

**Exploring the Interaction of Mood States and Food Purchasing Behaviour – Insights
from an ESM study**

Chiara Jetter

Department of Psychology, University of Twente

2024-202000384 BSc Thesis

Mirjam Radstaak

24.06.2025

Abstract

Food purchasing has a wide impact on our society's health and our environment and is influenced by psychological factors. This study examined the relationship between mood and food purchasing by employing the approach of an Experience Sampling Method (ESM) which proves to be an ecologically valid method to provide new insights into real-world behaviour. It was hypothesized that a higher combined mood score, indicating higher positive relative to negative mood, would lead to healthier food items bought. Furthermore, it was hypothesized that unhealthy food purchases are linked to a more positive mood, as reflected in a higher combined mood score.

The study included 24 participants of mostly female German students. They were asked to fill in a mood questionnaire of six items (a self-adapted version of the Positive and Negative Affect Scale; PANAS-x) and record their food purchases through either a photo diary, or, if unable to do so, through one multiple choice question (Healthy and Unhealthy Eating Behaviour Scale; HUEBS). This design was employed through an app and participants were prompted to answer the questionnaires three times per day for seven days.

Multilevel analysis showed that there was no effect of mood on food purchasing items in terms of their healthiness. In the reverse association, there was no effect of the healthy or unhealthy food bought on mood state.

This study contributes to the existing research, emphasizing the ESM as approach by using ecologically valid data, going beyond artificial lab settings or retrospective surveys. Since there was no interaction found between mood and food purchasing, it may be that budgetary reasons were a stronger predictor on healthy food purchases than mood.

Introduction

Food choices play a central role not only in personal health, but also in societal well-being and environmental sustainability because they influence chronic disease risk, healthcare systems, and contribute significantly to environmental challenges such as greenhouse gas emissions and resource depletion (Chen, 2024; Kushi et al., 2006; Monteiro et al., 2019). Understanding how and why people buy food might inform interventions that promote healthier and more sustainable consumption patterns. People engage with food-related decisions regularly as part of their daily routines and established habits (Marshall, 2005) and populations' dietary choices and preferences might be influenced by social, attitudinal, and economic factors like income (Drewnowski, 1997). Accordingly, the topic of food has a wide impact. Sustainability is another factor that is majorly influenced by food choices. While organic products are often viewed as healthy alternative for the individual (Chen, 2007), sustainable food has a wider influence on the environment. Factors such as biodiversity, animal- and planet welfare, as well as carbon- and water footprints are all positively affected by sustainable food choices (Nguyen, 2018).

Food choices are a major contributor to health outcomes. Unhealthy products might be understood in their processing level which refers to the extent to which foods have been altered from their natural state through the addition of ingredients such as sugars, fats, salt, preservatives, or artificial additives, which has a direct effect on the foods nutritional value (Monteiro et al., 2019). Ultra-processed foods have been linked to cardiovascular diseases, mental illness, asthma, and gastrointestinal diseases (Monteiro et al., 2019), and further elevate the risk of diabetes and cancer (World Health Organization [WHO], 2020). The WHO (2020) promotes a balanced and healthy diet to reduce the risk of such diseases and malnutrition. Therefore, investigating whether food might be used as a tool for mood regulation when feeling negative is particularly beneficial. Understanding motivations for

unhealthy and ultra-processed food purchases might enhance knowledge about behaviour and dietary preferences. This could have an impact on public health regulations, mood control, and the economy.

While much research on food behaviour focuses on consumption and eating habits (Canetti et al., 2002; Gibson, 2006; Haedt-Matt & Keel, 2011; Köster & Mojet, 2015; Macht, 2008), the act of purchasing food is a distinct behaviour influenced by factors such as availability, intention, mood, and impulse. This study will examine food purchasing behaviour because it provides insight into the choices individuals make before consumption occurs, which is particularly relevant for interventions targeting healthier food environments. Mood as psychological factor may significantly shape food purchasing behaviour and provide more insights into unhealthy food purchasing behaviour.

Mood

Mood is a vital psychological construct. It is closely intertwined with the concepts of affect, feelings, and emotions (Beedie et al., 2005). Prior researchers describe mood as a subjective, general condition that is easily modified through external and internal factors (Furnham & Milner, 2013). Moreover, it is defined as affective responses to certain situations, rather than a general affective state (Gendolla, 2000).

Mood may influence behaviour in a variety of ways and is particularly relevant in the context of decision-making, with a dominant role in an individual's general affective state. Other than having a directional effect on behaviour by influencing behavioural preferences in accordance with a hedonic purpose, meaning the pursuit of pleasure or emotional gratification, mood states may lead to more efficient judgments when being in a good mood (Forgas, 1989; Gear et al., 2017; Gendolla, 2000). Accordingly, mood serves a key function, especially in decisions of consumers in regards of sustainability and food (Chen, 2007; Martini et al., 2024). Mood has been proven to influence processes of

evaluative nature, and the way behaviour is regulated (Holland et al., 2012). Considering mood as construct provides a vital measure on behavioural actions.

Not only does mood affect decision making processes, but also self-regulation and impulse control which has been linked to food related behaviours (eating and purchasing). Macht (2008) found that people in a negative mood are more likely to indulge in impulsive eating habits, being less likely to self-regulate and fight impulsive urges. Research has demonstrated that people are prone to manage their negative mood with unhealthy food as justification, using consumption to balance their current perception of feelings (AlAmmar et al., 2020). Food intake is influenced by mood states and their strength, and may be increased through both positive and negative feelings, indicating that both extremes diminish cognitive eating control (Köster & Mojet, 2015). When feeling bored, depressed, tired, tense, or in pain, a larger amount of food may be consumed. Accordingly, mood impacts consumption behaviour, the extent of which could potentially affect the diet and health of an individual (Canetti et al., 2002; Willner et al., 1998).

Mood also plays a role in determining the type of food consumed (Macht, 2008), particularly regarding its healthiness. Sweet and high fat foods, which are considered as unhealthy (Guertin et al., 2020), are mostly consumed by people that choose eating as way to regulate their mood (Köster & Mojet, 2015). Moreover, negative mood and stress are related to increased food consumption, especially in terms of unhealthy food (Gibson, 2006). Considering the opposite, positive mood such as feelings of joy have been shown to be associated with a higher consumption of healthy food (Macht, 2008).

While much of the literature focuses on how mood affects food intake, less is known about its role in food purchasing decisions. There have been differences shown in data of consumption and purchasing (De Oliveira et al., 2019). Therefore, purchasing tendencies, not including eating behaviours, are greatly impacted by mood and are worth to be studied on

their own. Since mood states affect the buying of food, the type of products bought provides further insight on how mood influences purchasing decisions. Emerging evidence suggests that mood influences the nutritional quality of the products selected. Sun et al. (2024) found that negative mood motivates purchasing and drives the consumption of unhealthy food, while the preference for healthier food options was enhanced by positive mood. This is supported by the studies linking positive emotions to purchases of sustainable or organic food items (Giray et al., 2022; Migliore et al., 2022; Spendrup et al., 2016), as such products are considered healthy (Chen, 2007). Altogether, positive mood is associated with purchasing healthy food while negative mood is related to buying unhealthy items (Lymann, 1982).

The Influence of Food Purchasing on Mood

In addition to mood influencing food purchasing decisions, food choices themselves may affect subsequent mood (Gibson, 2006). Research suggests that food, especially unhealthy or impulsive purchases, might act as a form of mood regulation (Köster & Mojet, 2015; Macht, 2008). Unhealthy food may have reinforcing effects for negative mood, since they seem to decrease pessimistic mood and pose as a reward in mood regulation (Christensen, 2001; Gibson, 2006; Sun et al., 2024). Food seems to be a valuable source to control mood and has an impact on how individuals feel. Studies showed that negative feelings were reduced in stressed individuals when eating foods that are high in sugar or carbohydrate, which may be interpreted as unhealthy (Christensen, 2001; Köster & Mojet, 2015). The study highlighted that the primary element in increasing positive mood and lowering negative mood, is the palatability of food, that describes how enjoyable the food is, which is often linked to sugar. Robbins and Fray (1980) support this assumption and claim that stress drives eating behaviour to decrease anxious feelings, and Macht (2008) indicates that food may be consumed as reaction to emotional strain. Therefore, people may exhibit a

strong desire for unhealthy food to improve their mood, and even view nutritious food as factor that could make them feel worse (AlAmmar et al., 2020).

Although several studies have explored the link between mood and food choices, much of this research relies on retrospective self-reports, written on paper, or artificial experimental settings (Davison et al., 2018; Forgas, 1989; Giray et al., 2022; Haedt-Matt & Keel, 2011; Jimoh et al., 2018; Spies et al., 1997). Such laboratory environments may limit real-world insight and might lack ecological validity (Boggiano et al., 2015). A more immediate, ecologically valid approach may offer deeper insight. While previous studies have applied such methods to understand emotional eating or food cravings (Haedt-Matt & Keel, 2011), few have investigated how mood affects food purchasing decisions in real-world contexts.

Experience Sampling Method (ESM)

ESM is data collection method in real time which allows for an instant assessment of behaviour and mood (Trull & Ebner-Priemer, 2009). Data is collected from the same individual across different times and events, using a within-person analysis, that enable the examination of elements happening at the same time for any participant (Boggiano et al., 2015). This method minimizes recall bias and increases ecological validity, making it especially useful for examining fluctuations in mood and their influence on behaviour in a natural setting (Moore et al., 2018; Wischmann, 2020; Van Berkel et al., 2017). A photo diary approach, integrated into the ESM may be used to explore the relation between food and mood. Studies using a digital photo diary decrease the burden on both researchers and participants (Davison et al., 2018), and provide vital insights into participants daily life (Bijoux & Myers, 2006).

This Study

This research aims to examine food purchasing behaviour in terms of healthy or unhealthy products and mood by employing an ESM design using photos and descriptions of food to measure the healthy and unhealthy food items purchased. The method has the advantages of providing insights while considering within-person differences and fluctuations, and demonstrating ecological validity, compared to research that examined food and mood in a laboratory setting only. To address this gap, the focus of this study will lie on 1) whether mood influences food purchasing behaviour, regarding healthy or unhealthy food items and 2) if the purchase of a healthy or unhealthy item influences mood. To assess this, a photo diary method will be applied through an ESM study which provides a unique approach to this topic. Based on prior research it is hypothesized that 1) higher combined mood scores, reflecting a predominance of positive over negative mood, are associated with the purchase of healthier food items. Further, it is hypothesized that 2) the purchase of an unhealthy food item has a (short-term) positive effect on the combined mood through regulating behaviour.

Methods

This study is part of a bigger research examining factors that might influence food purchasing behaviours. Only the relevant variables for this study are described in this report.

Design

This study employed a longitudinal ESM design. Repeated measures were gathered three times a day over a period of seven consecutive days. The influence of mood states was assessed over the nutritional value of food purchases in terms of processing level. Furthermore, the influence of the health of food item purchased on mood states was examined.

Participants

Participants were included in the final data set when meeting the requirements of being at least 18 years old and having adequate proficiency in the English language. They required a device with an established internet connection, browser function, and the Apple App Store or Google Play Store. For this study, the participants were acquired through convenience sampling, where the study was shared with personal networks and individuals were invited via word of mouth, and via the SONA System, an online recruitment tool of the University of Twente. A total of 24 participants took part in the study ($M_{\text{age}} = 22.01$, $SD = 0.43$). The sample included 18 women ($M_{\text{age}} = 22.12$, $SD = 2.04$), five men ($M_{\text{age}} = 22.00$, $SD = 1.87$), and one participant identifying as non-binary ($Age = 20$). The majority of participants were German ($n = 19$), followed by Turkish ($n = 3$), Dutch ($n = 1$), and Spanish ($n = 1$). In terms of highest achieved education, 21 participants completed secondary education, two had vocational training and one held a bachelor's degree.

Materials

To administer the study, the Twente Intervention and Interaction Machine (TIIM) app was utilized. It was designed by the University of Twente in the BMS Lab to ensure students

and researchers are able to collect data in an innovative way. Within the app, questionnaires may be created, and modules and items may be administered throughout different times of day, allowing participants to answer questionnaires, and take pictures of their purchases and upload them in an ESM-module for repeated measures.

