Nutritional epidemiology: new insights for meal analysis

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Abbreviations

24hDR	24-hour diet recall
BMI	Body mass index
EO	Eating occasion
EPIC	European prospective study into cancer and nutrition
FFQ	Food frequency questionnaire
GGM	Gaussian graphical model
ICC	Intra-class correlation
PCA	Principal component analysis
T2D	Type 2 diabetes

Summary

By retaining the meal structure of repeated non-consecutive 24-hour diet recalls in a sample of 814 adults from an EPIC-Potsdam sub-cohort study, we aimed to investigate the role of meals in the formation of commonly-used habitual dietary patterns, the origin of variance in dietary intake, as well as the relative importance of predictors of intake in the context of meals and individuals.

A commonly used method (Principal Component Analysis, PCA) and a novel method (networks using Gaussian Graphical Models, GGM) for deriving habitual dietary patterns were applied to habitual and meal-specific food intakes and compared to the correlation and consistency of consumption structures between 39 food groups. Multi-level linear regression models were applied to investigate variance in energy and macronutrient intake in the meal and participant levels and important predictors of intake were identified. Energy misreporting was considered in sensitivity analyses.

The findings showed different correlation structures between meals. Breakfast was the most consistent meal across the days, but dinner was the meal that contributed the most to the formation of habitual dietary patterns. Variance in energy and macronutrient intake was mostly explained by differences between meal types but not between individuals. Place of meal was the most important intake-level predictor of energy and macronutrient intake. Week/weekend day was important in the breakfast meal, and prior interval (hours passed since last meal) was especially important for the afternoon snack and dinner for carbohydrate intake. On the participant level, sex was the main predictor of energy and macronutrient intake. Energy misreporting accounted for a substantial proportion of the explained variance in carbohydrate intake, especially at the afternoon snack.

In conclusion, this thesis revealed that meals are important units of investigations for understanding habitual dietary intake and eating behavior. The here applied statistical methods offer a novel way to study diet in the context of meals and should be applied to different populations to better understand their eating behavior. This knowledge will provide pivotal information useful for planning interventions aiming to influence dietary intake.

Zusammenfassung

Die Rolle von Mahlzeiten in der Entstehung von häufig verwendeten habituellen Ernährungsmustern wurde untersucht. Im Speziellen wurden dabei der Ursprung der Varianz in der Nahrungsaufnahme und die relative Wichtigkeit von Prädiktoren für die Aufnahme im Rahmen von Mahlzeiten und Individuen betrachtet.

Die Datenanalyse basiert auf drei 24-Stunden-Ernährungsprotokollen von 814 Erwachsenen aus einer Querschnittsstudie der EPIC-Potsdam-Kohorte. Verzehrsdaten wurden in 39 Lebensmittelgruppen eingeordnet. Zwei Methoden, eine etablierte (Hauptkomponentenanalyse, PCA) und eine neuere (Netzwerke mit Gaussian Graphische Modelle, GGM) wurden zur Ableitung von Ernährungsmustern auf habituelle und Mahlzeit-spezifische Ernährungsdaten angewendet und bezüglich Korrelation und Konsistenz verglichen. Lineare multi-level Regressionsmodelle wurden angewendet, um die Varianz der Energie- und Makronährstoffaufnahme auf Mahlzeiten- und Teilnehmerebene zu untersuchen, wodurch wichtige Prädiktoren für die Aufnahme identifiziert wurden. Falschangaben in der Energieaufnahme (*Under-/Over-reporting*) wurden in Sensitivitätsanalysen berücksichtigt.

Unsere Ergebnisse zeigten unterschiedliche Korrelationsstrukturen zwischen den Mahlzeiten. Das Frühstück war die konsistenteste Mahlzeit über die Tage hinweg, aber das Abendessen war die Mahlzeit, die am meisten zur Entstehung habitueller Ernährungsmuster beitrug. Die Varianz bei der Aufnahme von Energie und Makronährstoffen wurde hauptsächlich durch Unterschiede zwischen den Mahlzeitentypen und nicht zwischen Individuen erklärt. Der Ort der Mahlzeit (z.B. außerhaus, zuhause) war der wichtigste Indikator für Energie- und Makronährstoffaufnahme. Ob es Wochentag oder Wochenendtag war, war beim Frühstück relevant, während der zeitliche Abstand zur letzten Mahlzeit besonders wichtig für den Nachmittagssnack und das Abendessen für Kohlehydrataufnahme war. Auf der Ebene der Teilnehmer war Geschlecht der Hauptindikator für Energie- und Makronährstoffaufnahme. Ein wesentlicher Teil der erklärten Varianz für Kohlehydrataufnahme, insbesondere beim Nachmittagssnack, entfiel auf Falschangaben in der Energieaufnahme.

Zusammenfassend konnte in dieser Promotionsschrift gezeigt werden, dass Mahlzeiten wichtige Untersuchungseinheiten sind, um die habituelle Ernährung und die Entstehung von Essgewohnheiten zu verstehen. Die verwendeten statistischen Methoden bieten einen neuartigen Weg, Ernährung im Kontext von Mahlzeiten zu untersuchen. Solche Methoden sollten auf verschiedene Bevölkerungen angewendet werden, um ihre Essgewohnheiten besser zu verstehen. Dieses Wissen liefert wichtige Informationen um Maßnahmen zur Beeinflussung der Nahrungsaufnahme zu entwerfen.

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1 Introduction

1.1 A short introduction into the trajectory of nutritional epidemiological research

Diet has been long considered to be an important contributor to health. The first observations linking diet and health date all the way back to centuries before Christ, when Greek physician Hippocrates made observations about the close link between food and health and disease, with the well-known proverb "*Let food be thy medicine and medicine be thy food*" and Greek philosopher Plato defined a healthy diet similar to the Mediterranean diet (1). Later, in the XVIII century diet was related to severe micronutrient deficiencies, such as vitamin C, where lemons and oranges were seen to be effective against scurvy, and thiamin, where parboiled rice was effective against beriberi (2-4).

In the present, nutritional epidemiologists' main focus is on chronic, non-communicative diseases such as cardiovascular diseases, type 2 diabetes (T2D), and cancer, whose prevalence has been steadily increasing in the last four decades (2, 5, 6). Unlike nutritional deficiencies, these diseases have several causes including genetic, environmental, occupational, psychosocial, and behavioral factors, which may act alone or interact with each other (2). Nevertheless, as with nutritional deficiencies, diet plays a role in the development of chronic, non-communicative diseases (7-10). Therefore, an adequate assessment and analysis of diet is especially important to investigate the role of diet in the complex multifactorial and long-lasting development of chronic diseases.

In large observational studies, diet is usually determined indirectly based on the reports of the study participants. The frequency and amount of foods consumed are asked and depending on the research question, nutrients can be calculated based on the food intakes. However, accurately measuring diet remains a challenge, as there is a very high variability in the foods/nutrients we consume daily. In addition, the foods we consume are highly related to each other, as we do not consume foods or nutrients in isolation (2). Finally, factors such as memory of the participant and misreporting might introduce bias. There are several self-report dietary assessment instruments, which attempt to capture the true intake; some are more appropriate to answer certain research questions than others but all have their limitations and degree of measurement error (11, 12).

The most frequently used method in large observational studies is the food-frequency questionnaire (FFQ), which estimates long-term food and beverage intake (usually the intake in the last 6 months or in the last year). This method is particularly useful for food groups that part of the population does not consume on a daily basis (i.e., episodically consumed foods) (11). However, the precision of FFQ diet data has been questioned (13, 14) and this method lacks meal-specific information (15). Another frequently used method in observational studies is the 24-hour diet recall (24hDR). For this method, study participants are asked to report all food and beverage intake during the previous day in a detailed meal-by-meal (and/or time of day) format. This method relies only on short-term memory and it provides detailed quantitative information (16). However, due to high variation in intake from day to day, multiple 24hDRs are needed to achieve modest precision of dietary intake (17, 18).

Dietary assessment instruments may be combined to minimize their weaknesses. For example, it is common to use a 24hDR calibrated with an FFQ. This improves the validity of infrequent intakes and adjusts for the high day-to-day variation in 24hDRs, especially if only one recall is available (11, 19). Nevertheless, as a single instrument, the (multiple, non-consecutive) 24hDR is considered the least biased self-report method (11).

1.1.2 Habitual diet and dietary patterns

Up until two decades ago, diet was mostly described in terms of nutrient content or intake of specific foods/food groups. Because certain nutrients or foods are not independent from each other, various statistical techniques have been used increasingly to consider the interrelation between foods and evaluate the overall, long-term diet, also known as the habitual diet (2, 20). Resulting habitual dietary patterns have been the preferred dietary exposure used in nutritional epidemiology for the last two decades. In general, dietary patterns can be defined as *a priori* (hypothesis-driven) or *a posteriori* (exploratory or data-driven). In *a priori* approaches, scores or indices are defined based on dietary guidelines or a reference, usually healthy diet (e.g., Mediterranean diet). Study participants receive a score in each of the components of the reference dietary quality score/diet index. The component scores are then summed up together and participants with higher scores reflect dietary intakes conforming to the reference score/index (21, 22). Such indices are often used in relation to chronic disease risk (22). However, comparability is limited across studies as a wide range of indices are available and their composition may also vary from study to study (23). *A posteriori* methods (from here on referred to as data-driven methods), on the

other hand, describe the diet of the investigated study sample. Therefore, data-driven dietary patterns are not related to a degree of how healthy/unhealthy they are, but rather reflect the diets consumed by the study participants (22). Although these patterns offer great opportunities to learn from the eating behavior of the studied population, comparisons across studies are also difficult, as the patterns are population-specific. However, these differences may be true and may be explained by sociocultural backgrounds (20).

Data-driven methods will be in the focus of this thesis, as they constitute a major part of today's nutritional epidemiological research. Various statistical methods are available for this purpose. A short description of the methods used within this thesis is provided below:

Principal component analysis (PCA). This method reduces the number of variables by creating linear combinations or patterns in a way that explains the most possible variance and is based on the correlation or covariance matrices of the original variables (food groups). The components or patterns are usually rotated orthogonally for improved interpretability; this results in patterns that are independent or uncorrelated from each other (24). The number of final patterns can be decided based on various parameters, with conventional or recommended thresholds of contribution to the explained variance (25). In PCA-derived dietary patterns, each food group obtains a loading or a weight in each of the resulting patterns and each participant is scored based on these loadings for their intake of each food. The final dietary pattern scores for each individual is the resulting sum of these scores. All individuals obtain a score for each pattern, which makes interpretation and tracing back to the foods actually consumed difficult (20, 22). This method is currently the preferred technique to obtain data-driven dietary patterns.

Gaussian graphical models (GGM) – derived dietary networks. GGMs are an established method in the area of metabolomics and genomics (26, 27). Recently, this method was applied to construct dietary patterns (28). These models produce probabilistic graphs that show the relation between the dietary components, offering an insight into how foods are consumed in relation to each other. Specifically, GGMs construct conditional independence networks between highly correlated variables in a dataset (29). Because of high interrelation of the variables, often a penalty or regularization parameter is introduced to reduce variance and avoid overfitting of the model and facilitate interpretation (30).

Every method for obtaining data-driven dietary patterns has its strengths and limitations and each of them might be more suitable than other depending on the research question. In the present, PCA is the most widely used method in nutritional epidemiological literature.

Habitual diet is currently used to derive most dietary patterns used in nutritional epidemiology. While this may uncover some general diet-disease relationships, it does not fully address the interrelation between foods, as these are consumed at specific times and in specific combinations, such as in meals or snacks. Habitual dietary patterns therefore are difficult to interpret and to understand in the context of eating behavior, which can be useful for the planning of interventions and dietary guidelines.

1.2 Eating occasions and the importance of meals

Daily dietary intake is structured into many eating occasions (EOs), which are the unit of dietary intake and are defined for the purpose of this thesis as any food/beverage intake at any time of the day. EOs may be meals, snacks, or simply beverage intake episodes. Understanding how meals impact dietary intake and diet quality might reveal important perspectives of diet-disease relationships (15). The way food intake is structured across the day, also known as chrono-nutrition, influences appetite, digestion, metabolism, and physiological adaptations and has been shown to be related to health outcomes such as obesity and other cardiometabolic disorders (31). Because of the known influence of diet on health, the goal of nutritional epidemiology is to study which diets are detrimental to and which promote health. In order to achieve this, it is important to understand how diet is shaped, i.e., through food intake structured in EOs including meals. Because of this, a meal-based approach of nutritional epidemiology could offer insights on how to change unwanted habits or favor specific ones.

1.2.1 Definitions of meals

Multiple definitions have been used in the literature to describe meals. Meals may be defined according to participant identification, time of day, may be food-based, or may use neutral definitions. Table 1 describes some previously published classifications (15, 32).

Table 1: Summary of different meal classification approaches

Approach	Description
Participant-identified	Participant identifies EO as breakfast, lunch, or dinner. Often a list of pre-defined meal labels is available. Snacks and other EOs are also reported by the participant using a meal label.
Time of day	Can be the largest EO in a specified range of time (e.g., morning, midday, afternoon, evening, or 06:00-10:00, 12:00-15:00, 18:00-21:00). It might also be the sum of all EOs occurring in this pre-specified time interval.
Food-based	Meals are defined according to their composition (e.g., number of food categories present in the meal) or nutritional profile/energy density. The use of this definition has been limited due to its complexity and heterogeneity of criteria.
Neutral	Definitions are based on time intervals between meals and/or minimum energy criteria. The following have been proposed and used in literature: - ≥ 15 minute time interval between EOs - ≥ 15 minute time interval between EOs plus ≥ 50 kcal - ≥ 30 minute time interval between EOs - ≥ 30 minute time interval between EOs plus ≥ 50 kcal - ≥ 60 minute time interval between EOs - ≥ 60 minute time interval between EOs plus ≥ 50 kcal

EO, eating occasion; kcal, (kilo)calories.

It has been shown that the definition of meal can importantly influence how meal patterns are characterized, which can impact the results of associations with health outcomes (32). In this study, the authors found that when comparing 8 different definitions of meals, the neutral definition of ≥ 15 minute time interval plus ≥ 50 calories (kcal) as well as the participant-identified definition performed best in terms of the proportion of variance in total amount of food consumed (32).

1.2.2 Dimensions of meals

Meals can be studied in terms of their patterning, their format, and their context. Patterning refers to timing, frequency, regularity/skipping, and spacing of meals. Format refers to the nutritional/food contents and combinations of the meals. Context refers to the environment around the meal, such as number of people present, place of the meal (e.g., at home, in a restaurant), activities during the meal (e.g., while watching TV), and other physical and psychosocial circumstances (15). Most available meal-based studies have concentrated in only one of the dimensions, mostly patterning (15, 33). However, all three dimensions are interrelated; for example, the composition of a meal (format) may depend on the place (context) and on the time since the last meal (patterning). Increasingly, studies are taking the multidimensionality of meals into account to explore this interrelation and have a deeper understanding of the factors affecting dietary intake (34-36).

1.2.3 Challenges and opportunities of meal-based studies

Analyzing dietary intake at the meal-level requires that we use specific dietary assessment methods that capture the EOs. This means that unless specific questions (usually about meal patterning) are added to a FFQ or another questionnaire, studies are unable to answer any meal-specific research question. Therefore, studies that examine meal patterns most often use 24hDRs or food/diet diaries/records. This is illustrated in Table 2, where various observational studies are listed by the dimension in focus and includes aspect(s) of the meal investigated, dietary assessment method, study design, and sample size. Beside the predominance of the 24hDRs, Table 2 shows that most studies have a cross-sectional design and are based on a relatively small study sample. Especially in the context of a large cohort study, the implementation of multiple 24hDRs rather than a FFQ can radically increase expenses and participant drop-outs (due to a higher participant burden). Therefore, most large cohort studies lack the data in the appropriate format to investigate meal-specific questions. In some cases, a sub-study is carried out where more detailed dietary data is collected and used for validation or calibration of a FFQ or other lifestyle and anthropometric measures (37-39). Because of these limitations, meal-based studies are rarely carried out in large, representative samples.

Table 2: Summary of observational studies and variables describing the three dimensions of meals

Dimension	Examples/selected studies	Aspect of meal investigated	Dietary assessment method	Study design Sample size
Patterning	*Park et al. 2017* (40)	Frequency and timing	2 non-consecutive 24hDRs	Cross-sectional n = 559
	Leech et al. 2017 (41)	Timing	2 non-consecutive 24hDRs	Cross-sectional n = 5 242
	Coulthard et al. 2016 (42)	Timing	Food diary (4 consecutive days)	Cross-sectional n = 1 620
	Popkin et al. 2010 (43)	Frequency and spacing	3 consecutive 24hDRs	Cross-sectional n = 65 250
	Vainik et al. 2015 (36)	Regularity/consistency	Eating behavior questionnaire over 10 days	Cross-sectional n = 139
	Mekary et al. 2012 (44)	Skipping and frequency	Selected FFQ questionnaire items	Prospective cohort (cross-sectional dietary data) n = 29 206
	Reutrakul et al. 2014 (45)	Breakfast skipping	Single 24hDR	Cross-sectional n = 194
	Holm et al. 2015 (33)	Meal frequency and skipping	Single day eating questionnaire	Cross-sectional n = 7 531
Format	*Holmbäck et al. 2009* (46)	Nutritional content	Diet history and 168-item dietary questionnaire	Cross-sectional n = 28 098
	Iqbal et al. 2017 (47)	Foods/food groups content (breakfast)	3 non-consecutive 24hDRs	Cross-sectional n = 668
	de Oliveira Santos et al. 2015 (48)	Foods/food groups content	2 non-consecutive 24hDRs	Cross-sectional n = 1 102

Table 2 continued

Dimension	Examples/selected studies	Aspect of meal investigated	Dietary assessment method	Study design Sample size
	Myhre et al. 2014 (49)	Foods/food groups content	2 non-consecutive 24hDRs	Cross-sectional n = 1 787
	Kearney et al. 2001 (34)	Food sequencing	2-day food record	Cross-sectional n = 2 025
Context	*O'Connor et al. 2008* (50)	Stressful events	7-day diary	Cross-sectional n = 422
	de Castro et al. 1992 (51)	Number of people present	7-day diary	Cross-sectional n = 153
	Mak et al. 2012 (52)	Number of people present and place of meal	4-day food diary	Cross-sectional n = 642
	Vainik et al. 2015 (36)	Place of meal, people present/social situation	Eating behavior questionnaire over 10 days	Cross-sectional n = 139
	Kearney et al. 2001 (34)	Place of meal	2-day food record	Cross-sectional n = 2 025
	Lipsky et al. 2017 (53)	Activities during the meal	Multiple (+3) non-consecutive 24hDRs	Prospective cohort n = 566
	Holm et al. 2015 (33)	Meal duration, TV watching, meals alone	Single day eating questionnaire	Cross-sectional n = 7 531

24hDR, 24-hour diet recall

Studying the meals offers the deepest insights into how diet is formed and knowledge from this research approach can be used to issue more understandable dietary guidelines that are more easily applicable by the population. Guidelines should not only be about what to eat, but should include instruction on how to achieve a healthy diet.

How do people with healthy diets achieve such a diet?

This is a key question for interventions and policies that seek to promote healthy eating in populations (33). Rather than just studying diet and food intake, meal-based studies have the advantage of studying characteristics or factors around the EOs or meals. Deciphering how diet is formed requires a deep understanding of the factors influencing it, therefore viewing diet as a behavior and studying factors surrounding and influencing this behavior, as it is the case in behavioral sciences. This behavior, called eating behavior, is a complex interaction between biological (physiological and genetic), psychological, and environmental (physical and social) factors (54).

1.2.4 What we know from meal-based studies and eating behavior

In many cultures, breakfast is considered the most important meal of the day and is thought to have effects on the diet quality the rest of the day and on cognitive function (55). Because of the perceived importance of the first meal of the day, there is a higher abundance of

evidence regarding breakfast than overall of EOs and other meals. In the following paragraphs, evidence from research on the breakfast meal, inter-meal interactions, and various factors related to food intake at meals will be discussed. Because these factors influence eating behavior, they are referred to as predictors of diet or food intake throughout this thesis.

Breakfast. Eating breakfast is usually associated with better health and cognition. Consequently, skipping is usually inversely associated with diet quality (33, 55) and associated with increased disease risk (44). However, the importance of the different meals for diet quality may be different in other sociocultural contexts, for instance, *Holm et al*. saw this association in Finland, but in Denmark the association was for lunch-skipping and in Sweden for dinner-skipping (33). Furthermore, not skipping breakfast has been associated with greater satiety for the rest of the day and therefore a lower daily energy intake (56). The composition of breakfast has also been seen to influence overall diet quality and the macronutrient composition of the other meals. Often, breakfast is relatively high in carbohydrates (although this may be culture-dependent), in which case, fewer carbohydrates will be consumed during the rest of the day and a similar pattern has been seen for the other macronutrients (56, 57). Finally, better overall breakfast quality has been associated with a healthier cardiometabolic profile (47).

Meal frequency/inter-meal interactions. In many industrialized countries the mean number of EOs in a day has increased in the last decades both in children and adults. Accordingly, in the US, the time between EOs has decreased and the total energy intake increased (43). Another study has observed that the time since the last meal, hereafter referred to as prior interval, affects meal size (56). Regarding the health effects of frequent/infrequent meals and therefore the recommended number of meals per day, mixed results can be found in the literature (58, 59) and often ambiguous dietary guidelines in this respect (60-62). For example, an observational study across 4 Nordic countries saw better dietary quality when 5 or more meals were consumed (33). Nevertheless, an intervention study on type 2 diabetes (T2D) patients saw that having 2 larger meals a day (breakfast and lunch) resulted in lower energy intake than having 6 smaller meals a day (63). At the same time, a study in the US in a study sample of men found that men eating 1-2 times per day had a higher risk of T2D than men eating 3 meals per day; however, additional EOs beyond the 3 main meals were associated with a greater risk of T2D (44). Frequency and time between meals is not just important within a day; day-to-day consistency in diet in terms of energy content and diet quality are recommended by dietary guidelines and are important for the development of

healthy habits. A recent study found meal consistency to be greatest in the morning meal (36). Another aspect of consistency is regularity of meals, meaning the meals at specific times. This is thought to be relevant for our circadian rhythm and to have an impact on our metabolic health (64).

Biological predictors. Age, sex, and genes affect eating behavior (35, 65). Physiologically, women have a slower metabolism than men and therefore have lower energy needs. Similarly for age, energy needs depend greatly on body weight and development period; children and adolescents have a higher metabolism but weigh less than adults. Because of the energy needs (but also environmental factors), number of meals consumed per day may be different in the different age groups. For instance, children in the US typically consume 3 meals and 2 or more snacks per day, while only half of adolescents have 3 meals a day (and most often 2 or more snacks per day) (60). Finally, genetic factors might also influence metabolism and taste receptors and therefore food preferences (54, 65). Another biological predictor is social jetlag, which is the chronic discrepancy between our inner clock and our social clock. Most people who are active members of society in an urban environment are affected by social jetlag, which has been associated with higher meal irregularity and higher risk of chronic diseases and obesity (64).

Psychological predictors. As any other behavior, eating behavior partly depends on cognition and self-control. Therefore, emotions and personality traits play an important role. Stressful events have an effect on the types of food selected and the amount consumed. These effects can differ in men and women and overweight/obese participants. In general, stressful events are associated with a less healthy eating behavior (50). Similar to stress and general emotions, personality traits play a role in the expression of eating behavior. The personality trait of self-control is associated with a higher meal consistency; however, self-control is at the same time dependent on other predictors of food intake such as the time of the meal and the place of meal (36).

Physical environment. Physical availability and accessibility of foods influence food intake. Environments with difficult access to fruits and vegetables, as is the case in many low-income neighborhoods, result in lower intakes of these foods. The same is true for unhealthy foods, which are often easily available in convenient stores in low-income neighborhoods (65). A similar effect is observed when eating out of home; when the food is presented in a restaurant, for instance, the availability and accessibility are maximized and are dependent on the portion size served at the establishment. Due to greater availability and accessibility,

larger portion sizes result in increased food intake (56). Portion sizes have grown in the last years; they are especially larger in out-of-home meal settings such as restaurants, bars, and cafeterias (56, 66). Furthermore, out of home meals might be different in macronutrient composition than meals at home, with higher energy from fat and protein and lower micronutrient intake (34, 67). Reasons for the observed higher energy intake when meals are consumed out of home, other than a larger portion size, include foods with higher energy densities, and lack of consumer information and/or healthy choices. Together, these characteristics of the environment make it more difficult for individuals to adhere to specific dietary regimes and control/remain aware of their intake (67). Finally, another important aspect of the physical environment that affects our eating behavior is other activities during the meal. Various studies have investigated the effect of TV watching during meals. It has been observed that meal frequency is higher, with more snacking and greater overall caloric intake (56, 68).

Social environment. Meal size and duration are greater when eaten with other people, especially in large groups (51, 69), independently of the meal (breakfast, lunch, or dinner), and resulting in higher carbohydrate, fat, protein, and total caloric intake (56). The observed larger size of the meal could be mediated by the duration of the meal (70). However, not just the number of people present, but the type of social relationship might affect meals: a study by *de Castro* (69) found that meals eaten with the family were larger and faster than meals eaten alone, but meals with friends were even larger than with family and were of longer duration. The presence of men had this effect on women's meals but not on other men's meals. Despite the association found in many studies of more people present at meals and larger meal size with a lower dietary quality, the contrary, eating alone, could also provide an environment that promotes unhealthy eating: *Holm et al*. (33) found that eating alone was associated with lower diet quality in Finland and Sweden but not in Denmark and Norway. The socioeconomic status also has effects on dietary intake and diet quality. Because of different health literacy and education, occupation, purchase power, food environment, and other differing factors, individuals in higher socioeconomic classes eat overall a more healthy diet than their counterpart in a lower status (71). Less is known though about the socioeconomic status effects on meal-specific intakes. Finally, because of cross-cultural differences in the environment, traditions, beliefs, and role of food in society, it is not surprising that cultural factors play a role in eating behavior. Various studies have documented such differences not only in different countries (33, 72), but also according to the degree of urbanization (55), where the changes in physical activity, air quality, sleeping patterns, among others, have an important impact on our eating behavior. Therefore, due to

the sociocultural and environmental impacts on eating behavior, meals have to be studied in the cultural context in which the dietary guidelines are being developed (34).

1.3 Aim and research questions

The aim of this thesis is to provide a better understanding of the role that the different meals play for dietary intake and eating behavior. Figure 1 shows how habitual dietary intake arises from every meal intake. With this information as the basis of this research, we investigated the relationships among the different foods consumed at the habitual level, on single days, and on meals and investigated the origin and the predictors of dietary intake variation, both within and between individuals.

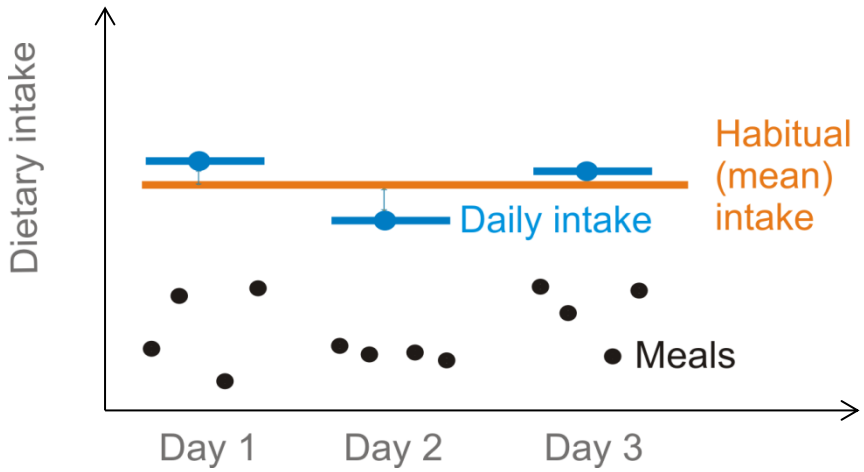

Figure 1: Habitual dietary intake and its relationship with daily and meal intakes

The sum of all meal intakes (black) make up the daily intake (blue). The average of daily intakes during a longer period of time makes up the habitual dietary intake (orange).

