim (2.56% indicated no preference; see Figure 4d). Different than in Study 1, our logistic regression analysis revealed that in Study 2, only perceived taste pleasantness difference explained preference for a drink with claim ($OR = 3.04$, $SE = 1.71$, 95% CI [1.21, 11.63], $p = .048$; see Supplementary Table S7 for all model results).

3.3.2 | fMRI results

Data quality check

Prior to analyzing the MRI data, we assessed its quality (see Section 3.1.4). Results are summarized in the Supplementary Material (Section 2.2.1, Supplementary Table X).

Taste and flavor response in the brain

Within regions associated with taste processing (see Section 3.2.2), tasting a drink *vs.* rinsing increased activation in bilateral caudate and left orbital gyrus, and swallowing drinks *vs.* swallowing rinsing solution increased activation in left insula, right operculum, and left anterior cingulate cortex (see Supplementary Table S8 and Supplementary Figure S5).

Effect of the "protein-rich" claim on valuation and taste processing

We tested whether the "protein-rich" claim modulated activity magnitude in brain regions previously associated with valuation and taste processing. Regions that exhibited an increased activity were used as seed regions in subsequent functional connectivity analyses.

Claim > No claim, SVC analyses: We found no significant activation difference in ROIs associated with valuation (vmPFC, bilateral vS/NAcc, left lateral OFC, dlPFC; see Section 3.2.2), neither for tasting nor for swallowing drinks presented with *vs.* without the "protein-rich" claim. However, activation in a left lateral OFC cluster increased when viewing cue claim *vs.* no claim ([*x*, *y*, *z*] = [−18, 32, −13], $k = 2$, *z*-value = 3.53, *T*-value = 3.94, $p_{FWE} < .05$; see Figure 5a, left).

Claim > no claim, functional connectivity: There was no significantly increased functional connectivity between the lateral OFC cluster and the rest of the brain neither when viewing cues, tasting, or swallowing drinks.

No claim > claim, SVC analyses: We found no significant differences in the ROIs' activity during the cue and swallow phases. On the other hand, during tasting, we found an increased activity in a cluster extending into the left NAcc and pallidum ([*x*, *y*, *z*] = [−15, 2, −7], $k = 5$, *z*-value = 3.51, *T*-value = 3.91, $p_{FWE} < .05$ for tasting drinks without *vs.* with the "protein-rich" claim; see Figure 5a, right and Supplementary Figure S6 for additional coronal slices showing overlap with adjacent structures).

No claim > claim, functional connectivity: We found an increase in functional connectivity between the cluster extending into the left NAcc (see previous paragraph) and a cluster of the middle frontal gyrus when swallowing drinks without *vs.* with the "protein-rich" claim ([*x*, *y*, *z*] = [24, 32, 23], $k = 73$, *z*-value = 4.41, *T*-value = 5.22,

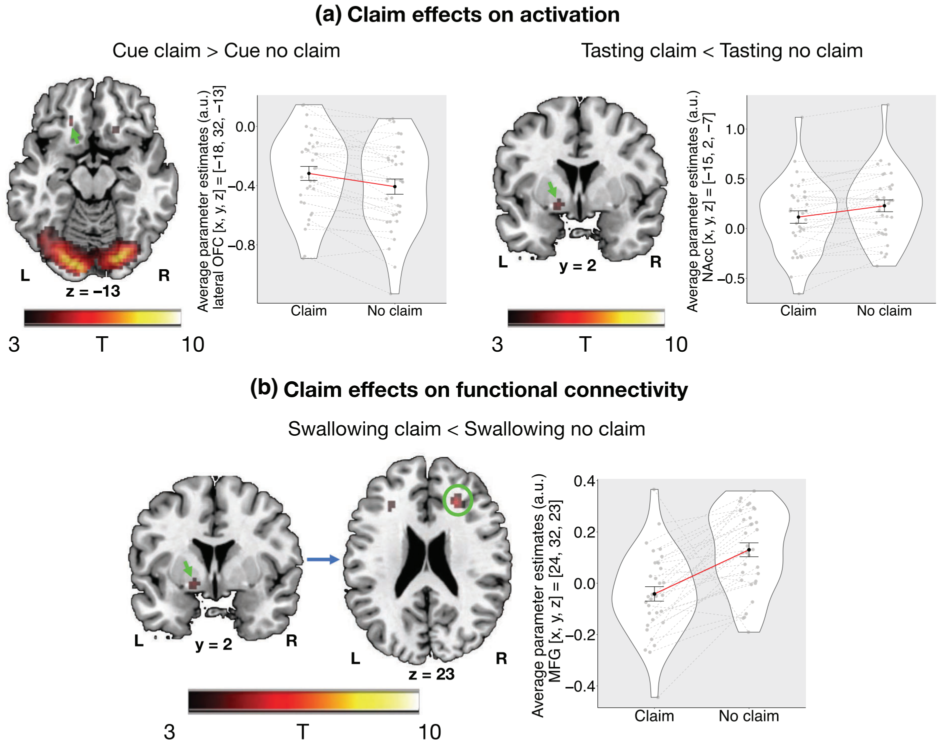

FIGURE 5 Claim effects on brain activation (a) and task-dependent functional connectivity (b). (a) Viewing the "protein-rich" cue claim *vs.* no claim was associated with an increased activity in a cluster in lateral OFC (green arrow upper left). Tasting drinks without *vs.* with the "protein-rich" claim was associated with an increased activity in a cluster extending into the left NAcc (green arrow upper right). These activations survive thresholding at $p_{FWE} < .05$ when small volume correcting over regions associated with valuation (common valuation mask, see Methods). (b) Swallowing drinks without *vs.* with the "protein-rich" claim was associated with an increased functional connectivity between the cluster extending into the left NAcc (green arrow) and a cluster in right middle frontal gyrus (green circle). This increased connectivity survives thresholding at $p_{FWE} < .05$ across the whole brain. T-maps are overlayed on the ch2bet template. Black dots on the violin plots are mean parameter estimates across participants, whereas gray dots are individual mean parameter estimates. The red line connects the mean parameter estimates, whereas the dashed gray lines connect the individual mean parameter estimates. Error bars represent the standard error of the mean. L: left; R: right; a.u.: arbitrary units; $n = 33$.

$p_{FWE} < .05$; see Figure 5b). This analysis revealed no other significant activations.

4 | DISCUSSION

Despite being widely used, the behavioral and neural effects of nutrition claims on food perception and valuation are not well understood. To assess the effects of nutrition claims on expectations, perception, and valuation, we conducted two studies. In Study 1, we tested and compared the behavioral effects of a "fat-reduced" claim with those of a "protein-rich" claim. We found that both claims influenced only expected but not perceived taste; there were no differences between both claims in these effects. The "fat-reduced" claim decreased expected and perceived satiation, whereas the "protein-rich" claim increased only expected satiation. Both claims increased expectations and perceptions of healthiness, however, the "protein-rich" claim increased healthiness expectations significantly more than the "fat-reduced" claim, with no additional costs on pleasantness. In Study 2, we assessed whether the "protein-rich" claim impacted perceived taste pleasantness, valuation, and their neural correlates. In this study, we replicated several of the findings from Study 1 and further found that the "protein-rich" claim increased willingness to pay for otherwise equal drinks and was associated with an increased activity in left lateral OFC during cue viewing, a decreased activity in a cluster extending into left NAcc during tasting, and a decreased functional connectivity between the NAcc cluster and a cluster in right middle frontal gyrus during swallowing.

4.1 | Behavioral results

4.1.1 | Effects of nutrition claims on expected and perceived taste pleasantness

In both studies, we found that nutrition claims influenced only expected but not perceived taste pleasantness. While previous studies have reported similar findings (Levin & Gaeth, 1988; Norton et al., 2013), others have reported that nutrition claims influence both expected and perceived pleasantness (Bialkova et al., 2016; Liem et al., 2012; Ng et al., 2011; Oostenbach et al., 2019; Piqueras-Fiszman & Spence, 2015). These inconsistencies may be due to differences in claims, food products, sample characteristics, and combination of these factors across studies (Benson et al., 2018; Bialkova et al., 2016; Choi et al., 2012; Kaur et al., 2017).

While previous research has shown effects on perceived pleasantness in dieting, restrained eaters or individuals with obesity (Cavanagh & Forestell, 2013; Irmak et al., 2011; Ng et al., 2011; Wansink & Chandon, 2006), we tested hungry healthy participants with healthy eating styles. Either nutrition claims do not influence perceived pleasantness in healthy participants, or the effect is so small that we cannot assess it with our study design, with which we could exclude small-to-medium effect sizes according to Cohen's criteria (Cohen, 1988; Cohen's $d \geq 0.23$ and $d \geq 0.34$, for Studies 1 and 2, respectively). More powerful studies are needed to pursue this question.

As both claims decreased expected taste pleasantness but not perceived taste, they led to positive taste prediction errors. This finding, together with the fact that drink preference was explained by perceived rather than expected taste pleasantness, suggests that exposure may be a good strategy to update negative expectations associated with claims and perhaps increase their acceptance. Indeed, previous studies have shown that single and repeated exposure to certain stimuli, including food products, positively impact preference and acceptance of products (Appleton et al., 2018; Ballard et al., 2017; Zajonc, 1968). Future studies could investigate whether nutrition claims enhance or attenuate exposure effects.

We found that both the "protein-rich" and the "fat-reduced" claim had similar effects on expected and perceived pleasantness, suggesting that the type of the claim may be less relevant for pleasantness, and more relevant for other attributes. To our knowledge, there are no previous experimental studies comparing the effects of fat and protein claims like we did, therefore, these novel findings and our interpretation should be further explored in the future.