Mood States

To measure mood states, six items from the Positive and Negative Affect Scale – Expanded (PANAS-x; Watson and Clark, 1999) were used (App. B). The questionnaire was reduced to six items to decrease the burden on the participants. Participants indicated the extent to which they felt happy, enthusiastic, interested (PA items) and irritable, upset, and sad (NA items) on a five-point Likert-scale with the rankings of “very slightly or not at all”, “a little”, “moderately”, “quite a bit”, and “extremely” (Figure 1). The average of the negative mood items is subtracted from the average of the positive mood items in each iteration to compute a combined mood score (Rush & Hofer, 2015; Woodworth et al., 2016). The result will be a score on a scale from -4 to 4, where a score below 0 suggests negative mood, and a score above 0 indicates positive mood. A score of 0 equals a neutral mood state. The internal consistency of both scales was good (PA: $\alpha = 0.78$, 95% CI [0.74, 0.81]; NA: $\alpha = 0.81$, 95% CI [0.78, 0.84]).

Unhealthy Food Purchases Assessment

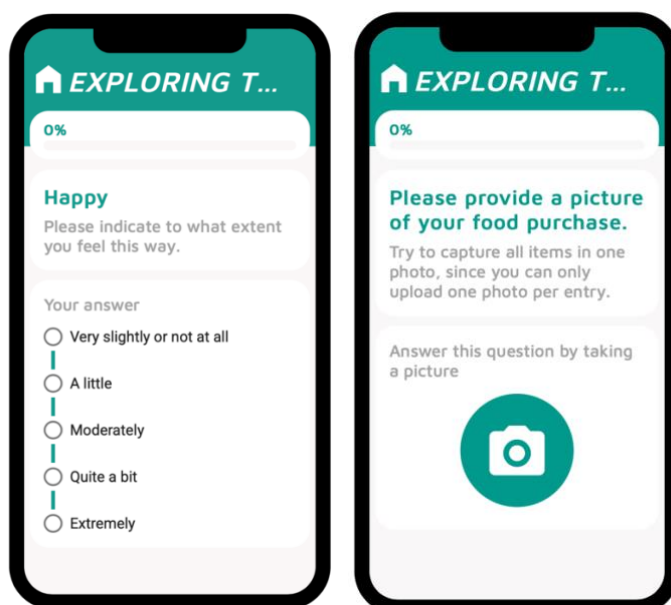
Participants were asked whether they have purchased food, and they had the option to indicate “Yes” or “No”. Upon selecting “Yes”, they had to indicate whether they had a picture of the food or if they are able to take one. When providing a positive answer, they were redirected and asked to offer a picture (Figure 1). In the case that participants may use the photo diary option, they upload a picture of the food they have bought. When they answered “No”, they were asked to choose an item that best reflected their purchase. When they had more than one purchase, they were asked to describe it in the “Other” option of the item. The

items were shown as multiple-choice answers and based on the Healthy and Unhealthy Eating Behaviour Scale (HUEBS; Guertin et al., 2020). Of 22-items, twelve are classified as healthy food choices (fruits, vegetables, whole grains, lean meats, natural sweeteners, ...), while ten items are regarded as unhealthy food choices (refined grains, snack food, sugar-sweetened beverages, pre-packages meals, fast-food, ...). The whole list is shown in Appendix C. The scale measures the self-reported frequency of engaging in healthy or unhealthy food behaviour, based on dietary guidelines. It demonstrates strong internal consistency and convergent validity (Guertin et al., 2020).

The pictures provided and the responses to the HUEBS scale were classified using the Nova Classification (Monteiro et al., 2016). Research showed that the processing level of a food item is a strong indicator of its nutritional quality and healthiness (Monteiro et al., 2019). The scale sorts of food items based on the degree to which they are processed in four groups ranging from ranking 1 “Unprocessed or Minimally Processed Foods”, ranking 2 “Oils, Fats, Salt, and Sugar”, ranking 3 “Processed Foods”, to ranking 4 “Ultra-processed Foods” (App. D).

Figure 1

Example Items: Mood & Food Purchasing Behaviour



Procedure

The University of Twente Ethics Committee granted approval for this study with the number 250589. To administer the study, the participants were directed to a link from SONA to a website containing the necessary instructions to download the TIIM app. They were given a QR code or letter code through which they could access the study within the application and become a registered participant.

The first section of the questionnaire included a welcome page, highlighting the purpose of the study and its instructions. This was followed by an informed consent form, which provided a detailed description of participants' rights to the anonymity and confidentiality of the data gathered, as well as their right to withdraw at any point within the duration of the study. After accepting to partake in the study, a set of demographic questions pertaining to age, gender, nationality, and education level were presented. Participants were then directed to answer questions about mood states, after which they were instructed to indicate their food purchasing choices with a photo of the food purchase or describe the item along multiple options when they were unable to provide a picture. The modules which included the self-assessment questionnaires opened each day at 10 am., 2 pm., and 6pm over a period of seven days. At those times, reminders were automatically sent out asking to complete the mood and photo diary questionnaires in the app. The questionnaires were available until the next reminder since another option was not possible within the app. There were no incentives or prompts included. The data collection took place from 12.03.2025 until 10.05.2025.

Data Analysis

To analyse the data gathered from questionnaire, data was derived from the TIIM Dashboard using Excel, and transferred onto R Studio. The scripts may be found within

Appendix E. All data that was gathered was included in the final dataset (App. F) and descriptive statistics were calculated for the study variables and food categories.

To test the first hypothesis, an advanced multilevel analysis was computed, using person-mean centring to assess within-person effects, and estimate how mood swings might influence food purchasing behaviour, with time as predictor. Thereby, mood was applied as lagged variable, using the iteration prior to a purchase as indicator since participants most likely had already bought an item when receiving the notification. In this case, the mood state is the independent variable, and the nutritional value of food purchases is the dependent variable. Adding random slopes for lagged mood did not improve model fit, suggesting limited variability in mood effects between participants.

To test the second hypothesis, another advanced model employing person-mean centring was conducted to isolate within-person effects, thereby examining how fluctuations in mood relate to food purchasing behaviour. In this analysis, the mood measurements from the same iteration as the purchase were used to examine the reversed association. Here, mood state is the dependent variable, and the nutritional value of food purchases is the independent variable.

The single-measure ICC (ICC1) was 0.30, indicating that 30% of the total variance in mood was due to stable differences between participants, with the remaining 70% reflecting within-person fluctuations over time. The average-measure ICC (ICC1k) was 0.91, demonstrating that the aggregated mood scores across repeated measurements reliably reflect stable mood levels within individuals. These results support the use of multilevel modelling to appropriately handle the nested structure of the data.

Results

Descriptive Statistics

The dataset included 254 measurements collected from 24 participants over seven days. Participants contributed between 1 and 21 measurements each ($M = 10.58$, $SD = 6.11$). Combined mood states ranged from $[-4 - 4]$, with person-level mood scores ranging from -0.63 to 2.67 ($M = 0.67$, $SD = 1.45$), indicating an overall tendency towards positive mood. The mean Nova classification ranged from 1.33 to 4 ($M = 2.80$, $SD = 1.33$), indicating that the average purchase was moderately processed to highly processed food items (Table 1).

Participants bought a total of 228 food items, which were coded across several categories (Table 2). While fruits and vegetables were the most frequently purchased single category ($n = 44$; 19.3%), a larger proportion of the purchases consisted of more processed or unhealthy items, with approximately 103 (45.2%) items falling into clearly ultra-processed categories such as snacks ($n = 40$; 17.54%), sugar-sweetened beverages ($n = 34$; 14.91%), and pre-packaged foods ($n = 29$; 12.72%). Other healthy considered products made up a smaller proportion such as eggs ($n = 4$; 1.75%), pasta ($n = 3$; 1.32%), and water or tea ($n = 5$; 2.19%). This aligns with the average Nova classification ($M = 2.80$, $SD = 1.33$), indicating that participants predominantly purchased moderately to highly processed foods across the study period.

Table 1

Overview of Participant Measurements, Mood, and Nova Scores

N Iterations per Participant	Mean Combined Mood	Mean Nova
20	0.491	2.8
8	- 0.625	3.2
21	1.23	3.25

10	1.13	3.56
6	2.17	3.3
17	1.02	4
12	2.31	3.71
16	1.28	4
16	0.463	2.67
1	2.67	2.71
10	0.926	2.55
14	1.63	2.11
4	2.17	4
8	1.14	2.27
8	-0.485	3
11	1.53	1.33
22	0.0128	3.33
10	2.56	2.71
2	-0.334	4
4	1.83	2.78
14	0.222	2.12
2	0.166	NA
5	2.1	2.15
13	1.28	3

Table 2*Food Items Categories*

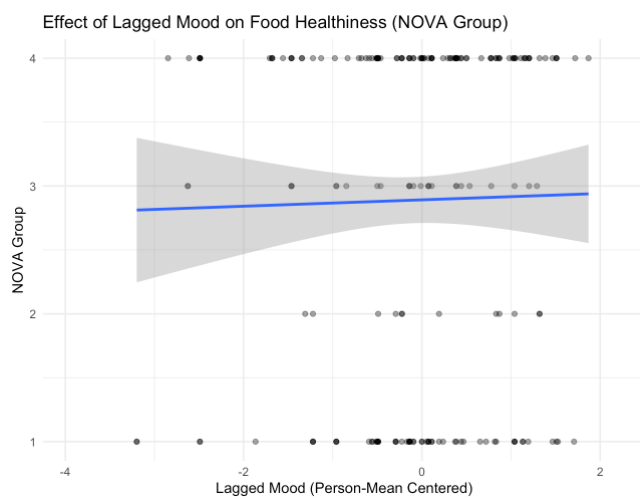
Category	N Purchases	Nova
Fruits and Vegetables	44	1
Snacks	40	4
Sugar Sweetened Beverages or Alcohol	34	4
Prepackaged Food	29	4
Dairy Product	21	2-4 (low fat dairy vs highly processed)
Bread Product	11	1-3 (whole grain bread vs white bread)
Meat	8	1, 4 (lean meats vs fat)
Water or Tea	5	1
Eggs	4	1
Pasta	3	1
Other	29	1-4

Advanced Analyses

Model 1: Effect of Mood on Food Healthiness

The analysis with a multilevel model showed no significant effect of lagged mood deviations on food processing level, $B = 0.013$, $SE = 0.083$, $t(196) = 0.15$, $p = .879$ (Figure 2). However, a small but significant negative effect of Time was found, $B = -0.047$, $SE = 0.021$, $t(181) = -2.23$, $p = .027$, indicating that participants' purchases became marginally less processed over time.

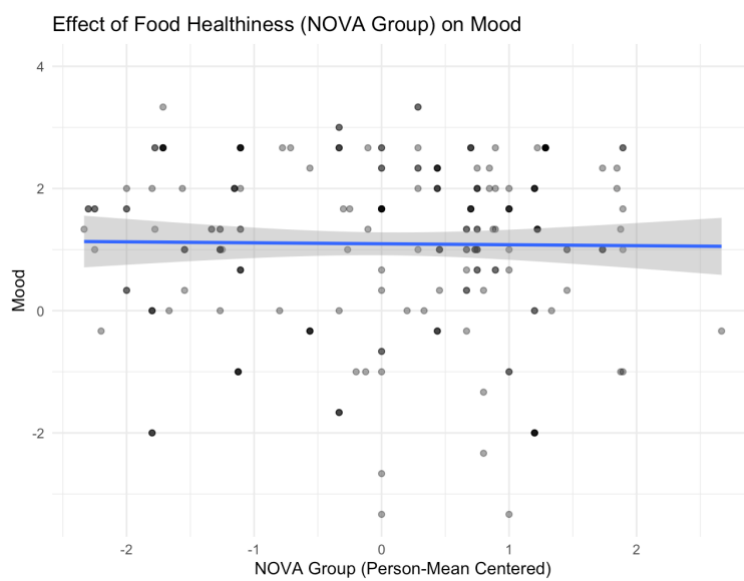
Figure 2



Model 2: Effect of Food Healthiness on Mood

A reciprocal linear mixed-effects model was computed to assess whether within-person deviations in food healthiness (person-mean centred NOVA scores) predicted concurrent mood, controlling for time, and including random intercepts for participants. The effect of Nova group on mood was not significant, $B = -0.022$, $SE = 0.063$, $t(172) = -0.34$, $p = .736$ (Figure 3).