Specifically, we address the following research questions in this thesis:

1. How do foods relate to each other in terms of correlations, consistency, and frequency of consumption at the different meal types, in single days, and at the habitual level? (Results sections 3.1.1 and 3.1.2)

2. How do the different meal types contribute to the formation of exploratory habitual dietary patterns (PCA and GGM-dietary networks) and can we relate these dietary patterns to the meal-specific features observed in question 1? (Results sections 3.1.3 and 3.1.4)

3. What role do meal types and individuals play in explaining the variance in energy and macronutrient intake? (Results section 3.2.1)

4. Which aspects of eating behavior are important predictors of dietary intake, and is their impact meal-type dependent? (Results section 3.2.2)

2 Methods

2.1 EPIC-Potsdam validation sub-study

For this thesis, data from the validation sub-study of the European Prospective Investigation into Cancer and Nutrition (EPIC)-Potsdam study were used. The EPIC-Potsdam study is a cohort study that is part of the multicenter EPIC study in which 10 European countries have followed participants for over 15 years (73). The EPIC-Potsdam study sample comprises of 27 548 men and women aged 35-64 at recruitment (between 1994-1998) from the general population of Potsdam, Germany and the surrounding areas. Further details about the EPIC-Potsdam study design and recruitment are available elsewhere (74). The cohort has been followed every 2-3 years to obtain new lifestyle- and health-related information. Information about incident chronic diseases is obtained directly from hospitals and treating physicians (75).

From 2009 to 2012 a sub-sample of the EPIC-Potsdam participants was selected for the validation sub-study. The aim of this study was to obtain a more detailed assessment of exposures such as nutrition, anthropometry, and physical activity. Participants were selected randomly from the cohort on an age- and sex-stratified basis. Eligible participants were active EPIC-Potsdam participants who had given their consent to participate in follow-up interviews, who had a current address in the state of Brandenburg or Berlin, and with a known phone number. Recruitment took place from August 2010 to December 2012. The total number of invited individuals was 1 447, of which 816 men and women participated. All participants gave informed consent and the study was approved by the Ethics Committee of the Medical Association of the State of Brandenburg. Further details about the study design are available elsewhere (76). The study was registered in clinicaltrials.gov with the identifying number NCT03216161.

2.2 Dietary assessment

A total of 2 431 24hDRs were collected. Participants provided up to three 24hDRs each (mean = 2.99) (Table 3). The first 24hDR was recorded during the first study center visit by a trained interviewer. The following two 24hDRs were performed over the telephone on randomly chosen days, including weekends, by trained interviewers. The standardized computerized 24hDR program EPIC-Soft was used for all records (77) and all records were collected within a period of 4-24 months (mean = 7 months).

Table 3: Number of 24hDRs per participant

	Number of 24hDRs provided		
	3	2	1
Number of participants (%)	806 (99.0%)	5 (0.6%)	3 (0.4%)

Food intake was recorded in grams of food for every EO, 11 EOs in total (Table 4). EOs were recorded with participant-identified labels and the time of the day during the EOs was documented. Food intakes were converted into nutrient intakes using the German nutrient database 'Bundeslebensmittel-schlüssel' (BLS, version 3.01).

Table 4: Eating occasions used in the 24hDRs

Eating occasion No.	Eating occasion participant-identified label
1	Before breakfast
2	Breakfast
3	During morning
4	Before lunch
5	Lunch
6	After lunch
7	During afternoon (afternoon snack)
8	Before dinner
9	Dinner
10	After dinner
11	During evening

Note. Reprinted from Schwedhelm et al. *PLOS ONE* 2018 (Supporting information) (78)

For studying meals, four main EOs were selected: breakfast, lunch, during afternoon (afternoon snack), and dinner. This selection was based on observed peaks in the contribution to the whole day's food intake (in grams), shown below in Figure 2.

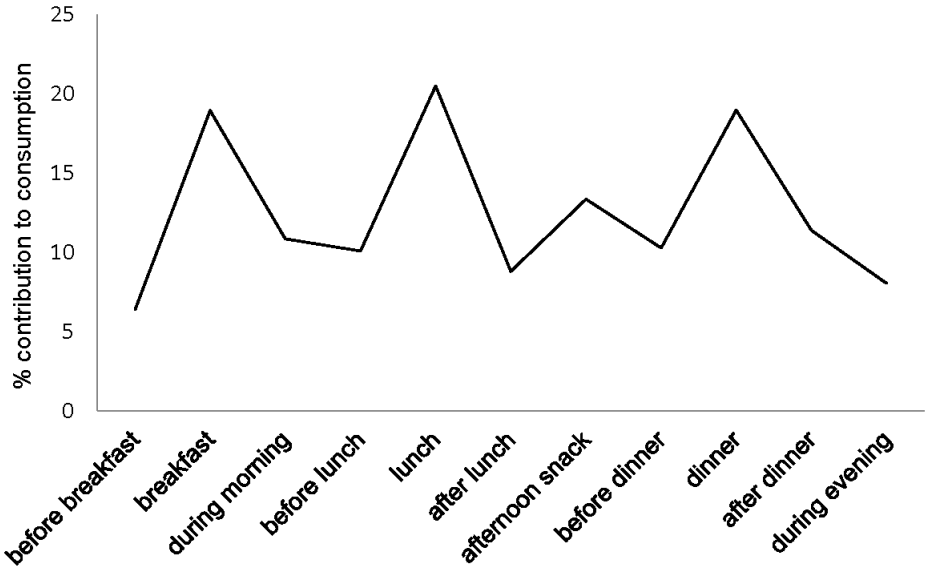

Figure 2: Mean contribution of eating occasions to food consumption over the day

% amount in grams, n = 814

Note. Reprinted from Schwedhelm et al. *Am J Clin Nutr* 2018 (79)

For food-based analyses, foods were collapsed into 39 food groups as has been done in previous studies (80, 81) and averaged over the days and meals to derive the habitual and meal intakes, respectively. **Table S1** lists the 39 food groups and their descriptions.

2.3 Assessment of further variables

Sociodemographic and lifestyle data were collected through self-reported questionnaires during the first study center visit. Body mass index (BMI) was calculated as the ratio of weight in kg to height squared in meters. Body weight and height were measured in the study center following standardized protocols consistent with WHO guidelines (82). Energy expenditure was measured with a combined heart rate and uniaxial accelerometer (Actiheart, CamNtech, Cambridge, UK) (83), which was worn during 7 consecutive days. These data are available only for 682 of the 816 study participants. Total energy expenditure (TEE) was calculated from the Actiheart-device as the sum of activity energy expenditure, diet-induced thermogenesis as 10% of TEE, and resting energy expenditure (from the Schoefield Equations) (84, 85). Physical activity level is given by the ratio of TEE to resting energy expenditure (REE) (TEE/REE). Under 1.4 was considered as extremely inactive, 1.4 to <1.7 as sedentary, 1.7 to <2.0 as moderately active, 2.0 to <2.4 as vigorously active, and from 2.4 up as extremely active.

2.4 Statistical methods

2.4.1 Final study sample

For the analyses in this thesis, two of the 816 participants were excluded; one due to dementia and another due to a younger age than the inclusion criteria (< 35 years old at EPIC-Potsdam recruitment). Therefore, the main analyses are based on a sample of 814 individuals. Analyses using objectively measured physical activity (from heart rate monitor and accelerometer) were based on data from 682 participants due to missing physical activity information. Figure 3 shows the flow chart for the selection of study participants.

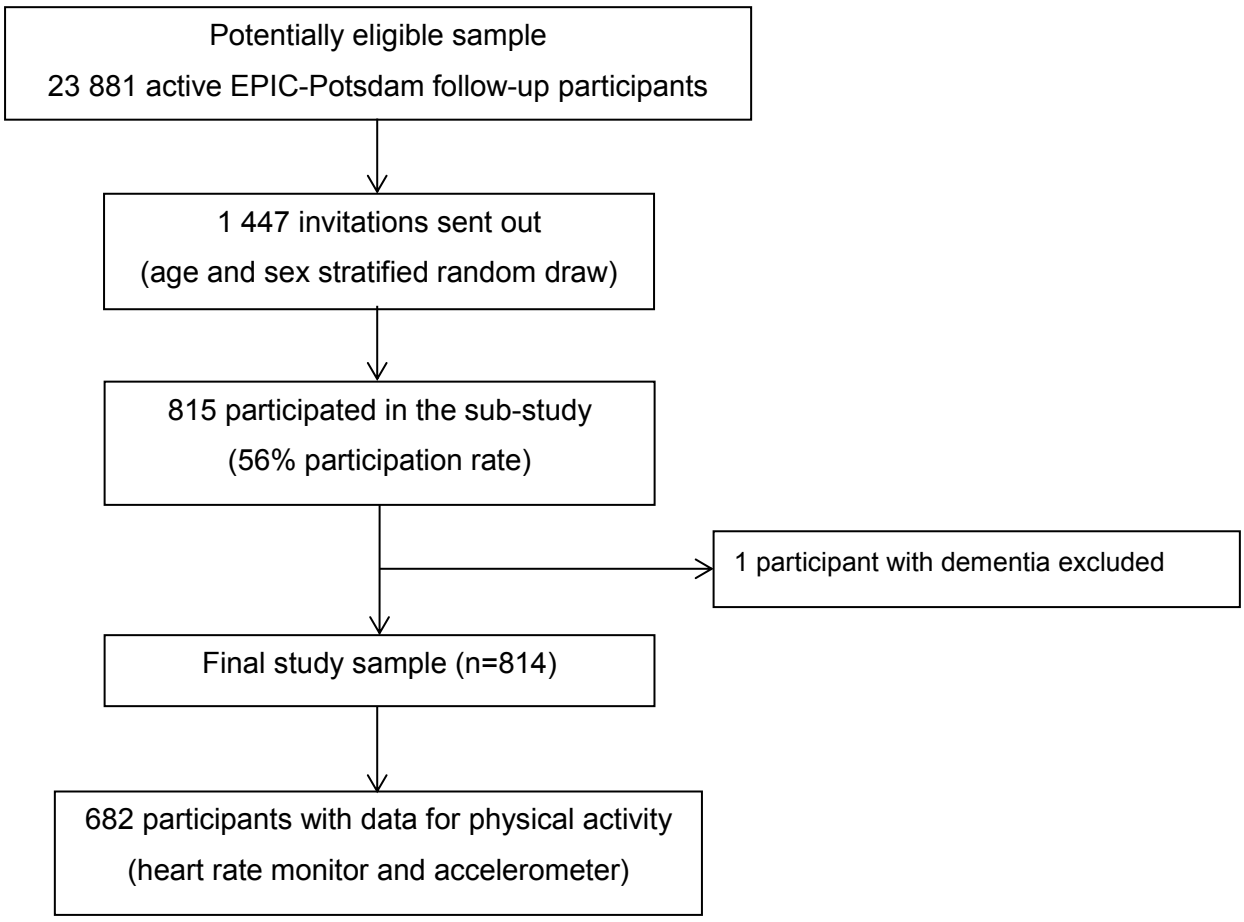

Figure 3: Flow-chart of participants in the validation sub-study within the EPIC-Potsdam cohort

2.4.2 Food groups: correlations and frequencies

The variables of food group intakes were non-normally distributed with extreme values (outliers). Therefore, correlation analyses were performed using Spearman correlation coefficients to identify correlation arrangements at the levels of consumption of the meal types, single days, and habitual. Meal-type level analyses were performed from individuals' mean meal intakes (e.g., the mean of the three breakfast intakes, mean of the three lunch intakes, etc.). To further explore the observed relationships, intra-class correlation (ICC) coefficient was calculated for each food group as a measure of consistency of consumption over days and meals. Three participants with only one 24hDR were excluded from this analysis (n=811). The range for the ICC is from 0 (no agreement in food consumption over the days/meals) to 1 (perfect agreement in food consumption over the days/meals). Frequency of consumption was calculated in percent (%) times that the foods were consumed (out of all respective eating occasions). Statistical software SAS, version 9.4, and SAS Enterprise Guide, version 6.1 (SAS Institute, Cary, NC) was used for these analyses.

2.4.3 Derivation of dietary patterns

Exploratory habitual dietary patterns were derived with two methods: PCA, for being the most often used method, and GGM dietary networks, as this constitutes a novel method also based on correlations and with the advantage of providing a visual representation of the relation between all foods.

PCA statistical methods

Because the data were non-normally distributed and included outliers, the assumption of normality needed for traditional PCA using Pearson correlation is violated (25, 86). Therefore, consistent with the food groups correlations analyses, *a posteriori* PCA-derived dietary patterns at the habitual level were derived based on Spearman correlations. Factor loadings were calculated after a varimax rotation to obtain uncorrelated components that are more easily interpretable (24). To obtain more clear patterns and avoid noise, we applied an often-used threshold ($\geq$ |0.3|) (87, 88) for considering factor loadings as important contributors to a pattern and for labeling these patterns according to the food groups with the highest loadings. Four factors were retained based on scree plot analysis.

Individual pattern scores were calculated for each of the retained components, taking into account all food groups (including those with factor loadings < |0.3|). Similarly, individual pattern scores were obtained for the different days and meals (mean meal intakes) using the

respective intakes and the obtained PCA standardized scoring coefficients. The contribution of single days and different meals to the PCA-derived habitual dietary patterns was calculated by correlating pattern scores for days and meals with pattern scores at the habitual-level. Statistical software SAS, version 9.4, and SAS Enterprise Guide, version 6.1 (SAS Institute, Cary, NC) was used for PCA derivation and habitual as well as meal-type specific dietary pattern scores.

GGM-dietary networks statistical methods

GGMs describe conditional independence between variables, i.e., the relationship between two variables independent of the effect of other variables. They can be used to produce probabilistic graphs in which nodes represent variables (i.e., food groups) and edges represent a relationship between the variables. These graphs can be quantified using partial correlations, under the assumption of a normal distribution. Edges represent conditional dependencies between food groups revealed by partial correlation coefficients. The absence of an edge between 2 food groups indicates conditional independence between them. Continuous edges show positive partial correlations while broken edges show negative partial correlations. Line thickness is proportional to the strength of the correlations between food groups. Partial correlations in the results are referred to as corr. for simplicity purposes.

A high-dimensional multivariate data set can have no or few 0 values, which would form very dense, less informative graphical representations of the networks. For this reason, regularization methods for covariance estimation are available. Regularization is achieved by choosing a penalty parameter ($\lambda > 0$), which reduces the variance and helps avoid overfitting of the model (avoiding the false inclusion of edges) (30). Various methods are available for choosing the penalty parameter λ. Due to the non-normal distribution of the data, the meal and habitual dietary networks were derived through SGCGMs (Semiparametric Gaussian Copula Graphical Models), which is a nonparametric extension of GGMs. It performs the nonparanormal skeptic (Spearman/Kendall estimates preempt transformations to infer correlation) transformation in order to perform semiparametric analyses suited for highly skewed data (89, 90). This transformation is based on a nonparametric ranking of correlation coefficient estimators using Spearman's rho and Kendall's tau and offers an alternative for estimating high dimensional undirected graphical models without requiring normal distribution of the underlying data (91).

Meal type and habitual GGM dietary networks were derived by estimating skeptic transformed inverse covariance matrices using the “huge” R package (90, 92). The selection of the optimal penalization λ was performed with a tenfold cross-validated graphical lasso (glasso), which was run in R with the package “nethet” (93). Statistical software SAS, version 9.4, and SAS Enterprise Guide, version 6.1 (SAS Institute, Cary, NC) was used for data processing and for running R (proc iml to run R within SAS). The estimated sparse networks were exported for formatting to CorelDRAW Graphics Suite X3 (Corel GmbH, Munich; www.corel.de). Food groups were considered to form a network when three or more groups were related to each other. The proportion of (direction-specific) relations (i.e. edges) from meal type-specific networks present also in the habitual network was used as measure of the degree of appearance or reflection in the habitual network. Meal-type specific networks were derived from all meal type (breakfast, lunch, afternoon snack, dinner) observations, as opposed to from the mean meal type intakes like the previously described correlation and PCA analyses in order to retain the true occasion-clustered structure of the intakes.

2.4.4 Energy and macronutrients: explained variance and predictors of intake

Energy intake was analyzed as kilocalories (kcal) per meal, while macronutrients were in grams per meal. For each outcome variable (kcal, carbohydrates, protein, and fat), zero values were excluded from analysis and log transformed the non-zero values to achieve a normal distribution. The origin of the zero values was mostly from energy-free beverages such as water (with 0 kcal and 0 grams for all macronutrients), or sweetened beverages, including coffee with sugar (with 0 grams of fat and protein). Due to their nature and low occurrence, exclusion of zero values was not expected to alter or bias the data, while favoring their normalization, which is an assumption of parametric models like the one used in these analyses. The frequency of the excluded observations (zero values) was 251 (2.8%), 242 (2.7%), 305 (3.3%), and 449 (4.9%) for energy, carbohydrates, protein, and fat, respectively. The hierarchical structure of the data is as follows: participant (level 3), meal type (level 2), and the actual intake level (level 1). Multi-level linear regression models were fitted with random intercepts for participant and meal type, allowing these to vary in dietary intake.

The ICC coefficients were calculated in the intercept-only model by dividing the variance at the level of interest by the total variance. The ICC indicates the proportion of variance at each level (94, 95). For the three-level model, the following equations were used:

$$ICC_{ID} = \frac{\sigma_{ID}^2}{\sigma_{ID}^2 + \sigma_{meal}^2 + \sigma_e^2}$$ Participant level

$$ICC_{meal} = \frac{\sigma_{meal}^2}{\sigma_{ID}^2 + \sigma_{meal}^2 + \sigma_e^2}$$ Meal-type level

$$ICC_e = \frac{\sigma_e^2}{\sigma_{ID}^2 + \sigma_{meal}^2 + \sigma_e^2}$$ Intake level

where σ_{ID}^2, σ_{meal}^2, and σ_e^2 are the variances at the third (participant), second (meal type), and first (intake) level, respectively. The following relevant covariates (predictors of dietary intake) were added: sex, age, BMI, physical activity, education level, current occupation, smoking status, duration of prior interval, place of meal, special day, season, and week/weekend day to the multilevel regression model to measure their relative importance in explaining the variation in the outcome variables at each level in in a structural equation modeling (SEM) framework. This approach allows modeling of complex relationships between variables and their ordering into the different levels of the multilevel regression analysis, providing covariance and correlation matrices separately by level, whereas conventional multilevel models or hierarchical linear models (HLM) do not easily allow this break-down in a random intercept model (96, 97). Intake-level covariates were added to the first level (specific meal on a specific day) and participant-level covariates were added to the highest level (participant level). Since no covariates are specific to the meal types (variables being the same for all breakfast meals, all lunch meals, all afternoon snacks, or all dinner meals) but this is a level of high interest for the pursued research question, analyses were stratified by meal type and fitted a two-level model (level 1: intake level; level 2: participant level). Results can be interpreted as the meal type-specific relative importance of predictors at the intake and participant levels, respectively.

Selection and description of covariates

Based on literature and availability of the data, the following covariates were included as predictors of dietary intake: sex, age, BMI, self-reported physical activity (hours of physical activity per week in the last 12 months including: sports, gardening, physical work, housework, cycling), education level, current occupation, smoking status, duration of prior interval (hours passed since last intake), place of meal (home, restaurant, work, or other), whether it was a special day or not (religious holiday, celebration meal, travel, or holidays), season (winter: October-March; summer: April-September), and whether it was a weekday (considered as Monday-Thursday) or weekend day (considered as Friday-Sunday). Data were missing for 1 person for education level, 9 persons for current occupation and smoking status, and 4 persons for physical activity. Missing values were imputed using single imputation by regression (98) according to BMI, age, and sex. Predicted values of multivariable linear regression were imputed for continuous variables. For categorical variables, multivariable logistic regression models were fitted for every classification group and missing values were replaced by the category with the highest probability.

The meal type-stratified two-level random intercept model can be described as:

Level 1 (intake level/within model):

$$Y_{ij} = \beta_{0j} + \beta_1 weekend_{ij} + \beta_2 season_{ij} + \beta_3 specialday_{ij} + \beta_4 priorinterval_{ij} + \beta_5 placeofmeal_{ij} + e_{ij}$$

Level 2 (participant level/between model):

$$\beta_{0j} = \gamma_{00} + \gamma_{01} bmi_j + \gamma_{02} age_j + \gamma_{03} sex_j + \gamma_{04} p\_activity_j + \gamma_{05} education_j + \gamma_{06} occupation_j + \gamma_{07} smoking_j + u_{0j}$$

where *i* denotes the number of observations/intakes; *j* denotes the number of participants; β_{0j} is the random intercept for the participants; the other βs are the fixed slopes of the level 1 predictors; Y_{00} is the model grand mean; the other *Y*s are the slopes for the level 2 predictors; e_{ij} is the level 1 residual; and u_{0j} is the level 2 residual for the random intercept. Categorical covariates were added as dummies. Reference group for place of meal was home, for education was no vocational training/current training, for occupation was no job/retired, and for smoking was never smokers.

Sensitivity analyses were adjusted for energy misreporting for 682 participants with data on energy expenditure, adding energy misreporting as a categorical variable (indicating underreporting, over-reporting, or plausible reporting) to the participant level/between model. Energy misreporting was calculated and used by *Gottschald et al*. (99) in a recent publication on the same study sample. This calculation was based on a cutoff of ± 1 SD for the energy intake (EI) to TEE ratio according to sex, age, and BMI stratified estimates of variation published by Huang et al. (100) using usual energy intake calculated with the NCI method (19, 101). A ratio of EI/TEE < 0.81 indicates under-reporting and a ratio of > 1.19 is indicative of over-reporting (99, 100).

R^2 and Pratt index

The methods described by Liu et al. (97) were used for estimating R^2 at each level of the regression model with random intercepts and the Pratt Index (PI). The R^2 is a measure of the model fit, defined as the total standardized variance in a population explained by a regression model with normally distributed residuals. In a SEM framework, the covariance matrix of the observed individual variables can be partitioned into the different levels of the model, resulting in an R^2 with additive property for random-intercept regression models. The PI is a measure based on the standardized regression coefficient, the simple correlation between the response variable and explanatory variable, and on R^2 and is calculated by levels using the following equation:

$$PI_j = \frac{\hat{b}_j * r_j}{R^2}$$

where *j* denotes the number of observations/intakes at level 1 (intake level/within model) or the number of participants at level 2 (participant level/between model); $\hat{b}_j$ is the j_{th} standardized regression coefficient ("beta") and r_j is the zero-order correlation between the response variable and the j_{th} explanatory variable, estimated from the maximum-likelihood covariance matrix. The PI represents the proportion of R^2 explained by each explanatory variable, ordering predictors in terms of their importance in a multiple regression analysis. For the purpose of this thesis, a Pratt Index of $\geq$10% was considered as important.

For obtaining the explained variance in energy and macronutrient intake as well as the analyses on the relative importance of predictors of intake, MPlus Version 7 (Muthén & Muthén, Los Angeles, CA, USA) was used. Statistical software SAS, version 9.4, and SAS Enterprise Guide, version 6.1 (SAS Institute, Cary, NC) was used for data processing.

3 Results

Baseline characteristics of all 814 participants are shown on Table 5. Participants were in average 65.5 years old (aged between 47 and 81) and had a mean BMI of 27.5 kg/m^2. According to self-reported physical activity (hours of physical activity per week in the last 12 months including: sports, gardening, physical work, housework, cycling), participants did on average 22.6 hours of physical activity per week. However, according to the objectively measured physical activity on 682 of the participants, about half of all participants were sedentary (53.0%). Only 10.3% of participants were current smokers. While most women were never smokers (60.8%), most men were former smokers (57.2%). A large proportion of the participants had a university degree (44.2%), of which the majority was male. A third of the participants had no vocational training (32.8%), and the remaining 23% had a technical college degree. Most participants did not have a current occupation (62%). Underreporting of energy intake (EI/TEE < 0.81) was present in 39.6% of all participants and it was more common in women (45.4%) than in men (34%).

Table 5: Baseline socio-demographic and lifestyle characteristics of the studied population sample

Characteristics	Total n = 814	Men n = 411	Women n = 403
Age, y	65.5 ± 8.4[1]	66.4 ± 8.0	64.5 ± 8.7
BMI, kg/m^2	27.5 ± 4.4	27.7 ± 3.9	27.4 ± 4.8
Hours of self-reported physical activity/week[3]	22.6 ± 14.7	20.7 ± 14.0	24.7 ± 15.0
Physical activity level (ratio TEE/REE) (%)[4]			
Extremely inactive (< 1.4)	136 (19.9)[2]	72 (20.6)	64 (19.1)
Sedentary (1.4 to < 1.7)	363 (53.0)	168 (48.1)	195 (58.0)
Moderately active (1.7 to < 2.0)	159 (23.2)	98 (28.1)	61 (18.1)
Vigorously active (2.0 to < 2.4)	25 (3.6)	10 (2.9)	15 (4.5)
Extremely active (≥ 2.4)	2 (0.3)	1 (0.3)	1 (0.3)
Smoking status (%)			
Never smoker	377 (46.3)	132 (32.1)	245 (60.8)
Former smoker	353 (43.4)	235 (57.2)	118 (29.3)
Smoker	84 (10.3)	44 (10.7)	40 (9.9)
Education level (%)			
No vocational training / current vocational training	267 (32.8)	124 (30.2)	143 (35.5)
Technical college	187 (23.0)	63 (15.3)	124 (30.8)
University	360 (44.2)	224 (54.5)	136 (33.7)
Current occupation (%)			
Full time (≥35h/week)	248 (30.5)	141 (34.3)	107 (26.7)
Part time/hourly (<35h/week)	61 (7.5)	18 (4.4)	43 (10.7)
No job/retired	505 (62.0)	252 (61.3)	253 (62.8)
Energy misreporting (%)[4]			
EI/TEE < 0.81	270 (39.6)	118 (34.0)	152 (45.4)
0.81 ≤ EI/TEE ≤ 1.19	359 (52.6)	187 (53.9)	172 (51.3)
EI/TEE > 1.19	53 (7.8)	42 (12.1)	11 (3.3)

EI, energy intake; TEE, total energy expenditure; REE, resting energy expenditure

[1] Mean ± SD, all such values

[2] Frequency (%), all such values

[3] self-reported. Includes the following activities done in the past 12 months: sports, gardening, physical work, housework, cycling

[4] *n*=682

A total of n=2 411 breakfast observations (mean time 08:02), n=2 236 lunch observations (mean time 12:37), n=2 119 afternoon snack observations (mean time 15:31), and n=2 346 dinner observations (mean time 18:45) were available. Out of the four main meals, lunch contributed the most to the amount of food consumed over the day (grams/eating occasion), with 20.5%, followed by dinner (19.0%), breakfast (18.9%), and afternoon snack (13.3%) (Figure 2). Mean intakes of the food groups per meal type and mean habitual intakes are shown on **Table S2**, and mean energy and macronutrient intakes by day and by meal-type are shown in Table 6 for all participants, for men, and for women. In general, dietary intakes were lower among women than among men. For men, dinner was the meal with the highest

energy intake, while for women it was lunch. Carbohydrate and protein intake were highest during lunch and fat intake was highest during dinner (for both men and women).