4.1.2 | Effects of nutrition claims on expected and perceived healthiness

In line with previous research we found that nutrition claims increased expectations and perceptions of healthiness (Benson et al., 2018; Chrysochou & Grunert, 2014; Oostenbach et al., 2019; Prada et al., 2021; Williams, 2005). Comparing the two nutrition claims, we found that the "protein-rich" claim influenced expected healthiness more than the "fat-reduced" claim. This observed difference aligns with the findings of André et al. (2019), who conducted several survey studies and found that healthiness increases for claims that are scientific and focus on the presence of a positive attribute (e.g., protein) rather than on the removal of a negative attribute (e.g., fat). Interestingly, we found that both claims increased perceived healthiness even after sampling otherwise equal drinks. Healthiness is considered as an abstract food attribute (Rangel, 2013) reflecting rather long-term benefits of consuming a certain food, and it may require more cognitive rather than sensory processing. As such, it is conceivable that healthiness may not be influenced by a short-term exposure to food, but is more strongly influenced by labels and claims.

4.1.3 | Effects of nutrition claims on expected and perceived satiating quality

Our findings are in line with previous research showing that reduced-fat claims decrease expectations and perception of satiating quality (Chandon & Wansink, 2012; Faulkner et al., 2014; Wansink & Chandon, 2006). Different than the "fat-reduced" claim, we found that the "protein-rich" claim increased expected satiating quality; this is consistent with the fact that proteins are largely considered as satiating nutrients (Chambers et al., 2015). Interestingly, we found that perceived satiating quality for the same drinks changed depending on the claim with which they were presented: while the "protein-rich" claim slightly increased the ratings, the "fat-reduced" claim decreased them. These findings support the importance of labeling as a strategy targeting portion size control and satiation (Benson et al., 2018; Chambers et al., 2015; Gibson-Moore, 2009; Van Kleef et al., 2012). In this context, our results suggest that including a "protein-rich" claim increases expectations of satiating quality and may thus positively impact portion size selection.

Our exploratory analyses revealed gender differences in the effects of the "protein-rich" and "fat-reduced" claims on expected satiating quality. More specifically, in Study 1 we found that compared to men, women exhibited a higher claim effect on expected satiation for the "protein-rich" claim compared to the "fat-reduced" claim. Furthermore, in this study, the effect of the "protein-rich" claim on expected satiation was higher for women than for men. We, however, could not replicate the effects of the "protein-rich" claim in Study 2, suggesting these associations may not be as robust. Indeed, gender specific differences on nutrition claim effects have not been systematically reported in previous literature (Dean et al., 2007; Prada et al., 2021; Steinhauser & Hamm, 2018). Importantly, our studies were not designed to assess associations between gender and claim effects, and therefore our results should be considered accordingly. For instance, we did not counterbalance gender in Study 1, which resulted in a different number of men and women in each condition (Protein condition: 27 men, 30 women; Fat condition: 16 men, 37 women). The association between gender and nutrition claims effects on valuation should be clarified in future studies designed to specifically assess such effects.

4.1.4 | Effects of nutrition claims on willingness to pay

We found that participants were willing to pay more for protein-rich drinks, which they expected to be less tasty, but healthier and more satiating, than for conventional drinks. This finding aligns with previous research showing that participants are willing to pay more for food they perceive as healthy, especially if it is presented with labels that highlight their nutritious value (Enax et al., 2015a). Previous research has shown that salient nutrition labels impact valuation by decreasing the weight of taste and increasing the weight of healthiness in food decisions (Enax et al., 2016; Rramani et al., 2020). Along these lines, we found that while for conventional drinks WTP ratings were explained only by expected taste pleasantness ratings, for protein-rich drinks they were explained only by expected satiation ratings. These results may indicate that the presence of nutrition claims may decrease the impact of taste and increase the impact of other attributes such as expected satiety on valuation. Such effects could be more specifically tested in future studies. Importantly, we assessed WTP only before sampling the drinks, not during or after. Therefore, we cannot conclude whether exposure to the taste and flavor of drinks impacts participants' WTP. Future studies including a WTP measure after and/or during every sampling should assess these effects more specifically.

4.2 | fMRI results

Our fMRI task elicited responses in regions previously implicated in taste and flavor processing such as bilateral caudate, orbital part of the inferior frontal gyrus, insula, frontal operculum, and anterior cingulate cortex (Avery et al., 2020; de Araujo et al., 2003; Grabenhorst et al., 2008; van Rijn et al., 2018; Veldhuizen et al., 2011). These results support the notion that our fMRI task could reliably evoke and measure taste and flavor responses in the brain.

We found an increased activity in left lateral OFC when viewing cues for drinks that were expected to be less tasty, but healthier, and more satiating ("protein-rich" drinks). Lateral OFC is associated with evaluation of taste pleasantness (Bender et al., 2009; Kringelbach et al., 2003) and inhibition of rewarding responses (Elliott, 2000; Kringelbach, 2005; van der Laan et al., 2014) and supports representations of the nutritive attributes of food (Suzuki et al., 2017) and their healthiness (Londerée & Wagner, 2021). Thus, claim effects on lateral OFC activation may reflect changes in the representation of food items, which were revealed in participants' expectations. This hypothesis is consistent with previous findings from Courtney et al. (2018) who showed that providing caloric information on food images alters the representation of these food items in lateral OFC. Future studies using multivariate approaches may be more suitable to investigate the changes in neural representation of food items by claims.

We found no difference in neural activity in regions associated with valuation (vS/NAcc, vmPFC, dlPFC, lateral OFC) when tasting nor when swallowing drinks presented with *vs.* without the "protein-rich" claim. By contrast, we found an increased activity in a cluster extending into the left NAcc when tasting drinks presented without *vs.* with the "protein-rich" claim, despite no difference in taste pleasantness ratings at the behavioral level. NAcc is among other functions involved in reward anticipation (Berridge et al., 2010; Knutson et al., 2008; O'Doherty et al., 2002; Small et al., 2008). As drinks without claim were expected to be less healthy but tastier, our finding might reflect the expectation of a better taste of drinks without the claim. Such an interpretation is also concordant with literature on placebo effects supporting that vS/NAcc activity may reflect motivational aspects associated with a certain stimulus, rather than its rewarding properties. In other words, an increased vS/NAcc activity may reflect participants' wanting to believe or expect that a certain stimulus is better than others (Wager & Atlas, 2015; Schmidt et al., 2017). Furthermore, considering that drinks without claims were expected to be not only tastier but also less healthy, the increased activity in left NAcc when tasting drinks without *vs.* with claims partially supports the unhealthy-tasty intuition (Raghunathan et al., 2006), whereby healthier food is expected to be less tasty. Contrary to this intuition, however, higher healthiness expectations did not negatively impact reported perceived taste pleasantness.

Previous research has shown that context-dependent beliefs and expectations often override experienced pleasantness (Plassmann et al., 2008; Schmidt et al., 2017; Wager & Atlas, 2015). We could not replicate such effects with nutrition claims, possibly because claim-induced expectations may not have been as strong and/or they may have been "updated" once participants were exposed to even more sensory characteristics of the stimuli. Such an explanation is likely considering that we did not find an increased activity in left NAcc during swallowing drinks but only during tasting them. During swallowing, we found an increased task-dependent functional connectivity between the cluster extending into the left NAcc and a cluster of the right middle frontal gyrus. Middle frontal gyrus is a region involved in successful action cancelation (Dambacher et al., 2014), in processing conflicting information and error monitoring (Suárez-Pellicioni et al., 2013), and in reorienting attention from endogenous (goal-driven, top-down) to exogenous (stimulus-driven, bottom-up) control (Chica et al., 2013; Corbetta et al., 2008; Japee et al., 2015). Considering this, it is possible that when additional sensory information becomes available (e.g., flavor), attention may be redirected to the perceived stimulus characteristics thereby "updating" expectations or reducing their effects on perceived pleasantness. To our knowledge, right middle frontal gyrus has not been commonly associated with contextual effects on taste valuation in past research; therefore, this finding and its interpretation should be validated in future studies.

Altogether our fMRI findings suggest that when less sensory information is present, during cue viewing and tasting as opposed to flavoring, expectations may modulate neural activity associated with reward processing. However, once additional sensory information becomes available, bottom-up processes may contribute to updating expectations or reducing their effect on valuation. This interpretation implies that while nutrition claims may initially induce a top-down bias on valuation through the expectations that they elicit, this is not sustained when additional sensory information becomes available, possibly due to attention reorientation processes that may relate to stimuli re-evaluation. Future studies should examine these effects more closely.

4.3 | Limitations and suggestions for future research

Our studies have limitations which could be considered in future research. First, the way we assessed perceived satiating quality may not be ideal, especially since many satiety signals may not arise immediately at the moment of consumption (Ahima & Antwi, 2008; Chambers et al., 2015; Wright et al., 2016). Measuring hormones in the blood (e.g., ghrelin like in Crum et al., 2011) may be a better measure of satiety that could be considered in future studies. Second, even though in both our studies we used protein-rich and fat-reduced milk-mix drinks, we did not present the drinks with the two nutrition claims at once. Considering that many foods, especially novel functional foods, contain multiple claims on their packaging, it is relevant to assess the effects of different nutrition claims presented together. Third, we assessed WTP only before sampling the drinks, so we could not assess claim effects on WTP after exposure. Furthermore, our WTP measure was hypothetical. Different than incentivized WTP measures, hypothetical WTP measures do not have a tangible and real consequence for the participants and may therefore lead to overestimated values, even though they are generally reported to be valid and efficient in assessing subjective preference (Schmidt & Bijmolt, 2020). When using incentivized measures, it is more likely that participants incorporate longer-term consequences in valuation, since their behavior impacts the outcome. By contrast, in our study, independent of their ratings, participants had to taste the different drinks. Not using incentivized measures may explain why we did not find an effect of nutrition claims on the activity of regions associated with integration of longer-term consequences in valuation such as dlPFC (Enax et al., 2015a; Schmidt et al., 2017). Future studies on the effects of nutrition claims should consider using incentivized measures and assess valuation pre- and post-exposure to certain stimulus characteristics. Finally, while our fMRI study was adequately powered to reveal taste and flavor responses in the brain, it may not have been sufficiently powerful to detect smaller effects. While the effects of claims on expectations are robust, the effects of these expectations on perceived pleasantness are likely smaller and may be detected only in more powerful studies requiring larger sample sizes.