Figure 3



Discussion

Summary

This study was conducted to investigate whether mood states exert an influence on unhealthy food purchasing decisions in terms of their processing level and vice versa, using the ESM approach. The results showed that a combined mood score, reflecting positive and negative mood, did not affect whether a healthy or unhealthy food item is bought.

Participants were not influenced in their food purchasing choices through their mood.

Therefore, hypothesis one that a higher combined mood score, indicating positive mood, is linked to healthy purchases, must be rejected since there is no effect given. The results also indicate that there is no influence of food purchasing choices regarding their health on mood. Participants did not show a higher combined mood score based on previous bought healthy or unhealthy food items. Accordingly, hypothesis two that unhealthy food purchases will lead to a positive mood has to be rejected as there was no impact measured. However, a significant effect was found using time as predictor, indicating that participants bought less processed food as the study progressed.

Theoretical Implications

The results are not in line with previous studies showing that positive mood lead to healthier food purchases, as well as buying healthier food items leading to mood improvements due to the effects of food items high in sugar or fat being used as mood regulation and enhancing mood on a short-term basis, and studies linking positive mood to healthy purchases (Köster & Mojet, 2015; Gibson, 2006; Macht, 2008). There might be several reasons for finding no impact of both mood on food purchasing as well as food choices on mood. Real-world data might potentially differ from the previous laboratory findings. This might be due to factors that are not considered in laboratory settings compared to natural settings, such as money. Many prior studies investigating mood and food behaviour

were conducted in laboratory or online experimental settings, often with hypothetical or unrestricted purchasing tasks (Forgas, 1989; Giray et al., 2022; Spies et al., 1997). In contrast, this study examined real-world food purchases in daily life where individuals face actual financial limitations. Budget constraints and food prices likely play a dominant role in food choice, potentially overriding mood effects. In such situations, participants may prioritize affordability and convenience over mood-regulated preferences, especially in student populations with limited financial resources (Drewnowski & Darmon, 2005; Papadaki et al., 2007). In line with this, participants in the current study frequently purchased ultra-processed foods, which are typically more accessible and cost-effective than healthier or more sustainable options. (Drewnowski & Darmon, 2005). Moreover, most of the food that is nowadays available in the grocery stores is highly processed. Given that most of the participants were students in their early twenties, this tendency to buy processed food due to convenience and financial reasons, more often than another group of people, may reflect a purchasing pattern, with prior research showing that students living away from home are often more likely to purchase less healthy options such as fresh vegetables and fruits, and often bought unhealthy items like alcohol, fast food, and items with added sugar (Papadaki et al., 2007). Therefore, these participants might have looked for the fastest and most affordable food items which are often pre-packaged meals or fast food, being categorized as ultra-processed and unhealthy. The lack of mood impact may further indicate that automatic, habitual processes might outweigh emotional states when making food decisions in routine settings in the real world (Földi, 2014). While mood may impact behaviour and decisions, grocery shopping may be considered a habit where many people might always buy similar items regardless of mood. Habitual purchasing patterns may limit the flexibility for mood to influence decisions. Many individuals repeatedly buy the same types of foods regardless of mood, relying on automatic routines developed over time, further based on prices and money

(Singh, 2014; Al-Sayyed et al., 2025). This habitual component may attenuate short-term mood effects that might otherwise influence single consumption decisions in controlled settings.

The finding of participants buying less processed food items as the study progressed might be due to the cognitive dissonance effects, as participants became increasingly aware of inconsistencies in their behaviour and self-perception, and attempted to resolve them (Stone & Cooper, 2001). Further, participants might have felt to act socially desirable over time for others or themselves during documenting their food purchases (Hebert et al., 1995). Becoming aware of their diet and nutrition of the food they buy might have led to a slight change in behaviour (Burke et al., 2011). This suggests that ESM studies do not merely capture real-life behaviour passively but may themselves act as a subtle intervention. By prompting repeated reflection and awareness, they might influence the very behaviours they aim to observe, highlighting the method's dual role as both measurement and behavioural cue.

Contrary to expectations, purchasing unhealthy food items did not lead to mood changes in this study. The absence of a significant association between food purchases and subsequent mood may similarly reflect the complexity of real-world purchasing contexts. While previous research has suggested that unhealthy food consumption can temporarily elevate mood through hedonic reward mechanisms (Gibson, 2006; Macht, 2008;), this effect may be less pronounced in actual shopping situations. In daily life, food purchasing decisions may be less emotionally charged than food consumption itself. In real contexts, purchased food may not be consumed right away or may be intended for later, delaying any potential mood regulatory effect. This temporal gap may weaken the immediate connection between purchase behaviour and mood that has been observed in consumption studies (Gibson, 2006; Macht, 2008).

Limitations and Directions for Future Research

Factors that could have limited the scope and the results of this study might be the methodology of using an app. The TIIM app is still in development, and throughout the course of the study, the researchers have been in steady contact with the developers of the app to navigate through the process. Participants have reached out about not being able to save the data, ultimately leading to important data being lost for different participants and their entries. Post-hoc inspection revealed data loss due to app limitations, resulting in incomplete time-series entries for several participants. Therefore, the data and the results might have been skewed and less accurate in real-life settings.

The assessment of the variables of both mood and food purchases through the HUEBS might lack construct validity as the measurement might not accurately capture the understanding of the variables of each participant. Participants might have different definitions of the items presented, as the terms were applicable to different food items. Further, shortened versions of the PANAS-x are not validated across all populations but were used to decrease the burden on the participants. This study had high ecological validity as the study progressed through real-life conditions. Using a standardized procedure ensured that all participants received the same instructions, and questions, minimizing variability. Nevertheless, especially when using the HUEBS items, it is not clear how many items the participants bought and indicated. They were instructed to provide information on each food item, selecting one HUEBS category per item, or typing it in the "Other" option. However, some participants could have described one item along several categories which might have led to different results. Therefore, an indicator of the amount bought seemed to be missing.

This study enables several pathways for future research. Collecting more information about the participants and their food purchasing habits could be beneficial. Requesting the

number of items bought in relation to the research could further enhance understanding of the topic and prevent misunderstanding in interpreting the results.

Sample bias is one of the possible risks to the study's validity and reliability, particularly due to the over representation of populations, such as German female students which may limit generalizability. Another element that could compromise validity and reliability is self-report bias or social desirability in the replies (Hebert et al., 1995; Krumpal, 2011). The lack of information about the participants or their purchases might be another limitation. While we assessed the type of item bought through photos and descriptions, there is no indication about the general diet of a person, or their budget which could have functioned as moderator in the relationship between food and mood. Therefore, in future research, other variables could be investigated such as the perception of their diet in terms of healthiness and how that might influence their purchasing habits in connection to mood. Future studies could examine a baseline measure of dietary identity or restraint, using a new scale such as the Three-Factor Eating Questionnaire (De Lauzon et al., 2004) or the Dutch Eating Behaviour Questionnaire (Domoff, 2015). Individuals with high dietary restraint may show stronger mood-related changes in food purchasing behaviour due to internal conflict or goal-driven regulation. Moreover, conducting a study to explore long-term effects of mood on food purchasing, perhaps with the confounding variable of documenting and reporting one's purchases in ESM studies, might be worth to examine. This could be supported by this study's finding that over time, the participants seemed to have bought healthier food items. Another way to expand current research could be by using ESM but also passive smartphone tracking. During this study, reminders were sent regardless of whether participants bought food. However, using tracking to log grocery visits could give clearer insights into shopping habits and the exact time frame.

Conclusion

This study makes a valuable contribution to the existing body of knowledge in research on mood and food purchasing behaviour. By employing the Experience Sampling Method and a photo diary, it explored the dynamic interplay between mood and food choices in a real-world context. Although no significant effects were found using advanced multilevel modelling, a behavioural trend emerged; participants gradually purchased fewer processed foods over time. This suggests that self-monitoring may subtly encourage healthier purchasing patterns. Overall, the study not only highlights the complexity of everyday food decisions but also supports the feasibility of ecological data collection methods, paving the way for more context-sensitive research in this field.

Reference List

- Al-Sayyed, H. F., AbuZeinah, Z. F., & Al-Awwad, N. J. (2025). Food purchasing pattern is correlated to gender, educational level, and income: Results from the food purchasing habits survey. *PLOS ONE*, 20(6), e0322781. <https://doi.org/10.1371/journal.pone.0322781>
- AlAmmar, W. A., Albeesh, F. H., & Khattab, R. Y. (2020). Food and Mood: the Corresponsive Effect. *Current Nutrition Reports*, 9(3), 296–308. <https://doi.org/10.1007/S13668-020-00331-3/TABLES/1>
- Beedie, C. J., Terry, P. C., & Lane, A. M. (2005). Distinctions between emotion and mood. *Cognition and Emotion*, 19(6), 847–878. <https://doi.org/10.1080/02699930541000057>
- Bijoux, D., & Myers, J. (2006). Interviews, Solicited Diaries and Photography: “New” Ways of Accessing Everyday Experiences of Place. *Graduate Journal of Asia-Pacific Studies*, 4(1), 44–64. www.arts.auckland.ac.nz/gjaps
- Boggiano, M. M., Wenger, L. E., Turan, B., Tatum, M. M., Sylvester, M. D., Morgan, P. R., Morse, K. E., & Burgess, E. E. (2015). Real-time sampling of reasons for hedonic food consumption: further validation of the Palatable Eating Motives Scale. *Frontiers in Psychology*, 6(JUN), 744. <https://doi.org/10.3389/FPSYG.2015.00744>
- Burke, L. E., Wang, J., & Sevvick, M. A. (2011). Self-monitoring in weight loss: A systematic review of the literature. *Journal of the American Dietetic Association*, 111(1), 92–102. <https://doi.org/10.1016/j.jada.2010.10.008>
- Canetti, L., Bachar, E., & Berry, E. M. (2002). Food and emotion. *Behavioural Processes*, 60(2), 157–164. [https://doi.org/10.1016/S0376-6357\(02\)00082-7](https://doi.org/10.1016/S0376-6357(02)00082-7)
- Chen, M. F. (2007). Consumer attitudes and purchase intentions in relation to organic foods in Taiwan: Moderating effects of food-related personality traits. *Food Quality and Preference*, 18(7), 1008–1021. <https://doi.org/10.1016/J.FOODQUAL.2007.04.004>

- Chen, Z. (2024). Research on the Influence of Consumer Purchasing Behavior on the Market Supply and Demand Relationship. *Modern Economics & Management Forum*, 5(4), 679. <https://doi.org/10.32629/MEMF.V5I4.2562>
- Christensen, L. (2001). The Three-Factor Eating Questionnaire-R18 is able to distinguish among different eating patterns in a general population. *Clinical Nutrition*, 20(6), 839–847. <https://doi.org/10.1054/CLNU.2001.0420>
- Davison, B. K., Quigg, R., & Skidmore, P. M. L. (2018). Pilot Testing a Photo-Based Food Diary in Nine- to Twelve- Year Old- Children from Dunedin, New Zealand. *Nutrients* 2018, Vol. 10, Page 240, 10(2), 240. <https://doi.org/10.3390/NU10020240>
- De Lauzon, B., Romon, M., Deschamps, V., Lafay, L., Borys, J. M., Karlsson, J., Ducimetière, P., Charles, M. A., & the Fleurbaix Laventie Ville Santé (FLVS) Study Group. (2004). The Three-Factor Eating Questionnaire-R18 is able to distinguish among different eating patterns in a general population. *European Journal of Clinical Nutrition*, 58(2), 293–299. <https://doi.org/10.1038/sj.ejcn.1601839>
- De Oliveira, D. C. R. S., De Moura Souza, A., Levy, R. B., Sichieri, R., & Verly-Jr, E. (2019). Comparison between household food purchase and individual food consumption in Brazil. *Public Health Nutrition*, 22(5), 841–847. <https://doi.org/10.1017/S1368980018002987>
- Domoff, S. E. (2015). Dutch Eating Behavior Questionnaire (DEBQ). In: *Encyclopedia of Feeding and Eating Disorders*. Springer. https://doi.org/10.1007/978-981-287-087-2_7
- Drewnowski, A. (2005). The economics of obesity: dietary energy density and energy cost. *The American Journal of Clinical Nutrition*, 82(1 Suppl), 265S–273S. <https://doi.org/10.1093/ajcn/82.1.265S>
- Drewnowski, A. (1997). Taste preferences and food intake. *Annual Review of Nutrition*, 17(Volume 17, 1997), 237–253. <https://doi.org/10.1146/ANNUREV.NUTR.17.1.237/CITE/REFWORKS>

Földi, L. (2014). Changes of food purchasing habits. *European Scientific Journal*, 10(10), 385–392.