Table 6: Mean participants' dietary intake

Intake variable	Day[1] (n=814)	Breakfast (n=814)	Lunch (n=808)	Afternoon snack (n=804)	Dinner (n=814)
Energy, kcal					
All	2 058 ± 593[2]	451 ± 199	528 ± 224	263 ± 191	524 ± 222
Men	2 341 ± 600	521 ± 213	583.3 ± 249	292 ± 208	609 ± 230
Women	1 770 ± 422	380 ± 154	471 ± 177	232 ± 167	438 ± 175
Carbohydrate, g					
All	204.1 ± 62.2	50.1 ± 22.8	46.9 ± 24.5	30.6 ± 21.4	40.6 ± 19.9
Men	226.6 ± 66.9	56.2 ± 25.5	51.6 ± 28.0	33.7 ± 22.3	46.4 ± 22.3
Women	181.2 ± 47.0	44.0 ± 17.8	42.2 ± 19.1	27.5 ± 10.0	34.6 ± 14.9
Protein, g					
All	74.5 ± 23.8	14.5 ± 8.2	26.1 ± 15.2	6.4 ± 6.9	22.2 ± 11.6
Men	84.0 ± 24.6	16.8 ± 9.1	29.1 ± 16.8	7.0 ± 7.9	25.4 ± 11.8
Women	64.8 ± 18.4	12.2 ± 6.3	23.1 ± 12.6	5.8 ± 5.8	19.0 ± 10.5
Fat, g					
All	93.0 ± 33.0	21.1 ± 12.6	24.7 ± 12.8	12.0 ± 10.4	27.4 ± 13.9
Men	106.5 ± 33.8	25.1 ± 13.8	27.2 ± 14.1	13.4 ± 11.5	32.1 ± 14.4
Women	79.1 ± 25.7	16.9 ± 9.7	22.2 ± 10.7	10.5 ± 9.0	22.7 ± 11.6

[1] All 11 eating occasions
[2] Mean ± SD, all such values

3.1 The role of meals in dietary pattern formation

The following section describes the observed relations between food groups at the meal-type level (breakfast, lunch, afternoon snack, and dinner), followed by the description of these relations at the habitual level, and finally the comparison between both (meal-type and habitual levels). The level of the single days (all meals in one day) was also assessed but only discussed in terms of consistency and frequency of consumption, since the structure of the correlations between food groups was similar across the three days. Further, habitual dietary patterns derived with a frequently used method (PCA) are discussed and how these relate to the correlation structures of food groups in the different meal types. The novel method of GGM for derivation of dietary networks provides a further insight into this correlation structure and what is retained from meals and what is new when dietary patterns are presented at the habitual level.

3.1.1 Correlations between food groups

In general, for the different meal types strong positive correlations were observed for food groups typically eaten together and strong negative correlations for food groups that are

typically substitutes of each other. *Bread* and *cheese* showed strong positive correlations across all meal types. As to meal type-specific correlation structures, the following strong correlations (depicted in **Figures 4-7** in the form of heat maps) were observed:

Breakfast

There were strong positive correlations between *breakfast cereals* and *milk & dairy,* between *other cereals* (mainly due to oatmeal and porridge-type cereals) and *nuts*, *bread* with *processed meats*, *cheese, margarine, butter*, and *sugar & confectionery*, and strong positive correlations between *other vegetables* and *sauces, red meat*, and *poultry*. The strongest negative correlations were between *margarine* and *butter* and between *coffee* and *tea* (Figure 4).

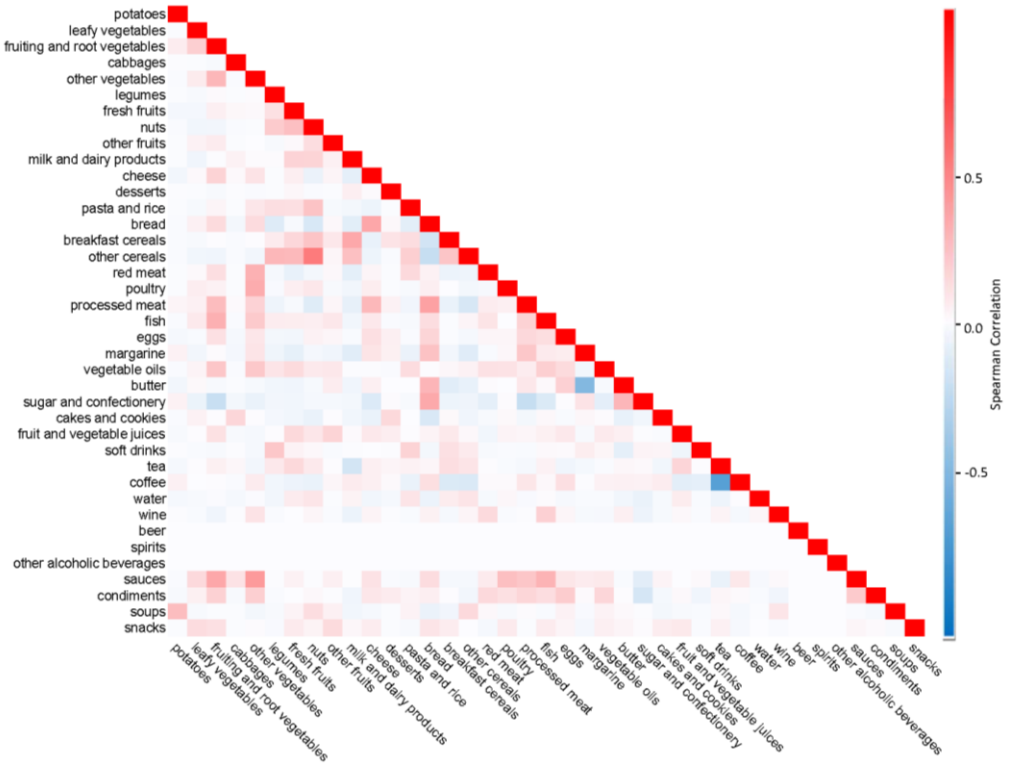

Figure 4: Breakfast correlation heat map

Spearman correlation matrix for average breakfast food intake in grams by food groups (n=814). The color corresponds to the strength of correlations (red: positive correlation; white: no correlation; blue: negative correlation)

Lunch

Strong positive correlations were observed between *cakes & cookies* and *coffee*, between *potatoes* and *cabbages*, *red meat*, *other vegetables* and *sauces*, between *red meat* and *cabbages,* and *other vegetables,* as well as *between processed meat* and *condiments*. Strong negative correlations were between *bread* and *potatoes*, *potatoes* and *cheese*, *pasta & rice* and *potatoes*, and *coffee* and *tea* (Figure 5).

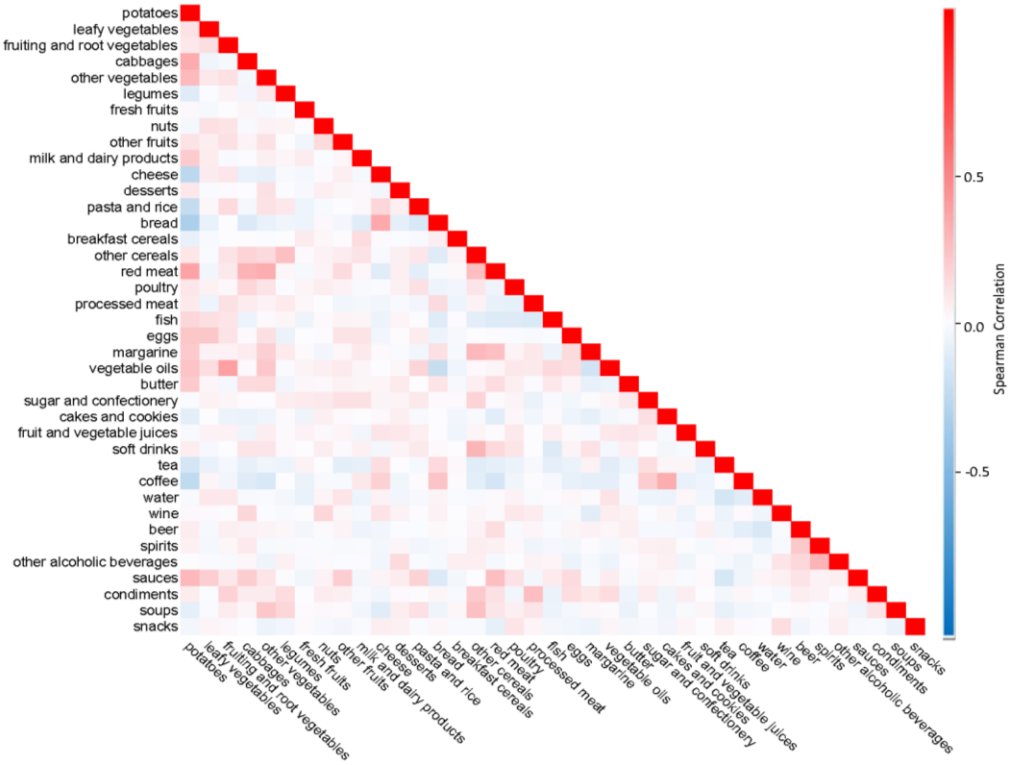

Figure 5: Lunch correlation heat map

Spearman correlation matrix for average lunch food intake in grams by food group (n=808). The color corresponds to the strength of correlations (red: positive correlation; white: no correlation; blue: negative correlation)

Afternoon snack

Afternoon snack showed the strongest correlations. Positive correlations were seen for *bread* with *butter*, *margarine*, and *processed meat*, for *cake & cookies* with *coffee*, for *other vegetables* with *soups*, *vegetable oils*, and *red meat*, for fruiting & root vegetables with other vegetables, *red meat*, *processed meat*, and *margarine*, and for *potatoes* with *cabbages*, other vegetables, *red meat*, and *soups*. On the other side, *water* with *cakes & cookies*, *coffee* with *tea*, and *coffee* with *water* correlated strongly negative (Figure 6).

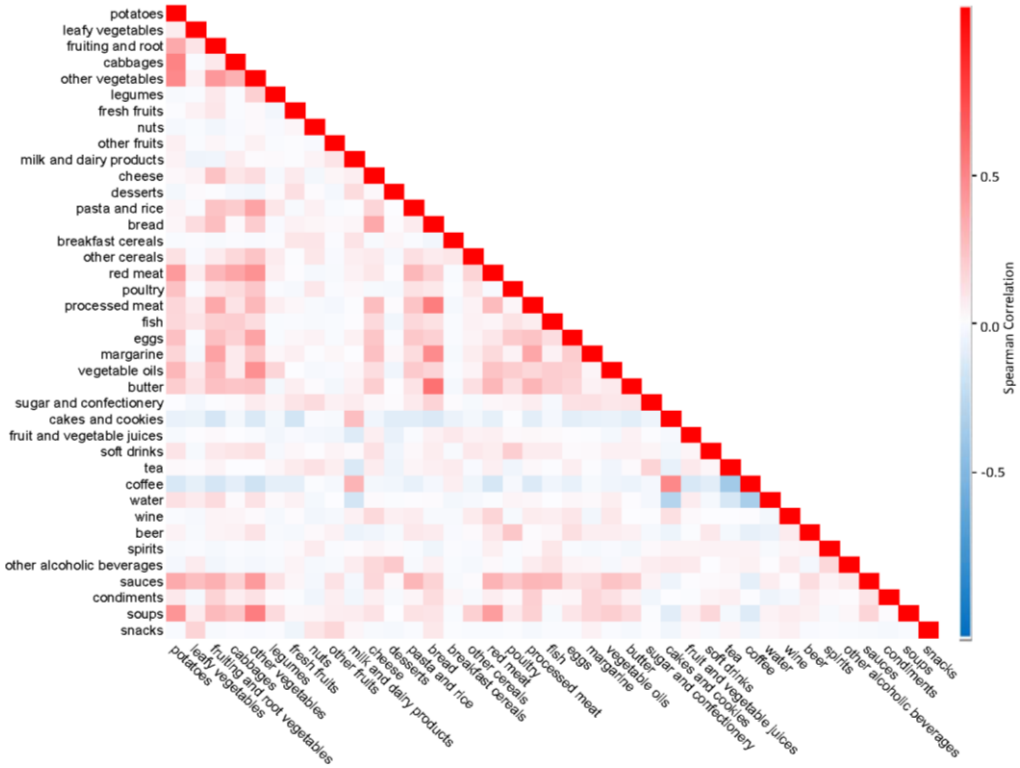

Figure 6: Afternoon snack correlation heat map

Spearman correlation matrix for average afternoon snack food intake in grams by food group (n=804). The color corresponds to the strength of correlations (red: positive correlation; white: no correlation; blue: negative correlation)

Dinner

Out of the four meals, dinner showed the weakest correlations among food groups. Among the strongest positive ones, there were *potatoes* with *cabbages*, *other vegetables*, *red meat*, *vegetable oils*, *sauces*, and *soups*, also *vegetable oils* with *leafy vegetables*, *other vegetables*, and *fruiting & root vegetables*, strong positive correlations between *bread* and *butter*, *margarine*, *processed meat*, and *cheese*, also between *sauces* and *leafy vegetables* and *other vegetables*, and finally strong positive correlations between *other vegetables* and *red meat* and *poultry*. As for negative correlations, the ones between *bread* and *potatoes*, *butter* and *margarine*, and *water* and *tea* were relatively strong (Figure 7).

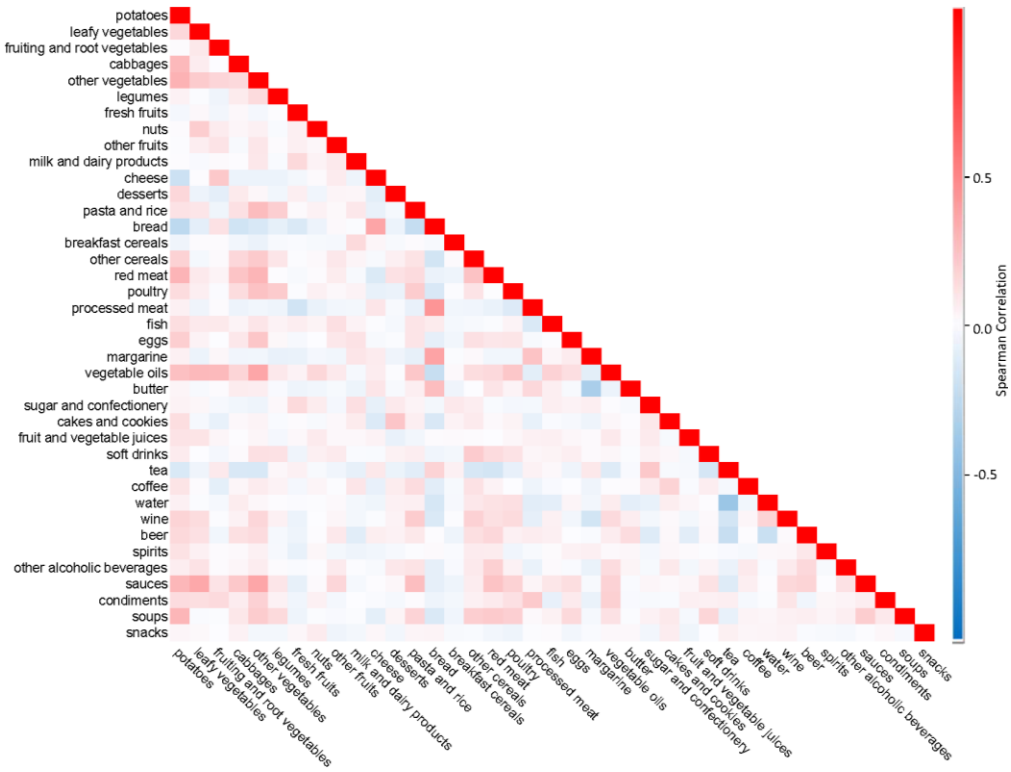

Figure 7: Dinner correlation heat map

Spearman correlation matrix for dinner food intake in grams by food group (n=814). The color corresponds to the strength of correlations (red: positive correlation; white: no correlation; blue: negative correlation)

Habitual diet

At the habitual level, some of the strong correlations observed at meals were retained, including *bread* with *margarine, butter, cheese, processed meats,* and with *sugar & confectionery,* the ones between *potatoes* with *cabbages, red meat,* and *margarine,* strong positive correlations between *vegetable oils* and *fruiting & root vegetables,* between *breakfast cereals* and *milk & dairy,* and between *processed meat* and *condiments.* As for strong negative correlations, the following ones were retained at the habitual level: *potatoes and pasta & rice, butter and margarine,* and the ones between *tea* with *coffee* and *tea* with *water.* In some cases these correlations were seen in only one meal type, such as the strong positive correlation between *breakfast cereal*s and *milk & dairy* (previously seen at breakfast only). In general, correlations were weaker for habitual diet than for meals, although the strength of the correlations as well as the correlation structure was similar to those observed for dinner. Figure 8 shows the correlation structure between food groups at the habitual level in the form of a heat map.

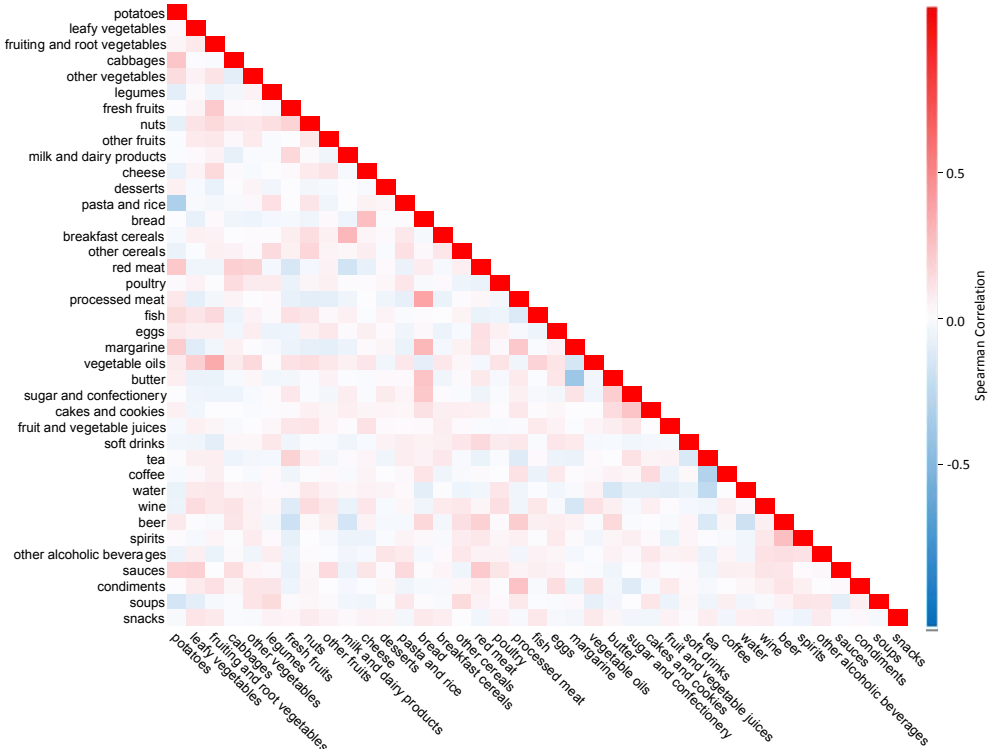

Figure 8: Habitual diet correlation heat map

Spearman correlation matrix for habitual food intake in grams by food group (n=814). The color corresponds to the strength of correlations (red: positive correlation; white: no correlation; blue: negative correlation)

Note. Reprinted from Schwedhelm et al. *Am J Clin Nutr* 2018 (79)

3.1.2 Consistency and frequency of consumption

Consistency of consumption

Consistency of food intake for every meal type and across days is shown through the ICC on Table 7. Consumption of foods was the most consistent across days and across breakfast meals. Out of the four main meals, breakfast showed the highest consistency of consumption. At this meal, the most consistently consumed food groups were *tea* (ICC=0.69), *milk & dairy* (ICC=0.63), *coffee* (ICC=0.61), *margarine* (ICC=0.60), *butter* (ICC=0.59), *breakfasts cereals* (ICC=0.54), *sugar & confectionery* (ICC=0.53), and *fresh fruits* (ICC=0.50). Lunch, afternoon snack, and dinner showed very low consistency of consumption. Across days, *margarine* (ICC=0.62), *coffee* (ICC=0.58), *tea* (ICC=0.55), *water* (ICC=0.54), and *butter* (ICC=0.53) showed high consistency.

Table 7: Within-individual consistency of consumption across meal types and days

	Intra-class correlation (ICC)[1]				
Food group	Breakfast	Lunch	Afternoon snack	Dinner	Day
Potatoes	0.00	0.22	0.00	0.10	0.17
Leafy vegetables	0.00	0.04	0.00	0.08	0.03
Fruiting and root vegetables	0.36	0.05	0.08	0.12	0.12
Cabbages	0.00	0.03	0.00	0.05	0.04
Other vegetables	0.03	0.03	0.01	0.02	0.00
Legumes	0.47	0.02	0.33	0.00	0.29
Fresh fruits	**0.50**[2]	0.10	0.04	0.20	0.33
Nuts	0.36	0.02	0.00	0.07	0.19
Other fruits	0.00	0.04	0.00	0.00	0.01
Milk and dairy products	**0.63**	0.14	0.08	0.30	0.45
Cheese	0.41	0.06	0.00	0.14	0.22
Desserts	0.00	0.09	0.00	0.14	0.09
Pasta, rice	0.00	0.04	0.00	0.01	0.04
Bread	0.44	0.19	0.09	0.35	0.45
Breakfast cereals	**0.54**	0.19	0.00	0.34	0.45
Other cereals	0.46	0.00	0.00	0.01	0.09
Red meat	0.10	0.07	0.02	0.05	0.11
Poultry	0.00	0.00	0.00	0.01	0.00
Processed meat	0.44	0.07	0.08	0.17	0.22
Fish	0.31	0.01	0.00	0.09	0.08
Eggs	0.17	0.05	0.00	0.01	0.11
Margarine	**0.60**	0.16	0.12	0.45	**0.62**
Vegetable oils	0.20	0.10	0.01	0.13	0.11
Butter	**0.59**	0.13	0.03	0.30	**0.53**
Sugar and confectionery	**0.53**	0.02	0.07	0.07	0.38

Table 7 continued

Food group	Intra-class correlation (ICC)[1]				
	Breakfast	Lunch	Afternoon snack	Dinner	Day
Cakes and cookies	0.16	0.00	0.18	0.02	0.18
Fruit and vegetable juices	0.33	0.20	0.10	0.21	0.38
Soft drinks	0.01	0.05	0.07	0.22	0.35
Tea	**0.69**	0.23	0.29	0.41	**0.55**
Coffee	**0.61**	0.20	0.36	0.13	**0.58**
Water	0.24	0.23	0.13	0.21	**0.54**
Wine	0.00	0.21	0.00	0.20	0.32
Beer	.	0.19	0.11	0.28	0.48
Spirits	.	0.00	0.04	0.00	0.12
Other alcoholic beverages	.	0.00	0.00	0.00	0.00
Sauces	0.22	0.05	0.00	0.00	0.02
Condiments	0.37	0.01	0.03	0.06	0.18
Soups	0.41	0.05	0.00	0.08	0.09
Snacks	0.15	0.00	0.00	0.00	0.04

[1] *n*=811 participants with at least two 24hDR; across all available observations

[2] ICC $\geq$ 0.50 in bold

Note. Data from Schwedhelm et al. *Am J Clin Nutr* 2018 (79)

Linking correlations and consistency of consumption

Some of the strongest correlations between food intakes in the breakfast meal (Figure 4) relate to consistency of consumption for the breakfast meal (Table 7). For example, the strong positive correlation between *breakfast cereals* and *milk & dairy* intake (in grams) is reflected by high consistency (ICC=0.54 and 0.63, respectively), and the strong negative correlations between *margarine* and *butter* and between *tea* and *coffee* related to high consistency (ICC=0.60, 0.59, 0.69, and 0.61, respectively). However, other strong correlations involving *fruiting & root vegetables* and *other vegetables* did not relate to high consistency of consumption across breakfasts. Despite the very strong correlations observed in the afternoon snack meal (Figure 6), consistency of consumption was very low (Table 7). At the habitual level, links between correlations (Figure 8) and consistency of consumption (Table 7) could be observed. For instance, *breakfast cereals* and *milk & dairy* correlated positively and both food groups showed the same and relatively high consistency (ICC=0.45), despite appearing only in the breakfast meal (out of the four main meals). *Margarine* and *butter*, as well as *coffee* and *tea*, showed a strong negative correlation and high consistency as well (ICC=0.62, 0.53, 0.58, and 0.55, respectively).

Frequency of consumption

The food consumption frequencies as percent (%) times that the foods were consumed are shown in Table 8. At breakfast, the most frequently consumed foods were *milk & dairy* (68.5%), *bread* (88.6%), *sugar & confectionery* (66.9%), and *coffee* (72.8%). Out of the four main meals, lunch showed in general a low frequency of consumption, suggesting a high variability in the composition of lunch meals. During afternoon snacks, most food groups showed a low frequency of consumption, while a few food groups were consumed very frequently. The most frequently consumed food groups during the afternoon snacks were *coffee* and *cakes & cookies* (63.3% and 51.6%, respectively). During dinners, the most frequently consumed foods were *bread* (72.0%), *processed meat* (53.7%), and *fruiting & root vegetables* (52.6%). On single days, frequencies of consumption were very high for most of the food groups, which was due to the cumulative effect of all eating occasions in a day. The most frequently consumed food groups on days were *bread* (98.1%), *water* (92.5%) and *coffee* (92.1%).

Table 8: Frequency of consumption of food groups across meal type and days

	Frequency of consumption (%)[1]				
Food group	Breakfast (n=2 411)	Lunch (n=2 236)	Afternoon snack (n=2 119)	Dinner (n=2 346)	Days (n=2 431)
Potatoes	0.0	49.1	1.2	9.9	54.3
Leafy vegetables	0.7	8.6	0.3	9.3	17.7
Fruiting & root vegetables	11.3	35.4	2.4	52.6	72.5
Cabbages	0.0	17.0	0.4	5.0	20.6
Other vegetables	2.6	45.3	1.5	27.7	60.8
Legumes	1.0	3.3	0.4	1.5	5.5
Fresh fruits	28.6	35.2	12.4	25.2	81.7
Nuts	4.4	1.7	0.9	1.7	13.4
Other fruits	0.7	3.1	0.4	2.9	7.6
Milk & dairy	68.5	29.7	47.3	19.5	86.8
Cheese	40.8	10.2	2.0	47.4	73.7
Desserts	0.0	7.3	3.5	1.5	14.2
Pasta & rice	0.8	13.2	0.6	4.1	16.9
Bread	88.6	23.2	8.6	72.0	98.1
Breakfast cereals	6.1	0.6	0.2	0.4	7.5
Other cereals	4.4	11.4	0.9	3.9	21.2
Red meat	1.5	26.5	1.2	10.5	34.8
Poultry	0.5	8.0	0.3	5.6	13.4
Processed meat	33.8	30.6	3.6	53.7	78.5
Fish	4.4	8.4	0.6	12.2	22.4
Eggs	16.5	9.7	0.7	6.1	30.5
Margarine	32.0	24.1	2.7	32.7	55.5

Table 8 continued

Food group	Frequency of consumption (%)[1]				
	Breakfast (n=2 411)	Lunch (n=2 236)	Afternoon snack (n=2 119)	Dinner (n=2 346)	Days (n=2 431)
Vegetable oils	2.5	27.0	0.9	18.7	41.1
Butter	46.6	28.2	3.9	36.5	69.2
Sugar & confectionery	66.9	17.3	20.1	17.1	85.3
Cakes & cookies	2.0	3. 6	51.6	1.7	56.4
Fruit & vegetable juices	12.3	13.2	5.2	12.2	40.8
Soft drinks	0.3	6.4	1.8	5.1	15.0
Tea	24.6	8.9	11.9	29.6	57.6
Coffee	72.8	9.7	63.3	1.8	92.1
Water	16.6	45.9	26.0	36.6	92.5
Wine	0.3	3.3	2.1	5.8	21.9
Beer	0.0	4.0	1.6	12.7	26.0
Spirits	0.0	0.1	0.4	0.4	3.7
Other alcoholic beverages	0.0	0.7	0.9	0.9	5.8
Sauces	3.9	29.4	1.7	20.6	46.3
Condiments	11.5	17.7	4.8	19.1	41.1
Soups	1.0	22.0	1.0	7.3	27.9
Snacks	0.6	0.5	0.2	1.1	2.2

[1] Percent days or meals where the foods were consumed (n=814). Over a period of 3 observations (24hDRs). If less than 3 recalls were available, the total of the available observations counted as 100%; days and meals were treated as independent observations. Descriptive results.