5 | CONCLUSION

In our two studies we found that nutrition claims impacted expectations of taste pleasantness, healthiness, and satiating quality, but did not impact perceived taste pleasantness. We found that the "protein-rich" claim increased healthiness expectations significantly more than the "fat-reduced" claim, at no additional cost on expected and perceived pleasantness. Our fMRI results suggest that while claim-induced expectations may modulate reward-associated responses during cue viewing and tasting otherwise equal drinks, such effects are not sustained during swallowing these drinks. Our results support two strategies that could increase acceptance for foods with nutrition claims. First, with our studies we provide experimental evidence supporting that higher healthiness expectations do not negatively impact perceived taste pleasantness. Considering this, it may be more efficient to use nutrition claims that elicit higher healthiness expectations, especially claims that highlight the presence of nutrients with more positive associations. Second, we found that even though nutrition claims elicited negative taste pleasantness expectations, exposure to foods with such claims positively surprised participants and impacted their preference. This indicates that exposing participants to foods with nutrition claims may modulate their negative expectations and even increase acceptance for such foods. Overall, our studies provide novel insights into the effects of two different nutrition claims, especially the "protein-rich" claim, on expected and perceived attributes of the same food and point out possible novel neural correlates of nutrition claim effects on expectations during tasting and swallowing otherwise equal drinks.

ACKNOWLEDGMENTS

The authors would like to thank Dr. Karl Meier and Dr. Peter Trautner for helping with the implementation of the fMRI paradigm; Omar Salah Ahmed for helping with programming; Bettina Mahlow, Nayara Atella-Hödtke, Jana Paus, Lena Michaelis, Dominik Suri, and Aenne Läufer for their help with participant recruitment and data collection; Dr. Holger Gerhardt for his valuable input on the experimental design and data analyses; Prof. Dr. Ulrich Ettinger, Prof. Dr. Wolfram Kunz, and Daniela Schelski for their support during data collection; Dr. Richard Höchenberger for providing the software for the taste threshold measurement.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The behavioral data, the group level fMRI contrast parameter maps, and ROI masks are openly available in the Harvard Dataverse at: https://dataverse.harvard.edu/privateurl.xhtml?token=3373c390-d771-4bd8-9470-d8ab356874c0.

ETHICS STATEMENT

The study was approved by the local ethical committee of the University of Bonn, Medical Center (No. 077/19) and all participants provided written informed consent according to the declaration of Helsinki.

PEER REVIEW

The peer review history for this article is available at: https://publons.com/publon/10.1002/brb3.2828.

REFERENCES

Ahima, R. S., & Antwi, D. A. (2008). Brain regulation of appetite and satiety. *Endocrinology and Metabolism Clinics of North America*, *37*, 811–823. https://doi.org/10.1016/j.ecl.2008.08.005

André, Q., Chandon, P., & Haws, K. (2019). Healthy through presence or absence, nature or science?: A framework for understanding front-of-package food claims. *Journal of Public Policy & Marketing*, *38*, 172–191. https://doi.org/10.1177/0743915618824332

Appleton, K. M., Hemingway, A., Rajska, J., & Hartwell, H. (2018). Repeated exposure and conditioning strategies for increasing vegetable liking and intake: Systematic review and meta-analyses of the published literature. *American Journal of Clinical Nutrition*, *108*, 842–856. https://doi.org/10.1093/ajcn/nqy143

Avery, J. A., Liu, A. G., Ingeholm, J. E., Riddell, C. D., Gotts, S. J., & Martin, A. (2020). Taste quality representation in the human brain. *Journal of Neuroscience*, *40*, 1042–1052. https://doi.org/10.1523/JNEUROSCI.1751-19.2019

Ballard, I. C., Hennigan, K., & McClure, S. M. (2017). Mere exposure: Preference change for novel drinks reflected in human ventral tegmental area. *Journal of Cognitive Neuroscience*, *29*, 793–804. https://doi.org/10.1162/jocn_a_01098

Bartra, O., McGuire, J. T., & Kable, J. W. (2013). The valuation system: A coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. *Neuroimage*, *76*, 412–427. https://doi.org/10.1016/j.neuroimage.2013.02.063

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*. 10.18637/jss.v067.i01

Belei, N., Geyskens, K., Goukens, C., Ramanathan, S., & Lemmink, J. (2012). The best of both worlds? Effects of attribute-induced goal conflict on consumption of healthful indulgences. *Journal of Marketing Research*, *49*, 900–909. https://doi.org/10.1509/jmr.10.0155

Bender, G., Veldhuizen, M. G., Meltzer, J. A., Gitelman, D. R., & Small, D. M. (2009). Neural correlates of evaluative compared with passive tasting. *European Journal of Neuroscience*, *30*, 327–338. https://doi.org/10.1111/j.1460-9568.2009.06819.x

Benson, T., Lavelle, F., Bucher, T., McCloat, A., Mooney, E., Egan, B., Collins, C. E., & Dean, M. (2018). The impact of nutrition and health claims on consumer perceptions and portion size selection: Results from a nationally representative survey. *Nutrients*, *10*, 656. https://doi.org/10.3390/nu10050656

Berridge, K. C., Ho, C.-Y., Richard, J. M., & DiFeliceantonio, A. G. (2010). The tempted brain eats: Pleasure and desire circuits in obesity and eating disorders. *Brain Research*, *1350*, 43–64. https://doi.org/10.1016/j.brainres.2010.04.003

Bertrams, A., & Dickhäuser, O. (2009). Messung dispositioneller Selbstkontroll-Kapazität. *Diagnostica*, *55*, 2–10. https://doi.org/10.1026/0012-1924.55.1.2

Bialkova, S., Sasse, L., & Fenko, A. (2016). The role of nutrition labels and advertising claims in altering consumers' evaluation and choice. *Appetite*, *96*, 38–46. https://doi.org/10.1016/j.appet.2015.08.030

Bock, O., Baetge, I., & Nicklisch, A. (2014). hroot: Hamburg registration and organization online tool. *European Economic Review*, *71*, 117–120. https://doi.org/10.1016/j.euroecorev.2014.07.003

Bradley, M. M., & Lang, P. J. (1994). Measuring emotion: The self-assessment manikin and the semantic differential. *Journal of Behavior Therapy and Experimental Psychiatry*, *25*, 49–59. https://doi.org/10.1016/0005-7916(94)90063-9

Brett, M., Jean-Luc, A., Romain, V., & Jean-Baptiste, P. (2002). Region of interest analysis using an SPM toolbox [abstract]. Presented at the 8th International Conference on Functional Mapping of the Human Brain. NeuroImage, *16*.

Cavanagh, K. V., & Forestell, C. A. (2013). The effect of brand names on flavor perception and consumption in restrained and unrestrained eaters. *Food Quality and Preference*, *28*, 505–509. https://doi.org/10.1016/j.foodqual.2012.12.004

Cecchini, M., & Warin, L. (2016). Impact of food labelling systems on food choices and eating behaviours: A systematic review and meta-analysis of randomized studies. *Obesity Reviews*, *17*, 201–210. https://doi.org/10.1111/obr.12364

Chambers, L., McCrickerd, K., & Yeomans, M. R. (2015). Optimising foods for satiety. *Trends in Food Science & Technology*, *41*, 149–160. https://doi.org/10.1016/j.tifs.2014.10.007

Chan, C., Patch, C., & Williams, P. (2005). Australian consumers are sceptical about but influenced by claims about fat on food labels. *European Journal of Clinical Nutrition*, *59*, 148–151. https://doi.org/10.1038/sj.ejcn.1602038

Chandon, P., & Wansink, B. (2012). Does food marketing need to make us fat? A review and solutions. *Nutrition Reviews*, *70*, 571–593. https://doi.org/10.1111/j.1753-4887.2012.00518.x

Chica, A. B., Bartolomeo, P., & Lupiáñez, J. (2013). Two cognitive and neural systems for endogenous and exogenous spatial attention. *Behavioural Brain Research*, *237*, 107–123. https://doi.org/10.1016/j.bbr.2012.09.027

Choi, H., Paek, H.-J., & Whitehill King, K. (2012). Are nutrient-content claims always effective? *International Journal of Advertising*, *31*, 421–443. https://doi.org/10.2501/IJA-31-2-421-443

Chrysochou, P., & Grunert, K. G. (2014). Health-related ad information and health motivation effects on product evaluations. *Journal of Business Research*, *67*, 1209–1217. https://doi.org/10.1016/j.jbusres.2013.05.001

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd edn.). Lawrence Erlbaum Associates: New York.