Food and Agriculture Organization. (2019). *The state of the world's biodiversity for food and agriculture*. FAO. <https://openknowledge.fao.org/server/api/core/bitstreams/b620989c-407b-4caf-a152-f790f55fec71/content>

Forgas, J. P. (1989). Mood effects on decision making strategies. *Australian Journal of Psychology*, 41(2), 197–214. <https://doi.org/10.1080/00049538908260083>

Furnham, A., & Milner, R. (2013). The impact of mood on customer behavior: Staff mood and environmental factors. *Journal of Retailing and Consumer Services*, 20(6), 634–641. <https://doi.org/10.1016/J.JRETCONSER.2013.06.001>

Gear, T., Shi, H., Davies, B. J., & Fets, N. A. (2017). The impact of mood on decision-making process. *EuroMed Journal of Business*, 12(3), 242–257. <https://doi.org/10.1108/EMJB-04-2016-0013/FULL/PDF>

Gendolla, G. H. E. (2000). On the Impact of Mood on Behavior: An Integrative Theory and a Review. *Review of General Psychology*, 4(4), 378–408. https://doi.org/10.1037/1089-2680.4.4.378/ASSET/A9885636-B265-43CE-9D5A-B45C886BC1B6/ASSETS/IMAGES/LARGE/10.1037_1089-2680.4.4.378-FIG1.JPG

Giray, C., Yon, B., Alniacik, U., & Girisken, Y. (2022). How does mothers' mood matter on their choice of organic food? Controlled eye-tracking study. *Journal of Business Research*, 144, 1175–1185. <https://doi.org/10.1016/J.JBUSRES.2022.02.059>

Guertin, C., Pelletier, L., & Pope, P. (2020). The validation of the Healthy and Unhealthy Eating Behavior Scale (HUEBS): Examining the interplay between stages of change and motivation and their association with healthy and unhealthy eating behaviors and physical health. *Appetite*, 144. <https://doi.org/10.1016/J.APPET.2019.104487>

- Haedt-Matt, A. A., & Keel, P. K. (2011). *Revisiting the affect regulation model of binge eating: A meta-analysis of studies using ecological momentary assessment*. *Psychological Bulletin*, 137(4), 660–681. <https://doi.org/10.1037/a0023660>
- Hebert, J. R., Clemow, L., Pbert, L., Ockene, I. S., & Ockene, J. K. (1995). Social desirability bias in dietary self-report may compromise the validity of dietary intake measures. *International Journal of Epidemiology*, 24(2), 389–398. <https://doi.org/10.1093/ije/24.2.389>
- Holland, R. W., de Vries, M., Hermesen, B., & van Knippenberg, A. (2012). Mood and the attitude-behavior link: The happy act on impulse, the sad think twice. *Social Psychological and Personality Science*, 3(3), 356–364.
https://doi.org/10.1177/1948550611421635/ASSET/D2D31F1F-10D6-4971-B082-2E2A817C91B5/ASSETS/IMAGES/LARGE/10.1177_1948550611421635-FIG4.JPG
- Jimoh, F., Lund, E. K., Harvey, L. J., Frost, C., Lay, W. J., Roe, M. A., Berry, R., & Finglas, P. M. (2018). Comparing Diet and Exercise Monitoring Using Smartphone App and Paper Diary: A Two-Phase Intervention Study. *JMIR Mhealth Uhealth* 2018;6(1):E17
<https://Mhealth.Jmir.Org/2018/1/E17>, 6(1), e7702. <https://doi.org/10.2196/MHEALTH.7702>
- Krumpal, I. (2011). Determinants of social desirability bias in sensitive surveys: A literature review. *Quality & Quantity*, 47(4), 2025–2047. <https://doi.org/10.1007/s11135-011-9640-9>
- Köster, E. P., & Mojet, J. (2015). From mood to food and from food to mood: A psychological perspective on the measurement of food-related emotions in consumer research. *Food Research International*, 76(P2), 180–191. <https://doi.org/10.1016/J.FOODRES.2015.04.006>
- Kushi, L. H., Byers, T., Doyle, C., Bandera, E. V., McCullough, M., Gansler, T., Andrews, K. S., & Thun, M. J. (2006). American Cancer Society Guidelines on Nutrition and Physical Activity for Cancer Prevention: Reducing the Risk of Cancer With Healthy Food Choices and Physical Activity. *CA: A Cancer Journal for Clinicians*, 56(5), 254–281.
<https://doi.org/10.3322/CANJCLIN.56.5.254>

- Leigh Gibson, E. (2006). Emotional influences on food choice: Sensory, physiological and psychological pathways. *Physiology & Behavior*, 89(1), 53–61.
<https://doi.org/10.1016/J.PHYSBEH.2006.01.024>
- Lyman, B. (1982). The nutritional values and food group characteristics of foods preferred during various emotions. *Journal of Psychology*, 112, 121–127. <https://doi.org/10.1080/00223980.1982.9915363>
- Macht, M. (2008). How emotions affect eating: A five-way model. *Appetite*, 50(1), 1–11.
<https://doi.org/10.1016/J.APPET.2007.07.002>
- Marshall, D. (2005). Food as ritual, routine or convention. *Consumption Markets & Culture*, 8(1), 69–85. <https://doi.org/10.1080/10253860500069042>
- Martini, M., La Barbera, F., Schmidt, S., Rollero, C., & Fedi, A. (2024). Differentiating emotions in the theory of planned behaviour: evidence of improved prediction in relation to sustainable food consumerism. *BRITISH FOOD JOURNAL*, 126(2), 698–714.
<https://doi.org/10.1108/BFJ-05-2023-0357>
- Migliore, G., Schifani, G., Tóth, J., Zheng, Q., Zeng, H., Xiu, X., & Chen, Q. (2022). *Pull the Emotional Trigger or the Rational String? A Multi-Group Analysis of Organic Food Consumption*. <https://doi.org/10.3390/foods11101375>
- Monteiro, C. A., Cannon, G., Levy, R., Moubarac, J.-C., Jaime, P., Martins, A. P., Canella, D., Louzada, M., & Parra, D. (2016). NOVA. The star shines bright. *World Nutrition*, 7(1-3), 28–38.
- Monteiro, C. A., Cannon, G., Levy, R., Moubarac, J.-C., Jaime, P., Paula Martins, A., Canella, D., Louzada, M., Parra Also with Camila Ricardo, D., Calixto, G., Machado, P., Martins, C., Martinez, E., Baraldi, L., Garzillo, J., & Sattamini, I. (2016). *The Food System*. 7(3).

- Monteiro, C. A., Cannon, G., Lawrence, M., Costa Louzada, M. L., & Pereira Machado, P. (2019). Ultra-processed foods, diet quality, and health using the NOVA classification system. *Rome: FAO*.
- Moore, S. A., Brown, S. L., & Biegel, D. E. (2018). Using multiple methods to more fully understand causal relations: Positive affect enhances social relationships. *Journal of Health Psychology*, 23(11), 1407–1418. <https://doi.org/10.1177/1359105316656225>
- Nguyen, T. T. (2018). Sustainable food systems: Concept and framework. *Food and Agriculture Organization of the United Nations (FAO)*. <https://www.fao.org/3/ca2079en/CA2079EN.pdf>
- Papadaki, A., Hondros, G., Scott, J. A., & Kapsokefalou, M. (2007). Eating habits of university students living at, or away from home in Greece. *Appetite*, 49(1), 169–176. <https://doi.org/10.1016/j.appet.2007.01.008>
- Robbins, T. W., & Fray, P. J. (1980). Stress-induced eating: Fact, fiction or misunderstanding? *Appetite*, 1(2), 103–133. [https://doi.org/10.1016/S0195-6663\(80\)80015-7](https://doi.org/10.1016/S0195-6663(80)80015-7)
- Rush, A. J., & Hofer, S. M. (2014). Differences in within- and between-person factor structure of positive and negative affect: Analysis of two intensive measurement studies using multilevel SEM. *Psychological Assessment*, 26(2), 462–473. <https://doi.org/10.1037/a0035664>
- Singh, M. (2014). Mood, food and obesity. *Frontiers in Psychology*, 5, 925. <https://doi.org/10.3389/fpsyg.2014.00925>
- Spendrup, S., Hunter, E., & Isgren, E. (2016). Exploring the relationship between nature sounds, connectedness to nature, mood and willingness to buy sustainable food: A retail field experiment. *Appetite*, 100, 133–141. <https://doi.org/10.1016/J.APPET.2016.02.007>
- Spies, K., Hesse, F., & Loesch, K. (1997). Store atmosphere, mood and purchasing behavior. *International Journal of Research in Marketing*, 14(1), 1–17. [https://doi.org/10.1016/S0167-8116\(96\)00015-8](https://doi.org/10.1016/S0167-8116(96)00015-8)

- Stone, J., & Cooper, J. (2001). A self-standards model of cognitive dissonance. *Journal of Experimental Social Psychology*, 37(3), 228–243. <https://doi.org/10.1006/jesp.2000.1446>
- Sun, R., Chen, J., & Urminsky, O. (2024). *From Mood to Food: How Does Emotional Environment Predict Food Purchases?* <https://doi.org/10.2139/SSRN.4905569>
- The NOVA Food Classification System*. (n.d.). Retrieved April 14, 2025, from <http://tinyurl.com/BRdietary>
- Trull, T. J., & Ebner-Priemer, U. W. (2009). Using Experience Sampling Methods/Ecological Momentary Assessment (ESM/EMA) in clinical assessment and clinical research: Introduction to the special section. *Psychological Assessment*, 21(4), 457–462. <https://doi.org/10.1037/a0017653>
- Van Berkel, N., Ferreira, D., & Kostakos, V. (2017). The Experience Sampling Method on mobile devices. *ACM Computing Surveys*, 50(6), 93. <https://doi.org/10.1145/3123988>
- Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and Validation of Brief Measures of Positive and Negative Affect: The PANAS Scales. *Journal of Personality and Social Psychology*, 54(6), 1063–1070. <https://doi.org/10.1037/0022-3514.54.6.1063>
- Watson, D., & Clark, L. A. (1999). *The PANAS-X: Manual for the Positive and Negative Affect Schedule – Expanded Form*. University of Iowa.
- Willner, P., Benton, D., Brown, E., Cheeta, S., Davies, G., Morgan, J., & Morgan, M. (1998). “Depression” increases “craving” for sweet rewards in animal and human models of depression and craving. *Psychopharmacology*, 136(3), 272–283. <https://doi.org/10.1007/S002130050566/METRICS>
- Wischmann, M. (2020). *An Experience Sampling Study on Binge Watching and its relation to Healthy and Unhealthy snacking Bachelor Thesis*.

Woodworth, R. J., & Lang, A. R. (2016). Happy Days: Positive psychology interventions effects on affect in an N-of-1 trial. *The Journal of Positive Psychology*, 11(5), 480–

489. <https://doi.org/10.1080/17439760.2015.1117121>

World Health Organization. (2020). *Healthy diet*. <https://www.who.int/news-room/fact-sheets/detail/healthy-diet>

Appendix

Appendix A

AI Usage Statement

During the preparation of this work, I used Microsoft Word (Editor function), Google Scholar, and Mendeley for text processing, literature search, and reference management. These tools may contain AI-powered features such as grammar correction, search optimization, or citation formatting. After using these tools, I thoroughly reviewed and edited the content as needed, taking full responsibility for the final outcome.