Note. Data from Schwedhelm et al. *Am J Clin Nutr* 2018 (79)

Linking correlations and frequency of consumption

The most frequently consumed food groups were involved in strong correlations (positive or negative) with at least another food group. However, not all food groups with strong correlations were consumed frequently. At breakfast, frequencies of consumption did not contribute to explain the strong correlations seen in Figure 4. At lunch, potatoes were the most frequently consumed food (in grams) (49.1%), which also showed strong correlations with other food groups (Figure 5). At afternoon snacks, the strong positive correlation between *coffee* and *cakes & cookies* (Figure 6) was linked to a high frequency of consumption (63.3% and 51.6%, respectively). At dinner, correlations for *bread* with *cheese* and with *processed meat* (Figure 7) were related to frequency of consumption (consumed on 72.0%, 47.4%, and 53.7% of the dinners, respectively). Finally, across days, only *bread* and *processed meat* had a strong correlation at the habitual level (Figure 8) and were also consumed frequently (98.1% and 78.5%, respectively).

3.1.3 Principal Component Analysis

Based on habitual food intake, four dietary patterns explaining 20.92% of the variance in food intake were retained based on scree plot analysis (**Figure S1**). The factor loadings for the PCA-habitual dietary patterns as well as the average habitual food intakes in grams per day are shown in Table 9 for orientation. Pattern 1 was characterized by high intake of *leafy vegetables*, *fruiting & root vegetables*, *fresh fruits*, *nuts*, *fish*, *vegetable oils* and *wine*, and by low intake of *margarine* and explained 6.13% of the total variance. Pattern 2 was characterized by high intake of *potatoes, cabbages, red meat, beer, sauces* and *condiments,* and by low intake of *fresh fruits*, *milk & dairy*, and *tea*; it explained 5.49% of the total variance. Pattern 3 was characterized by a high intake of *bread*, *processed meat*, *butter*, *sugar & confectionery*, and *cakes & cookies* and a low intake of *water*. This dietary pattern explained an additional 4.74% of the total variance. Finally, pattern 4 was characterized by a high consumption of *legumes*, *pasta & rice*, *other cereals, other alcoholic beverages*, and *soups* and by a low intake of *potatoes*. This last pattern explained an additional 4.56% of the total variance.

Table 9: Average food intake and factor loadings for the PCA-derived habitual dietary patterns

		Factor loadings for dietary patterns[1]			
Food groups	Average habitual intake (g/d)	Pattern 1	Pattern 2	Pattern 3	Pattern 4
Potatoes	81.7	0.07	**0.35***	0.09	**-0.61**
Leafy vegetables	11.6	**0.41**	0.13	-0.19	-0.02
Fruiting & root vegetables	103	**0.55**	0.06	0.01	-0.13
Cabbages	22.5	0.06	**0.35**	-0.09	-0.11
Other vegetables	32.9	0.19	0.26	-0.05	0.01
Legumes	6.64	0.00	0.02	-0.05	**0.42**
Fresh fruits	231	**0.37**	**-0.37**	0.08	-0.12
Nuts	3.95	**0.45**	0.03	0.00	0.27
Other fruits	10.2	0.29	0.21	-0.01	0.04
Milk & dairy	167	0.20	**-0.35**	0.03	-0.04
Cheese	37.4	0.28	0.05	0.22	0.04
Desserts	17.6	-0.05	0.02	0.02	0.02
Pasta & rice	23.1	0.07	-0.12	0.01	**0.54**
Bread	113	-0.08	0.11	**0.68**	-0.08
Breakfast cereals	3.40	0.28	-0.14	0.04	0.14
Other cereals	5.30	0.12	0.08	0.16	**0.38**
Red meat	39.5	-0.12	**0.54**	0.07	-0.10
Poultry	14.8	0.09	0.19	-0.15	0.15
Processed meat	60.8	-0.25	0.28	**0.39**	-0.09
Fish	24.1	**0.37**	0.00	0.03	-0.08

Table 9 continued

Food groups	Average habitual intake (g/d)	Factor loadings for dietary patterns[1]			
		Pattern 1	Pattern 2	Pattern 3	Pattern 4
Eggs	18.7	0.11	0.29	0.07	-0.06
Margarine	13.2	**-0.31**	0.16	0.17	-0.29
Vegetable oils	5.06	**0.58**	0.13	-0.11	-0.03
Butter	17.6	0.06	0.04	**0.47**	0.10
Sugar & confectionery	38.0	0.00	-0.19	**0.54**	0.01
Cakes & cookies	59.2	0.08	0.02	**0.43**	0.11
Fruit & vegetable juices	94.5	0.25	-0.08	0.22	0.00
Soft drinks	48.1	-0.17	0.21	0.01	0.20
Tea	355	0.23	**-0.38**	0.22	-0.12
Coffee	447	-0.06	0.22	0.09	0.12
Water	740	0.08	0.04	**-0.44**	0.01
Wine	57.3	**0.30**	0.26	-0.06	0.28
Beer	173	-0.07	**0.51**	0.28	0.12
Spirits	1.59	-0.08	0.26	0.12	0.22
Other alcoholic beverages	4.99	-0.01	0.15	0.05	**0.37**
Sauces	24.2	0.16	**0.40**	-0.04	-0.05
Condiments	2.79	0.12	**0.31**	-0.04	0.06
Soups	51.8	-0.17	0.04	0.08	**0.42**
Snacks	1.60	0.25	-0.02	0.02	0.02
Total variance explained (%)	20.92 (all factors)	6.13	5.49	4.74	4.56

* Factor loadings with an absolute value $\geq$ 0.30 in bold

[1] Habitual dietary patterns were PCA-derived using Spearman correlation matrix

Note. Data from Schwedhelm et al. *Am J Clin Nutr* 2018 (79)

The Spearman correlation coefficients for the habitual dietary pattern scores, which are a measure for adherence to the dietary patterns, are shown in the first rows of Table 10. Pattern 1, which was high in fruits and vegetables, correlated inversely with pattern 2 and with pattern 4, which were low in these food groups, among other differences (corr=-0.65 and -0.61, respectively). Pattern 2 correlated positively with pattern 4 (corr=0.61); these patterns were both low in fruits and vegetables but were different in terms of the contribution of cereals, legumes, and meats. Pattern 3, which was high in *cakes & cookies, bread*, and foods frequently added to bread such as cheese, was slightly inversely correlated with pattern 2 and pattern 4 (corr=-0.20, -0.16, respectively) and slightly positively correlated with pattern 1 (corr=0.15). Also depicted on Table 10, pattern scores for the PCA-derived patterns applied at the meal level showed different correlations for each meal type, suggesting every meal type contributed differently to the formation of the PCA-habitual dietary patterns. Pattern scores for pattern 1 correlated strongest for dinner meals, followed by lunch and breakfast meals, and afternoon snacks last (corr=0.60, 0.53, 0.53, and 0.34, respectively). Pattern scores for pattern 2 also correlated strongest for dinner meals, followed by breakfast, lunch, and afternoon snacks (corr=0.59, 0.51, 0.42, and 0.39,

respectively). Correlations for pattern 3 pattern scores were also strongest for dinner meals, followed by lunch, then afternoon snacks, and breakfast last (corr=0.60, 0.58, 0.44, and 0.33, respectively). Finally, pattern scores for pattern 4 correlated strongest for lunch meals, followed by dinner, breakfast, and afternoon snacks (corr=0.60, 0.53, 0.36, and 0.26, respectively). The contribution of single day intakes to the formation of PCA-habitual dietary patterns are not shown, as results showed little variation across days and patterns.

Table 10: Spearman correlations of habitual dietary pattern scores at the habitual and meal levels

Dietary pattern scores (habitual and meal levels)[1]	Habitual dietary pattern scores			
	Pattern 1	Pattern 2	Pattern 3	Pattern 4
Habitual diet				
Pattern 1	1.00[2]	.	.	.
Pattern 2	-0.65	1.00	.	.
Pattern 3	0.15	-0.20	1.00	.
Pattern 4	-0.61	0.61	-0.16	1.00
Breakfast	0.53	0.51	0.33	0.36
Lunch	0.53	0.42	0.58	0.60
Afternoon snack	0.34	0.39	0.44	0.26
Dinner	0.60	0.59	0.60	0.53

[1] Habitual level refers to the average daily food consumption; meal level refers to the meal-specific average food consumption. Habitual dietary patterns were PCA-derived using Spearman correlation matrix.
[2] All values on the table had probability < 0.0001.

Note. Data from Schwedhelm et al. *Am J Clin Nutr* 2018 (79)

3.1.4 Dietary networks using Gaussian Graphical Models

Breakfast network

The GGM analysis identified one breakfast network (Figure 9) composed of three different groups of foods. Starting with the food groups on the lower left, the breakfast network shows that *breakfast cereals, other cereals*, *fresh fruits*, *milk & dairy*, *nuts*, and *legumes* were consumed together. The correlation between *nuts* and *other cereals* was especially strong (corr=0.47). There was also a very strong negative correlation between *tea* and *coffee* (corr=-0.64), and a moderately strong negative correlation between *tea* and *milk & dairy* (corr=-0.24). These food groups connected to the second group of food groups through negative correlations between *other cereals* and *breakfast cereals* with *bread*. *Bread* plays a central role in this group, and is directly positively related to consumption of *butter*

(corr=0.30), *sugar & confectionery* (corr=0.34), *margarine* (corr=0.25), *processed meat* (corr=0.38), *cheese* (corr=0.34), and *eggs* (corr=0.20), where *butter* and *margarine* correlated strongly negative with each other (corr=-0.52), and *sugar & confectionery* and *processed meat* correlated moderately negative with each other (corr=-0.17). The third group of foods in the breakfast network is connected to consumption of *processed meat* through the food group of *fruiting & root vegetables* (corr=0.21) and is composed of food groups that resemble more a later meal, such as vegetables, *sauces*, *red meat*, *poultry*, and *fish*. All correlations in this group were positive.

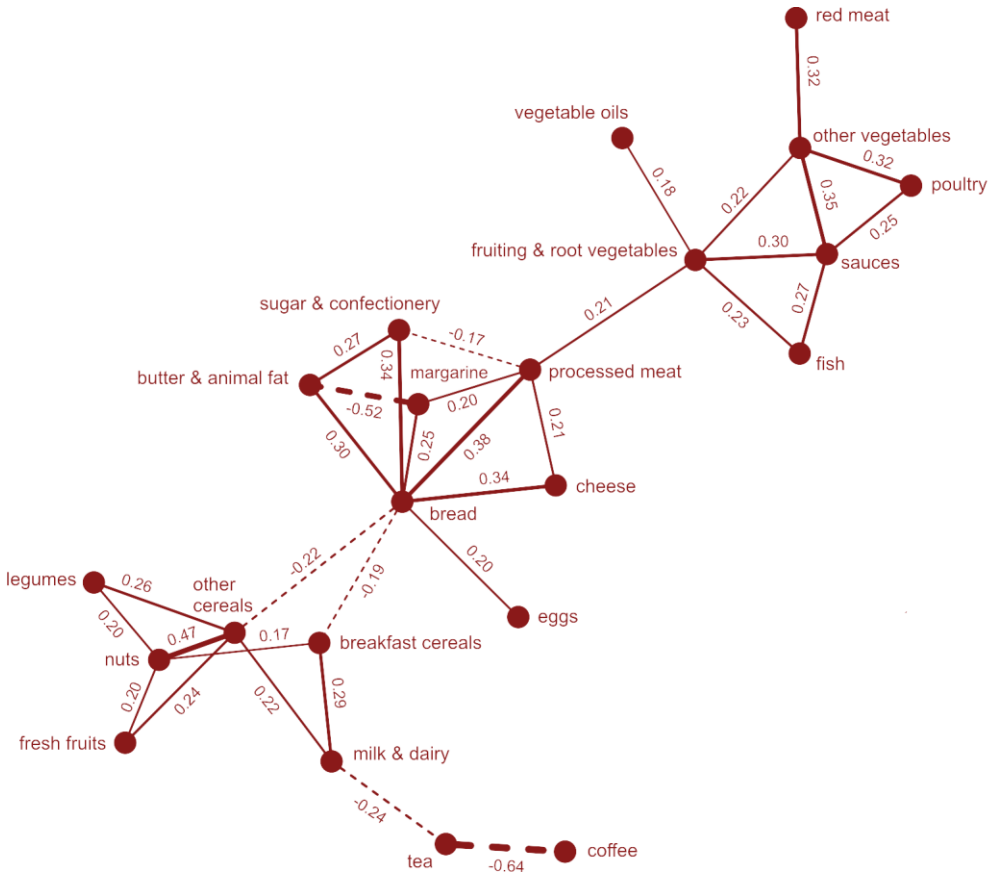

Figure 9: Breakfast GGM dietary network

Nodes represent food groups. Edges represent conditional dependencies between food groups revealed by partial correlation coefficients

Lunch network

GGM identified one lunch network for this meal (Figure 10). With a more complex structure, this network reflects a variable consumption of foods. On the upper right, the network shows a combination of foods formed by *coffee*, *cakes & cookies* and *milk & dairy*. The central part

of this network is found around *red meat* and *potatoes*, which were often consumed together with vegetables such as *cabbages* and *other vegetables*. *Red meat* was inversely related to *fish* (corr=-0.17) and to *processed meat* (corr=-0.22). *Potatoes* correlated strongly negative with *bread* (corr=-0.32) and *pasta & rice* (corr=-0.34).

Figure 10: Lunch GGM dietary network

Nodes represent food groups. Edges represent conditional dependencies between food groups revealed by partial correlation coefficients

Afternoon snack network

The identified afternoon snack network (Figure 11) is similar to the lunch network in that it reflects a variable food intake, however, it is formed by stronger partial correlations among food groups. On the lower right, strong positive correlations show the concomitant consumption of *coffee* with *milk & dairy* (corr=0.45) and *cakes & cookies* (corr=0.46). *Coffee* intake correlates strongly negative with *tea* (corr=-0.37) intake and with *water* (corr=-0.32) intake (also negatively correlated to *cakes & cookies*, corr=-0.25). These food groups related to the rest of the network through a negative correlation between *cakes & cookies* and *bread*

(corr=-0.24). In the upper part of the network, *bread*, *fruiting & root vegetables*, *red meat, potatoes,* and *sauces* played central roles in a more complex structure of relating between food groups. *Bread* was consumed with *margarine*, *processed meat*, *cheese*, and *butter*. *Fruiting & root vegetables* were consumed with *red meat*, *margarine*, *sauces*, *other vegetables*, and *potatoes. Red meat* was consumed with *cabbages, soups, potatoes, other vegetables, sauces*, and *fruiting & root vegetables*. *Potatoes* were consumed with *poultry, soups, cabbages, red meat, sauces*, and *other vegetables*. Finally, *sauces* were more likely to be consumed with vegetables, *fish*, and *pasta & rice*. The strongest partial correlations were between *bread* and *butter*, between *bread* and *processed meat*, and between *potatoes* and *cabbages* (corr=0.56, 0.51, and 0.50, respectively).

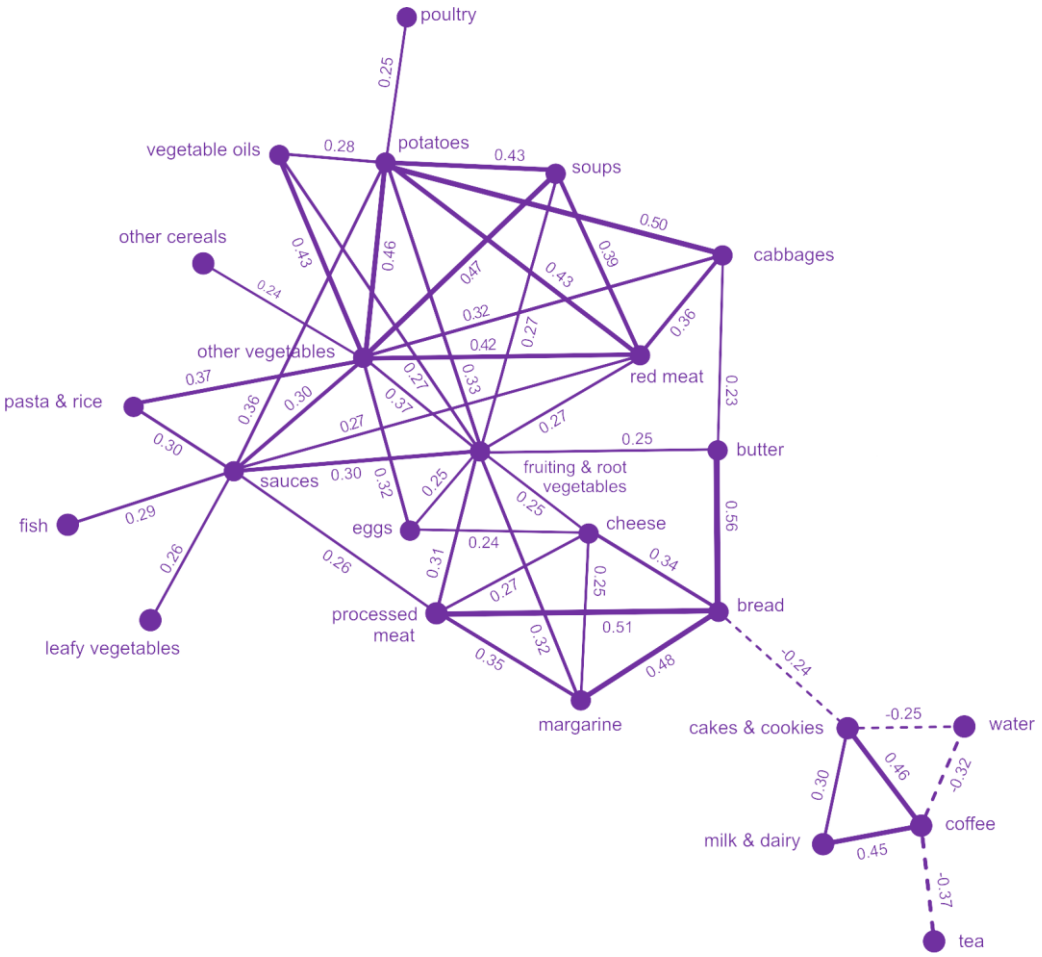

Figure 11: Afternoon snack GGM dietary network

Nodes represent food groups. Edges represent conditional dependencies between food groups revealed by partial correlation coefficients

Dinner networks

Two dinner networks were identified by the GGM analysis, a major and a smaller network (Figure 12). *Bread, potatoes, sauces*, and *other vegetables* play a central role in the major network. *Bread* and the food groups with positive correlations were separated from the rest of the network through negative correlations (*bread* and *pasta & rice*, corr=-0.21; *bread* and *potatoes*, corr=-0.32), suggesting that *bread* is not consumed in the presence of *pasta & rice* or *potato* intake. *Bread* was consumed with *processed meat, margarine, butter,* and *cheese,* but was not often consumed when *potato* or *pasta & rice* were consumed. *Butter* and *margarine*, as well as *bread* and *potatoes* correlated strongly negative (corr=-0.37 and -0.32, respectively). *Potatoes* were consumed with *other vegetables, red meat, cabbages,* and *soups*. *Other vegetables* were also consumed with *sauces, vegetable oils, condiments, eggs, poultry,* and *red meat*. Finally, *sauces* were consumed with *leafy vegetables* and with *pasta & rice*. The smaller dinner network (upper right in Figure 12) consisted of *sweets & confectionery* and beverages (*tea, beer, water*) where *tea* correlated negatively with *beer* and *water* (corr=-0.24 and -0.40, respectively) and *tea* correlated positively with *sugar & confectionery* (corr=0.25).

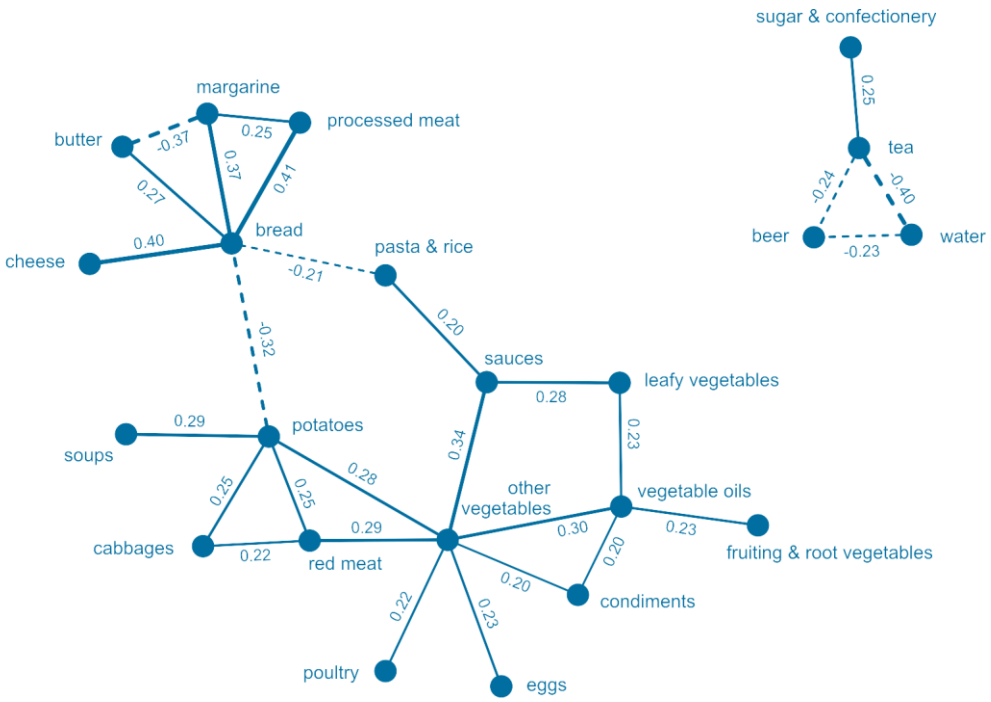

Figure 12: Dinner GGM dietary networks

Nodes represent food groups. Edges represent conditional dependencies between food groups revealed by partial correlation coefficients

Habitual network

GGM analysis identified one habitual network (Figure 13), which was formed by a complex structure of highly-interrelated food groups. In general, the habitual network showed weaker partial correlations than the meal networks, and out of the 39 food groups, 33 of them were part of this complex network, demonstrating the high-interrelation between foods. *Soft drinks, wine,* and *spirits* formed part of this network but did not show in any of the meal networks. The following food groups played central roles in this network: *bread, beer, red meat*, and *potatoes*. Strong positive partial correlations were seen between *bread* and *margarine* (corr=0.29)*, bread* and *processed meat* (corr=0.36)*, beer* and *spirits* (corr=0.26), *milk & dairy* and *breakfast cereals* (corr=0.29), and *fruiting & root vegetables* with *vegetable oils* (corr=0.34). Strong negative partial correlations were seen between *margarine* and *butter* (corr=-0.39), between *potatoes* and *pasta & rice* (corr=-0.32), and between *tea* and *coffee* (corr=-0.30).

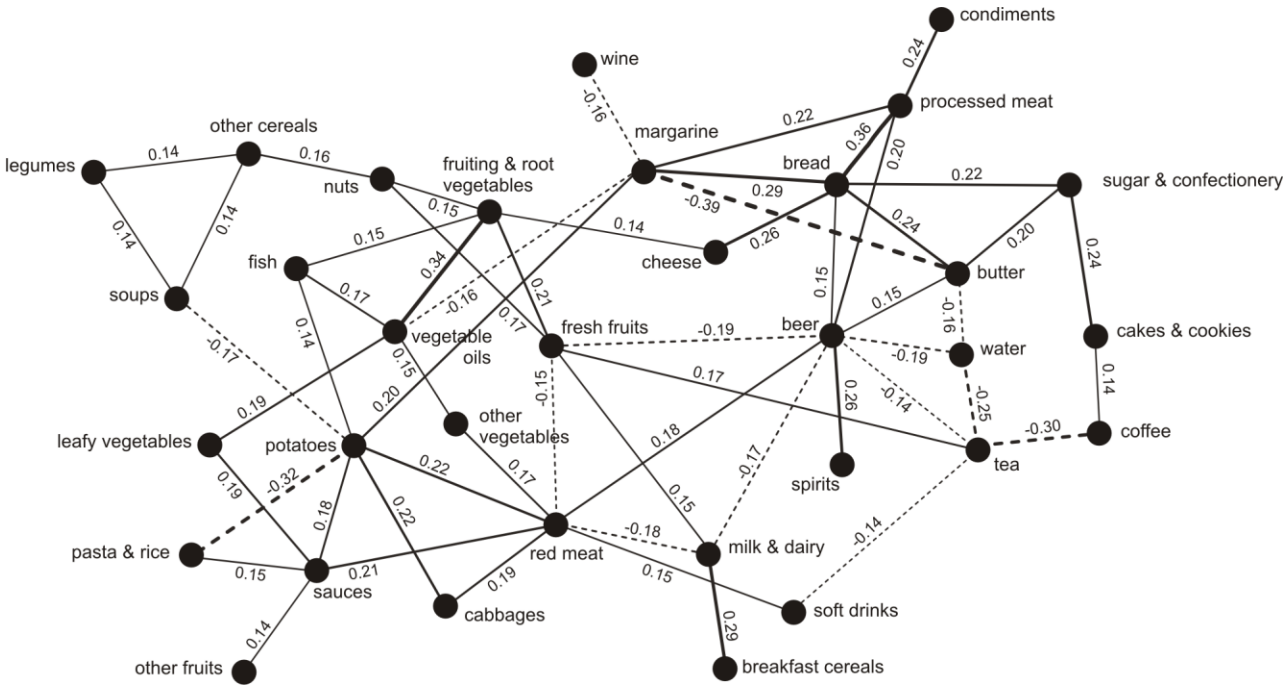

Figure 13: Habitual GGM dietary network

Nodes represent food groups. Edges represent conditional dependencies between food groups revealed by partial correlation coefficients

Comparison of meal and habitual dietary networks

The strongest partial correlations were seen for the afternoon snack dietary network and the weakest for the habitual network. In general, partial correlations between foods were in the same direction (positive or negative) in meal-specific and habitual networks, with one exception: *soups* and *potatoes*, which showed a positive partial correlation in the afternoon snack and dinner networks and negative in the habitual network. Bread and potatoes played central roles in all of the meal networks (except for potatoes in the breakfast network), and also in the habitual network. However, not only food groups playing central roles or showing especially strong correlations were retained from the meal networks to the habitual network, for example, the relation between *breakfast cereals* and *milk & dairy* appeared with a correlation of 0.29 both in the breakfast network and in the habitual network. Although this correlation was fairly strong in breakfast, this was the only meal where it was observed. Another example is *processed meat* and *condiments*, which out of the four main meals was only observed in the lunch network with a partial correlation of 0.19; nevertheless, this relation appeared in the habitual network with a stronger partial correlation of 0.24. On the other hand, food groups with strong correlations in the habitual networks were not necessarily present in the meal networks, for example *beer* and *spirits*, with a partial correlation of 0.26 in the habitual network, was not present in any of the meal-specific networks. The strength of the correlations did not seem to be predictive of whether correlations observed at meals would remain in the habitual network or not; some strong correlations were not retained and some weaker correlations were retained. For instance, *other vegetables* and *sauces* showed strong partial correlations in the breakfast, afternoon snack, and dinner networks, but this relation was not observed in the habitual network, while *legumes* and *soups*, a not particularly strong relation in the lunch network, was also observed in the habitual network.