Corbetta, M., Patel, G., & Shulman, G. L. (2008). The reorienting system of the human brain: From environment to theory of mind. *Neuron*, *58*, 306–324. https://doi.org/10.1016/j.neuron.2008.04.017

Cornil, Y., Plassmann, H., Aron-Wisnewsky, J., Poitou-Bernert, C., Clément, K., Chabert, M., & Chandon, P. (2022). Obesity and responsiveness to food marketing before and after bariatric surgery. *Journal of Consumer Psychology*, *32*, 57–68. https://doi.org/10.1002/jcpy.1221

Courtney, A. L., PeConga, E. K., Wagner, D. D., & Rapuano, K. M. (2018). Calorie information and dieting status modulate reward and control activation during the evaluation of food images. *PLoS ONE*, *13*, e0204744. https://doi.org/10.1371/journal.pone.0204744

Crum, A. J., Corbin, W. R., Brownell, K. D., & Salovey, P. (2011). Mind over milkshakes: Mindsets, not just nutrients, determine ghrelin response. *Health Psychology Journal*, *30*, 424–429. https://doi.org/10.1037/a0023467

Dambacher, F., Sack, A. T., Lobbestael, J., Arntz, A., Brugman, S., & Schuhmann, T. (2014). The role of right prefrontal and medial cortex in response inhibition: Interfering with action restraint and action cancellation using transcranial magnetic brain stimulation. *Journal of Cognitive Neuroscience*, *26*, 1775–1784. https://doi.org/10.1162/jocn_a_00595

de Araujo, I. E. T., Kringelbach, M. L., Rolls, E. T., & Hobden, P. (2003). Representation of Umami taste in the human brain. *Journal of Neurophysiology*, *90*, 313–319. https://doi.org/10.1152/jn.00669.2002

Dean, M., Shepherd, R., Arvola, A., Vassallo, M., Winkelmann, M., Claupein, E., Lähteenmäki, L., Raats, M. M., & Saba, A. (2007). Consumer perceptions of healthy cereal products and production methods. *Journal of Cereal Science*, *46*, 188–196. https://doi.org/10.1016/j.jcs.2007.06.007

Eickhoff, S. B., Stephan, K. E., Mohlberg, H., Grefkes, C., Fink, G. R., Amunts, K., & Zilles, K. (2005). A new SPM toolbox for combining probabilistic cytoarchitectonic maps and functional imaging data. *Neuroimage*, *25*, 1325–1335. https://doi.org/10.1016/j.neuroimage.2004.12.034

Elliott, R. (2000). Dissociable functions in the medial and lateral orbitofrontal cortex: Evidence from human neuroimaging studies. *Cerebral Cortex*, *10*, 308–317. https://doi.org/10.1093/cercor/10.3.308

Enax, L., Hu, Y., Trautner, P., & Weber, B. (2015a). Nutrition labels influence value computation of food products in the ventromedial prefrontal cortex. *Obesity*, *23*, 786–792. https://doi.org/10.1002/oby.21027

Enax, L., Krajbich, I., & Weber, B. (2016). Salient nutrition labels increase the integration of health attributes in food decision-making. *Judgment & Decision Making*, *11*, 460–471. Available at: http://journal.sjdm.org/16/16620/jdm16620.html

Enax, L., Krapp, V., Piehl, A., & Weber, B. (2015b). Effects of social sustainability signaling on neural valuation signals and taste-experience of food products. *Frontiers in Behavioral Neuroscience*, *9*, 247. https://doi.org/10.3389/fnbeh.2015.00247

Esteban, O., Birman, D., Schaer, M., Koyejo, O. O., Poldrack, R. A., & Gorgolewski, K. J. (2017). MRIQC: Advancing the automatic prediction of image quality in MRI from unseen sites. *PLoS ONE*, *12*, e0184661. https://doi.org/10.1371/journal.pone.0184661

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*, 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Faulkner, G. P., Pourshahidi, L. K., Wallace, J. M. W., Kerr, M. A., McCaffrey, T. A., & Livingstone, M. B. E. (2014). Perceived 'healthiness' of foods can influence consumers' estimations of energy density and appropriate portion size. *International Journal of Obesity*, *38*, 106–112. https://doi.org/10.1038/ijo.2013.69

Gearhardt, A. N., Bragg, M. A., Pearl, R. L., Schvey, N. A., Roberto, C. A., & Brownell, K. D. (2012). Obesity and public policy. *Annual Review of Clinical Psychology*, *8*, 405–430. https://doi.org/10.1146/annurev-clinpsy-032511-143129

Gibson-Moore, H. (2009). Satiation, satiety and their effects on eating behaviour. *Nutrition Bulletin*, *34*, 412–416. https://doi.org/10.1111/j.1467-3010.2009.01777.x

Gortmaker, S. L., Swinburn, B. A., Levy, D., Carter, R., Mabry, P. L., Finegood, D. T., Huang, T., Marsh, T., & Moodie, M. L. (2011). Changing the future of obesity: Science, policy, and action. *Lancet*, *378*, 838–847. https://doi.org/10.1016/S0140-6736(11)60815-5

Grabenhorst, F., & Rolls, E. T. (2008). Selective attention to affective value alters how the brain processes taste stimuli. *European Journal of Neuroscience*, *27*, 723–729. https://doi.org/10.1111/j.1460-9568.2008.06033.x

Grabenhorst, F., Rolls, E. T., & Bilderbeck, A. (2008). How cognition modulates affective responses to taste and flavor: Top-down influences on the orbitofrontal and pregenual cingulate cortices. *Cerebral Cortex*, *18*, 1549–1559. https://doi.org/10.1093/cercor/bhm185

Grunert, S. C. (1989). Ein Inventar zur Erfassung von Selbstaussagen zum Ernährungsverhalten. *Diagnostica*, *35*, 67–179.

Hardikar, S., Höchenberger, R., Villringer, A., & Ohla, K. (2017). Higher sensitivity to sweet and salty taste in obese compared to lean individuals. *Appetite*, *111*, 158–165. https://doi.org/10.1016/j.appet.2016.12.017

Hare, T. A., Camerer, C. F., & Rangel, A. (2009). Self-control in decision-making involves modulation of the vmPFC valuation system. *Science (80-.)*, *324*, 646–648. https://doi.org/10.1126/science.1168450

Hare, T. A., Malmaud, J., & Rangel, A. (2011). Focusing attention on the health aspects of foods changes value signals in vmPFC and improves dietary choice. *Journal of Neuroscience*, *31*, 11077–11087. https://doi.org/10.1523/JNEUROSCI.6383-10.2011

Hawkes, C., Smith, T. G., Jewell, J., Wardle, J., Hammond, R. A., Friel, S., Thow, A. M., & Kain, J. (2015). Smart food policies for obesity prevention. *Lancet*, *385*, 2410–2421. https://doi.org/10.1016/S0140-6736(14)61745-1

Hersey, J. C., Wohlgenant, K. C., Arsenault, J. E., Kosa, K. M., & Muth, M. K. (2013). Effects of front-of-package and shelf nutrition labeling systems on consumers. *Nutrition Reviews*, *71*, 1–14. https://doi.org/10.1111/nure.12000

Höchenberger, R., & Ohla, K. (2017). Rapid estimation of gustatory sensitivity thresholds with SIAM and QUEST. *Frontiers in Psychology*, *8*, 1–13. https://doi.org/10.3389/fpsyg.2017.00981

Höchenberger, R., & Ohla, K. (2019). Repeatability of taste recognition threshold measurements with QUEST and Quick Yes–No. *Nutrients*, *12*, 24. https://doi.org/10.3390/nu12010024

Irmak, C., Vallen, B., & Robinson, S. R. (2011). The Impact of product name on dieters' and nondieters' food evaluations and consumption. *Journal of Consumer Research*, *38*, 390–405. https://doi.org/10.1086/660044

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., EISPACK authors, Heisterkamp, S., Van Willigen, B., Ranke, J., & R Core Team. (2020). nlme: Linear and nonlinear mixed effects models. Available at: https://cran.r-project.org/package=nlme

Japee, S., Holiday, K., Satyshur, M. D., Mukai, I., & Ungerleider, L. G. (2015). A role of right middle frontal gyrus in reorienting of attention: A case study. *Frontiers in Systems Neuroscience*, *9*, 1–16. https://doi.org/10.3389/fnsys.2015.00023

Kaur, A., Scarborough, P., & Rayner, M. (2017). A systematic review, and meta-analyses, of the impact of health-related claims on dietary choices. *International Journal of Behavioral Nutrition and Physical Activity*, *14*, 93. https://doi.org/10.1186/s12966-017-0548-1

Knutson, B., Wimmer, G. E., Kuhnen, C. M., & Winkielman, P. (2008). Nucleus accumbens activation mediates the influence of reward cues on financial risk taking. *Neuroreport*, *19*, 509–513. https://doi.org/10.1097/WNR.0b013e3282f85c01

Kringelbach, M. L. (2005). The human orbitofrontal cortex: Linking reward to hedonic experience. *Nature Reviews Neuroscience*, *6*, 691–702. https://doi.org/10.1038/nrn1748

Kringelbach, M. L., O'Doherty, J., Rolls, E. T., & Andrews, C. (2003). Activation of the human orbitofrontal cortex to a liquid food stimulus is correlated with its subjective pleasantness. *Cerebral Cortex*, *13*, 1064–1071. https://doi.org/10.1093/cercor/13.10.1064

Lakens, D. (2017). Equivalence tests: A practical primer for t tests, correlations, and meta-analyses. *Social Psychological and Personality Science*, *8*, 355–362. https://doi.org/10.1177/1948550617697177

Lenth, R. V. (2016). Least-squares means: The R package lsmeans. *Journal of Statistical Software*, 69. 10.18637/jss.v069.i01

Levin, I. P., & Gaeth, G. J. (1988). How consumers are affected by the framing of attribute information before and after consuming the product. *Journal of Consumer Research*, *15*, 374. https://doi.org/10.1086/209174

Liem, D. G., Miremadi, F., Zandstra, E. H., & Keast, R. S. J. (2012). Health labelling can influence taste perception and use of table salt for reduced-sodium products. *Public Health Nutrition*, *15*, 2340–2347. https://doi.org/10.1017/S136898001200064X

Linder, N. S., Uhl, G., Fliessbach, K., Trautner, P., Elger, C. E., & Weber, B. (2010). Organic labeling influences food valuation and choice. *Neuroimage*, *53*, 215–220. https://doi.org/10.1016/j.neuroimage.2010.05.077

Londerée, A. M., & Wagner, D. D. (2021). The orbitofrontal cortex spontaneously encodes food health and contains more distinct representations for foods highest in tastiness. *Social Cognitive and Affective Neuroscience*, *16*, 816–826. https://doi.org/10.1093/scan/nsaa083

Lüdecke, D. (2021). sjPlot: Data visualization for statistics in social science.