Appendix B

Mood State Questionnaire

Here is an example of a PANAS checklist, from a survey designed to measure emotions. You are asked to report to what extent you have felt this way during the time period being measured (right now, past few hours, past week, etc.).

1	2	3	4	5
very slightly or not at all	a little	moderately	quite a bit	extremely
<input type="checkbox"/> cheerful	<input type="checkbox"/> sad	<input type="checkbox"/> active	<input type="checkbox"/> angry at self	
<input type="checkbox"/> disgusted	<input type="checkbox"/> calm	<input type="checkbox"/> guilty	<input type="checkbox"/> enthusiastic	
<input type="checkbox"/> attentive	<input type="checkbox"/> afraid	<input type="checkbox"/> joyful	<input type="checkbox"/> downhearted	
<input type="checkbox"/> bashful	<input type="checkbox"/> tired	<input type="checkbox"/> nervous	<input type="checkbox"/> sheepish	
<input type="checkbox"/> sluggish	<input type="checkbox"/> amazed	<input type="checkbox"/> lonely	<input type="checkbox"/> distressed	
<input type="checkbox"/> daring	<input type="checkbox"/> shaky	<input type="checkbox"/> sleepy	<input type="checkbox"/> blameworthy	
<input type="checkbox"/> surprised	<input type="checkbox"/> happy	<input type="checkbox"/> excited	<input type="checkbox"/> determined	
<input type="checkbox"/> strong	<input type="checkbox"/> timid	<input type="checkbox"/> hostile	<input type="checkbox"/> frightened	
<input type="checkbox"/> scornful	<input type="checkbox"/> alone	<input type="checkbox"/> proud	<input type="checkbox"/> astonished	
<input type="checkbox"/> relaxed	<input type="checkbox"/> alert	<input type="checkbox"/> jittery	<input type="checkbox"/> interested	
<input type="checkbox"/> irritable	<input type="checkbox"/> upset	<input type="checkbox"/> lively	<input type="checkbox"/> loathing	
<input type="checkbox"/> delighted	<input type="checkbox"/> angry	<input type="checkbox"/> ashamed	<input type="checkbox"/> confident	
<input type="checkbox"/> inspired	<input type="checkbox"/> bold	<input type="checkbox"/> at ease	<input type="checkbox"/> energetic	
<input type="checkbox"/> fearless	<input type="checkbox"/> blue	<input type="checkbox"/> scared	<input type="checkbox"/> concentrating	
<input type="checkbox"/> disgusted	<input type="checkbox"/> shy	<input type="checkbox"/> drowsy	<input type="checkbox"/> dissatisfied with self	

with self

Indicate to what extent you feel this way

(On a scale of 1-5

1 very slightly or not at all

2 a little

3 moderately

4 quite a bit

5 extremely)

Negative items:

... upset

... irritable

... sad

Positive items:

... enthusiastic

... interested

... happy

Appendix C

HUEBS scale

Healthy eating

- I eat fruits
- I eat vegetables
- I eat whole grains (e.g., brown rice, buckwheat, quinoa, oats)
- I eat foods that are low in saturated fats and cholesterol
- I eat foods that are high in monounsaturated and polyunsaturated fats (e.g., fish, olive oil, avocados, nuts and seeds)
- I use natural sweeteners (e.g., raw honey, maple syrup, coconut sugar, dates)
- I drink water
- I eat foods that are boiled, steamed, grilled, or poached
- I eat lean meats, such as poultry, fish, and eggs
- I eat low-fat dairy products (e.g., low-fat milk, yogurt, sour cream, cheese)
- I eat legumes (e.g., beans, lentils, peas, peanuts)

Unhealthy eating

- I eat refined grains (e.g., white rice, white bread, white flour)
- I use white sugar or artificial sweeteners
- I eat snack foods, such as chips, chocolate, and/or candy
- I drink sugar-sweetened beverages, such as soft drinks, fruit juices, and sports drinks
- I eat foods that are deep-fried (e.g., fries, fried chicken)
- I eat frozen and/or pre-packaged meals
- I eat processed meats, such as sausages, bacon, and/or cold-cuts
- I add salt to my food
- I eat fast-food
- I eat pastries and/or baked goods (e.g., croissants, pie, cake, muffins, brownies)
- I consume more than 10 alcoholic drinks (for women) and more than 15 alcoholic drinks (for men) per week

Appendix D

Nova Classification

GROUP 1: UNPROCESSED OR MINIMALLY PROCESSED FOODS

Unprocessed or Natural foods are obtained directly from plants or animals and do not undergo any alteration following their removal from nature.

Minimally processed foods are natural foods that have been submitted to cleaning, removal of inedible or unwanted parts, fractioning, grinding, drying, fermentation, pasteurization, cooling, freezing, or other processes that may subtract part of the food, but which do not add oils, fats, sugar, salt or other substances to the original food.

EXAMPLES

- Natural, packaged, cut, chilled or frozen vegetables, fruits, potatoes, and other roots and tubers
- bulk or packaged grains such as brown, white, parboiled and wholegrain rice, corn kernel, or wheat berry
- fresh or pasteurized vegetable or fruit juices with no added sugar or other substances
- grains of wheat, oats and other cereals
- grits, flakes and flours made from corn, wheat or oats, including those fortified with iron, folic acid or other nutrients lost during processing
- dried or fresh pasta, couscous, and polenta made from water and the grits/flakes/flours described above
- eggs
- lentils, chickpeas, beans, and other legumes
- dried fruits
- nuts, peanuts, and other seeds without salt or sugar
- fresh and dried herbs and spices (e.g., oregano, pepper, thyme, cinnamon)

- fresh and dried mushrooms and other fungi or algae
- fresh and dried herbs and spices
- fresh, chilled or frozen meat, poultry, fish and seafood, whole or in the form of steaks, fillets and other cuts
- fresh or pasteurized milk; yoghurt without sugar
- tea, herbal infusions
- coffee
- tap, spring and mineral water

GROUP 2: OILS, FATS, SALT, AND SUGAR

Group 2 is also called **Processed Culinary Ingredients**. These are products extracted from natural foods or from nature by processes such as pressing, grinding, crushing, pulverizing, and refining. They are used in homes and restaurants to season and cook food and thus create varied and delicious dishes and meals of all types, including broths and soups, salads, pies, breads, cakes, sweets, and preserves.

Use oils, fats, salt, and sugar in small amounts for seasoning and cooking foods and to create culinary preparations. As long as they are used in moderation in culinary preparations based on natural or minimally processed foods, oils, fats, salt, and sugar contribute toward diverse and delicious diets without rendering them nutritionally unbalanced.

EXAMPLES

- oils made from seeds, nuts and fruits, to include soybeans, corn, oil palm, sunflower or olives
- white, brown and other types of sugar and molasses obtained from cane or beet
- honey extracted from honeycombs

- syrup extracted from maple trees
- starches extracted from corn and other plants
- butter
- lard
- coconut fat
- refined or coarse salt, mined or from seawater
- Also any food combining 2 of these, such as 'salted butter'

GROUP 3: PROCESSED FOODS

Processed foods are products manufactured by industry with the use of salt, sugar, oil or other substances (Group 2) added to natural or minimally processed foods (Group 1) to preserve or to make them more palatable. They are derived directly from foods and are recognized as versions of the original foods. They are usually consumed as a part of or as a side dish in culinary preparations made using natural or minimally processed foods. Most processed foods have two or three ingredients.

EXAMPLES

- canned or bottled legumes or vegetables preserved in salt (brine) or vinegar, or by pickling
- canned fish, such as sardine and tuna, with or without added preservatives
- Tomato extract, pastes or concentrates (with salt and/or sugar) fish
- fruits in sugar syrup (with or without added antioxidants)
- beef jerky
- bacon
- salted or sugared nuts and seeds

- salted, dried, smoked or cured meat or
- coconut fat
- freshly-made cheeses
- freshly-made (unpackaged) breads made of wheat flour, yeast, water and salt
- fermented alcoholic beverages such as beer, alcoholic cider, and wine

GROUP 4: ULTRA-PROCESSED FOODS

Ultra-processed foods are industrial formulations made entirely or mostly from substances extracted from foods (oils, fats, sugar, starch, and proteins), derived from food constituents (hydrogenated fats and modified starch), or synthesized in laboratories from food substrates or other organic sources (flavor enhancers, colors, and several food additives used to make the product hyper-palatable). Manufacturing techniques include extrusion, moulding and preprocessing by frying. Beverages may be ultra-processed. Group 1 foods are a small proportion of, or are even absent from, ultra-processed products.

EXAMPLES

- fatty, sweet, savory or salty packaged snacks
- biscuits (cookies)
- ice creams and frozen desserts
- chocolates, candies and confectionery in general
- cola, soda and other carbonated soft drinks
- ‘energy’ and sports drinks
- canned, packaged, dehydrated (powdered) and other ‘instant’ soups, noodles, sauces, desserts, drink mixes and seasonings
- sweetened and flavored yogurts, including fruit yogurts

- dairy drinks, including chocolate milk
- sweetened juices
- margarines and spreads
- pre-prepared (packaged) meat, fish and vegetables
- pre-prepared pizza and pasta dishes
- pre-prepared burgers, hot dogs, sausages
- pre-prepared poultry and fish 'nuggets' and 'sticks'
- other animal products made from remnants
- packaged breads, hamburger and hot dog buns
- baked products made with ingredients such as hydrogenated vegetable fat, sugar, yeast, whey, emulsifiers, and other additives
- breakfast cereals and bars
- infant formulas & drinks, and meal replacement shakes (e.g., 'slim fast')
- pastries, cakes and cake mixes
- distilled alcoholic beverages such as whisky, gin, rum, vodka, etc.

Appendix E

R-Code

```
install.packages("lme4")
install.packages("tidyverse")
install.packages("lmerTest") # optional, adds p-values
```

```
library(tidyverse)
library(lme4)
library(lmerTest)
```

#PRELIMINARY ANALYSIS

```
#load the data
data <- read_csv("data_foodstudy.csv")

data <- read.csv("data_foodstudy.csv", sep = ";")

glimpse(data)

#rename data
names(data)[names(data) ==
"combined.mood.score..positive.negative..from..4...4..above.0..positive...below.0..negative..0
..neutral"] <- "Combined_Mood"

data <- read.csv("data_foodstudy.csv", sep = ";")
data$ID <- as.factor(data$ID) # make sure ID is a factor

data$combined.mood <- as.numeric(data$combined.mood)

#reload data with decimals
data <- read.csv("data_foodstudy.csv", sep = ";", dec = ",")
```

```

#fix combined.mood variable
data$combined.mood <- as.numeric(gsub(",", ".", data$combined.mood))

#running multi level model
model <- lmer(NOVA.Group ~ combined.mood + (1 | ID), data = data)

summary(model)

ggplot(data, aes(x = combined.mood, y = NOVA.Group)) +
  geom_point() +
  geom_smooth(method = "lm") +
  theme_minimal()

#numeric format
data$combined.mood <- as.numeric(data$combined.mood)
data$NOVA.Group <- as.numeric(data$NOVA.Group)

#descriptive statistics
descriptives <- data %>%
  summarize(
    Mean_Combined_Mood = mean(combined.mood, na.rm = TRUE),
    SD_Combined_Mood = sd(combined.mood, na.rm = TRUE),
    Mean_NOVA_Group = mean(NOVA.Group, na.rm = TRUE),
    SD_NOVA_Group = sd(NOVA.Group, na.rm = TRUE)
  )

print(descriptives)

#shapiro wilk test for residual normality
#extracting residuals
residuals_model <- resid(model)

#running Shapiro-Wilk test
shapiro.test(residuals_model)