Also not all relations seen in the habitual network were present in the meal-specific networks, and strength of the partial correlations was in this case also not predictive of whether relations observed in the habitual network actually came from the main meals (meal-specific networks); correlations that were not seen in the meals were mostly weaker (below 0.20), although this was not always the case: *beer* and *spirits* (corr=0.26), *sugar & confectionery* and *cakes & cookies* (corr=0.24), and *fresh fruits* and *fruiting & root vegetables* (corr=0.21).

The extent to which the meal networks were reflected in the habitual dietary network by estimating the percentage of connections between foods in the meal-specific networks that were also present in the habitual dietary network. The results suggest that the dinner network was best reflected in the habitual network, with 64.3% of the dinner network relations between food groups present in the habitual network. Dinner was followed by breakfast, of which 50.0% of the relations were also present in the habitual network, followed by lunch (36.2% of the relations in the habitual network), and finally by afternoon snack, of which only 33.3% of the relations were retained in the habitual network. Figure 14 highlights the relations found also in the habitual network.

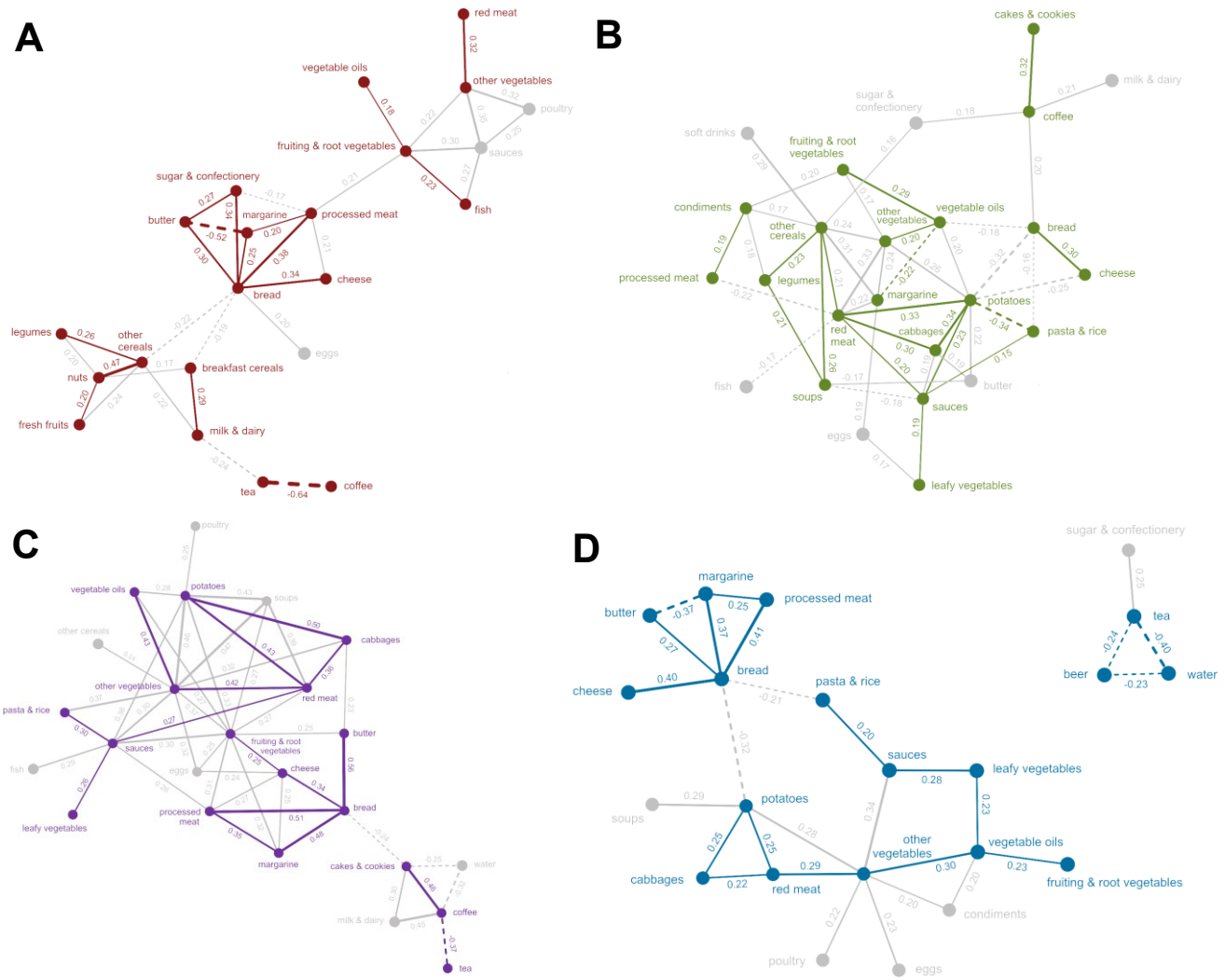

Figure 14: Meal networks emphasizing relations also present in the habitual network

(A) 50.0% of the breakfast network was present in the habitual network; (B) 36.2% of the lunch network was present in the habitual network; (C) 33.3% of the afternoon snack network was present in the habitual network; (D) 64.3% of the dinner networks were present in the habitual network.

Note. Data from Schwedhelm et al. *PLOS ONE* 2018 (Supporting information) (78)

As for the habitual network, 66.1% of the relations were coming from the main meals (also present in the meal-specific networks), leaving 33.9% of the relations that were not present in any of the meal-specific networks. Figure 15 shows highlighted in red all connections on the habitual network that are not present in any of the meal networks.

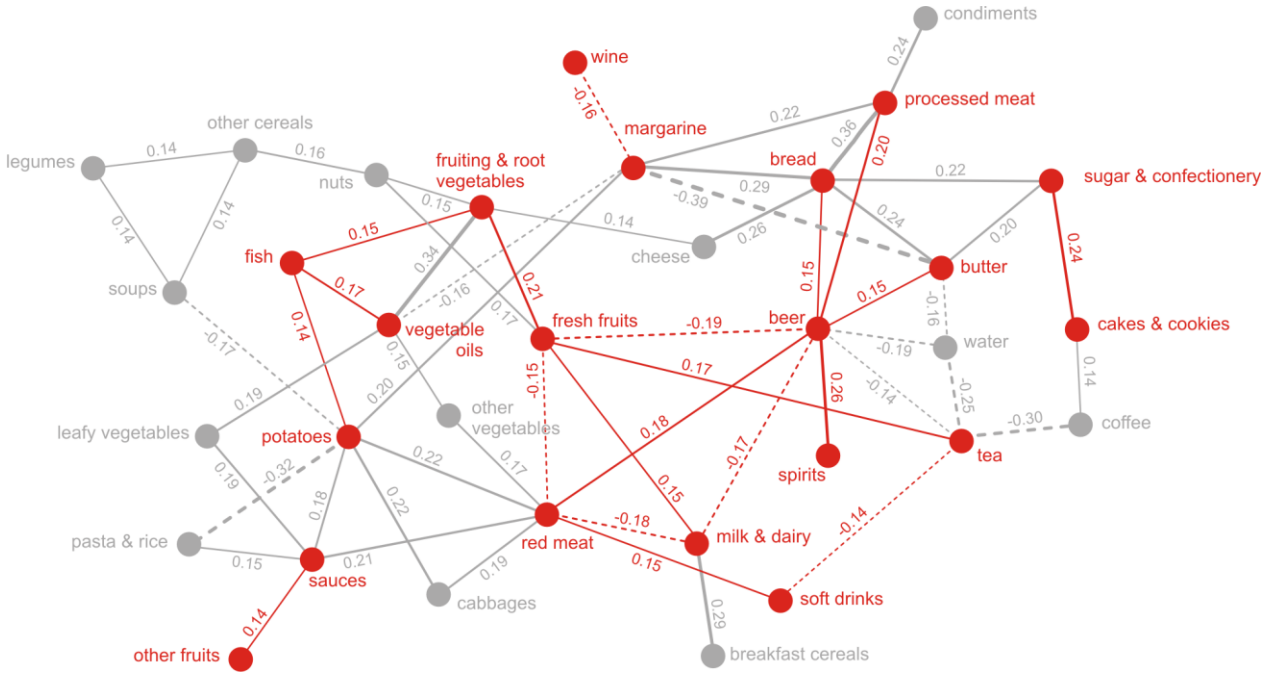

Figure 15: Habitual network emphasizing relations not found in any of the meal-type dietary networks

Note. Data from Schwedhelm et al. *PLOS ONE* 2018 (Supporting information) (78)

3.2 Variation and predictors of dietary intake in its different levels

In free-living humans, dietary intake varies across specific EOs, across days, and across individuals. Understanding this variation is informative about eating behavior. In studies with multiple 24hDRs applied on random days, the variation across days does not contribute to our understanding of eating behavior, since the days do not have special defining characteristics that can explain variation in intake. Rather, the type of the meal (breakfast, lunch, afternoon snack, and dinner) can be informative. Therefore, the variation of energy and macronutrient intake was explored by hierarchically ordering dietary data as follows: intake across specific EOs (level 1: intake level), intake across meal types (level 2: meal type), and intake across individuals (level 3: participants). Figure 16 illustrates this hierarchy and the relevant covariates at their respective level of occurrence that were investigated for the purpose of this thesis. The details on the total number of observations and observations per meal type and participant are in **Table S3**.

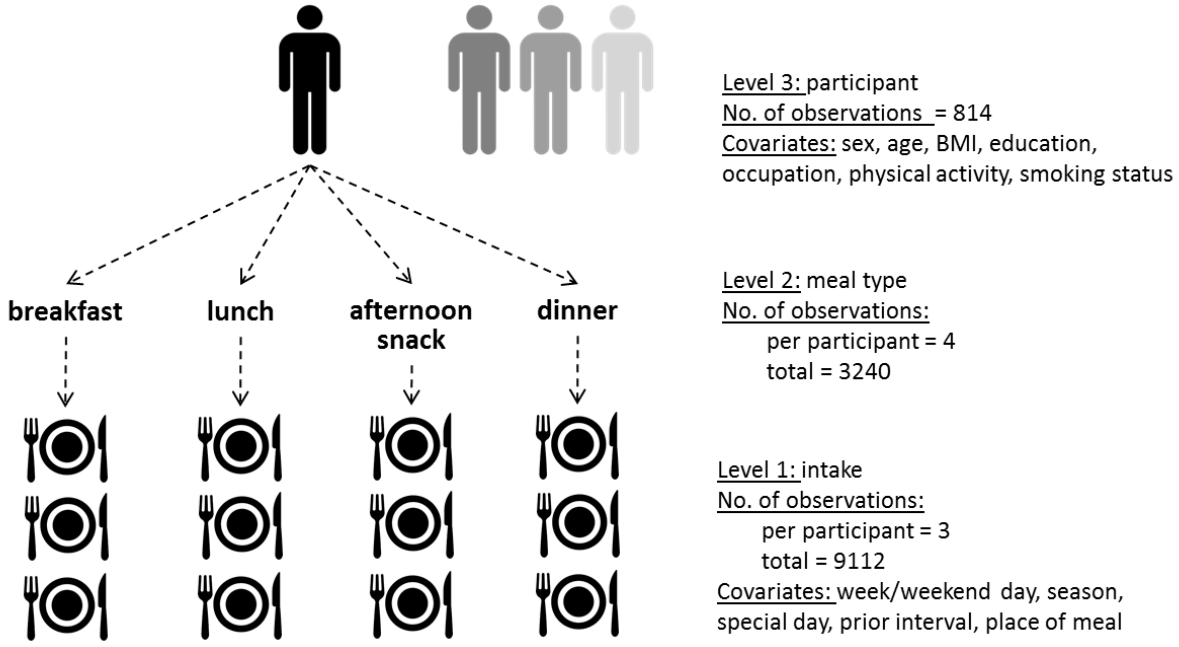

Figure 16: Hierarchical structure of the data

3.2.1 Sources of variation

Differences between meal types explained large proportions of the variance in energy and all macronutrient intakes (carbohydrates, protein, and fat). Explained variance at the meal-type level was 39% for energy, 25% for carbohydrates, 47% for protein, and 33% for fat intake. Differences between participants, however, did not explain much of the variance in intake; this was 0% for energy and protein intake, and 3% for both carbohydrates and fat (Figure 17).

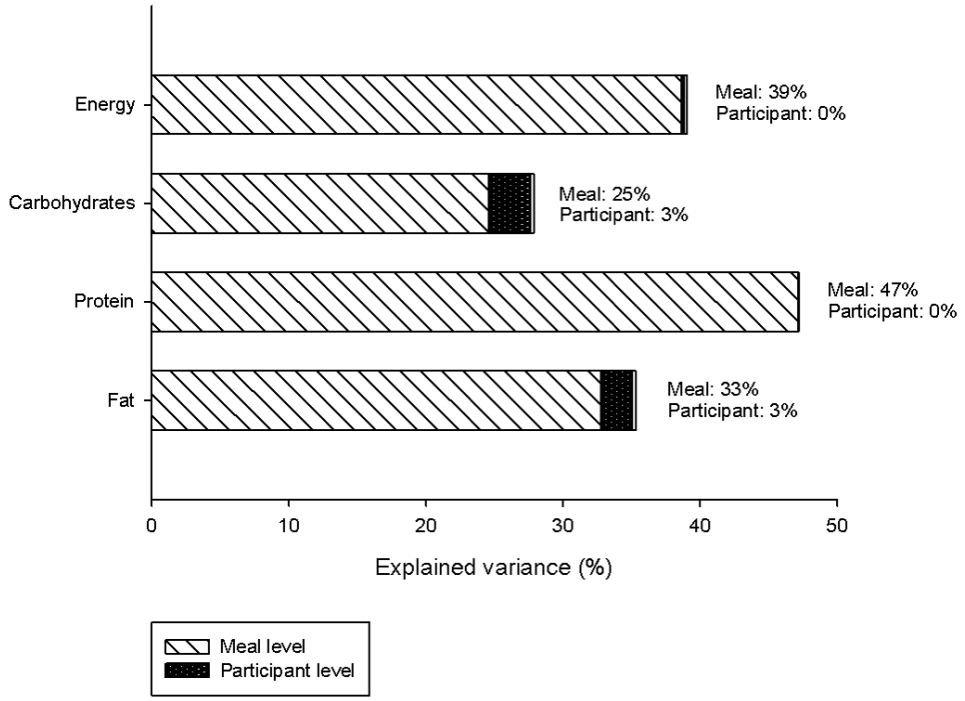

Figure 17: Percent explained variance for energy and macronutrient intake by meal and participant levels

3.2.2 Predictors of dietary intake

As mentioned in the introduction, the day of the week (whether is on a weekday or weekend day), the season of the year, the prior interval (time in hours since the last meal), and the place of meal have been discussed in literature as predictors of dietary intake. Information about the kind of day of the recall, in terms of whether it was a celebration day, religious holiday, etc. (special day or not), which can potentially also influence dietary intake was also available. As these are specific to each intake (eating occasion), they are regarded as intake-level predictors of dietary intake. Known predictors at the participant level include

age, sex, BMI, physical activity level, education level, current occupation (the last two as giving information of the socioeconomic status) and smoking status. These covariates were added to the regression models at their respective level (intake level or participant level) stratified by meal type (Figure 16).

The relative importance of intake-level and participant-level covariates in terms of the explained variance in energy and macronutrient intake, as well as the direction of association for important predictors (covariates accounting for $\geq$10% of the explained variance) are shown on Table 11, and **Table 12** shows the sensitivity analyses, where the models are further adjusted for energy misreporting. In supplementary tables, the detailed results of the random intercept multilevel regression analyses and corresponding Pratt Indices are shown for the main analysis (**Tables S4-S7**) and sensitivity analysis (**Tables S8-S11**).

Table 11: Relative importance of predictors of energy and macronutrient intake[1]

Covariates[2]	Energy (kcal/meal)				Carbohydrates (g/meal)				Protein (g/meal)				Fat (g/meal)			
	Breakfast	Lunch	Afternoon snack	Dinner	Breakfast	Lunch	Afternoon snack	Dinner	Breakfast	Lunch	Afternoon snack	Dinner	Breakfast	Lunch	Afternoon snack	Dinner
Intake-level covariates																
Week/weekend day (y/n)	24%↑[3]	10% ↑	12% ↑	1%	13% ↑	12% ↑	11% ↑	0%	35% ↑	17% ↑	6%	1%	32% ↑	18% ↑	9%	6%
Season (winter/ summer)	3%	0%	1%	4%	10% ↓	22% ↓	2%	5%	1%	0%	1%	4%	1%	2%	0%	10% ↑
Special day (y/n)	0%	10% ↑	7%	16% ↑	0%	9%	5%	29% ↑	4%	1%	10% ↑	15% ↑	1%	9%	9%	9%
Prior interval (hours)	1%	10% ↑	27% ↑	17% ↑	1%	0%	30% ↑	50% ↑	4%	0%	34% ↑	13% ↑	0%	4%	25% ↑	8%
Place of meal (ref: home)																
work	45% ↓	60% ↓	43% ↓	18% ↓	65% ↓	34% ↓	40% ↓	10% ↓	17% ↓	59% ↓	41% ↓	16% ↓	28% ↓	38% ↓	45% ↓	39% ↓
restaurant	27% ↑	4%	1%	43% ↑	13% ↑	12% ↓	1%	4%	40% ↑	8%	2%	51% ↑	37% ↑	8%	4%	27% ↑
other	0%	6%	10% ↑	1%	0%	4%	11% ↑	0%	1%	15% ↓	6%	0%	1%	22% ↓	10% ↑	4%
R-squared	**0.044**	**0.023**	**0.106**	**0.030**	**0.021**	**0.005**	**0.065**	**0.010**	**0.048**	**0.042**	**0.074**	**0.023**	**0.046**	**0.022**	**0.083**	**0.014**
Participant-level covariates																
BMI (kg/m^2)	3%	1%	2%	2%	8%	4%	1%	1%	0%	0%	2%	19% ↑	4%	0%	0%	5%
Age (years)	17% ↑	12% ↑	0%	1%	14% ↑	12% ↑	0%	0%	9%	7%	6%	2%	7%	36% ↑	0%	4%
Sex (M/W)	64% ↓	66% ↓	76% ↓	90% ↓	41% ↓	65% ↓	68% ↓	95% ↓	71% ↓	74% ↓	32% ↓	68% ↓	86% ↓	54% ↓	63% ↓	80% ↓
Education level (ref. no training/ current training)																
technical college	0%	1%	0%	2%	0%	2%	0%	2%	3%	3%	0%	1%	1%	0%	0%	7%
university	0%	1%	0%	2%	2%	0%	0%	2%	3%	2%	0%	9%	3%	1%	3%	0%
Occupation (ref. no job/ retired)[4]																
full time	0%	6%	0%	1%	3%	0%	3%	0%	2%	9%	53% ↑	2%	0%	1%	3%	0%
part time/hourly	5%	0%	1%	1%	8%	0%	0%	0%	6%	0%	0%	0%	0%	0%	1%	3%
Physical activity (h/week)	1%	7%	2%	0%	1%	6%	2%	0%	1%	2%	3%	0%	2%	7%	4%	0%
Smoking status (ref. never smoker)																
current smoker	5%	4%	25% ↑	0%	21% ↑	13% ↑	33% ↑	0%	0%	0%	1%	0%	0%	0%	0%	3%
former smoker	6%	1%	0%	5%	4%	0%	0%	8%	9%	6%	7%	0%	1%	2%	29% ↓	0%
R-squared	**0.179**	**0.276**	**0.072**	**0.282**	**0.172**	**0.253**	**0.067**	**0.203**	**0.102**	**0.212**	**0.033**	**0.253**	**0.120**	**0.220**	**0.063**	**0.220**

[1] Pratt Index, in % contribution to the variance explained by the model (R^2). Might not add up to 100% due to rounding errors from parameter estimates
[2] for dichotomous variables, the information shown is for the underlined category (reference category not underlined)
[3] arrows show the direction of association for covariates accounting for ≥ 10% of the explained variance (important predictors)
[4] full time: ≥ 35h/week; part time/hourly: < 35 h/week.

Energy

Intake-level predictors

Week/weekend day. Whether it was a weekday or a weekend day seems to be an important predictor of the explained variance. There was a higher predicted intake during weekends at breakfast, accounting for 24% of the explained variance. However, for the other meals, this predictor was of lesser importance (10% at lunch, 12% at the afternoon snack, and 1% at dinner) (Table 11).

Season. Whether the recall was in the summer months or in the winter months did not account for much of the explained variance of energy intake in any of the meals (0-4%) (Table 11).

Special day. Whether the participants defined the recalled day as a normal day or special day (religious holiday, celebration meal, travel, or holidays) was an important predictor of the explained variance of energy intake at lunch and at dinner, accounting for 10% and 16% of the explained variance, respectively, predicting a higher energy intake (Table 11).

Prior interval. Duration of prior interval was an important predictor at lunch (10%), afternoon snack (27%), and dinner (17%), predicting a higher energy intake (Table 11).

Place of meal. This was the most important predictor for energy intake (among the intake-level covariates), especially when the place of meal was at work. Having the meal at work predicted a lower intake than when the meal was at home for the meals: breakfast, lunch, and afternoon snack (but not dinner), accounting for 45%, 60%, and 43% of the explained variance, respectively. When the meal took place at a restaurant, this was an important predictor for energy intake at breakfast and dinner, accounting for 27% and 43% of the explained variance, respectively, and predicting a higher intake (Table 11).

The total standardized variance explained by the model (model fit) was as follows: $R^2_{breakfast}$=0.044, R^2_{lunch}=0.023, $R^2_{afternoon\ snack}$=0.106, and R^2_{dinner}=0.030 (Table 11).

Participant-level predictors

BMI. This was not an important predictor of energy intake, as it only accounted for 1-3% of the explained variance of energy intake (Table 11).

Age. Age accounted for 17% of the explained variance at breakfast and 12% at lunch, predicting a higher intake of energy with higher age (Table 11).

Sex. Sex was the main predictor of energy intake at the participant level. This was consistent across all four main meals, and predicted a lower intake in women in comparison to men. At breakfast it had the lowest relative importance, accounting for 64% of the explained variance, and at dinner it had the highest, accounting for 90% of the explained variance (Table 11).

Education level. This was not an important predictor of energy intake (Table 11).

Occupation. Current occupation seemed to account for more of the explained variance for fully employed participants at lunch and partly/hourly employed participants at breakfast, however, it was not an important predictor of energy intake (Table 11).

Physical activity. More of the explained variance was accounted for by physical activity at lunch; however, it was still not an important predictor of energy intake (Table 11).

Smoking status. Current smoking accounted for 25% of the participant-level explained variance for energy intake at the afternoon snack and predicted a higher intake in current smokers versus never smokers (Table 11).

The model fit was $R^2_{breakfast}$=0.179, R^2_{lunch}=0.276, $R^2_{afternoon\ snack}$=0.072, and R^2_{dinner}=0.282 (Table 11).

Sensitivity analysis

Considering under- (EI/TEE < 0.81) and over-reporting (EI/TEE > 1.19) of energy in the models (shown in Table 12) resulted in important changes, as this was an important predictor of energy intake at the participant level. At the intake level, however, results were not substantially different from the main results, with the exception of an increase in the explained variance when the place of meal was work

(for the lunch meal). At the participant level, energy misreporting accounted for a large proportion of the explained variance of energy intake; it was the lowest at breakfast (35%) and highest at afternoon snack (69%). Due to the relativity of these analyses, the proportions of explained variance accounted for by the other factors were reduced. Nevertheless, sex remained an important predictor of energy intake, accounting for 23 to 48% of the explained variance, being lowest at afternoon snack and highest at dinner. The importance of current smoking at afternoon snack also dropped (25% to 9%). In general, the participant-level model fits were better in the sensitivity analysis compared to the main results: $R^2_{breakfast}$=0.250, R^2_{lunch}=0.415, $R^2_{afternoon\ snack}$=0.231, and R^2_{dinner}=0.410 (Table 12).

Table 12: Relative importance of predictors of energy and macronutrient intake; sensitivity analyses adjusting for energy misreporting[1]

Covariates[3]	Energy (kcal/meal)				Carbohydrates (g/meal)				Protein (g/meal)				Fat (g/meal)			
	Breakfast	Lunch	Afternoon snack	Dinner	Breakfast	Lunch	Afternoon snack	Dinner	Breakfast	Lunch	Afternoon snack	Dinner	Breakfast	Lunch	Afternoon snack	Dinner
Intake-level covariates																
Week/weekend day (y/n)	27%↑[4]	6%	11% ↑	3%	16% ↑	2%	10% ↑	1%	35% ↑	15% ↑	5%	1%	34%↑	27% ↑	8%	11% ↓
Season (winter/ summer)	3%	0%	1%	5%	12% ↓	17% ↓	4%	7%	1%	0%	1%	10% ↑	2%	2%	0%	13% ↑
Special day (y/n)	1%	7%	5%	15% ↑	0%	9%	3%	21% ↑	1%	1%	7%	16% ↑	2%	9%	5%	7%
Prior interval (hours)	1%	14% ↑	29% ↑	20% ↑	0%	0%	33% ↑	50% ↑	3%	4%	38% ↑	13% ↑	2%	13% ↑	30% ↑	10%↑
Place of meal (ref: home)																
work	41% ↓	75% ↓	45% ↓	21% ↓	61% ↓	43% ↓	40% ↓	13% ↓	17% ↓	69% ↓	40% ↓	18% ↓	27% ↓	36% ↓	42% ↓	32% ↓
restaurant	24% ↑	0%	1%	36% ↑	7%	20% ↑	0%	0%	41% ↑	6%	3%	39% ↑	33% ↑	7%	7%	19% ↑
other	4%	0%	9%	0%	4%	9%	11% ↑	5%	1%	4%	7%	2%	0%	6%	8%	9%
R-squared	**0.049**	**0.029**	**0.118**	**0.033**	**0.035**	**0.009**	**0.065**	**0.011**	**0.052**	**0.040**	**0.082**	**0.021**	**0.056**	**0.019**	**0.087**	**0.021**
Participant-level covariates																
BMI (kg/m^2)	0%	0%	0%	4%	1%	0%	0%	0%	3%	1%	0%	15% ↑	0%	0%	0%	7%
Age (years)	7%	1%	0%	2%	9%	5%	0%	0%	0%	0%	6%	2%	1%	11% ↑	2%	0%
Sex (M/W)	44% ↓	35% ↓	23% ↓	48%	28% ↓	38% ↓	26% ↓	46% ↓	53% ↓	30% ↓	9%	41% ↓	59% ↓	21% ↓	26% ↓	37% ↓
Education level (ref. no training/ current training)																
technical college	0%	0%	0%	0%	0%	1%	1%	0%	1%	2%	2%	0%	0%	2%	1%	1%
university	0%	0%	1%	3%	2%	0%	1%	4%	4%	0%	1%	1%	2%	1%	1%	1%
Occupation (ref. no job/ retired)[5]																
full time	0%	1%	1%	0%	0%	0%	0%	0%	1%	8%	22% ↑	0%	0%	7%	1%	1%
part time/hourly	5%	0%	0%	0%	9%	0%	0%	0%	6%	0%	7%	0%	0%	0%	3%	2%
Physical activity (h/week)	1%	6%	0%	0%	2%	5%	0%	0%	1%	3%	0%	0%	2%	4%	1%	0%
Smoking status (ref. never smoker)																
current smoker	4%	3%	9%	0%	20% ↑	11% ↑	11% ↑	0%	0%	0%	1%	2%	0%	0%	0%	2%
former smoker	5%	0%	0%	4%	2%	0%	0%	3%	1%	1%	3%	0%	1%	0%	12% ↓	0%
Energy misreporting																
EI/TEE < 0.81	16% ↓	41% ↓	61% ↓	23% ↓	13% ↓	32% ↓	56% ↓	31% ↓	15% ↓	40% ↓	34% ↓	17% ↓	14% ↓	42% ↓	29% ↓	33% ↓
EI/TEE > 1.19	19% ↑	12% ↑	8%	18% ↑	14% ↑	11% ↑	9%	20% ↑	15% ↑	16% ↑	17% ↑	15% ↑	24% ↑	13% ↑	30% ↑	19% ↑
R-squared	**0.250**	**0.415**	**0.231**	**0.410**	**0.223**	**0.382**	**0.201**	**0.310**	**0.127**	**0.362**	**0.118**	**0.345**	**0.157**	**0.356**	**0.167**	**0.380**

[1] n=682 participants with activity sensor data
[2] Pratt Index, in % contribution to the variance explained by the model (R^2). Might not add up to 100% due to rounding errors from parameter estimates
[3] for dichotomous variables, the information shown is for the underlined category (reference category not underlined)
[4] arrows show the direction of association for covariates accounting for ≥ 10% of the explained variance (important predictors)
[5] full time: ≥ 35h/week; part time/hourly: < 35 h/week

Carbohydrates

Intake-level predictors

Week/weekend day. Intake on a weekend day was predictive of higher carbohydrate intake, accounting for 13% of the explained variance at breakfast, 12% at lunch, 11% at afternoon snack, but it was not predictive of carbohydrate intake at dinner (0%) (Table 11).