Lundström, J. N., Boesveldt, S., & Albrecht, J. (2011). Central processing of the chemical senses: An overview. *ACS Chemical Neuroscience*, *2*, 5–16. https://doi.org/10.1021/cn1000843

Lyn, R., Heath, E., & Dubhashi, J. (2019). Global implementation of obesity prevention policies: A review of progress, politics, and the path forward. *Current Obesity Reports*, *8*, 504–516. https://doi.org/10.1007/s13679-019-00358-w

Maldjian, J. A., Laurienti, P. J., Kraft, R. A., & Burdette, J. H. (2003). An automated method for neuroanatomic and cytoarchitectonic atlas-based interrogation of fMRI data sets. *Neuroimage*, *19*, 1233–1239. https://doi.org/10.1016/S1053-8119(03)00169-1

Malik, V. S., Willett, W. C., & Hu, F. B. (2013). Global obesity: Trends, risk factors and policy implications. *Nature Reviews Endocrinology*, *9*, 13–27. https://doi.org/10.1038/nrendo.2012.199

McClure, S. M., Li, J., Tomlin, D., Cypert, K. S., Montague, L. M., & Montague, P. R. (2004). Neural correlates of behavioral preference for culturally familiar drinks. *Neuron*, *44*, 379–387. https://doi.org/10.1016/j.neuron.2004.09.019

McLaren, D. G., Ries, M. L., Xu, G., & Johnson, S. C. (2012). A generalized form of context-dependent psychophysiological interactions (gPPI): A comparison to standard approaches. *Neuroimage*, *61*, 1277–1286. https://doi.org/10.1016/j.neuroimage.2012.03.068

Mela, D. J. (2001). Determinants of food choice: Relationships with obesity and weight control. *Obesity Research*, *9*, 249S–255S. https://doi.org/10.1038/oby.2001.127

Nagl, M., Hilbert, A., de Zwaan, M., Braehler, E., & Kersting, A. (2016). The German version of the Dutch eating behavior questionnaire: Psychometric properties, measurement invariance, and population-based norms. *PLoS ONE*, *11*, e0162510. https://doi.org/10.1371/journal.pone.0162510

Ng, J., Stice, E., Yokum, S., & Bohon, C. (2011). An fMRI study of obesity, food reward, and perceived caloric density. Does a low-fat label make food less appealing? *Appetite*, *57*, 65–72. https://doi.org/10.1016/j.appet.2011.03.017

Nobrega, L., Ares, G., & Deliza, R. (2020). Are nutritional warnings more efficient than claims in shaping consumers' healthfulness perception? *Food Quality and Preference*, *79*, 103749. https://doi.org/10.1016/j.foodqual.2019.103749

Norton, J. E., Fryer, P. J., & Parkinson, J. A. (2013). The effect of reduced-fat labelling on chocolate expectations. *Food Quality and Preference*, *28*, 101–105. https://doi.org/10.1016/j.foodqual.2012.08.004

O'Doherty, J. P., Deichmann, R., Critchley, H. D., & Dolan, R. J. (2002). Neural responses during anticipation of a primary taste reward. *Neuron*, *33*, 815–826. https://doi.org/10.1016/S0896-6273(02)00603-7

Okamoto, M., & Dan, I. (2013). Extrinsic information influences taste and flavor perception: A review from psychological and neuroimaging perspectives. *Seminars in Cell & Developmental Biology*, *24*, 247–255. https://doi.org/10.1016/j.semcdb.2012.11.001

Oostenbach, L. H., Slits, E., Robinson, E., & Sacks, G. (2019). Systematic review of the impact of nutrition claims related to fat, sugar and energy content on food choices and energy intake. *Bmc Public Health [Electronic Resource]*, *19*, 1296. https://doi.org/10.1186/s12889-019-7622-3

European Union Parliament (2006). Regulation (EC) No 1924/2006 of the European Parliament and of the Council of 20 December 2006 on nutrition and health claims made on foods. Available at: https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2006:404:0009:0025:En:PDF

Piqueras-Fiszman, B., & Spence, C. (2015). Sensory expectations based on product-extrinsic food cues: An interdisciplinary review of the empirical evidence and theoretical accounts. *Food Quality and Preference*, *40*, 165–179. https://doi.org/10.1016/j.foodqual.2014.09.013

Plassmann, H., O'Doherty, J., Shiv, B., & Rangel, A. (2008). Marketing actions can modulate neural representations of experienced pleasantness. *Proceedings of the National Academy of Sciences*, *105*, 1050–1054. https://doi.org/10.1073/pnas.0706929105

Plassmann, H., & Weber, B. (2015). Individual differences in marketing placebo effects: Evidence from brain imaging and behavioral experiments. *Journal of Marketing Research*, *52*, 493–510. https://doi.org/10.1509/jmr.13.0613

Pliner, P., & Hobden, K. (1992). Development of a scale to measure the trait of food neophobia in humans. *Appetite*, *19*, 105–120. https://doi.org/10.1016/0195-6663(92)90014-W

Prada, M., Saraiva, M., Sério, A., Coelho, S., Godinho, C. A., & Garrido, M. V. (2021). The impact of sugar-related claims on perceived healthfulness, caloric value and expected taste of food products. *Food Quality and Preference*, *94*, 104331. https://doi.org/10.1016/j.foodqual.2021.104331

R Core Team (2020). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing Available at: https://www.r-project.org/[Accessed May 27, 2020]

Raghunathan, R., Naylor, R. W., & Hoyer, W. D. (2006). The unhealthy = tasty intuition and its effects on taste inferences, enjoyment, and choice of food products. *Journal of Marketing*, *70*, 170–184. https://doi.org/10.1509/jmkg.70.4.170

Rangel, A. (2013). Regulation of dietary choice by the decision-making circuitry. *Nature Neuroscience*, *16*, 1717–1724. https://doi.org/10.1038/nn.3561

Rolls, E. T., Huang, C. C., Lin, C. P., Feng, J., & Joliot, M. (2020). Automated anatomical labelling atlas 3. *Neuroimage*, *206*, 116189. https://doi.org/10.1016/j.neuroimage.2019.116189

Rramani, Q., Krajbich, I., Enax, L., Brustkern, L., & Weber, B. (2020). Salient nutrition labels shift peoples' attention to healthy foods and exert more influence on their choices. *Nutrition Research*, *80*, 106–116. https://doi.org/10.1016/j.nutres.2020.06.013

RStudio Team (2019). RStudio: Integrated Development for R. Available at: https://rstudio.com

Schloerke, B., Cook, D., Larmarange, J., Briatte, F., Marbach, M., Thoen, E., Elberg, A., & Crowley, J. (2021). GGally: Extension to "ggplot2." Available at: https://cran.r-project.org/package=GGally%0D

Schmidt, J., & Bijmolt, T. H. A. (2020). Accurately measuring willingness to pay for consumer goods: a meta-analysis of the hypothetical bias. *Journal of the Academy of Marketing Science*, *48*, 499–518. https://doi.org/10.1007/s11747-019-00666-6

Schmidt, L., Skvortsova, V., Kullen, C., Weber, B., & Plassmann, H. (2017). How context alters value: The brain's valuation and affective regulation system link price cues to experienced taste pleasantness. *Science Reports*, *7*, 8098. https://doi.org/10.1038/s41598-017-08080-0

Small, D. M., Veldhuizen, M. G., Felsted, J., Mak, Y. E., & McGlone, F. (2008). Separable substrates for anticipatory and consummatory food chemosensation. *Neuron*, *57*, 786–797. https://doi.org/10.1016/j.neuron.2008.01.021

Sonnenberg, L., Gelsomin, E., Levy, D. E., Riis, J., Barraclough, S., & Thorndike, A. N. (2013). A traffic light food labeling intervention increases consumer awareness of health and healthy choices at the point-of-purchase. *Preventive Medicine (Baltim)*, *57*, 253–257. https://doi.org/10.1016/j.ypmed.2013.07.001

Sörqvist, P., Hedblom, D., Holmgren, M., Haga, A., Langeborg, L., Nöstl, A., & Kågström, J. (2013). Who needs cream and sugar when there is eco-labeling? Taste and willingness to pay for "eco-friendly" coffee. *PLoS ONE*, *8*, e80719. https://doi.org/10.1371/journal.pone.0080719

Spence, C. (2015). Multisensory flavor perception. *Cell*, *161*, 24–35. https://doi.org/10.1016/j.cell.2015.03.007

Steinhauser, J., & Hamm, U. (2018). Consumer and product-specific characteristics influencing the effect of nutrition, health and risk reduction claims on preferences and purchase behavior—A systematic review. *Appetite*, *127*, 303–323. https://doi.org/10.1016/j.appet.2018.05.012