```

```
#residual plot for homocedasticity and linearity
```

```
#fitted values (predictions from the model)
```

```
fitted_values <- fitted(model)
```

```
#plot residuals vs fitted values
```

```
plot(fitted_values, residuals_model,
```

```
  xlab = "Fitted Values",
```

```
  ylab = "Residuals",
```

```
  main = "Residuals vs Fitted Values")
```

```
abline(h = 0, col = "red")
```

```
#vizualising normality with q-q plot
```

```
#Q-Q Plot
```

```
qqnorm(residuals_model)
```

```
qqline(residuals_model, col = "red")
```

```
#factor analysis
```

```
#loading sheet with mood states
```

```
mood_data <- read_csv("moodstates.csv")
```

```
mood_data <- read.csv("moodstates.csv", sep = ";")
```

```
install.packages("psych")
```

```
library(psych)
```

```
#selecting mood items
```

```
mood_items <- mood_data %>% select(Happy, Enthusiastic, Interested, Irritable, Upset, Sad)
```

```
rlang::last_trace()
```

```
#factor analysis
```

```
fa_mood <- fa(mood_items, nfactors = 1, rotate = "none") # One factor solution
```

```

print(fa_mood)

#KMO Measure of Sampling Adequacy
KMO(mood_items)

#Bartlett's Test of Sphericity
cortest.bartlett(mood_items)

#Cronbach's alpha for mood scale
alpha(mood_items)

#Cronbach's Alpha with auto reverse-keying
alpha(mood_items, check.keys = TRUE)

#running model where mood predicts purchase
library(dplyr)

#creating lagged mood within each participant
data <- data %>%
  group_by(ID) %>%
  arrange(ID, Iteration) %>% # Important to sort by ID and iteration
  mutate(lagged_mood = lag(combined.mood)) %>%
  ungroup()

#fixing lagged mood values
data$lagged_mood <- as.numeric(gsub(",", ".", data$lagged_mood))

#creating purchase indicator: 1 = bought food, 0 = did not
data$Purchased <- ifelse(!is.na(data$NOVA.Group), 1, 0)

#multilevel model: Lagged mood predicting NOVA Group (food healthiness)
model_mood_to_food <- lmer(NOVA.Group ~ lagged_mood + (1 | ID), data = data)
summary(model_mood_to_food)

```

```

#fix combined.mood
data$combined.mood <- as.numeric(gsub(",", ".", data$combined.mood))

#multilevel model: Purchase predicting current mood, Nova group
#keeping only rows where NOVA group is not missing
data_purchase_only <- data %>% filter(!is.na(NOVA.Group))

model_food_healthiness_to_mood <- lmer(combined.mood ~ NOVA.Group + (1 | ID), data =
data_purchase_only)
summary(model_food_healthiness_to_mood)

#plots
#mood -> food
library(ggplot2)

ggplot(data, aes(x = lagged_mood, y = NOVA.Group)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(x = "Lagged Mood", y = "NOVA Group (Processing Level)",
    title = "Mood (previous time) Predicting Food Healthiness") +
  theme_minimal()

#nova -> mood
ggplot(data_purchase_only, aes(x = NOVA.Group, y = combined.mood)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(x = "NOVA Group (Processing Level)", y = "Combined Mood Score",
    title = "Food Healthiness Predicting Mood") +
  theme_minimal()

```

#ANALYSIS WITH COMPLETE DATASET

```

library(dplyr)
library(psych)
library(lme4)
library(lmerTest)
library(ggplot2)

#load data again
data <- read.csv("data_foodstudy.csv", sep = ";")
demographics <- read.csv("demographpics.csv", sep = ";")
moodstates <- read.csv("moodstates.csv", sep = ";")

#cronbachs alpha
#select mood items
mood_items <- moodstates %>% dplyr::select(Happy, Enthusiastic, Interested, Sad, Upset,
Irritable)
mood_items <- moodstates %>% select(Happy, Enthusiastic, Interested, Irritable, Upset, Sad)

#run Cronbach's alpha (auto-checks for reverse-coded items)
moodstates <- moodstates %>%
  mutate(across(c(Happy, Enthusiastic, Interested, Sad, Upset, Irritable), ~
as.numeric(as.character(.))))

mood_items <- moodstates %>% select(Happy, Enthusiastic, Interested, Sad, Upset, Irritable)
psych::alpha(mood_items, check.keys = TRUE)

#descriptive statistics
data$combined.moood <- as.numeric(as.character(data$combined.moood))

descriptives <- data %>%
  summarize(
    Mean_Combined_Mood = mean(combined.moood, na.rm = TRUE),
    SD_Combined_Mood = sd(combined.moood, na.rm = TRUE),
    Mean_NOVA_Group = mean(NOVA.Group, na.rm = TRUE),

```

```

    SD_NOVA_Group = sd(NOVA.Group, na.rm = TRUE)
  )

print(descriptives)

data <- data %>% rename(combined.mood = combined.moood)

#demographics
#sample size
nrow(demographics)

#gender
demographics %>%
  group_by(Gender) %>%
  summarize(
    Count = n(),
    Mean_Age = round(mean(Age, na.rm = TRUE), 2),
    SD_Age = round(sd(Age, na.rm = TRUE), 2)
  )

#age
mean(demographics$Age, na.rm = TRUE)
sd(demographics$Age, na.rm = TRUE)

#nationality
demographics %>%
  count(Nationality) %>%
  arrange(desc(n))

#education
demographics %>%
  count(Highest.Level.of.Education) %>%
  arrange(desc(n))

```

```

#person-mean
data$combined.mood <- as.numeric(gsub(",", ".", data$combined.mood))

person_descriptives <- data %>%
  group_by(ID) %>%
  summarize(
    N_Observations = n(),
    Mean_Mood = mean(combined.mood, na.rm = TRUE),
    Mean_NOVA = mean(NOVA.Group, na.rm = TRUE)
  )

print(person_descriptives, n = Inf)

#person mean centered
data <- data %>%
  group_by(ID) %>%
  mutate(
    person_mean_mood = mean(combined.mood, na.rm = TRUE),
    mood_centered = combined.mood - person_mean_mood
  ) %>%
  ungroup()

#running LMM
library(dplyr)

#creating lagged mood within each participant
data <- data %>%
  group_by(ID) %>%
  arrange(ID, Iteration) %>% # Important to sort by ID and iteration
  mutate(lagged_mood = lag(combined.mood)) %>%
  ungroup()

#fixing lagged mood values
data$lagged_mood <- as.numeric(gsub(",", ".", data$lagged_mood))

```



```

#creating purchase indicator: 1 = bought food, 0 = did not
data$Purchased <- ifelse(!is.na(data$NOVA.Group), 1, 0)

#multilevel model: Lagged mood predicting NOVA Group (food healthiness)
model_mood_to_food <- lmer(NOVA.Group ~ lagged_mood + (1 | ID), data = data)
summary(model_mood_to_food)

#fix combined.mood
data$combined.mood <- as.numeric(gsub(",", ".", data$combined.mood))

#multilevel model: Purchase predicting current mood, Nova group
#keeping only rows where NOVA group is not missing
data_purchase_only <- data %>% filter(!is.na(NOVA.Group))

model_food_healthiness_to_mood <- lmer(combined.mood ~ NOVA.Group + (1 | ID), data =
data_purchase_only)
summary(model_food_healthiness_to_mood)

#plots
#mood -> food
library(ggplot2)

ggplot(data, aes(x = lagged_mood, y = NOVA.Group)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(x = "Lagged Mood", y = "NOVA Group (Processing Level)",
       title = "Mood (previous time) Predicting Food Healthiness") +
  theme_minimal()

#nova -> mood
ggplot(data_purchase_only, aes(x = NOVA.Group, y = combined.mood)) +
  geom_point() +

```

```
geom_smooth(method = "lm", se = FALSE) +
labs(x = "NOVA Group (Processing Level)", y = "Combined Mood Score",
     title = "Food Healthiness Predicting Mood") +
theme_minimal()
```

#LMM with lagged mood centered and time

```
data <- data %>%
  group_by(ID) %>%
  arrange(ID, Iteration) %>%
  mutate(
    person_mean_mood = mean(combined.mood, na.rm = TRUE),
    mood_centered = combined.mood - person_mean_mood,
    lagged_mood_centered = lag(mood_centered)
  ) %>%
  ungroup()
```

```
model <- lmer(NOVA.Group ~ lagged_mood_centered + Iteration + (1 | ID), data = data)
summary(model)
```

#slopes

```
model_random_slope <- lmer(NOVA.Group ~ lagged_mood_centered + Iteration + (1 +
  lagged_mood_centered | ID), data = data)
summary(model_random_slope)
```

#LMM food->mood with person mean centered

```
data <- data %>%
  group_by(ID) %>%
  arrange(ID, Iteration) %>%
  mutate(
    person_mean_nova = mean(NOVA.Group, na.rm = TRUE),
    nova_centered = NOVA.Group - person_mean_nova
  ) %>%
  ungroup()
```

```
model_food_to_mood <- lmer(combined.mood ~ nova_centered + Iteration + (1 | ID), data =
data)
```

```
summary(model_food_to_mood)
```

```
#slope
```

```
model_food_random_slope <- lmer(combined.mood ~ nova_centered + Iteration + (1 +
nova_centered | ID), data = data)
```

```
summary(model_food_random_slope)
```

```
#plot lagged mood -> food
```

```
ggplot(data, aes(x = lagged_mood_centered, y = NOVA.Group)) +
  geom_point(alpha = 0.4) +
  geom_smooth(method = "lm", se = TRUE) +
  labs(
    title = "Effect of Lagged Mood on Food Healthiness (NOVA Group)",
    x = "Lagged Mood (Person-Mean Centered)",
    y = "NOVA Group"
  ) +
  theme_minimal()
```

```
#plot food -> mood
```

```
ggplot(data, aes(x = nova_centered, y = combined.mood)) +
  geom_point(alpha = 0.4) +
  geom_smooth(method = "lm", se = TRUE) +
  labs(
    title = "Effect of Food Healthiness (NOVA Group) on Mood",
    x = "NOVA Group (Person-Mean Centered)",
    y = "Mood"
  ) +
  theme_minimal()
```

```
#ICC
```

```

library(psych)
library(tidyr)
library(dplyr)

#reshape mood data to wide format: one row per participant, columns = repeated measures
wide_mood <- data %>%
  select(ID, Iteration, combined.mood) %>%
  pivot_wider(names_from = Iteration, values_from = combined.mood)

#remove ID column
icc_data <- wide_mood %>% select(-ID)

#calculate ICC
icc_result <- ICC(icc_data)
print(icc_result)

duplicates <- data %>%
  group_by(ID, Iteration) %>%
  summarize(n = n(), .groups = "drop") %>%
  filter(n > 1)

print(duplicates)

data_unique <- data %>%
  group_by(ID, Iteration) %>%
  summarize(combined.mood = mean(combined.mood, na.rm = TRUE),
    .groups = "drop")

wide_mood <- data_unique %>%
  pivot_wider(names_from = Iteration, values_from = combined.mood)

icc_data <- wide_mood %>% select(-ID)

icc_result <- ICC(icc_data)

```

```

print(icc_result)

#exploratory
#gender
data_full <- data %>%
  left_join(demographics, by = "ID")

model_gender <- lmer(NOVA.Group ~ lagged_mood_centered * Gender + Iteration + (1 |
ID), data = data_full)
summary(model_gender)

#time
model_time_interaction <- lmer(NOVA.Group ~ lagged_mood_centered * Iteration + (1 |
ID), data = data)
summary(model_time_interaction)

#education
model_education <- lmer(NOVA.Group ~ lagged_mood_centered *
Highest.Level.of.Education + Iteration + (1 | ID), data = data_full)
summary(model_education)

#age
model_age <- lmer(NOVA.Group ~ lagged_mood_centered * Age + Iteration + (1 | ID), data
= data_full)
summary(model_age)

#non linear effects
data <- data %>%
  mutate(mood_centered_sq = mood_centered^2)

model_quad <- lmer(NOVA.Group ~ lagged_mood_centered + mood_centered_sq +
Iteration + (1 | ID), data = data)
summary(model_quad)

```

```
#cronbachs alpha per item
```

```
library(psych)
```

```
# Positive Affect items
```

```
pa_items <- moodstates %>% select(Happy, Enthusiastic, Interested)
```

```
psych::alpha(pa_items, check.keys = TRUE)
```

```
# Negative Affect items
```

```
na_items <- moodstates %>% select(Sad, Upset, Irritable)
```

```
psych::alpha(na_items, check.keys = TRUE)
```