Season. This covariate accounted for 22% of the explained variance at lunch and for 10% at breakfast, predicting a lower carbohydrate intake in the summer (Table 11).

Special day. Whether it was a special day was an important predictor of carbohydrate intake at dinner, accounting for 29% of the explained variance in the intake level, predicting a higher carbohydrate intake when it was a special day. In the other meals, special day was not an important predictor, though it also accounted for 9% and 5% of the explained variance at lunch and afternoon snack, respectively (Table 11).

Prior interval. The time since the last meal was the most important intake-level covariate for dinner, accounting for 50% of the explained variance and was the second most important predictor for afternoon snack, accounting for 30% of the explained variance. In both cases, a longer prior interval was associated with a higher carbohydrate intake. For breakfast and lunch, this was not an important predictor of carbohydrate intake (Table 11).

Place of meal. As for energy intake, also in the case of carbohydrates place of meal (workplace) was the most important intake-level predictor at breakfast, lunch, and afternoon snack, accounting for 65%, 34%, and 40% of the explained variance, respectively. Having the meal at work was predictive of a lower carbohydrate intake (compared to having the meal at home). The other places of meal accounted for a lower amount of the explained variance: at a restaurant, it accounted for 13% and 12% at breakfast and lunch, respectively; having the meal in another place accounted for 11% of the explained variance at afternoon snack (Table 11).

The models had fits of $R^2_{breakfast}$=0.021, R^2_{lunch}=0.005, $R^2_{afternoon\ snack}$=0.065, and R^2_{dinner}=0.010 (Table 11).

Participant-level predictors

BMI. BMI accounted only for 8% of the explained variance at breakfast and 4% at lunch, therefore this was not a very important predictor of carbohydrate intake at the participant level (Table 11).

Age. Higher age was predictive of higher intakes of carbohydrates, accounting for 14% and 12% of the explained variance at breakfast and lunch, respectively (Table 11).

Sex. This was the main predictor of carbohydrate intake, accounting for 41%, 65%, 68%, and 95% of the explained variance at the participant level at breakfast, lunch, afternoon snack, and dinner, respectively, predicting a lower intake of carbohydrates in women than in men (Table 11).

Education level. Education level was not an important predictor of carbohydrate intake at any of the meals (Table 11).

Occupation. Current occupation was not an important predictor of carbohydrate intake at any of the meals. Still, it accounted for 8% of the explained variance at breakfast for participants employed part time/hourly (Table 11).

Physical activity. Physical activity was not an important predictor of carbohydrate intake at any of the meals (Table 11).

Smoking status. Current smoking was an important predictor at breakfast, lunch, and afternoon snack, respectively accounting for 21%, 13%, and 33% of the explained variance for carbohydrate intake at the participant level, predicting a higher carbohydrate intake in current smokers than in never smokers (Table 11).

Model fits were $R^2_{breakfast}$=0.172, R^2_{lunch}=0.253, $R^2_{afternoon\ snack}$=0.067, and R^2_{dinner}=0.203 (Table 11).

Sensitivity analysis

At the intake level, most results remained substantially unchanged. However, at lunch, the relative importance of week/weekend day decreased after adjusting for energy misreporting, and the relative importance of place of meal increased. At the participant level, energy misreporting, especially for EI/TEE < 0.81 (indicative of

under-reporting) was a very important predictor of carbohydrate intake. Overall, energy misreporting (over- and under-reporting) accounted for 27-65% of the explained variance, being lowest at breakfast and highest at afternoon snack. Sex still accounted for 26-46% of the explained variance in the different meals. Current smoking remained an important predictor at breakfast (20%) but not as important at afternoon snack as it was in the main results (previously accounting for 33% of the explained variance, vs. 11% in the sensitivity analysis). The participant-level model fits were improved compared to the main analysis: $R^2_{breakfast}$=0.223, R^2_{lunch}=0.382, $R^2_{afternoon\ snack}$=0.201, and R^2_{dinner}=0.310 (Table 12).

Protein

Intake-level predictors

Week/weekend day. This accounted for 35% of the explained variance at breakfast and 17% at lunch (but not much at afternoon snack or dinner), predicting a higher protein intake if the recalled day was on a weekend day (Table 11).

Season. Whether it was summer or winter did not account for an important part of the explained variance for any of the meal types (Table 11).

Special day. Special day accounted for 15% of the explained variance for protein intake at dinner and for 10% at afternoon snack. A higher protein intake was predicted on special days (Table 11).

Prior interval. The time since the last meal was an important predictor at afternoon snack and dinner, accounting for 34% and 13% of the explained variance in protein intake, respectively, predicting a higher protein intake with a longer prior interval (Table 11).

Place of meal. Having the meal at a restaurant was the most important predictor of the explained variance in protein intake at breakfast and dinner, accounting for 40% and 51% of the explained variance at the intake level, respectively and predicting a higher protein intake for restaurant meals than for meals at home. The workplace was the most important predictor at lunch and afternoon snack, accounting for 59% and 41% of the explained variance at the intake level, respectively and predicting a lower intake when at work than when at home (Table 11).

The model fits were as follows: $R^2_{breakfast}$=0.048, R^2_{lunch}=0.042, $R^2_{afternoon\ snack}$=0.074, and R^2_{dinner}=0.023 (Table 11).

Participant-level predictors

BMI. BMI was an important predictor for explained variance in protein intake at dinner, where it accounted for 19% of the explained variance, predicting a higher protein intake with higher BMI. At the other meals, this was an unimportant predictor of protein intake (Table 11).

Age. Age accounted for 6-9% of the explained variance at breakfast, lunch, and afternoon snack, and only for 2% at dinner, and is therefore not considered as an important predictor of protein intake (Table 11).

Sex. Sex was the main predictor of protein intake at the participant level, accounting for 71%, 74%, 32%, and 68% of the explained variance at breakfast, lunch, afternoon snack, and dinner, respectively. It predicted lower intake by women than by men (Table 11).

Education level. Education level was generally unimportant for all meals. Still, university level education accounted for 9% of the explained variance at dinner (Table 11).

Occupation. At the afternoon snack, full time occupation was the most important predictor, which accounted for 53% of the explained variance, predicting a higher protein intake by full-time employed participants than by those who are retired/not employed. At lunch, a full time current occupation accounted for 9% of the explained variance but at the other meals it was relatively unimportant (Table 11).

Physical activity. Physical activity did not have an important impact on fat intake in any of the meals (Table 11).

Smoking status. It was not an important predictor of protein intake, nevertheless, past smoking (former smoking) accounted for 6-9% of the explained variance at breakfast, lunch, and afternoon snack (Table 11).

The model fit for the participant-level part of the models were $R^2_{breakfast}$=0.102, R^2_{lunch}=0.212, $R^2_{afternoon\ snack}$=0.033, and R^2_{dinner}=0.253 (Table 11).

Sensitivity analysis

At lunch, the workplace as the place of meal was more important after adjusting for energy misreporting (accounting for 69% of the explained variance at the intake level, vs. 59% in the main analysis). At dinner, season accounted for 10% of the explained variance at this level (vs. only 4% in the main analysis), where protein intake was greater in the summer season. Also at dinner, place of meal decreased in importance as a predictor of protein intake when the meal was in restaurants, accounting for 39% of the explained variance (down from 51% in the main analysis). The largest differences in the sensitivity analysis, however, were on the participant-level covariates: sex remained the main predictor of protein intake at breakfast and dinner (accounting for 53% and 41% of the explained variance, respectively), but energy misreporting, namely under-reporting (EI/TEE < 0.081), was the main predictor at lunch and afternoon snack (accounting for 40% and 34% of the explained variance, respectively). BMI remained an important predictor for protein intake at dinner, accounting for 15% of the explained variance at the participant level. Age and current smoking were no longer important predictors of protein intake after adjusting for energy misreporting. Nevertheless, a full time current occupation remained an important predictor of protein intake at afternoon snack, accounting for 22% of the explained variance. The participant-level model fits were better than in the main analysis, with $R^2_{breakfast}$=0.127, R^2_{lunch}=0.362, $R^2_{afternoon\ snack}$=0.118, and R^2_{dinner}=0.345 (Table 12).

Fat

Intake-level predictors

Week/weekend day. Whether the meal was on a weekday or weekend day was an important predictor of fat intake for breakfast and lunch meals, accounting for 32% and 18% of the explained variance and predicting a higher intake in the weekend (Table 11).

Season. The season was an important predictor of fat intake only for the dinner meals, accounting for 10% of the explained variance and predicting a higher intake in the summer (Table 11).

Special day. Whether it was a religious holiday, celebration meal, travel, or holidays was not a very important predictor of fat intake. Nevertheless, it accounted for 8-9% of the explained variance at lunch, afternoon snack, and dinner (Table 11).

Prior interval. The time since the last meal was an important predictor of fat intake at the intake level for the afternoon snack meal only, where it accounted for 25% of the explained variance, predicting a higher fat intake with a longer prior interval (Table 11).

Place of meal. The main predictor of fat intake at the intake level was place of meal. When the meal was consumed in a restaurant, the fat intake was greater in the breakfast and dinner compared to home meals, accounting for 37% and 27% of the explained variance in this level, respectively. When the meal was consumed at work, the fat intake was less in all four meals compared to home meals, accounting for 28% of the explained variance at breakfast, 38% at lunch, 45% at the afternoon snack, and 39% at dinner. Finally, when the meal was consumed in another place (on-the-go), fat intake was lower at lunch (22% of the explained variance) but higher at the afternoon snack (10% of the explained variance) (Table 11).

The model fits for the intake level part of the models were $R^2_{breakfast}$=0.046, R^2_{lunch}=0.022, $R^2_{afternoon\ snack}$=0.083, and R^2_{dinner}=0.014 (Table 11).

Participant-level predictors

BMI. This was not an important predictor of fat intake at any of the meals (Table 11).

Age. At lunch, age accounted for 36% of the explained variance, predicting a higher fat intake with higher age. In the other meals age was not an important predictor of fat intake at the participant level (Table 11).

Sex. Sex was the main participant-level predictor of fat intake, accounting for 86% of the explained variance at breakfast, 54% at lunch, 63% at afternoon snack, and 80% at dinner, predicting a lower intake in women than in men (Table 11).

Education level. This covariate had little relative importance as a predictor of fat intake at the participant level (Table 11).

Occupation. Current occupation was also not an important predictor of fat intake at the participant level (Table 11).

Physical activity. Like education level and occupation, physical activity did not account for an important part of the explained variance (Table 11).

Smoking status. Compared to never smoking, only former smoking at the afternoon snack was an important predictor of fat intake at the participant level, accounting for 29% of the explained variance; fat intake was lower in former smokers than in never smokers (Table 11).

The fit for the participant-level part of these models were $R^2_{breakfast}$=0.120, R^2_{lunch}=0.220, $R^2_{afternoon\ snack}$=0.063, and R^2_{dinner}=0.220 (Table 11).

Sensitivity analysis

At lunch, the relative importance of week/weekend day and prior interval increased by 9% each, while the importance of place of meal (other place) decreased by 16%. Nevertheless, results at the intake level were mostly consistent with the main analysis. As for the participant-level part of the model, energy misreporting was, together with sex, the main predictor of fat intake. Overall, energy misreporting (over- and under-reporting) accounted for 38%-59% of the explained variance, being lowest at breakfast and highest at afternoon snack. Specifically, reporting a lower energy intake than the energy expenditure (EI/TEE < 0.81) was greatest at lunch, where it accounted for 42% of the explained variance. The importance of the other participant-level covariates decreased proportionally; sex accounted for 59%, 21%, 26%, and 37% of the explained variance in fat intake at breakfast, lunch, afternoon snack, and dinner, respectively. Age was still an important predictor at lunch, accounting for 11% of the explained variance (down from 36% in the main analysis) and current smoking was also still an important predictor at the afternoon snack, where it accounted for 12% of the explained variance in fat intake (down from 29% in the main analysis). The participant-level model fits were improved in the sensitivity analysis: $R^2_{breakfast}$=0.157, R^2_{lunch}=0.356, $R^2_{afternoon\ snack}$=0.167, and R^2_{dinner}=0.380 (Table 12).

4 Discussion

In the past few decades, the interest in diet has mostly concentrated on habitual dietary patterns. Such constructs, however, are difficult to interpret in terms of eating behavior, as people consume foods in meals. With this in mind, there has been a recent increase in nutritional epidemiological studies focusing on meals. Thus, the aim of this thesis was to elucidate the role of meals in the formation of commonly used habitual dietary patterns and in displaying of eating behavior through investigating correlations between foods as well as the origin of dietary intake variability, both within and between individuals. The statistical methods presented in this thesis offer a novel way to assess dietary intake in the context of meals. Such methods can be applied to different populations to better understand their eating behavior. This knowledge will provide pivotal information useful for planning interventions aiming to influence dietary intake.

4.1 The role of meals in dietary pattern formation

Firstly, habitual dietary patterns derived with methods based on the correlation/covariance matrices of the original variables (i.e., PCA and GGM networks) related to some extent but not fully to the correlation structures between foods at each of the main meals. Strong positive correlations like the one between bread and cheese and strong negative correlations like the one between butter and margarine were present in the habitual dietary patterns as well as in the meal networks and correlation analyses. However, the strength of the correlations was generally weaker at the habitual level than at the meal level and some correlations in the habitual level were not explained, as well as correlations from the meals that were not reflected at the habitual level. The meals with the strongest correlations were afternoon snack, followed by breakfast. However, these two meals were the least reflected in the PCA habitual dietary patterns. Out of the four main meals, dinner played the most important role in the formation of habitual dietary patterns derived with both PCA and GGM methods. Finally, for PCA habitual dietary patterns, breakfast played a less important role in their formation due to the high consistency of this meal, therefore, not contributing greatly to the variance explained, which is the basis of PCA. These findings suggest that consistent meals are underrepresented with the PCA method but not with the GGM networks method to derive habitual dietary patterns. The consistency of a meal is however not necessarily related to the importance or impact of a meal's contribution to the overall dietary intake. In fact, large, consistent meals could offer a good opportunity for dietary interventions aimed at

improving diet quality in the long term, as adherence to dietary recommendations could be facilitated.

Some explanations exist for the weaker correlations between food groups observed at the habitual level, also observed in the habitual dietary patterns derived with GGM networks; these may arise due to an increased intra-subject variability of meal-aggregated data, such as the one from FFQs (102). Furthermore, some of the differences observed between analyses based on the habitual diet and meal-specific analyses might be due to habitual dietary intake data also reflecting participants' overall dietary preferences or being affected by other characteristics of the participants (103). Also, intakes at smaller EOs, such as snacks, are not considered in the main meals but are considered at the habitual level. When interpreting the habitual dietary patterns often used in nutritional epidemiological studies, researchers and public policy experts should be aware that such constructs do not reflect the food intake consumed at meals.

The GGM networks revealed the dependency structure between food groups, helping further explain correlations between food groups. A recent study by *Iqbal et al*. (28) using this method in the whole cohort of the EPIC-Potsdam study (from which the study sample analyzed in this thesis was drawn) revealed networks at the habitual level (derived from FFQ data) which showed a few similarities with the here presented networks, although they were structurally still very different due to the different format of the dietary exposure and therefore do not represent meal level intake-specific relationships. Some common characteristics with the identified dietary networks and correlation analyses were the positive correlations between red meat and sauces, fruits and vegetables, and the negative correlation between margarine and butter. Furthermore, similar to the identified habitual network, potatoes, red meat, and cabbages had a central role in their principal networks (28). The method of GGM networks applied to dietary data is a new concept and it offers great potential for analyzing and visualizing complex, highly interrelated data structures often seen in the field of nutritional epidemiology. Furthermore, building scores of adherence, as in PCA dietary patterns, is possible with this method, therefore offering great practical potential for diet-disease studies (104). Not surprisingly, GGM networks and PCA share considerable similarity, as both are based on correlations. However, GGM networks offer greater insight about the combination of intakes in relation to each other, characteristic important in meal-based analyses since the high interrelation has its core at the meal level (20). Therefore, GGM networks are an important tool for understanding dietary intake when applied to meal-specific data.

To our knowledge, no study has focused on relating commonly-used habitual dietary patterns to food intake in meals. Notwithstanding, few studies have applied methods often used on the habitual level to meal-structured data to derive dietary patterns. *Woolhead et al.* (105) applied PCA to food diary information in a sample of Irish adults to derive meal-specific dietary patterns. In total, the authors found 63 different meal patterns. However, differences between meal-level and habitual-level patterns were not within the scope of this study, therefore rendering this study incomparable to the here discussed findings. Other meal-based studies have mostly concentrated in one dimension or aspect of meals. For instance, *Vainik et al*. (36) investigated the impact of place of meal, people present or social situation, as well as regularity or consistency of consumption on dietary intake and found that eating patterns were more consistent in the morning than in the evening (36), which is in line with the finding of a consistent breakfast meal. Other studies have focused rather on one meal, namely breakfast; *Reutrakul et al*. (45) focused on breakfast skipping, and *Iqbal et al*. (47) focused on breakfast quality and its association with cardiometabolic risk profiles.

4.2 Variation and predictors of dietary intake in its different levels

Dietary intake varies greatly within and between individuals. The results showed that the differences between meal types explain a large part of this variation whereas differences between individuals explained only a very limited amount, which concentrated mostly on individual preferences regarding carbohydrates or fat. The remaining, unexplained variance in intake corresponds to the intake level, meaning the specific intake occasion on a specific day. The most important predictors explaining the variance at the intake level were place of meal (for all meal types), week/weekend day (for breakfast meal mostly), and prior interval (for the afternoon snack and dinner meals). At the participant level, the main predictor was sex (for all meal types). However, the investigated predictors only explained a limited part of the variation of energy and macronutrient intake within the type of meal. Also, energy misreporting appears to be an important predictor, especially for afternoon snacks in respect to carbohydrate intake. These findings suggest that the context of meals determine energy and macronutrient intake to an important extent. Therefore, if there is the intention of modifying dietary intake in terms of energy and macronutrient intake, considering the context of meals will be very important

Few studies have investigated the within-person variance in dietary intake other than by day. However, there are many situational factors affecting dietary intake, and such factors arise in the specific meals or intake occasions. A recent study compared within-person eating

behavior and energy intake when breakfast was omitted versus on the days with breakfast consumption. They found that skipping breakfast shifted the lunch meal earlier in time and resulted in a larger intake at lunch than when breakfast was consumed. However, the overall diet quality in terms of energy and macronutrient density was similar overall in the day (106). In comparison, not enough participants in the study sample used for these analyses skipped breakfast and therefore investigating this factor was not possible. Nevertheless, such an impact of breakfast skipping would have been reflected in the results through an exceptionally large prior interval (time from dinner the previous day until the next intake episode – after the missed breakfast –on the following day). As observed in the results, prior interval actually had a greater impact in the carbohydrate intake for meals later in the day (afternoon, evening). This finding suggests that efforts to reduce dietary intake (especially intake of carbohydrates), such as efforts targeting weight loss, might be more effective if longer prior intervals in the morning and shorter ones in the afternoon and evening meals are emphasized. Another study investigating the impact of contextual factors was the one by de *Castro et al*. (35), which observed positive associations of meal size with number of people present and with hunger. In the data used for this thesis, information about number of people present at each meal as well as information about the hunger level of participants was missing, but our findings for duration of the prior interval in our study relates to the observation of *de Castro et al*. of larger meal size with longer after-meal intervals in the afternoon and evening (35).

The here presented results showed that whether the meal took place on a weekday or weekend day was an important predictor of the explained variance in energy as well as in all three macronutrients at breakfast and at lunch, but less so at the later meals (afternoon snack and dinner), predicting a higher intake on weekends. Other studies have similarly documented a higher energy intake on weekends. For example, Yang et al. (107) observed a higher energy intake resulting from higher fat and alcohol intake in a study sample of Canadian adults, despite observing lower intakes of carbohydrates and protein. The discrepancies between the results on this thesis and the results of Yang et al. in terms of carbohydrate and protein intake could be due to differences in the population and cultural background.

Season contributed to the explained variance for carbohydrate intake at breakfast and fat intake at dinner. However, this contribution was small relative to the other predictors of intake, which could be due to a rather homogeneous population in terms of socioeconomic level. If lower socioeconomic levels were better represented in the study population used for

the purpose of this thesis, a higher impact of seasonality on food choice would be expected, which would then be reflected in energy and macronutrient intake. Other studies have observed a larger impact of the seasons on diet. For instance, one study observed a peak in daily intake (11-14% higher intake) in fall compared to the other seasons (35). Another study assessed season similarly to how it was done in these analyses as fall/winter and spring/summer and found food energy density to be higher in fall/winter (108). A systematic review and meta-analysis on the topic observed a higher energy intake in winter (109). None of these studies assessed the effect of season on specific meal types

The last intake-level predictor of intake to be discussed is place of meal. This was the main intake-level predictor, predicting a higher intake in breakfast and dinner when the meal was in a restaurant. Various studies have investigated the effect of out-of-home meals on meal size and dietary intake. It has been shown for example, that out-of-home meals result in increased food intake due to larger portion sizes and ambience factors such as lighting and music, which prolong the meal duration (56). However, the place of meal could have a greater effect on meal size depending on the weight of the individuals. A study suggests that overweight/obese individuals are more susceptible to environmental cues when eating out of home (110). In our study sample, the majority of participants were overweight or obese and this could therefore partly explain the importance of restaurant as the place of meal for energy and macronutrient intake. Other contextual factors of meals have been found to impact food intake: at friends' places, restaurants, bars, and cafeterias, portion sizes are larger, while at home, at work, and at school, they are smaller (66). This was in line with the findings of this thesis in that meals at restaurants predicted a higher intake and meals at work a lower intake.

Also for participant-level predictors there haven't been any meal-specific studies to our knowledge. However, in general, a study found that age, sex, and self-efficacy were associated with fat intake while education level was not related (111). These findings are in line with the results of this thesis in that sex and age (at selected meal types) were predictors of intake and that education level was not. A study on personality and situation predictors of consistent eating patterns found physical activity to be a predictor of eating consistency (36). This association was not found in the here investigated study population.

As for smoking status, a previous study covering all EPIC study centers across Europe observed a lower carbohydrate intake in some of the study centers, but not the EPIC-Potsdam center (112), of which our study population is a sub-cohort. While the analyses

here presented showed a higher intake of carbohydrates in current vs never smokers at breakfast, lunch, and afternoon snack, the absence of such an association in the above described EPIC study might be due to differences in the distribution of participants across smoking categories in the sub-cohort study in comparison to the full EPIC-Potsdam cohort.

Finally, a very important predictor of dietary intake (reporting) in this study was misreporting of energy, which was calculated as a participant-level covariate with the usual intakes. A recent study in the same population found that cakes and cookies were especially underreported (99). Because in the German culture, cakes and cookies are often consumed in the afternoon, together with coffee, the observed important role of energy underreporting of carbohydrates in the afternoon snack that was observed in the present analyses can be related to the underreporting of cakes and cookies previously observed in this study population. Previous studies have related underreporting of energy with sex (more frequent in women), and BMI or adiposity (more likely in overweight/obese people) (113-115). However, energy over-reporting has been less explored. Reasons for the over-reporting of energy observed in this thesis could be that food intake during unstructured meals, such as afternoon snacks, is more difficult to keep track of and report accurately.

5 Strengths and limitations

The investigation presented within this thesis has its strengths and limitations. Until now, little research has been done at the meal level and most research has been done on limited aspects of meals, i.e., patterning, format, or context. In this thesis, aspects from all three dimensions of meals were investigated:

- Patterning: consistency and frequency of consumption, predictors of dietary intake (prior interval);
- Format: correlations between food groups, meal dietary patterns with GGM networks, contribution of meals to habitual dietary patterns (PCA, GGM networks);
- Context: predictors of dietary intake (place of meal, weekday/weekend day, season, special day);

while retaining the perspective of the individual and the accompanying participant-level (between-person) influencing factors.

Strengths specific to the study design used for the analyses include the three non-consecutive 24hDRs for each participant with information structured by EOs. Few large epidemiological studies have assessed dietary intake on multiple occasions and most evaluate it by applying one FFQ, which does not provide meal-specific information. Furthermore, as mentioned in the introduction, dietary assessment is more precise from 24hDRs than from FFQs (if 24hDRs are applied on multiple, random days) (13, 14). Moreover, the multiple 24hDRs were performed by trained interviewers using the standardized EPIC-Soft program used already in various studies. Thanks to these study design characteristics, these data were suitable for answering the meal-related research questions. Furthermore, the EPIC-Potsdam validation sub-study provided ample information surrounding each meal, such as the time since the last meal and the place of the meal. Thanks to this extensive dataset, it was possible to assess the impact of such factors on dietary intake.

Strengths related to the methodology used include the application of robust and novel statistical methods to analyze the data. Methods were adapted according to the distribution of the data (for example, PCAs were performed with Spearman correlation coefficients instead of the usual Pearson coefficients). Also, novel methods in the field of nutritional epidemiology were used: both the methods of GGM networks and the calculation of the Pratt Index as an application in multi-level models are established methods in other fields such as

metabolomics and genomics (GGM networks) (27, 116) and public health and the education sector (Pratt Index) (117, 118). These methods have great potential to investigate dietary intake in the context of meals and hope that this thesis has provided the framework for the application of such methods.