Suárez-Pellicioni, M., Núñez-Peña, M. I., & Colomé, À. (2013). Abnormal error monitoring in math-anxious individuals: Evidence from error-related brain potentials. *PLoS ONE*, *8*, e81143. https://doi.org/10.1371/journal.pone.0081143

Suzuki, S., Cross, L., & O'Doherty, J. P. (2017). Elucidating the underlying components of food valuation in the human orbitofrontal cortex. *Nature Neuroscience*, *20*, 1780–1786. https://doi.org/10.1038/s41593-017-0008-x

Tangney, J. P., Baumeister, R. F., & Boone, A. L. (2004). High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *Journal of Personality*, *72*, 271–324. https://doi.org/10.1111/j.0022-3506.2004.00263.x

van der Laan, L. N., de Ridder, D. T. D., Viergever, M. A., & Smeets, P. A. M. (2014). Activation in inhibitory brain regions during food choice correlates with temptation strength and self-regulatory success in weightconcerned women. *Frontiers in Neuroscience*, *8*, 1–10. https://doi.org/10.3389/fnins.2014.00308

Van Kleef, E., Van Trijp, J. C. M., Van Den Borne, J. J. G. C., & Zondervan, C. (2012). Successful development of satiety enhancing food products: Towards a multidisciplinary agenda of research challenges. *Critical Reviews in Food Science and Nutrition*, *52*, 611–628. https://doi.org/10.1080/10408398.2010.504901

van Rijn, I., de Graaf, C., & Smeets, P. A. M. (2018). It's in the eye of the beholder: Selective attention to drink properties during tasting influences brain activation in gustatory and reward regions. *Brain Imaging and Behavior*, *12*, 425–436. https://doi.org/10.1007/s11682-017-9710-2

van Strien, T., Frijters, J. E. R., Bergers, G. P. A., & Defares, P. B. (1986). The Dutch Eating Behavior Questionnaire (DEBQ) for assessment of restrained, emotional, and external eating behavior. *International Journal of Eating Disorders*, *5*, 295–315. https://doi.org/10.1002/1098-108X(198602)5:2⟨295::AID-EAT2260050209⟩3.0.CO;2-T

van Trijp, H. C. M., & van der Lans, I. A. (2007). Consumer perceptions of nutrition and health claims. *Appetite*, *48*, 305–324. https://doi.org/10.1016/j.appet.2006.09.011

Veldhuizen, M. G., Albrecht, J., Zelano, C., Boesveldt, S., Breslin, P., & Lundström, J. N. (2011). Identification of human gustatory cortex by activation likelihood estimation. *Human Brain Mapping*, *32*, 2256–2266. https://doi.org/10.1002/hbm.21188

Wager, T. D., & Atlas, L. Y. (2015). The neuroscience of placebo effects: Connecting context, learning and health. *Nature Reviews Neuroscience*, *16*, 403–418. https://doi.org/10.1038/nrn3976

Wansink, B., & Chandon, P. (2006). Can "low-fat" nutrition labels lead to obesity? *Journal of Marketing Research*, *43*, 605–617. https://doi.org/10.1509/jmkr.43.4.605

Watson, A. B. (2017). QUEST+: A general multidimensional Bayesian adaptive psychometric method. *Journal of Vision (Charlottesville, Va.)*, *17*, 10. https://doi.org/10.1167/17.3.10

Wickham, H. (2007). Reshaping data with the reshape package. *Journal of Statistical Software*, *21*, 1–20. Available at: http://www.jstatsoft.org/v21/i12/

Wickham, H. (2016). ggplot2: Elegant graphics for data analysis. Available at: https://ggplot2.tidyverse.org

Wickham, H., & Bryan, J. (2019). readxl: Read Excel files. Available at: https://cran.r-project.org/package=readxl

Wickham, H., François, R., Henry, L., & Müller, K. (2021). dplyr: A grammar of data manipulation. Available at: https://cran.r-project.org/package=dplyr

Williams, P. (2005). Consumer understanding and use of health claims for foods. *Nutrition Reviews*, *63*, 256–264. https://doi.org/10.1301/nr.2005.jul.256-264

Wilson, B. (2019). Protein mania: The rich world's new diet obsession. *Guard*, . Available at: https://www.theguardian.com/news/2019/jan/04/protein-mania-the-rich-worlds-new-diet-obsession

World Health Organization (2021). Obesity and overweight. Available at: https://www.who.int/en/news-room/fact-sheets/detail/obesity-and-overweight [Accessed May 27, 2022]

Wright, H., Li, X., Fallon, N. B., Crookall, R., Giesbrecht, T., Thomas, A., Halford, J. C. G., Harrold, J., & Stancak, A. (2016). Differential effects of hunger and satiety on insular cortex and hypothalamic functional connectivity. *European Journal of Neuroscience*, *43*, 1181–1189. https://doi.org/10.1111/ejn.13182

Zajonc, R. B. (1968). Attitudinal effects of mere exposure. *Journal of Personality and Social Psychology*, *9*, 1–27. https://doi.org/10.1037/h0025848

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Rramani, Q., Barakat, Y., Jacob, G., Ohla, K., Lim, S. X. L., Schicker, D., Freiherr, J., Saruco, E., Pleger, B., Weber, B., & Schultz, J. (2022). Nutrition claims influence expectations about food attributes, attenuate activity in reward-associated brain regions during tasting, but do not impact pleasantness. *Brain and Behavior*, e2828. https://doi.org/10.1002/brb3.2828

4. Review article published during the qualification phase: context and summary

In addition to the research articles mentioned above, during the qualification phase, my co-authors and I also published a review article on interindividual differences in intertemporal choice:

Keidel K*, **Rramani Q***, Weber B, Murawski C, Ettinger U. Individual Differences in Intertemporal Choice. Front Psychol 2021; 12: 991. https://doi.org/10.3389/fpsyg.2021.643670

Decisions between rewards that are delivered at different points in time are known as intertemporal choices. In general, people tend to prefer rewards that are available earlier than rewards available later, even when the earlier reward is smaller—up to a certain degree—than the later reward. This phenomenon is referred to as temporal or delay discounting. Despite its ubiquity in humans and non-human animals, intertemporal decisions are subject to considerable individual differences. In this critical narrative review, my co-authors and I summarize and synthesize findings from psychology, economics, neuroscience, and genetics on interindividual differences in intertemporal choice. We particularly highlight limitations of the reviewed work and offer suggestions for future research.

As mentioned in the Introduction, complex food choices often represent a trade-off between short-term (e.g., taste) and long-term rewards (e.g., health). According to the framework described in section 2.2, while an increased consideration for long-term rewards is associated with making optimal food choices, a decreased consideration for such rewards contributes to suboptimal choice. Considering these, complex food choices represent a special intertemporal choice problem. Therefore, understanding individual differences in intertemporal decision-making offers insights into possible differences in food decisions.

* Shared first authorship.

5. Additional research article published during the qualification phase: context and summary

During the qualification phase, I contributed to an additional behavioral study investigating the effects of repeated exposure on perceived food attributes. My contributions to this study include a major share in designing the study, conducting the experiments, analyzing and interpreting the data, and co-writing the original manuscript draft. This study is published and is available at:

Schicker D*, **Rramani Q***, Lim SXL, Saruco E, Pleger B, Schultz J, Weber B, Freiherr J, Ohla K. Taste It! 7-Day Exposure to a Protein-Enriched Milk Drink Increases Its Smell, Taste, and Flavor Familiarity and Facilitates Acquisition of Taste Familiarity of a Novel Protein Drink. Food Qual Prefer 2023; 106: 104808. https://doi.org/10.1016/j.foodqual.2023.104808

In Publication 3, my co-authors and I found that exposure may modulate the effects of expectations on perception (see 3.3). However, how repeated exposure relates to food perception and how the sensory aspects drive such effects remains unknown. To fill these gaps, we investigated which sensory components (smell, taste, flavor) and which perceptual facets (intensity, familiarity, pleasantness) are affected by exposure to a protein-enriched drink and whether exposure effects generalize to a similar drink. To this end, we ran a randomized controlled trial including 101 healthy, non-dieting participants. The study consisted of three phases. Phase I took place in the lab and consisted of smelling, tasting, sampling, and rating four different chocolate milk drinks. After this, participants were assigned either a control drink (CD) or a protein-enriched milk drink (intervention drink, PD) which they consumed and evaluated at home for a period of seven days (Phase II). After seven days, participants returned to the lab (Phase III) and repeated the same procedure as in Phase I with the four initial drinks and an additional protein-enriched novel drink.

We found that exposure to the PD slightly improved ratings of perceived smell and taste pleasantness and increased perceived familiarity of its smell, taste, and flavor. The perception of the other non-exposed drinks did not change. Compared to the CD, exposure to the PD increased taste familiarity of the similar, but novel, drink. This finding suggests

* Shared first authorship.

that the “acquired taste” may transfer to similar foods. While exposure to the PD did not directly change its perceived pleasantness, it did increase its familiarity, which in turn was associated with perceived pleasantness for all modalities. Altogether these results suggest that a seven-day exposure to an unfamiliar protein-enriched drink is sufficient to increase its familiarity, which positively impacts its perception. The transfer of the acquired taste familiarity to a novel drink indicates that exposure may be a good strategy to increase acceptance of similar drinks.

6. Discussion

Food decisions are specific value-based decisions with a high impact on our present and future well-being. Like other value-based decisions, food decisions are sensitive to contextual factors. Contextual effects are complex, possibly exerted through different channels, and may favor both optimal and suboptimal decisions. A better understanding of contextual effects on food-related decision-making may contribute to developing and employing more effective strategies that promote healthy eating. Inspired by these considerations, during the qualification phase I conducted and published three studies that address contextual effects on food-related decision-making and the possible mechanisms underlying these effects. More specifically, I investigated whether attention, emotions, and expectations mediate or moderate the effect of relevant context on food valuation and choice.