Appendix F

Dataset Excel Sheet

ID	Iteration	negative mood average	positive mood average	combined mood	Food	food item	NOVA Group
12477	1.	1	3.666	2,666	no		
12477	2.	1	4	3	no		
12477	3.	1	3	2	yes pic	fanta can	4
12477	3.	1	3	2	yes pic	prepackaged salad	4
12477	3.	1	3	2	yes pic	2 frozen baguettes	4
12477	3.	1	3	2	yes pic	2 ofenkäse	2
12477	4.	eins komma drei	2	0,666	no		
12477	5.	1	1	0	no		
12477	6.	1	3.333	2,333	yes pic	two energy drinks	4
12477	6.	1	3.333	2,333	yes pic	two durstlöscher	4
12477	6.	1	3.333	2,333	yes pic	one beer	3
12477	6.	1	3.333	2,333	yes pic	prepackaged sandwich	4
12477	6.	1	3.333	2,333	yes pic	two frozen pizza	4
12477	7.	1.666	3.333	1,666	yes but no input?		
12477	8.	2	eins komma sechs	-0,333	yes pic	grated cheese	3
12477	8.	2	eins komma sechs	-0,333	yes pic	spätzle	3
12477	8.	2	eins komma sechs	-0,333	yes pic	bread roll	3
12477	8.	2	eins komma sechs	-0,333	yes pic	sour gummie bears	4
12477	8.	2	eins komma sechs	-0,333	yes pic	chips	4
12477	8.	2	eins komma sechs	-0,333	yes pic	4 sugary drinks	4

12477	8.	2	eins komma sechs	-0,333	yes pic	one beer	3
12477	9.	1.666	2	0,333	no		
12477	10.	1.333	eins komma sechs	0,333	no		
12501	1.	2	2.333	0,333	yes pic	cream	3
12501	1.	2	2.333	0,333	yes pic	frozen rasberries	1
12501	2.	1.666	3	1,333	no		
12501	3.	2.666	1.333	-1,333	no		
12501	4.	1.333	2	0,666	no		
12501	5.	1	2.333	1,333	no		
12501	6.	2	2.333	0,333	yes pic	pizza in a restaurant	4
12501	7.	1	2	1	yes pic	orange juice	4
12501	7.	1	2	1	yes pic	pancakes	3
12501	7.	1	2	1	yes pic	strawberries	1
12501	7.	1	2	1	yes pic	vanilla sauce	3
12501	7.	1	2	1	yes pic	mozzarella	3
12501	7.	1	2	1	yes pic	tomatoes	1
12501	7.	1	2	1	yes pic	meat	4
12501	7.	1	2	1	yes pic	pineapple	1
12501	8.	1	2.333	1,333	/		
12501	9.	1.333	3	1,666	/		
12501	10.	1	3.666	2,666	/		
12431	1.	1.666	3	1,666	no		
12431	2.	1	3	2	yes picture sent	bubble tea	4
12431	2.	1	3	2	yes picture sent	frozen broccoli philo vegan	4
12431	2.	1	3	2	yes picture sent	fruit snack	4
12431	3.	1.333	2.333	1	no		
12431	4.	1.333	2.666	1,333	yes picture sent	coca cola can	4
12431	4.	1.333	2.666	1,333	yes picture sent	fries	4
12431	5.	1.666	1.333	-0,333	no		
12431	6.	1.333	1.666	0,333	no		

12431	7.	1	2.666	1,666	no		
12431	8.	1	1.666	0,666	no		
12431	9.	1.333	3	1,666	yes pic	grapes	1
12431	9.	1.333	3	1,666	yes pic	feta cheese	3
12431	9.	1.333	3	1,666	yes pic	blueberries	1
12431	10.	1.333	3	1,666	no		
12431	11.	1.333	2	0,666	no		
12431	12.	1.333	1	-0,333	no		
12431	13.	1.333	2	0,666	yes sent	stroopwaffels	4
12431	13.	1.333	2	0,666	yes sent	skyr squeeze drink	4
12431	14.	1.666	2.333	0,666	no		
12431	15.	1	2.666	1,666	no		
12431	16.	1	2.333	1,333	no		
12431	17.	1	3	2	no		
12431	18.	1	3.333	2,333	yes no pic	snack foods	4
12431	19.	1	2.666	1,666	no		
12431	20.	1.333	2.333	1	yes picture	fruit drink	4
12431	20.	1.333	2.333	1	yes picture	oats	1
12431	20.	1.333	2.333	1	yes picture	butter	2
12431	20.	1.333	2.333	1	yes picture	frozen kiwi	4
12431	20.	1.333	2.333	1	yes picture	pastries or baked goods	4
12431	21.	1	2.333	1,333	/		
12495	1.	4	1.666	-2,333	no		
12495	2.	4	1	-3	no		
12495	3.	3	2	-1	no		
12495	4.	2	2	0	no		
12495	5.	1.333	1.666	0,333	no		
12495	6.	1.666	1.666	0	yes	vegetables	1
12495	6.	1.666	1.666	0	yes	refined grains	3
12495	6.	1.666	1.666	0	yes	fast food	4
12495	7.	1.666	1.666	0	yes pic		
12495	8.	1	3	2	no		
12495	9.	1.666	2.333	0,666	no		
12495	10.	1	2.333	1,333	no		
12495	11.	1.333	2	0,666	no		
12495	12.	1	3.333	2,333	no		
12495	13.	1	3.666	2,666	no		
12495	14.	1	3.333	2,333	no		
12495	15.	1	3.333	2,333	no		

12495	16.	1.666	1.666	0	/		
12487	1.	1.666	3.333	1,666	no		
12487	2.	1.333	3.666	2,333	yes pic	steak/ meat in a restaurant with oil and sauce, tomatoes, potatoes, peppers, onions, and a little salad to the side	4
12487	3.	1.333	4	2,666	yes pic	rice bowl with vegetables like edamame and corn, deep fried meat ,sauce, fresh spinach and a boiled egg	4
12487	4.	4.333	1.666	-2,666	yes	pastries	4
12487	5.	2.666	1.333	-1,333	no		
12487	6.	1.666	3.333	1,666	yes	sugar sweetened beverages	4
12487	6.	1.666	3.333	1,666	yes	deep fried food	4
12487	6.	1.666	3.333	1,666	yes	salty food	4
12487	6.	1.666	3.333	1,666	yes	fast food	4
12487	7.	1.333	3.666	2,333	no		
12487	8.	2	1.666	-0,333	no		
12487	9.	1.666	2.333	0,666	no		
12487	10.	1	4	3	no		
12487	11.	1.333	2	0,666	yes pic	matcha latte	4
12487	12.	1.333	3.333	2	no		
12487	13.	1	3.333	2,333	/		
12487	14.	1.666	zwei komma sechs	1			
12487	15.	1.333	2.666	1,333			
12487	16.	1.333	3.333	2			
12485	1.	1	3.333	2,333	no		
12485	2.	1	3	2	no		
12485	3.	1	3	2	no		

12485	4.	1	2.333	1,333	no		
12485	5.	1.333	2.333	1	yes pic	rice bowl with vegetables like edamame and corn, deep fried meat ,sauce, fresh spinach and a boiled egg	4
12485	6.	1	4.333	3,333	yes	natural sweeteners	2
12485	6.	1	4.333	3,333	yes	white sugar or artificial sweeteners	4
12485	6.	1	4.333	3,333	yes	sugar sweetened beverages	4
12485	7.	1	3.666	2,666	no		
12485	8.	1	3.333	2,333	yes pic	pizza in restautant with mozzarrella and herbs and mushrooms	4
12485	9.	1.333	3.666	2,333	yes	pastries or baked goods	4
12485	10.	1.333	3.333	2	yes pic	rice noodles with vegetables and crushed peanuts, and sauce	4
12485	11.	1.333	3.666	2,333	no		
12485	12.	1.333	3.333	2	no		
12482	1.	1.666	3.666	2	no		
12482	2.	1	3.666	2,666	yes	white sugar or artificial sweeteners	4
12482	3.	1.333	1.666	0,333	yes but no input		
12482	4.	1	2	1	no		
12482	5.	1.666	1	-0,666	yes pic	fruit juice	4
12482	5.	1.666	1	-0,666	yes pic	white chocolate	4
12482	6.	1	2.666	1,666	yes but no input		
12482	7.	1	2.333	1,333	no		
12482	8.	1.333	1.333	0	no		

12482	9.	1.333	2.333	1	yes but no input		
12482	10.	1.333	1.333	0	yes but no input		
12482	11.	2	1.333	-0,666	yes but no input		
12482	12.	1	3.333	2,333	no		
12482	13.	1	3.333	2,333	no		
12482	14.	1.333	2	0,666	yes but no input		
12482	15.	1	2.666	1,666	no		
12482	16.	1	3.333	2,333	yes but no input		
12482	17.	1.333	2.333	1	/		
12479	1.	eins komma drei	3.333	2	no		
12479	2.	1	2.666	1,666	yes pic	rigatoni pasta	1
12479	2.	1	2.666	1,666	yes pic	crackers	4
12479	2.	1	2.666	1,666	yes pic	instant noodle carbonara	4
12479	2.	1	2.666	1,666	yes pic	pesto rosso	4
12479	2.	1	2.666	1,666	yes pic	mozzarella	3
12479	2.	1	2.666	1,666	yes pic	tomatoes	1
12479	2.	1	2.666	1,666	yes pic	prepackaged bread rools with stuff on it	4
12479	3.	1	3.666	2,666	no		
12479	4.	1	4.333	3,333	no		
12479	5.	1	3.666	2,666	yes pic	chips	4
12479	5.	1	3.666	2,666	yes pic	tortilla chips	4
12479	5.	1	3.666	2,666	yes pic	prepackaged guacamole	4
12479	6.	1	3.666	2,666	no		
12499	1.	1	3.666	2,666	yes	fruits	1
12499	1.	1	3.666	2,666	yes	vegetables	1
12499	1.	1	3.666	2,666	yes	foods low in saturated fats and cholesterol	1
12499	1.	1	3.666	2,666	yes	snack foods	4
12499	1.	1	3.666	2,666	yes	salty foods	4
12499	1.	1	3.666	2,666	yes	patries or baked goods	4
12499	1.	1	3.666	2,666	yes	alcohol	4
12270	1.	3	2.666	-0,333	yes	vegetables	1
12270	2.	2.666	3	0,333	yes pic	apple pie	4

12270	3.	2.666	3.333	0,666	no		
12270	4.	3.333	2.333	-1	yes pic	joghurt with rasberries	3
12270	5.	2.666	3	0,333	no		
12270	6.	3.333	2	-1,333	no		
12270	7.	4	1.666	-2,333	yes pic	bottle of schwipp schwapp, sugary beverage	4
12270	8.	4	2.666	-1,333	yes pic	apple pie	4
12545	1.	1.666	3	1,333	no		
12545	2.	1.666	4	2,333	yes pic	pepsi can	4
12545	3.	1.333	3.666	2,333	/		
12545	4.	1.333	4	2,666	/		
12546	1.	1	3.666	2,666	no		
12546	2.	1.333	2.333	1	yes pic	olives	1
12546	2.	1.333	2.333	1	yes pic	packaged veggie sausage	4
12546	2.	1.333	2.333	1	yes pic	camembert	3
12546	2.	1.333	2.333	1	yes pic	baguette	3
12546	2.	1.333	2.333	1	yes pic	lemon	1
12546	2.	1.333	2.333	1	yes pic	apple juice	4
12546	2.	1.333	2.333	1	yes pic	sweetened beverage	4
12546	2.	1.333	2.333	1	yes pic	pickles	3
12546	3.	1.333	2.666	1,333	yes	vegetables	1
12546	3.	1.333	2.666	1,333	yes	whole grains	1
12546	3.	1.333	2.333	1	yes	Foods that are high in monounsatur ated and polyunsaturat ed fats	2
12546	4.	1	3	2	no		
12546	5.	1	3.333	2,333	yes	alcohol	4
12546	6.	1	2	1	yes	water	1
12546	6.	1	2	1	yes	lean meats	1
12546	6.	1	1	0	yes	low fat dairy	1
12546	7.	1	2.666	1,666	no		
12546	8.	2.333	1.666	-0,666	/		
12030	1.	3.333	1.333	-2	yes pic	whole grain bread	1
12030	1.	3.333	1.333	-2	yes pic	honey	1