Despite these strengths, there are several limitations. Regarding the study design, the number of repeated 24hDRs was appropriate to separate the within and between variability and to achieve modest precision of dietary intake (17, 19). However, 4-6 applications of the 24hDR are recommended for a more precise estimation (18). Also, it is a general limitation in the field of nutritional epidemiology that the long-term daily intake is impossible to measure error-free (2, 12); apart from recall bias, misreporting and misclassification are important methodological issues that can create measurement error (119, 120). The results presented in this thesis are limited to this specific population, as behaviors (including eating behavior) are known to vary from population to population and cannot be generalized (33, 34, 55, 72). Nevertheless, the main contribution of this thesis lies with the methodology; the here presented meal-based analyses should be applied accordingly to the population of interest to learn about their specific meals composition and eating behavior.

The limitations specific to the methodology used within this thesis include the challenging structure of the meal-specific data. Working with dietary data in the meal format implies dealing with a challenging data distribution similar to that known of episodically consumed foods, with a high frequency of zeros and a resulting positively-skewed distribution (101). Non-parametric methods were applied when possible or data were transformed according to the method's assumptions (25, 89). Nevertheless, one calculation in this thesis was not possible to adapt to the skewed distribution: the ICC for consistency of consumption for every food group. Because transforming the data often affects interpretability, it was considered that as an exploratory analysis, the performed calculation still provides a decent estimate of within-person variability relative to the between-person variability of food consumption for comparing values across the different observations. Also related to the high frequency of zero values (in food group intakes), the average intake over the three recalled days was used as the habitual dietary intake instead of employing methods that improve accuracy of the long-term intake such as the NCI method (19). We did this in order to minimize convergence issues. Analyses were not adjusted for the FFQ intakes in order to retain comparability to the analyses on the meal level. Finally, the impact of some known predictors of dietary intake such as number of people present and meals in front of the TV (33, 53) could not be investigated, since this information was not collected in the 24hDRs.

6 Implications for public health and conclusion

Humans have been aware of a link between nutrition and health since thousands of years. Nevertheless, the complexity of our biology, the ever-changing environment, and the difficulties in assessing and analyzing diet have hindered the full elucidation of this link. The goal of nutritional epidemiology is to determine the relations between diet and health by using epidemiologic approaches (2). In order to achieve this, it is important to understand how diet is formed. This understanding is needed to know how to change unwanted habits and how to promote wanted ones. As diet originates in foods consumed together in EOs including meals, studying the meals offers the deepest insights into how diet is formed and knowledge from this research approach can be used to issue more understandable dietary guidelines that are more easily applicable by the population. Furthermore, because diet depends on sociocultural factors, meals have to be studied in the cultural context in which the dietary guidelines are being developed (34).

Up to now, little meal-based research has been done. Most nutritional epidemiological studies have concentrated on describing the habitual diet instead. Putting the frequently-described dietary constructs, i.e., habitual dietary patterns, in the context of meals allows for a better understanding and therefore better interpretation of such patterns, as well as to understand how these patterns can be influenced. Moreover, there is a large variation in dietary intake observed within and between individuals. For the purpose of characterizing individuals' diets by means of habitual dietary patterns, the variation seen within individuals is viewed as a limitation for a reliable and stable measurement of the long-term intake and therefore is reduced by calculating the usual or habitual diet (17, 19). However, such variation, not only between days and between individuals, but also between meals, is an important feature of eating behavior (121). Therefore, considering this variation offers a deeper insight into the origin and impact of factors determining dietary intake, such as individual characteristics and contextual factors of meals.

More evidence from large prospective cohort studies is needed to learn from the influence of meals on the overall diet and on eating behavior, especially as behaviors differ from population to population and therefore results in this research line are not generalizable. A common limitation for meal-based research is the lack of large cohort studies with extensive meal-specific dietary data such as repeated 24hDRs. Furthermore, information regarding the context of the meals is not always collected. Nevertheless, the meal-based approach in nutritional epidemiology will probably grow in the near future, as methods used to collect

meal data are improving. Recently, the Automated Self-Administered 24-hour diet recall (ASA24) was developed by the NCI, which collects meal-specific single or multiple day food records with contextual information and is freely available on the web or on the mobile phone (122). This tool is being increasingly used in large cohort studies across the USA and efforts to adapt it for measuring intakes in Canada and Great Britain are under way (122, 123). Tools such as ASA24, which make the collection of detailed and meal-specific data possible in large cohorts without incurring in high costs (124), might be the future of meal-based research.

In conclusion, this thesis applied novel meal-based analytical methods and revealed that considering meals is important for understanding habitual dietary patterns and eating behavior of the studied population. The here presented methods should be applied to populations of interest, as dietary intake and eating behavior differ in every population. Such methods will be useful ahead of the planning of interventions seeking to modify dietary intake and for the formulation of meal-based dietary advice.

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Supplementary tables

Table S1: List of 39 food groups used for food-based analyses

Food group code	Name	Description
1	Potatoes	Potatoes and sweet potatoes
2	Leafy vegetables	Leafy green vegetables
3	Fruiting & root vegetables	Fruiting vegetables: artichoke, avocado, eggplant, green beans, chili peppers, cucumber, bell peppers, tomatoes; Root vegetables: kohlrabi (German turnip), manioc, radish, beets, carrots
4	Cabbages	Broccoli, cauliflower, cabbage, sauerkraut
5	Other vegetables	Mushrooms, peas, corn, sprouts, garlic, onions, stalk vegetables (fennel, leek, celery, asparagus, bamboo shoots), vegetable mixes
6	Legumes	White beans, kidney beans, black beans, other beans, chick peas, lentils
7	Fresh fruits	All fresh fruits
8	Nuts	All nuts and seeds
9	Other fruits	Fruit mixes (for example in salads), dried fruits, canned fruits, olives
10	Milk & dairy	Milk, dairy beverages, yogurt, eggnog, quark, cream (dairy and non-dairy based), creamer
11	Cheese	All cheeses
12	Desserts	Mousse, pudding, cream desserts, milk and water based ice creams and sorbets
13	Pasta & rice	All pasta and rice
14	Bread	White bread, whole grain bread, crackers and breadcrumbs
15	Breakfast cereals	All breakfast cereals with exception of muesli and oatmeal
16	Other cereals	Cornstarch, dough, yeast dough, pretzel sticks, oatmeal flakes, whole grain rye flakes, wheat flour, spelt flour, chips (potato and from other cereals), dumplings, bread sticks
17	Red meat	Non-processed meats from: beef, veal, pork, lamb, rabbit, other red meat (kangaroo)
18	Poultry	Non-processed meats from: chicken, turkey, duck, goose
19	Processed meat	Meatballs, cured ham and meat breast, salami and sausages, bacon, meatloaf, corned beef, mortadella, liver pate, meat jelly
20	Fish	All fish and shellfish
21	Eggs	Whole egg, egg whites, and yolks
22	Margarine	Margarine
23	Vegetable oils	Vegetable oils
24	Butter	Butter and other animal fats (lard)
25	Sugar & confectionery	Honey, syrups, sugar, marmalades and jams, chocolate, chocolate bars and candies, candies, caramelized fruits and nuts, marzipan, chewing gum, licorice candy
26	Cakes & cookies	Cakes, pastries, cookies, pancakes and waffles
27	Fruit & vegetable juices	All fruit and vegetable juices
28	Soft drinks	Carbonated and non-carbonated soft drinks, alcohol free beer, tonic water, coconut milk

Table S1 continued

Food group code	Name	Description
29	Tea	Black tea, green tea, herbal and fruit infusions
30	Coffee	Coffee and coffee substitute drinks
31	Water	Water (sparkling and still)
32	Wine	All wines containing alcohol
33	Beer	All beer containing alcohol
34	Spirits	Vodka, whiskey, rum, cognac, gin, other spirits
35	Other alcoholic beverages	Punch, herbal liquors, mulled wine, sparkling wine, egg liquor, sherry, ouzo, Campari, martini, amaretto, cherries in alcohol, baileys, other alcoholic beverages
36	Sauces	Tomato-based sauces, dips and dressings, mayonnaise-based sauces, dessert sauces, other sauces
37	Condiments	Vinegar, mustard, herbs, salt, pepper, artificial sweetener
38	Soups	All soups and broths
39	Snacks	Bread snacks (gratin, tomato and cheese), puff pastries with fillings, spring rolls, breaded or fried vegetables, spreads, vegetarian sausages

Note. Reprinted from Schwedhelm et al. *PLOS ONE* 2018 (Supporting information) (78)

Table S2: Mean meal and habitual intake by food group

Food group	Breakfast (g/meal) (n=2 411)	Lunch (g/meal) (n=2 236)	Afternoon snack (g/meal) (n=2 119)	Dinner (g/meal) (n=2 346)	Habitual (g/day) (n=814)
Potatoes	0.0 ± 0.4	72.5 ± 92.3	1.5 ± 16.4	12.5 ± 44.8	81.7 ± 66.5
Leafy vegetables	0.2 ± 4.9	5.6 ± 26.0	0.2 ± 4.5	5.5 ± 24.4	11.6 ± 22.3
Fruiting & root vegetables	7.6 ± 30.0	33.9 ± 72.5	2.3 ± 18.5	56.2 ± 84.4	103.0 ± 83.7
Cabbages	0.0 ± 0.6	17.9 ± 47.9	0.4 ± 7.9	5.4 ± 31.1	22.5 ± 33.7
Other vegetables	0.3 ± 4.6	23.9 ± 58.4	0.6 ± 6.8	9.7 ± 35.0	32.9 ± 38.6
Legumes	1.2 ± 14.6	3.6 ± 25.4	0.7 ± 15.1	1.0 ± 10.6	6.6 ± 27.2
Fresh fruits	36.7 ± 72.1	52.7 ± 94.4	19.9 ± 67.5	38.4 ± 93.1	231.0 ± 154.0
Nuts	0.7 ± 4.6	0.2 ± 2.6	0.3 ± 5.2	0.2 ± 2.7	4.0 ± 10.2
Other fruits	1.2 ± 18.0	4.0 ± 28.9	0.7 ± 14.2	2.2 ± 25.1	10.2 ± 33.2
Milk & dairy	58.9 ± 97.2	32.4 ± 75.6	20.3 ± 52.6	26.3 ± 78.5	167.0 ± 153.0
Cheese	13.1 ± 20.1	3.3 ± 12.8	0.7 ± 5.9	18.3 ± 26.6	37.4 ± 27.1
Desserts	0.1 ± 2.8	9.2 ± 39.3	3.7 ± 23.7	1.9 ± 17.5	17.6 ± 33.8
Pasta & rice	0.3 ± 5.8	17.8 ± 55.3	0.5 ± 10.9	4.8 ± 31.1	23.1 ± 39.4
Bread	52.1 ± 33.4	10.5 ± 24.4	3.5 ± 13.7	41.2 ± 35.5	113.0 ± 48.4
Breakfast cereals	2.5 ± 11.7	0.3 ± 3.8	0.1 ± 3.1	0.2 ± 4.4	3.4 ± 12.1
Other cereals	1.3 ± 7.2	1.1 ± 7.5	0.2 ± 2.5	1.3 ± 10.9	5.3 ± 11.9
Red meat	0.9 ± 10.5	27.5 ± 56.6	1.4 ± 16.9	11.2 ± 40.0	39.5 ± 46.3
Poultry	0.2 ± 4.7	9.2 ± 35.8	0.4 ± 7.5	5.7 ± 30.0	14.8 ± 27.4
Processed meat	9.8 ± 18.1	21.0 ± 44.3	2.3 ± 16.0	25.1 ± 37.4	60.8 ± 46.1
Fish	1.7 ± 10.7	11.4 ± 43.1	0.6 ± 9.7	11.3 ± 40.8	24.1 ± 37.9
Eggs	10.2 ± 24.1	4.8 ± 19.5	0.4 ± 5.8	3.0 ± 15.4	18.7 ± 22.3
Margarine	5.2 ± 9.9	2.2 ± 5.9	0.3 ± 2.4	5.0 ± 9.4	13.2 ± 16.9
Vegetable oils	0.2 ± 2.1	2.8 ± 7.3	0.1 ± 1.4	2.0 ± 6.1	5.1 ± 6.4
Butter	7.8 ± 11.3	3.2 ± 7.7	0.5 ± 3.1	5.6 ± 11.0	17.6 ± 18.5
Sugar & confectionery	19.0± 22.3	2.2 ± 9.1	3.7 ± 11.8	2.1 ± 8.1	38.0 ± 29.7
Cakes & cookies	2.0 ± 17.2	4.2 ± 30.2	51. 1± 72.5	1.6 ± 14.5	59.2 ± 55.5
Fruit & vegetable juices	14.7 ± 49.7	16.1 ± 56.8	6.5 ± 36.5	14.6 ± 53.6	94.5 ± 144.0
Soft drinks	0.6 ± 13.2	7.8 ± 47.8	4.2 ± 35.8	13.1 ± 71.6	48.1 ± 126.0
Tea	84.9 ± 172.9	24.6 ± 86.5	34.6 ± 103.5	90.5 ± 157.4	355.0 ± 381.0
Coffee	220.4 ± 170.3	18.0 ± 63.1	152.9 ± 140.5	3.6 ± 31.0	447.0 ± 230.0
Water	28.5 ± 71.6	92.7 ± 127.5	59.8 ± 121.6	80.6 ± 130.1	740.0 ± 477.0
Wine	0.5 ± 10.5	5.9 ± 40.4	3.2 ± 25.8	12.1 ± 56.8	57.3 ± 101.0
Beer	0 ± 0	14.8 ± 78.1	7.4 ± 60.7	56.6 ± 164.4	173.0 ± 316.0
Spirits	0 ± 0	0.0 ± 0.7	0.1 ± 2.1	0.1 ± 2.4	1.6 ± 7.0
Other alcoholic beverages	0 ± 0	0.7 ± 12.3	0.8 ± 14.0	0.6 ± 9.8	5.0 ± 20.1
Sauces	0.4 ± 2.7	17.3 ± 37.7	0.5 ± 4.7	6.7 ± 19.7	24.2 ± 25.1
Condiments	0.3 ± 1.5	0.9 ± 3.5	0.2 ± 1.5	1.1 ± 3.8	2.8 ± 4.6
Soups	2.3 ± 24.4	36.2 ± 93.4	1.5 ± 19.9	12.0 ± 57.4	51.8 ± 74.8
Snacks	0.2 ± 2.7	0.6 ± 9.9	0.1 ± 2.7	0.7 ± 9.1	1.6 ± 8.7

Values are means ± SDs, all such values

Note. Reprinted from Schwedhelm et al. *PLOS ONE* 2018 (78)

Table S3: Number of 24hDR and meals, total and by participant

	Observations (n)
Total number of participants	814
Total number of 24hDR	2 430
Participants with number of 24hDR:	
3	805
2	6
1	3
0	0
Total number of main meals (intakes) consumed	9 112
Total number of breakfast meals	2 411
Participants with number of breakfast meals:	
3	789
2	19
1	6
0	0
Total number of lunch meals	2 236
Participants with number of lunch meals:	
3	642
2	144
1	22
0	6
Total number of afternoon snacks	2 119
Participants with number of afternoon snacks:	
3	557
2	201
1	46
0	10
Total number of dinner meals	2 346
Participants with number of dinner meals:	
3	729
2	74
1	11
0	0

Table S4: Random intercept Multilevel Regression Analysis and Corresponding Pratt for **energy intake** (kcal/meal)

Predictor[1]	Beta-weight	t-test	p-value	Correlation	Pratt Index[2]
BREAKFAST					
Within level (intake level)					
Week/weekend day (y/n)	0.097	3.899	0.000	0.110	0.243
Season (winter/ summer)	-0.036	-1.652	0.098	-0.037	0.030
Special day (y/n)	0.004	0.118	0.906	0.033	0.003
Prior interval (hours)	-0.024	-0.847	0.397	-0.010	0.005
Place of meal (ref. home)					
work	-0.137	-2.607	0.009	-0.143	0.445
restaurant	0.106	5.017	0.000	0.112	0.270
other	0.007	0.224	0.823	0.009	0.001
R-squared	**0.044**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	-0.084	-1.869	0.062	-0.065	0.031
Age (years)	0.145	2.337	0.019	0.212	0.172
Sex (M/W)	-0.342	-7.588	0.000	-0.335	0.640
Education level (ref. no training/ current training)					
technical college	-0.010	-0.218	0.828	-0.065	0.004
university	-0.014	-0.284	0.776	0.063	-0.005
Occupation (ref. no job/ retired)[3]					
full time	0.021	0.296	0.767	-0.064	-0.008
part time/hourly	-0.059	-1.175	0.240	-0.140	0.046
Physical activity (h/week)	0.043	1.141	0.254	0.040	0.010
Smoking status (ref. never smoker)					
current smoker	0.251	2.796	0.005	0.035	0.049
former smoker	0.177	1.986	0.047	0.059	0.058
R-squared	**0.179**				**SUM = 1.0**
LUNCH					
Within level (intake level)					
Week/weekend day (y/n)	0.043	1.858	0.063	0.055	0.103
Season (winter/ summer)	0.008	0.355	0.723	-0.005	-0.002
Special day (y/n)	0.044	1.851	0.064	0.050	0.096
Prior interval (hours)	0.044	1.990	0.047	0.053	0.101
Place of meal (ref. home)					
work	-0.115	-2.808	0.005	-0.120	0.600
restaurant	0.018	0.697	0.486	0.049	0.038
other	-0.049	-1.849	0.064	-0.030	0.064
R-squared	**0.023**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	-0.069	-1.033	0.302	-0.042	0.011
Age (years)	0.117	1.236	0.217	0.284	0.120
Sex (M/W)	-0.461	-6.799	0.000	-0.395	0.660
Education level (ref. no training/ current training)					
technical college	-0.034	-0.498	0.618	-0.043	0.005
university	-0.100	-1.465	0.143	-0.021	0.008
Occupation (ref. no job/ retired)[3]					

Table S4 continued

Predictor[1]	Beta-weight	t-test	p-value	Correlation	Pratt Index[2]
full time	-0.092	-0.878	0.380	-0.193	0.064
part time/hourly	-0.003	-0.034	0.973	-0.078	0.001
Physical activity (h/week)	0.137	2.166	0.030	0.149	0.074
Smoking status (ref. never smoker)					
current smoker	0.228	1.910	0.056	0.048	0.040
former smoker	0.115	0.921	0.357	0.030	0.013
R-squared	**0.276**				**SUM = 1.0**
AFTERNOON SNACK					
Within level (intake level)					
Week/weekend day (y/n)	0.098	3.970	0.000	0.128	0.118
Season (winter/ summer)	0.027	1.219	0.223	0.023	0.006
Special day (y/n)	0.069	2.792	0.005	0.114	0.074
Prior interval (hours)	0.152	6.425	0.000	0.189	0.271
Place of meal (ref. home)					
work	-0.191	-5.917	0.000	-0.238	0.429
restaurant	0.018	0.700	0.484	0.042	0.007
other	0.079	3.157	0.002	0.131	0.098
R-squared	**0.106**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	-0.034	-0.554	0.579	-0.042	0.020
Age (years)	-0.013	-0.144	0.885	0.039	-0.007
Sex (M/W)	-0.264	-4.249	0.000	-0.206	0.755
Education level (ref. no training/ current training)					
technical college	0.026	0.395	0.693	-0.014	-0.005
university	-0.018	-0.269	0.788	0.023	-0.006
Occupation (ref. no job/ retired)[3]					
full time	0.012	0.125	0.901	0.009	0.002
part time/hourly	-0.008	-0.143	0.887	-0.045	0.005
Physical activity (h/week)	0.045	0.869	0.385	0.024	0.015
Smoking status (ref. never smoker)					
current smoker	0.195	1.763	0.078	0.091	0.246
former smoker	0.044	0.396	0.692	-0.049	-0.030
R-squared	**0.072**				**SUM = 1.0**
DINNER					
Within level (intake level)					
Week/weekend day (y/n)	-0.022	-0.909	0.364	-0.015	0.011
Season (winter/ summer)	0.031	1.401	0.161	0.034	0.035
Special day (y/n)	0.056	2.385	0.017	0.085	0.159
Prior interval (hours)	0.066	3.006	0.003	0.079	0.174
Place of meal (ref. home)					
work	-0.070	-1.845	0.065	-0.075	0.175
restaurant	0.106	4.933	0.000	0.122	0.431
other	0.014	0.432	0.666	0.022	0.010
R-squared	**0.030**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.077	1.560	0.119	0.085	0.023
Age (years)	-0.077	-1.101	0.271	-0.032	0.009
Sex (M/W)	-0.507	-11.835	0.000	-0.502	0.903

Table S4 continued

Predictor[1]	Beta-weight	t-test	p-value	Correlation	Pratt Index[2]
Education level (ref. no training/ current training)					
technical college	-0.040	-0.737	0.461	-0.150	0.021
university	0.032	0.586	0.558	0.153	0.017
Occupation (ref. no job/ retired)[3]					
full time	0.017	0.241	0.809	0.084	0.005
part time/hourly	0.094	1.866	0.062	0.029	0.010
Physical activity (h/week)	0.068	1.577	0.115	-0.033	-0.008
Smoking status (ref. never smoker)					
current smoker	0.050	0.555	0.579	-0.167	-0.030
former smoker	0.076	0.844	0.399	0.180	0.049
R-squared	**0.282**				**SUM = 1.0**

[1] for dichotomous variables, the information shown is for the underlined category (reference category not underlined)
[2] might not add up to 100% due to rounding errors from parameter estimates
[3] full time: ≥ 35h/week; part time/hourly: < 35 h/week.

Table S5: Random intercept Multilevel Regression Analysis and Corresponding Pratt for **carbohydrate intake** (g/meal)

Predictor[1]	Beta-weight	t-test	p-value	Correlation	Pratt Index[2]
BREAKFAST					
Within level (intake level)					
Week/weekend day (y/n)	0.047	1.983	0.047	0.058	0.130
Season (winter/ summer)	-0.046	-2.000	0.046	-0.045	0.099
Special day (y/n)	-0.006	-0.208	0.835	0.008	-0.002
Prior interval (hours)	-0.021	-0.741	0.459	-0.011	0.011
Place of meal (ref. home)					
work	-0.116	-2.112	0.035	-0.118	0.652
restaurant	0.051	2.197	0.028	0.053	0.129
other	0.006	0.222	0.824	0.006	0.002
R-squared	**0.021**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	-0.122	-2.593	0.010	-0.109	0.077
Age (years)	0.107	1.624	0.104	0.224	0.139
Sex (M/W)	-0.273	-6.312	0.000	-0.256	0.406
Education level (ref. no training/ current training)					
technical college	0.030	0.631	0.528	-0.036	-0.006
university	0.043	0.902	0.367	0.084	0.021
Occupation (ref. no job/ retired)[3]					
full time	-0.047	-0.627	0.531	-0.106	0.029
part time/hourly	-0.094	-1.749	0.080	-0.144	0.079
Physical activity (h/week)	0.039	0.893	0.372	0.054	0.012
Smoking status (ref. never smoker)					
current smoker	0.349	3.924	0.000	0.102	0.207
former smoker	0.248	2.761	0.006	0.025	0.036
R-squared	**0.172**				**SUM = 1.0**
LUNCH					
Within level (intake level)					
Week/weekend day (y/n)	0.021	0.912	0.362	0.028	0.118
Season (winter/ summer)	-0.032	-1.449	0.147	-0.034	0.218
Special day (y/n)	0.022	1.009	0.313	0.021	0.092
Prior interval (hours)	0.001	0.057	0.954	0.004	0.001
Place of meal (ref. home)					
work	-0.040	-1.108	0.268	-0.042	0.336
restaurant	-0.029	-0.983	0.326	-0.020	0.116
other	0.010	0.456	0.648	0.018	0.036
R-squared	**0.005**				**SUM = 0.92**
Between level (participant level)					
BMI (kg/m^2)	-0.109	-1.500	0.134	-0.096	0.041
Age (years)	0.131	1.289	0.197	0.227	0.118
Sex (M/W)	-0.436	-5.266	0.000	-0.374	0.645
Education level (ref. no training/ current training)					
technical college	-0.056	-0.653	0.514	-0.094	0.021
university	-0.053	-0.670	0.503	0.050	-0.010
Occupation (ref. no job/ retired)[3]					

Table S5 continued

Predictor[1]	Beta-weight	t-test	p-value	Correlation	Pratt Index[2]
full time	-0.005	-0.037	0.971	-0.116	0.002
part time/hourly	0.030	0.356	0.722	-0.061	-0.007
Physical activity (h/week)	0.124	1.740	0.082	0.116	0.057
Smoking status (ref. never smoker)					
current smoker	0.313	2.249	0.025	0.105	0.130
former smoker	0.150	1.087	0.277	-0.009	-0.005
R-squared	**0.253**				**SUM = 1.0**
AFTERNOON SNACK					
Within level (intake level)					
Week/weekend day (y/n)	0.074	3.060	0.002	0.095	0.108
Season (winter/ summer)	0.039	1.711	0.087	0.036	0.022
Special day (y/n)	0.044	1.839	0.066	0.080	0.054
Prior interval (hours)	0.127	5.444	0.000	0.155	0.303
Place of meal (ref. home)					
work	-0.145	-4.556	0.000	-0.181	0.404
restaurant	0.013	0.544	0.587	0.030	0.006
other	0.066	2.884	0.004	0.106	0.108
R-squared	**0.065**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	-0.019	-0.285	0.775	-0.029	0.008
Age (years)	-0.040	-0.430	0.667	0.053	-0.032
Sex (M/W)	-0.253	-3.969	0.000	-0.181	0.683
Education level (ref. no training/ current training)					
technical college	0.035	0.521	0.603	0.006	0.003
university	-0.021	-0.304	0.761	0.004	-0.001
Occupation (ref. no job/ retired)[3]					
full time	-0.052	-0.512	0.609	-0.041	0.032
part time/hourly	0.004	0.080	0.936	-0.015	-0.001
Physical activity (h/week)	0.038	0.709	0.478	0.031	0.018
Smoking status (ref. never smoker)					
current smoker	0.212	1.975	0.048	0.104	0.329
former smoker	0.055	0.532	0.595	-0.056	-0.046
R-squared	**0.067**				**SUM = 1.0**
DINNER					
Within level (intake level)					
Week/weekend day (y/n)	-0.005	-0.207	0.836	-0.004	0.002
Season (winter/ summer)	0.022	1.003	0.316	0.024	0.053
Special day (y/n)	0.052	2.297	0.022	0.055	0.286
Prior interval (hours)	0.068	2.733	0.006	0.073	0.496
Place of meal (ref. home)					
work	-0.030	-1.036	0.300	-0.033	0.099
restaurant	0.014	0.380	0.704	0.030	0.042
other	-0.012	-0.428	0.668	-0.001	0.001
R-squared	**0.010**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	-0.050	-0.850	0.396	-0.041	0.010
Age (years)	-0.038	-0.458	0.647	0.021	-0.004
Sex (M/W)	-0.442	-7.832	0.000	-0.436	0.949

Table S5 continued

Predictor[1]	Beta-weight	t-test	p-value	Correlation	Pratt Index[2]
Education level (ref. no training/ current training)					
technical college	-0.027	-0.420	0.675	-0.118	0.016
university	0.022	0.360	0.719	0.135	0.015
Occupation (ref. no job/ retired)[3]					
full time	-0.011	-0.119	0.906	0.041	-0.002
part time/hourly	0.043	0.724	0.469	-0.004	-0.001
Physical activity (h/week)	0.018	0.366	0.714	-0.055	-0.005
Smoking status (ref. never smoker)					
current smoker	0.119	1.111	0.266	-0.100	-0.059
former smoker	0.119	1.143	0.253	0.138	0.081
R-squared	**0.203**				**SUM = 1.0**

[1] for dichotomous variables, the information shown is for the underlined category (reference category not underlined)
[2] might not add up to 100% due to rounding errors from parameter estimates
[3] full time: ≥ 35h/week; part time/hourly: < 35 h/week.