6.1. Summary and interpretation

In Publication 1, I investigated the causal role of disadvantageous social contexts on food decisions and whether these are mediated by emotional states. I found that at least in a non-dieting healthy population, lab-induced social disadvantage does not negatively impact food choices, even though it induces emotions of negative valence and high arousal. These findings suggest that targeting *acute* exposure to disadvantageous social contexts may not necessarily improve food choices in healthy individuals, possibly because the relation between food choices and social factors is more complex. Disparities in income, the low cost of unhealthy food, quality of life, and chronic rather than acute exposure to negative emotions and stress are additional factors associated with social disadvantage that I did not consider but that may modulate the relationship between food decisions and social disadvantage (McLaren, 2007; Robertson et al., 2007; Drewnowski, 2009; Harrison et al., 2010; Matthews et al., 2010). Disentangling such influences remains an important question for future research.

In Publication 2, I investigated the relationship between saliency, visual attention, and choice. I found that compared to numerical-only labels, salient nutrition labels induce shifts in attention allocation in favor of the healthier food alternative and increase the probability of making a healthy food choice. These findings are in line with the previous literature and support that directing attention to the nutritional information at the moment of decision-making impacts valuation and improves food choices (Hare et al., 2011; Enax et al., 2015, 2016). Overall, the findings that saliency manipulations impact attention and even modulate choices supports the trend towards salient nutrition labeling, as opposed to numerical-only labels. A more recent example of this trend is the Nutri-Score labeling system, which is a type of front-of-pack label that indicates the “healthiness” of a food item via colors and letters (Hercberg et al., 2021) and is already in use in several EU countries, including Germany.

In Publication 3, I investigated the impact of nutrition claims on expected and perceived food attributes. At the behavioral level, I found that nutrition claims decrease participants’ expectations of taste pleasantness and increase their expectations of healthiness, but do not impact perceived pleasantness. At the neural level, I found that the presence of a nutrition claim attenuates activity in the NAcc (associated with reward-processing and outcome evaluation; see section 2.2.2), during tasting otherwise equal drinks but not during swallowing them. By contrast, during swallowing, there was an increased functional connectivity between the NAcc and the middle frontal gyrus—a region prominently associated with shifts in attention allocation (Corbetta et al., 2008). These findings indicate that while nutrition claims may induce an initial top–down effect through expectations, these effects are not sustained upon exposure to more sensory information, possibly due to shifts in attention allocation. Furthermore, our findings suggest that exposure could increase acceptance of food that is expected to be healthy, but not necessarily tasty.

6.2. Limitations and suggestions for future research

Food-related decisions and other value-based decisions are subject to substantial interindividual differences in various aspects. Curiously, the consideration of interindividual differences as data rather than noise is relatively new in this area of research (Seghier and Price, 2018). In the context of food decisions, often highlighted interindividual variables are personality traits (Keller and Siegrist, 2015), especially trait self-control (see section 2.2.1, Hare et al., 2009; Hankonen et al., 2014), reward sensitivity (Volkow et al., 2011), and brain function and structure (Hare et al., 2009; Lawrence et al., 2012; Schmidt et al., 2018). My studies were not powered enough (small sample sizes) to adequately assess the relation between such individual differences and differences in food-related decisions, since the focus of my studies was the causal influence of context rather than individual differences. Important avenues for future research include defining additional interindividual variables that contribute to differences in food valuation and, more importantly, understanding how these different variables interact with or relate to contextual effects. The latter is particularly important since individual differences are often argued to explain why certain strategies introduced to improve food decisions may not be effective for everybody (Anastasiou et al., 2019; Jiang and Mao, 2021; Muzzioli et al., 2022).

In my studies, I only included healthy, non-dieting participants. It is possible that participants of different socio-demographic background or different health status may differ in their sensitivity to contextual influences. For instance, individuals with obesity seem to be particularly susceptible to eating in response to stress and negative emotions (Ganley, 1989; Singh, 2014; Privitera et al., 2019) as well as to negative food marketing consequences (Ng et al., 2011; Chandon and Wansink, 2012; Cornil et al., 2022). Comparing contextual effects on food decisions between normal-weighted individuals and individuals with obesity may further elucidate which contextual factors cause unhealthy eating, which perpetuate it, and which are a consequence of being overweight or having obesity.

An important limitation that is often pointed out when it comes to studying food decisions in the lab, is the external or ecological validity of the findings. Even though in the lab we use incentivized measures and present real stimuli, the experimental setting is still quite simple in comparison to shopping experiences outside the lab. For instance, in Publication 2 I found that salient labels attract attention and increase the probability of making a healthy food choice. However, in this study, participants were exposed to only labels and food items on a computer screen. By contrast, in a real supermarket, a myriad of stimuli competes for our attention, ranging from numerous colorful products to people around us to verbal announcements, etc. All these “distractors” make it much more difficult to pay attention to nutrition labels—which is the only way how they may impact our decisions (Van Loo et al., 2018). These differences in settings may explain why even though experimental studies show that certain nutrition labels are effective (Croker et al., 2020), their success in improving population-wide food choices remains limited (Muzzioli et al., 2022). To increase the ecological validity of these lab results, in the last years researchers have started to use virtual reality set-ups, and/or portable eye-tracking systems inside real supermarket settings to produce a more realistic but still controlled shopping environment

(Meißner et al., 2019; Xu et al., 2021). Such set-ups can be used in future studies to assess how contextual factors such as food labeling and internal states such as stress and negative emotions impact dietary choices in more realistic settings. Furthermore, such settings can also be used to assess possible interactions between these contexts and states more thoroughly (Fehr and Rangel, 2011).

In the studies included in this thesis, I focused on emotions, attention, and expectations as possible mechanisms underlying contextual influences on food-related decisions, but I did not compare these mechanisms and did not assess possible interactions between them. In Publication 3, I found that nutrition claims impact expectations but not perceived pleasantness, possibly due to shifts in attention allocation during outcome evaluation, i.e., sampling the delivered drinks. These results hint to possible interactions between expectations and attentional processes during valuation and outcome evaluation, that can be further investigated in future research.

Finally, while I used more traditional fMRI analyses during the qualification phase, multivariate machine learning techniques have become increasingly popular in neuroscience over the last few years (Haxby et al., 2014). These techniques make it possible to predict behavior from *patterns* of brain activation—rather than from mere differences in spatial averages of brain activation. They could, thus, be used to identify which contexts change the *representation* of food items in the brain.

6.3. Conclusion

The mechanisms underlying the effects of context on food decisions in humans are vaguely understood. Understanding these mechanisms does not only further our knowledge on food decisions but may also serve to increase the effectiveness of context as a tool to tackle unhealthy eating at a larger scale. The studies included in this thesis contribute to this endeavor by providing evidence on the effects of common contexts such as social factors and food marketing strategies and their possible underlying mechanisms, but also by generating hypotheses that can be tested in future research.

In this thesis, I show that, in a healthy population, (i) lab-induced social disadvantage affects emotions but does not impact food choices; (ii) compared to numerical-only labels, salient nutrition labels induce shifts in attention allocation and increase the probability of making healthier food choices; and (iii) nutrition claims affect expectations and attenuate activity in reward-associated brain regions during tasting, but do not affect perceived pleasantness. Based on these findings, effective strategies for promoting healthy eating may be: (i) including nutrition labels or claims that attract attention and provide information in a more salient manner; and (ii) exposing consumers to food with labels and claims thereby adjusting their context-induced expectations. Future research should more thoroughly—and possibly in more ecologically valid ways—assess the relationship between contextual effects on food decisions and individual-difference variables such as weight-status, personality traits, reward sensitivity, brain structure and function. A further research endeavor is investigating potential interactions between various food-relevant contexts, including decision makers' internal states, attentional processes, and product attributes.

In the studies described in this thesis, I used a neuroeconomics approach which enabled me to evaluate the relationship between several variables such as choices, neural activity, and eye movements. The data were acquired using various methods such as behavioral experiments, fMRI, and eye-tracking, thereby providing a more integrated view of value-based decision-making. Neuroeconomics has had a tremendous influence on the way decision-making is investigated, and it has significantly contributed to nutrition research. However, this multidisciplinary approach is still in its early stages, and its full potential to advance our understanding of food-related decision-making and value-based decision-making in general has yet to be realized. As Fehr and Rangel (2011) put it: "May we live in exciting times".