12030	1.	3.333	1.333	-2	yes pic	arizona icetea	4
12030	1.	3.333	1.333	-2	yes pic	lipton ice tea	4
12030	1.	3.333	1.333	-2	yes pic	farfalle pasta	1
12030	1.	3.333	1.333	-2	yes pic	reeses big cup	4
12030	1.	3.333	1.333	-2	yes pic	subway sandwich	4
12030	1.	3.333	1.333	-2	yes pic	sweets	4
12030	2.	2.333	2.333	0	no		
12030	3.	1.666	3.666	2	yes pic	chocolate cookie	4
12030	3.	1.666	3.666	2	yes pic	lays chips	4
12030	3.	1.666	3.666	2	yes pic	m&ms	4
12030	3.	1.666	3.666	2	yes pic	sweetened beverage	4
12030	3.	1.666	3.666	2	yes pic	fruit	1
12030	4.	2	3.666	1,666	no		
12030	5.	1.333	3.666	2,333	no		
12030	6.	1.333	3	1,666	no		
12030	7.	1.333	3	1,666	no		
12030	8.	1.333	3	1,666	no		
12030	9.	1	3	2	no		
12030	10.	1.333	3	1,666	no		
12030	11.	1.333	3	1,666	no		
12030	12.	1.666	3	1,333	no		
12030	13.	1.333	2.333	1	no		
12030	14.	2.666	2.333	-0,333	no		
12030	15.	/	2.666		no		
12030	16.	2	2	0	yes pic	shredded cheese	3
12030	16.	2	2	0	yes pic	hack/prepackaged meat	4
12030	16.	2	2	0	yes pic	clipper tea	2
12030	16.	2	2	0	yes pic	eggs	1
12030	16.	2	2	0	yes description	vegetables	1
12030	16.	2	2	0	yes description	whole grains	1
12030	16.	2	2	0	yes description	peanut butter	4
12030	17.	1	2.666	1,666	no		
12030	18.	1.333	3	1,666	no		
12030	19.	2	3.666	1,666	no		
12030	20.	1	3.333	2,333	no		

12521	1.	1.666	2.666	1	yes pic	dönertasche	4
12521	2.	1.333	3	1,666	yes pic	vanilla icecream with berries	4
12521	3.	4	3	-1	yes but no input		
12521	4.	1.333	3.333	2	yes pic	bread with strawberry marmelade and cream cheese	3
12521	5.	2.666	1.666	-1	yes pic	lindor chocolate praline	4
12521	6.	1.333	2.666	1,333	yes pic	bread with salami, eggs, tomatoes,	3
12521	7.	1	3	2	yes	fruits	1
12521	8.	1.666	3	1,333	yes	fruits	1
12521	8.	1.666	3	1,333	yes	whole grains	1
12521	8.	1.666	3	1,333	yes	low fat dairy products	2
12521	9.	1	3.666	2,666	yes	vegetables	1
12521	9.	1	3.666	2,666	yes	water	1
12521	9.	1	3.666	2,666	yes	lean meats	1
12521	9.	1	3.666	2,666	yes	low fat dairy products	2
12521	9.	1	3.666	2,666	yes	refined grains	3
12521	10.	1	4.333	3,333	yes no input		
12521	11.	2	2.666	0,666	yes pic	whole grain bread	1
12521	11.	2	2.666	0,666	yes pic	cucumber	1
12521	11.	2	2.666	0,666	yes pic	cream cheese	3
12521	11.	2	2.666	0,666	yes pic	eggs	1
12521	11.	2	2.666	0,666	yes pic	cheddar	3
12521	12.				yes pic	tea	1
12521	12.				yes pic	water	1
12521	12.				yes pic	bread	3
12521	12.				yes pic	eggs	1
12521	12.				yes pic	cheddar	3
12521	13.	1	3.666	2,666	yes pic	broccoli	1
12521	13.	1	3.666	2,666	yes pic	potatoes	1
12521	13.	1	3.666	2,666	yes pic	cream sauce	4
12521	14.	1	3.666	2,666	yes pic	prepackaged baguette with camemberts,	4

						walnuts, salad	
12548	1.	1.666	2.333	0,666	no		
12548	2.	1.666	2.333	0,666	yes	sugar sweetened beverage	4
12548	3.	2.666	1.666	-1	yes pic	croissant	4
12548	3.	2.666	1.666	-1	yes pic	white bread rolls	4
12548	4.	1.666	2	0,333	yes	vegetables	1
12548	4.	1.666	2	0,333	yes	whole grains	1
12548	5.	2.333	1	-1,333	no		
12548	6.	4.666	1.333	-3,333	yes pic	beer	3
12548	6.	4.666	1.333	-3,333	yes pic	pizza brezel thing	4
12548	7.	1.333	2.666	1,333	/		
12548	8.	1.333	2.666	1,333	/		
12559	1.	3	1.333	-1,666	yes	fruits	1
12559	1.	3	1.333	-1,666	yes	vegetables	1
12559	1.	3	1.333	-1,666	yes	foods that are boiled, steamed, grilled or poached	1
12559	2.	1	4	3	no		
12559	3.	1	4	3	no		
12559	4.	1	4	3	no		
12559	5.	2.333	2	-0,333	yes	frozen or prepackaged meals	4
12559	6.	1	3.666	2,666	yes	fruits	1
12559	6.	1	3.666	2,666	yes	vegetables	1
12559	6.	1	3.666	2,666	yes	lean meats	1
12559	7.	3.333	2.666	-0,666	no		
12559	8.	1	3	2	no		
12559	9.	1	4	3	yes pic	eggs	1
12559	10.	1	4	3	yes	vegetables	1
12559	11.	1	5	4	/		
12566	1.	2	1.333	-0,666	no		
12566	2.	2.333	1	-1,333	no		
12566	3.	1.333	2.333	1	yes pic	red bull can	4
12566	4.	2.666	1	-1,666	no		
12566	5.	1.333	1.666	0,333	yes pic	frozen fries	4

12566	5.	1.333	1.666	0,333	yes	pastries or baked goods	4
12566	6.	1.333	2.333	1	yes	fast food	4
12566	7.	1.666	1	-0,666	no		
12566	8.	1	1.666	0,666	yes pic	prepackaged rice (uncle bens)	4
12566	9.	2.666	1	-1,666	no		
12566	10.	2	1	-1	no		
12566	11.	1	1.666	0,666	no		
12566	12.	1	2.333	1,333	yes pic	spaghetti barilla	1
12566	13.	1.666	1.333	-0,333	no		
12566	14.	1.333	1.333	0	no		
12566	15.	1	1	0	yes pic	cider / alcohol	3
12566	16.	2.666	1	-1,666	no		
12566	17.	1	2.333	1,333	yes pic	prepackaged sausages	4
12566	17.	1	2.333	1,333	yes	foods high in monounsatur ated and polyunsaturat ed fats	2
12566	17.	1	2.333	1,333	yes	natural sweeteners	2
12566	17.	1	2.333	1,333	yes	sugar sweetened beverages	4
12566	18.	2.333	1	-1,333	no		
12566	19.	1.666	1.333	-0,333	yes pic	alcohol	4
12566	20.	1.333	2	0,666	no		
12566	21.	2.666	1.333	-1,333	no		
12566	22.	1.333	2.333	1	no		
12600	1.	1.333	3.666	2,333	no		
12600	2.	1.333	4	2,666	yes	natural sweeteners	2
12600	2.	1.333	4	2,666	yes	white sugar or artificial sweeteners	4
12600	2.	1.333	4	2,666	yes	pastries or baked goods	4
12600	3.	1.333	4	2,666	yes	vegetables	1
12600	3.	1.333	4	2,666	yes	foods boiled, steamed, grilled, poached	1
12600	3.	1.333	4	2,666	yes	refined grains	3

12600	3.	1.333	4	2,666	yes	salty food	4
12600	4.	1	4	3	no		
12600	5.	1	4.333	3,333	no		
12600	6.	1	4	3	no		
12600	7.	1	2.666	1,666	/		
12600	8.	1	3.666	2,666	/		
12600	9.	1	4	3	/		
12600	10.	1	1.666	0,666	/		
12631	1.	2.666	3	0,333	yes pic	cookie	4
12631	2.	4	3	-1	yes pic	white bread with cheese and dip	4
12633	1.	1	3.666	2,666	yes pic	zucchini	1
12633	1.	1	3.666	2,666	yes pic	meat	4
12633	1.	1	3.666	2,666	yes pic	soy cream	2
12633	1.	1	3.666	2,666	yes pic	rice	1
12633	2.	1	2.333	1,333	yes pic	white chocolate	4
12633	2.	1	2.333	1,333	yes pic	liquorice snack	4
12633	2.	1	2.333	1,333	yes pic	gummy bear snack	4
12633	2.	1	2.333	1,333	yes pic	oranges	1
12633	2.	1	2.333	1,333	yes pic	coca cola	4
12633	3.	1.333	2.333	1	no		
12633	4.				no		
12638	1.				yes but no input		
12638	2.	2.666	1.333	-1,333	no		
12638	3.	2.333	1.333	-1	no		
12638	4.	1	2.333	1,333	no		
12638	5.	1	2.333	1,333	yes	snacks	4
12638	6.	1	3	2	no		
12638	7.	1.333	2.333	1	no		
12638	8.	1	2.333	1,333	yes pic	beer	3
12638	9.	1	2.666	1,666	no		
12638	10.	1.666	1.333	-0,333	no		
12638	11.	2.333	1.333	-1	yes	fruits	1
12638	11.	2.333	1.333	-1	yes	vegetables	1
12638	11.	2.333	1.333	-1	yes	whole grains	1
12638	11.	2.333	1.333	-1	yes	foods high in monosaturate d or polyunsaturat ed fats	1

12638	11.	2.333	1.333	-1	yes	low fat dairy products	2
12638	11.	2.333	1.333	-1	yes	pastries or baked goods	4
12638	12.	1	2.666	1,666	yes but no input		
12638	13.	1	2	1	/		
12638	14.	1	2.333	1,333	/		
12660	1.	1.333	1.333	0	no		
12660	2.	1	1.333	0,333	no		
12687	1.	1	3	2	yes pic	pasta with mushrooms and cheese	3
12687	2.	1	3.333	2,333	yes pic	white bread	3
12687	2.	1	3.333	2,333	yes pic	pastries	4
12687	3.	1	3	2	yes pic	potato	1
12687	3.	1	3	2	yes pic	carrot	1
12687	3.	1	3	2	yes pic	meat	4
12687	3.	1	3	2	yes pic	mushrooms	1
12687	4.				yes pic	soft ice	4
12687	5.				yes pic	rice	1
12687	5.				yes pic	broccoli	1
12687	5.				yes pic	carrot	1
12687	5.				yes pic	chicken	3
12687	5.				yes pic	mushrooms	1
12691	1.	1.666	2.333	0,666	no		
12691	2.	1	2	1	no		
12691	3.	1	2	1	yes pic	pastries/ baked goods)	4
12691	4.	1	2.666	1,666	yes pic	chips	4
12691	4.	1	2.666	1,666	yes pic	ice tea can	4
12691	4.	1	2.666	1,666	yes pic	blueberries	1
12691	4.	1	2.666	1,666	yes pic	dark chocolate	3
12691	4.	1	2.666	1,666	yes pic	milk drink Kefir	3
12691	5.	1	2.333	1,333	no		
12691	6.	1	2.666	1,666	yes pic	bananas	1
12691	6.	1	2.666	1,666	yes pic	chewing gum	4
12691	6.	1	2.666	1,666	yes pic	sugary beverage	4
12691	7.	1	3	2	yes pic	baked goods with cheese	4
12691	7.	1	3	2	yes pic	salad	1
12691	8.	1.333	1.333	0	yes but no input		

12691	9.	1.666	1.333	-0,333	yes
12691	10.	1	2.666	1,666	yes
12691	11.				yes
12691	12.	1	1.666	0,666	/
12691	13.	1.333	2.333	1	/