6.4. References

Anastasiou K, Miller M, Dickinson K. The relationship between food label use and dietary intake in adults: A systematic review. Appetite 2019; 138: 280–291. https://doi.org/10.1016/j.appet.2019.03.025

Chandon P, Wansink B. Does food marketing need to make us fat? A review and solutions. Nutr Rev 2012; 70: 571–593. https://doi.org/10.1111/j.1753-4887.2012.00518.x

Corbetta M, Patel G, Shulman GL. The Reorienting System of the Human Brain: From Environment to Theory of Mind. Neuron 2008; 58: 306–324. https://doi.org/10.1016/j.neuron.2008.04.017

Cornil Y, Plassmann H, Aron-Wisnewsky J, Poitou-Bernert C, Clément K, Chabert M, Chandon P. Obesity and Responsiveness to Food Marketing Before and After Bariatric Surgery. J Consum Psychol 2022; 32: 57–68. https://doi.org/10.1002/jcpy.1221

Croker H, Packer J, Russell SJ, Stansfield C, Viner RM. Front of pack nutritional labelling schemes: a systematic review and meta-analysis of recent evidence relating to objectively measured consumption and purchasing. J Hum Nutr Diet 2020; 33: 518–537. https://doi.org/10.1111/jhn.12758

Drewnowski A. Obesity, diets, and social inequalities. Nutr Rev 2009; 67: 36–39. https://doi.org/10.1111/j.1753-4887.2009.00157.x

Enax L, Hu Y, Trautner P, Weber B. Nutrition labels influence value computation of food products in the ventromedial prefrontal cortex. Obesity 2015; 23: 786–792. https://doi.org/10.1002/oby.21027

Enax L, Krajbich I, Weber B. Salient nutrition labels increase the integration of health attributes in food decision-making. Judgm Decis Mak 2016; 11: 460–471. http://journal.sjdm.org/16/16620/jdm16620.html

Fehr E, Rangel A. Neuroeconomic Foundations of Economic Choice—Recent Advances. J Econ Perspect 2011; 25: 3–30. https://doi.org/10.1257/jep.25.4.3

Ganley RM. Emotion and eating in obesity: A review of the literature. Int J Eat Disord 1989; 8: 343–361. https://doi.org/10.1002/1098-108X(198905)8:3<343::AID-EAT2260080310>3.0.CO;2-C

Hankonen N, Kinnunen M, Absetz P, Jallinoja P. Why Do People High in Self-Control Eat More Healthily? Social Cognitions as Mediators. Ann Behav Med 2014; 47: 242–248. https://doi.org/10.1007/s12160-013-9535-1

Hare TA, Camerer CF, Rangel A. Self-Control in Decision-Making Involves Modulation of the vmPFC Valuation System. Science 2009; 324: 646–648. https://doi.org/10.1126/science.1168450

Hare TA, Malmaud J, Rangel A. Focusing Attention on the Health Aspects of Foods Changes Value Signals in vmPFC and Improves Dietary Choice. J Neurosci 2011; 31: 11077–11087. https://doi.org/10.1523/JNEUROSCI.6383-10.2011

Harrison M, Lee A, Findlay M, Nicholls R, Leonard D, Martin C. The increasing cost of healthy food. Aust N Z J Public Health 2010; 34: 179–186. https://doi.org/10.1111/j.1753-6405.2010.00504.x

Haxby JV, Connolly AC, Guntupalli JS. Decoding Neural Representational Spaces Using Multivariate Pattern Analysis. Annu Rev Neurosci 2014; 37: 435–456. https://doi.org/10.1146/annurev-neuro-062012-170325

Hercberg S, Touvier M, Salas-Salvado J. The Nutri-Score nutrition label. Int J Vitam Nutr Res 2022; 92: 147–157. https://doi.org/10.1024/0300-9831/a000722

Jiang Y, Mao T. A Survey on Cognitive Ability and Application of Food Nutrition Labels of Middle School Students in Beijing, China in 2020. J Food Nutr Res 2021; 9: 223–239. https://doi.org/10.12691/jfnr-9-4-8

Keller C, Siegrist M. Does personality influence eating styles and food choices? Direct and indirect effects. Appetite 2015; 84: 128–138. https://doi.org/10.1016/j.appet.2014.10.003

Lawrence NS, Hinton EC, Parkinson JA, Lawrence AD. Nucleus accumbens response to food cues predicts subsequent snack consumption in women and increased body mass index in those with reduced self-control. Neuroimage 2012; 63: 415–422. https://doi.org/10.1016/j.neuroimage.2012.06.070

Matthews KA, Gallo LC, Taylor SE. Are psychosocial factors mediators of socioeconomic status and health connections? A progress report and blueprint for the future. Ann N Y Acad Sci 2010; 1186: 146–173. https://doi.org/10.1111/j.1749-6632.2009.05332.x

McLaren L. Socioeconomic Status and Obesity. Epidemiol Rev 2007; 29: 29–48. https://doi.org/10.1093/epirev/mxm001

Meißner M, Pfeiffer J, Pfeiffer T, Oppewal H. Combining virtual reality and mobile eye tracking to provide a naturalistic experimental environment for shopper research. J Bus Res 2019; 100: 445–458. https://doi.org/10.1016/j.jbusres.2017.09.028

Muzzioli L, Penzavecchia C, Donini LM, Pinto A. Are Front-of-Pack Labels a Health Policy Tool? Nutrients 2022; 14: 771. https://doi.org/10.3390/nu14040771

Ng J, Stice E, Yokum S, Bohon C. An fMRI study of obesity, food reward, and perceived caloric density. Does a low-fat label make food less appealing? Appetite 2011; 57: 65–72. https://doi.org/10.1016/j.appet.2011.03.017

Privitera GJ, King-Shepard QW, Cuifolo KN, Doraiswamy PM. Differential food intake and food choice by depression and body mass index levels following a mood manipulation in a buffet-style setting. J Health Psychol 2019; 24: 199–208. https://doi.org/10.1177/1359105316650508

Robertson A, Lobstein T, Knai C, 2007: Obesity and socio-economic groups in Europe: Evidence review and implications for action. http://ec.europa.eu/health/ph_determinants/life_style/nutrition/documents/ev20081028_rep_en.pdf (date accessed: 27.05.2020)

Schmidt L, Tusche A, Manoharan N, Hutcherson C, Hare T, Plassmann H. Neuroanatomy of the vmPFC and dlPFC predicts individual differences in cognitive regulation during dietary self-control across regulation strategies. J Neurosci 2018; 3402–17. https://doi.org/10.1523/JNEUROSCI.3402-17.2018

Seghier ML, Price CJ. Interpreting and Utilising Intersubject Variability in Brain Function. Trends Cogn Sci 2018; 22: 517–530. https://doi.org/10.1016/j.tics.2018.03.003

Singh M. Mood, food, and obesity. Front Psychol 2014; 5: 925. https://doi.org/10.3389/fpsyg.2014.00925

Van Loo EJ, Grebitus C, Nayga RM, Verbeke W, Roosen J. On the Measurement of Consumer Preferences and Food Choice Behavior: The Relation Between Visual Attention and Choices. Appl Econ Perspect Policy 2018; 40: 538–562. https://doi.org/10.1093/aepp/ppy022

Volkow ND, Wang GJ, Baler RD. Reward, dopamine and the control of food intake: Implications for obesity. Trends Cogn Sci 2011; 15: 37–46. https://doi.org/10.1016/j.tics.2010.11.001

Xu C, Siegrist M, Hartmann C. The application of virtual reality in food consumer behavior research: A systematic review. Trends Food Sci Technol 2021; 116: 533–544. https://doi.org/10.1016/j.tifs.2021.07.015

7. Acknowledgments

First and foremost, I would like to thank my doctorate supervisor Prof. Dr. Bernd Weber. Thank you, Bernd, for your supervision, encouragement, support, trust, and positive attitude! I consider myself very lucky to have been part of your research group.

Second, I would like to thank my dissertation committee and especially Prof. Dr. Ulrich Ettinger. Thank you, Uli, for your collaboration, support, and friendly advice!

Third, I would like to thank my collaborators for their invaluable insights and their impeccable support. Xenia, Holger, Johannes, Zara, Ian, Burkhard, Kathrin, Doris, Jessica, Elodie, Shirley, George, and Youssef: I am forever going to be grateful to you.

Fourth, I would like to express my sincerest gratitude to PD Dr. Johannes Schultz and Dr. Holger Gerhardt. Thank you, Johannes, for your enthusiastic spirit, your constant encouragement, supervision, advice, and for always having an open door for my questions and ideas. It was a pleasure working with you and learning so much from you! Thank you, Holger, for your criticism ☺, your advice, for always pushing me to be better, for your support with programming, your help with data collection and data analyses, and for reading my thesis draft. Thank you also for the great and insightful conversations, the fun and competitive foosball sessions, and for pushing me to speak more German!

Fifth, I would like to thank all past and present members of the CENs and the Life and Brain who have made this journey much more beautiful for me. Thank you, dear frolleagues, for the friendly and supporting work environment, the great lunch conversations, the amazing Christmas parties, and all other social activities. Thank you, Xenia, for your contagious positive attitude, your rigor, your tremendous help, and your friendship; thank you, Angela, for your help with administrative issues, your encouragement, and your readiness to solve any problem; thank you, Federica, for the insightful conversations and for your support; thank you, Jana, for your research assistance, your professionalism, your support, and for constantly reassuring me that things were going to be fine; thank you, Daniela, for your help with data analyses, for the nice conversations, and for the fun foosball sessions; thank you, Omar, for providing support with any IT-related issue, and especially, for the discussions on “feminism” ☺; thank you, Nayara, Aenne, Tien, Lena, Lennard, Dominik, and Emir for your research assistance, your understanding and your patience; thank you, Bettina, for your help with participant recruitment and data collection at the Life and Brain; thank you, Dr. Peter Trautner, for your IT-support and for your great help with programming and fMRI data collection; thank you, Josie, for your collaboration and for reading my thesis draft; thank you, Ilinca and Niklas, for your support and for the valuable advice you shared with me at the beginning of this journey.

Sixth, I would like to thank my amazing friends. I am particularly grateful to André, Geni, Ben, Irina, Hyuntae, and Petra for their moral support, advice, and companionship.

Seventh, I would like to thank my parents, my sisters, my grandparents, my aunts, my uncle, and my in-laws for their constant support throughout it all. I wish to make you all as proud and as grateful as you make me every day. Viola, my dearest, you are my greatest inspiration! Most probably you will never read this, but it is all for you!

Finally, I would like to thank my husband, Duki! You have been my strongest support and have put up with all my stress, worries, and insecurities. Throughout this journey, I have discovered that decisions are complex, but choosing you has been the simplest and the best decision that I have ever made. I love you and will forever be in your debt.