Table S6: Random intercept Multilevel Regression Analysis and Corresponding Pratt for **protein intake** (g/meal)

Predictor[1]	Beta-weight	t-test	p-value	Correlation	Pratt Index[2]
BREAKFAST					
Within level (intake level)					
Week/weekend day (y/n)	0.126	5.592	0.000	0.133	0.349
Season (winter/ summer)	0.024	1.135	0.256	0.020	0.010
Special day (y/n)	0.026	0.888	0.374	0.064	0.035
Prior interval (hours)	-0.048	-1.721	0.085	-0.037	0.037
Place of meal (ref. home)					
work	-0.086	-1.891	0.059	-0.094	0.168
restaurant	0.133	7.019	0.000	0.145	0.402
other	0.017	0.547	0.584	0.025	0.009
R-squared	**0.048**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	-0.009	-0.214	0.831	0.007	-0.001
Age (years)	0.061	0.933	0.351	0.144	0.086
Sex (M/W)	-0.263	-5.655	0.000	-0.277	0.714
Education level (ref. no training/ current training)					
technical college	-0.031	-0.666	0.506	-0.091	0.028
university	0.034	0.695	0.487	0.093	0.031
Occupation (ref. no job/ retired)[3]					
full time	-0.040	-0.549	0.583	-0.054	0.021
part time/hourly	-0.059	-1.223	0.221	-0.104	0.060
Physical activity (h/week)	0.031	0.754	0.451	0.022	0.007
Smoking status (ref. never smoker)					
current smoker	0.123	1.515	0.130	-0.027	-0.033
former smoker	0.110	1.365	0.172	0.083	0.090
R-squared	**0.102**				**SUM = 1.0**
LUNCH					
Within level (intake level)					
Week/weekend day (y/n)	0.077	3.326	0.001	0.090	0.165
Season (winter/ summer)	0.011	0.512	0.609	-0.008	-0.002
Special day (y/n)	0.016	0.642	0.521	0.021	0.008
Prior interval (hours)	0.003	0.163	0.870	0.014	0.001
Place of meal (ref. home)					
work	-0.155	-4.647	0.000	-0.160	0.590
restaurant	0.044	1.729	0.084	0.077	0.081
other	-0.087	-3.028	0.002	-0.071	0.147
R-squared	**0.042**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	-0.031	-0.417	0.677	-0.002	0.000
Age (years)	0.073	0.627	0.531	0.208	0.072
Sex (M/W)	-0.415	-4.295	0.000	-0.378	0.740
Education level (ref. no training/ current training)					
technical college	-0.087	-1.145	0.252	-0.070	0.029
university	-0.134	-1.662	0.096	-0.032	0.020
Occupation (ref. no job/ retired)[3]					

Table S6 continued

Predictor[1]	Beta-weight	t-test	p-value	Correlation	Pratt Index[2]
full time	-0.112	-0.871	0.384	-0.167	0.088
part time/hourly	0.058	0.565	0.572	0.000	0.000
Physical activity (h/week)	0.067	1.100	0.271	0.066	0.021
Smoking status (ref. never smoker)					
current smoker	0.117	0.894	0.371	-0.058	-0.032
former smoker	0.107	0.805	0.421	0.108	0.055
R-squared	**0.212**				**SUM = 1.0**
AFTERNOON SNACK					
Within level (intake level)					
Week/weekend day (y/n)	0.056	2.249	0.024	0.077	0.058
Season (winter/ summer)	0.033	1.376	0.169	0.029	0.013
Special day (y/n)	0.071	2.632	0.008	0.104	0.100
Prior interval (hours)	0.146	5.452	0.000	0.174	0.343
Place of meal (ref. home)					
work	-0.159	-5.098	0.000	-0.192	0.413
restaurant	0.027	1.159	0.246	0.047	0.017
other	0.048	1.556	0.120	0.092	0.060
R-squared	**0.074**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.031	0.550	0.582	0.021	0.020
Age (years)	-0.022	-0.247	0.805	-0.089	0.059
Sex (M/W)	-0.118	-1.859	0.063	-0.088	0.315
Education level (ref. no training/ current training)					
technical college	0.008	0.123	0.902	-0.017	-0.004
university	-0.018	-0.271	0.786	0.009	-0.005
Occupation (ref. no job/ retired)[3]					
full time	0.134	1.467	0.142	0.130	0.528
part time/hourly	0.031	0.430	0.667	-0.010	-0.009
Physical activity (h/week)	0.060	1.123	0.261	0.015	0.027
Smoking status (ref. never smoker)					
current smoker	0.018	0.170	0.865	0.021	0.011
former smoker	-0.060	-0.588	0.556	-0.039	0.071
R-squared	**0.033**				**SUM = 1.0**
DINNER					
Within level (intake level)					
Week/weekend day (y/n)	-0.018	-0.748	0.455	-0.012	0.009
Season (winter/ summer)	0.030	1.380	0.167	0.030	0.039
Special day (y/n)	0.049	1.935	0.053	0.072	0.153
Prior interval (hours)	0.048	2.103	0.035	0.061	0.127
Place of meal (ref. home)					
work	-0.059	-2.032	0.042	-0.063	0.162
restaurant	0.102	4.037	0.000	0.116	0.514
other	-0.010	-0.292	0.770	-0.003	0.001
R-squared	**0.023**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.220	4.377	0.000	0.215	0.187
Age (years)	-0.087	-1.181	0.238	-0.065	0.022
Sex (M/W)	-0.409	-8.074	0.000	-0.420	0.679

Table S6 continued

Predictor[1]	Beta-weight	t-test	p-value	Correlation	Pratt Index[2]
Education level (ref. no training/ current training)					
technical college	-0.018	-0.308	0.758	-0.158	0.011
university	0.115	1.798	0.072	0.193	0.088
Occupation (ref. no job/ retired)[3]					
full time	0.040	0.509	0.610	0.120	0.019
part time/hourly	0.057	1.059	0.290	-0.007	-0.002
Physical activity (h/week)	0.070	1.527	0.127	-0.025	-0.007
Smoking status (ref. never smoker)					
current smoker	0.000	0.001	0.999	-0.147	0.000
former smoker	0.000	-0.003	0.998	0.141	0.000
R-squared	**0.253**				**SUM = 1.0**

[1] for dichotomous variables, the information shown is for the underlined category (reference category not underlined)
[2] might not add up to 100% due to rounding errors from parameter estimates
[3] full time: ≥ 35h/week; part time/hourly: < 35 h/week.

Table S7: Random intercept Multilevel Regression Analysis and Corresponding Pratt for **fat intake** (g/meal)

Predictor[1]	Beta-weight	t-test	p-value	Correlation	Pratt Index[2]
BREAKFAST					
Within level (intake level)					
Week/weekend day (y/n)	0.116	5.238	0.000	0.127	0.320
Season (winter/ summer)	-0.019	-0.893	0.372	-0.021	0.009
Special day (y/n)	0.008	0.276	0.782	0.045	0.008
Prior interval (hours)	-0.003	-0.117	0.907	0.008	-0.001
Place of meal (ref. home)					
work	-0.108	-2.435	0.015	-0.117	0.275
restaurant	0.127	5.777	0.000	0.135	0.373
other	0.017	0.514	0.608	0.019	0.007
R-squared	**0.046**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	-0.075	-1.645	0.100	-0.056	0.035
Age (years)	0.081	1.374	0.170	0.108	0.073
Sex (M/W)	-0.337	-7.742	0.000	-0.305	0.857
Education level (ref. no training/ current training)					
technical college	-0.036	-0.773	0.439	-0.035	0.011
university	-0.115	-2.410	0.016	-0.027	0.026
Occupation (ref. no job/ retired)[3]					
full time	0.035	0.517	0.605	-0.032	-0.009
part time/hourly	0.046	1.191	0.234	-0.019	-0.007
Physical activity (h/week)	0.064	1.499	0.134	0.040	0.021
Smoking status (ref. never smoker)					
current smoker	0.058	0.733	0.464	-0.038	-0.018
former smoker	0.024	0.309	0.758	0.052	0.010
R-squared	**0.120**				**SUM = 1.0**
LUNCH					
Within level (intake level)					
Week/weekend day (y/n)	0.059	2.665	0.008	0.067	0.180
Season (winter/ summer)	0.028	1.249	0.212	0.012	0.015
Special day (y/n)	0.045	1.979	0.048	0.046	0.094
Prior interval (hours)	0.025	1.133	0.257	0.032	0.036
Place of meal (ref. home)					
work	-0.090	-2.572	0.010	-0.093	0.380
restaurant	0.030	1.303	0.193	0.060	0.082
other	-0.078	-2.701	0.007	-0.061	0.216
R-squared	**0.022**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	-0.019	-0.254	0.800	0.009	-0.001
Age (years)	0.244	1.960	0.050	0.320	0.355
Sex (M/W)	-0.355	-3.338	0.001	-0.334	0.539
Education level (ref. no training/ current training)					
technical college	-0.029	-0.356	0.722	-0.026	0.003
university	-0.086	-1.065	0.287	-0.031	0.012
Occupation (ref. no job/ retired)[3]					

Table S7 continued

Predictor[1]	Beta-weight	t-test	p-value	Correlation	Pratt Index[2]
full time	-0.007	-0.054	0.957	-0.189	0.006
part time/hourly	0.018	0.197	0.844	-0.085	-0.007
Physical activity (h/week)	0.115	1.499	0.134	0.138	0.072
Smoking status (ref. never smoker)					
current smoker	0.096	0.724	0.469	-0.015	-0.007
former smoker	0.059	0.438	0.661	0.066	0.018
R-squared	**0.220**				**SUM = 1.0**
AFTERNOON SNACK					
Within level (intake level)					
Week/weekend day (y/n)	0.073	2.879	0.004	0.102	0.090
Season (winter/ summer)	-0.013	-0.548	0.584	-0.014	0.002
Special day (y/n)	0.066	2.468	0.014	0.107	0.085
Prior interval (hours)	0.131	5.245	0.000	0.158	0.249
Place of meal (ref. home)					
work	-0.175	-5.298	0.000	-0.212	0.447
restaurant	0.045	1.887	0.059	0.065	0.035
other	0.073	2.890	0.004	0.111	0.098
R-squared	**0.083**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	-0.010	-0.159	0.874	-0.022	0.003
Age (years)	-0.008	-0.095	0.924	-0.016	0.002
Sex (M/W)	-0.234	-3.620	0.000	-0.169	0.628
Education level (ref. no training/ current training)					
technical college	-0.003	-0.043	0.966	-0.004	0.000
university	-0.069	-1.073	0.283	-0.028	0.031
Occupation (ref. no job/ retired)[3]					
full time	0.052	0.551	0.581	0.041	0.034
part time/hourly	0.051	0.963	0.336	0.015	0.012
Physical activity (h/week)	0.070	1.394	0.163	0.037	0.041
Smoking status (ref. never smoker)					
current smoker	-0.074	-0.859	0.391	0.034	-0.040
former smoker	-0.206	-2.410	0.016	-0.089	0.291
R-squared	**0.063**				**SUM = 1.0**
DINNER					
Within level (intake level)					
Week/weekend day (y/n)	-0.030	-1.290	0.197	-0.027	0.058
Season (winter/ summer)	0.038	1.718	0.086	0.038	0.103
Special day (y/n)	0.031	1.347	0.178	0.040	0.089
Prior interval (hours)	0.028	1.175	0.240	0.038	0.076
Place of meal (ref. home)					
work	-0.074	-1.660	0.097	-0.074	0.391
restaurant	0.058	2.925	0.003	0.066	0.273
other	-0.027	-0.885	0.376	-0.020	0.039
R-squared	**0.014**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.105	2.226	0.026	0.113	0.054
Age (years)	0.081	1.183	0.237	0.102	0.038
Sex (M/W)	-0.415	-8.240	0.000	-0.422	0.796

Table S7 continued

Predictor[1]	Beta-weight	t-test	p-value	Correlation	Pratt Index[2]
Education level (ref. no training/ current training)					
technical college	-0.099	-1.660	0.097	-0.159	0.072
university	-0.003	-0.050	0.960	0.109	-0.001
Occupation (ref. no job/ retired)[3]					
full time	0.005	0.070	0.944	-0.042	-0.001
part time/hourly	0.137	2.717	0.007	0.053	0.033
Physical activity (h/week)	0.060	1.401	0.161	0.010	0.003
Smoking status (ref. never smoker)					
current smoker	-0.052	-0.598	0.550	-0.134	0.032
former smoker	-0.046	-0.522	0.602	0.120	-0.025
R-squared	**0.220**				**SUM = 1.0**

[1] for dichotomous variables, the information shown is for the underlined category (reference category not underlined)
[2] might not add up to 100% due to rounding errors from parameter estimates
[3] full time: ≥ 35h/week; part time/hourly: < 35 h/week.

Table S8: Random intercept Multilevel Regression Analysis and Corresponding Pratt for **energy intake** (kcal/meal); sensitivity analysis adjusting for energy misreporting[1]

Predictor[2]	Beta-weight	t-test	p-value	Correlation	Pratt Index[3]
BREAKFAST					
Within level (intake level)					
Week/weekend day (y/n)	0.108	3.867	0.000	0.123	0.271
Season (winter/ summer)	-0.038	-1.572	0.116	-0.040	0.031
Special day (y/n)	0.008	0.246	0.806	0.051	0.008
Prior interval (hours)	-0.024	-0.787	0.431	-0.012	0.006
Place of meal (ref. home)					
work	-0.138	-2.339	0.019	-0.146	0.411
restaurant	0.104	4.454	0.000	0.113	0.240
other	0.043	1.799	0.072	0.044	0.039
R-squared	**0.049**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.000	0.009	0.992	-0.033	0.000
Age (years)	0.082	1.252	0.211	0.206	0.068
Sex (M/W)	-0.309	-6.372	0.000	-0.353	0.436
Education level (ref. no training/ current training)					
technical college	-0.011	-0.220	0.826	-0.070	0.003
university	-0.011	-0.223	0.824	0.057	-0.003
Occupation (ref. no job/ retired)[4]					
full time	0.052	0.677	0.499	-0.045	-0.009
part time/hourly	-0.079	-1.395	0.163	-0.169	0.053
Physical activity (h/week)	0.052	1.315	0.189	0.051	0.011
Smoking status (ref. never smoker)					
current smoker	0.268	2.687	0.007	0.040	0.043
former smoker	0.204	2.071	0.038	0.059	0.048
Energy misreporting					
EI/TEE < 0.81	-0.154	-3.088	0.002	-0.263	0.162
EI/TEE > 1.19	0.176	5.712	0.000	0.267	0.188
R-squared	**0.250**				**SUM = 1.0**
LUNCH					
Within level (intake level)					
Week/weekend day (y/n)	0.035	1.389	0.165	0.049	0.059
Season (winter/ summer)	0.012	0.489	0.625	0.000	0.000
Special day (y/n)	0.040	1.570	0.116	0.051	0.070
Prior interval (hours)	0.058	2.489	0.013	0.069	0.138
Place of meal (ref. home)					
work	-0.144	-3.290	0.001	-0.151	0.750
restaurant	-0.005	-0.171	0.864	0.027	-0.005
other	-0.016	-0.577	0.564	0.008	-0.004
R-squared	**0.029**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.077	1.116	0.265	-0.011	-0.002
Age (years)	0.017	0.175	0.861	0.257	0.011
Sex (M/W)	-0.377	-5.255	0.000	-0.382	0.347
Education level (ref. no training/ current training)					

Table S8 continued

Predictor[2]	Beta-weight	t-test	p-value	Correlation	Pratt Index[3]
technical college	-0.027	-0.411	0.681	-0.054	0.004
university	-0.084	-1.155	0.248	-0.015	0.003
Occupation (ref. no job/ retired)[4]					
full time	-0.033	-0.322	0.747	-0.166	0.013
part time/hourly	0.017	0.217	0.828	-0.061	-0.002
Physical activity (h/week)	0.145	2.261	0.024	0.162	0.057
Smoking status (ref. never smoker)					
current smoker	0.186	1.494	0.135	0.076	0.034
former smoker	0.067	0.520	0.603	-0.014	-0.002
Energy misreporting					
EI/TEE < 0.81	-0.372	-5.107	0.000	-0.462	0.414
EI/TEE > 1.19	0.159	3.332	0.001	0.311	0.119
R-squared	**0.415**				**SUM = 1.0**
AFTERNOON SNACK					
Within level (intake level)					
Week/weekend day (y/n)	0.100	3.803	0.000	0.134	0.114
Season (winter/ summer)	0.035	1.432	0.152	0.029	0.009
Special day (y/n)	0.053	1.929	0.054	0.101	0.045
Prior interval (hours)	0.167	6.549	0.000	0.206	0.292
Place of meal (ref. home)					
work	-0.207	-6.037	0.000	-0.256	0.449
restaurant	0.019	0.643	0.520	0.044	0.007
other	0.079	2.968	0.003	0.129	0.086
R-squared	**0.118**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.086	1.356	0.175	-0.039	-0.015
Age (years)	-0.100	-1.100	0.271	0.020	-0.009
Sex (M/W)	-0.232	-3.663	0.000	-0.227	0.228
Education level (ref. no training/ current training)					
technical college	0.078	1.166	0.244	-0.010	-0.003
university	0.042	0.597	0.551	0.075	0.014
Occupation (ref. no job/ retired)[4]					
full time	0.047	0.459	0.646	0.023	0.005
part time/hourly	0.033	0.592	0.554	-0.004	-0.001
Physical activity (h/week)	0.016	0.312	0.755	-0.005	0.000
Smoking status (ref. never smoker)					
current smoker	0.182	1.621	0.105	0.115	0.091
former smoker	0.020	0.178	0.859	-0.076	-0.007
Energy misreporting					
EI/TEE < 0.81	-0.370	-5.603	0.000	-0.383	0.613
EI/TEE > 1.19	0.101	1.550	0.121	0.188	0.082
R-squared	**0.231**				**SUM = 1.0**
DINNER					
Within level (intake level)					
Week/weekend day (y/n)	-0.035	-1.359	0.174	-0.025	0.027
Season (winter/ summer)	0.039	1.573	0.116	0.042	0.050
Special day (y/n)	0.061	2.417	0.016	0.082	0.152

Table S8 continued

Predictor[2]	Beta-weight	t-test	p-value	Correlation	Pratt Index[3]
Prior interval (hours)	0.074	3.086	0.002	0. 088	0.197
Place of meal (ref. home)					
work	-0.081	-1.962	0.050	-0. 085	0.209
restaurant	0.101	4.221	0.000	0.116	0.355
other	-0.008	-0.227	0.821	0.003	-0.001
R-squared	**0.033**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.181	3.183	0.001	0.092	0.041
Age (years)	-0.216	-3.096	0.002	-0.045	0.024
Sex (M/W)	-0.410	-8.825	0.000	-0.482	0.482
Education level (ref. no training/ current training)					
technical college	0.033	0.597	0.551	-0.100	-0.008
university	0.075	1.284	0.199	0.152	0.028
Occupation (ref. no job/ retired)[4]					
full time	-0.003	-0.044	0.965	0.074	-0.001
part time/hourly	0.052	0.981	0.326	0.020	0.003
Physical activity (h/week)	0.045	1.030	0.303	-0.037	-0.004
Smoking status (ref. never smoker)					
current smoker	0.027	0.273	0.785	-0.169	-0.011
former smoker	0.092	0.953	0.340	0.180	0.040
Energy misreporting					
EI/TEE < 0.81	-0.302	-5.103	0.000	-0.310	0.228
EI/TEE > 1.19	0.236	6.623	0.000	0.309	0.178
R-squared	**0.410**				**SUM = 1.0**

EI: energy intake; TEE: total energy expenditure
[1] n=682 participants with activity sensor data
[2] for dichotomous variables, the information shown is for the underlined category (reference category not underlined)
[3] might not add up to 100% due to rounding errors from parameter estimates
[4] full time: ≥ 35h/week; part time/hourly: < 35 h/week.

Table S9: Random intercept Multilevel Regression Analysis and Corresponding Pratt for **carbohydrate intake** (g/meal); sensitivity analysis adjusting for energy misreporting[1]

Predictor[2]	Beta-weight	t-test	p-value	Correlation	Pratt Index[3]
BREAKFAST					
Within level (intake level)					
Week/weekend day (y/n)	0.068	2.567	0.010	0.081	0.157
Season (winter/ summer)	-0.066	-2.809	0.005	-0.066	0.124
Special day (y/n)	-0.007	-0.223	0.824	0.019	-0.004
Prior interval (hours)	-0.010	-0.323	0.747	0.001	0.000
Place of meal (ref. home)					
work	-0.144	-2.394	0.017	-0.148	0.609
restaurant	0.048	1.786	0.074	0.051	0.070
other	0.037	1.719	0.086	0.036	0.038
R-squared	**0.035**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	-0.037	-0.740	0.459	-0.066	0.011
Age (years)	0.087	1.255	0.209	0.226	0.088
Sex (M/W)	-0.236	-5.024	0.000	-0.268	0.284
Education level (ref. no training/ current training)					
technical college	0.024	0.485	0.628	-0.053	-0.006
university	0.059	1.217	0.224	0.092	0.024
Occupation (ref. no job/ retired)[4]					
full time	0.013	0.176	0.860	-0.073	-0.004
part time/hourly	-0.112	-1.888	0.059	-0.186	0.093
Physical activity (h/week)	0.053	1.156	0.248	0.068	0.016
Smoking status (ref. never smoker)					
current smoker	0.374	3.854	0.000	0.118	0.198
former smoker	0.270	2.761	0.006	0.018	0.022
Energy misreporting					
EI/TEE < 0.81	-0.121	-2.195	0.028	-0.241	0.131
EI/TEE > 1.19	0.144	4.376	0.000	0.220	0.142
R-squared	**0.223**				**SUM = 1.0**
LUNCH					
Within level (intake level)					
Week/weekend day (y/n)	0.010	0.387	0.699	0.019	0.021
Season (winter/ summer)	-0.039	-1.608	0.108	-0.039	0.169
Special day (y/n)	0.029	1.263	0.207	0.028	0.090
Prior interval (hours)	0.002	0.068	0.946	0.006	0.001
Place of meal (ref. home)					
work	-0.062	-1.557	0.119	-0.062	0.427
restaurant	-0.049	-1.500	0.134	-0.037	0.201
other	0.023	0.965	0.334	0.036	0.092
R-squared	**0.009**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	-0.003	-0.035	0.972	-0.091	0.001
Age (years)	0.096	0.890	0.374	0.200	0.050
Sex (M/W)	-0.379	-4.357	0.000	-0.384	0.381
Education level (ref. no training/ current training)					

Table S9 continued

Predictor[2]	Beta-weight	t-test	p-value	Correlation	Pratt Index[3]
technical college	-0.046	-0.515	0.607	-0.118	0.014
university	-0.013	-0.152	0.880	0.090	-0. 003
Occupation (ref. no job/ retired)[4]					
full time	0.117	0.857	0.391	-0.057	-0.017
part time/hourly	0.079	0.924	0.356	-0.041	-0.008
Physical activity (h/week)	0.139	1.919	0.055	0.123	0.045
Smoking status (ref. never smoker)					
current smoker	0.309	2.068	0.039	0.134	0.108
former smoker	0.132	0.898	0.369	-0.041	-0.014
Energy misreporting					
EI/TEE < 0.81	-0.298	-3.619	0.000	-0.415	0.324
EI/TEE > 1.19	0.154	2.401	0.016	0.281	0.113
R-squared	**0.382**				**SUM = 1.0**
AFTERNOON SNACK					
Within level (intake level)					
Week/weekend day (y/n)	0.071	2.693	0.007	0.092	0.100
Season (winter/ summer)	0.050	2.009	0.045	0.046	0.035
Special day (y/n)	0.027	1.028	0.304	0.064	0.027
Prior interval (hours)	0.132	5.188	0.000	0.160	0.325
Place of meal (ref. home)					
work	-0.144	-4.198	0.000	-0.180	0.399
restaurant	0.009	0.335	0.738	0.024	0.003
other	0.069	2.765	0.006	0.105	0.111
R-squared	**0.065**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.098	1.456	0.145	-0.014	-0.007
Age (years)	-0.111	-1.112	0.266	0.041	-0.023
Sex (M/W)	-0.241	-3.635	0.000	-0.218	0.261
Education level (ref. no training/ current training)					
technical college	0.096	1.373	0.170	0.020	0.010
university	0.037	0.489	0.625	0.047	0.009
Occupation (ref. no job/ retired)[4]					
full time	-0.009	-0.085	0.932	-0.028	0.001
part time/hourly	0.044	0.789	0.430	0.017	0.004
Physical activity (h/week)	0.034	0.631	0.528	0.023	0.004
Smoking status (ref. never smoker)					
current smoker	0.186	1.667	0.096	0.114	0.105
former smoker	0.023	0.214	0.831	-0.074	-0.008
Energy misreporting					
EI/TEE < 0.81	-0.326	-4.316	0.000	-0.343	0.556
EI/TEE > 1.19	0.096	1.532	0.125	0.180	0.086
R-squared	**0.201**				**SUM = 1.0**
DINNER					
Within level (intake level)					
Week/weekend day (y/n)	-0.010	-0.389	0.697	-0.009	0.008
Season (winter/ summer)	0.026	1.084	0.278	0.028	0.066
Special day (y/n)	0.049	2.032	0.042	0.046	0.205
Prior interval (hours)	0.072	2.602	0.009	0.076	0.497

Table S9 continued

Predictor[2]	Beta-weight	t-test	p-value	Correlation	Pratt Index[3]
Place of meal (ref. home)					
work	-0.037	-1.190	0.234	-0.039	0.131
restaurant	0.001	0.019	0.985	0.016	0.001
other	-0.031	-0.981	0.326	-0.019	0.054
R-squared	**0.011**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.059	0.879	0.379	-0.025	-0.005
Age (years)	-0.167	-1.905	0.057	0.006	-0.003
Sex (M/W)	-0.343	-5.511	0.000	-0.412	0.456
Education level (ref. no training/ current training)					
technical college	0.027	0.402	0.687	-0.091	-0.008
university	0.076	1.189	0.234	0.146	0.036
Occupation (ref. no job/ retired)[4]					
full time	-0.027	-0.278	0.781	0.044	-0.004
part time/hourly	-0.014	-0.217	0.828	-0.031	0.001
Physical activity (h/week)	0.004	0.076	0.939	-0.053	-0.001
Smoking status (ref. never smoker)					
current smoker	0.042	0.363	0.716	-0.103	-0.014
former smoker	0.072	0.637	0.524	0.118	0.027
Energy misreporting					
EI/TEE < 0.81	-0.290	-4.457	0.000	-0.331	0.310
EI/TEE > 1.19	0.211	4.911	0.000	0.298	0.203
R-squared	**0.310**				**SUM = 1.0**

EI: energy intake; TEE: total energy expenditure
[1] n=682 participants with activity sensor data
[2] for dichotomous variables, the information shown is for the underlined category (reference category not underlined)
[3] might not add up to 100% due to rounding errors from parameter estimates
[4] full time: ≥ 35h/week; part time/hourly: < 35 h/week.

Table S10: Random intercept Multilevel Regression Analysis and Corresponding Pratt for **protein intake** (g/meal); sensitivity analysis adjusting for energy misreporting[1]

Predictor[2]	Beta-weight	t-test	p-value	Correlation	Pratt Index[3]
BREAKFAST					
Within level (intake level)					
Week/weekend day (y/n)	0.130	5.233	0.000	0.138	0.345
Season (winter/ summer)	0.024	1.057	0.290	0.020	0.009
Special day (y/n)	0.012	0.387	0.698	0.062	0.014
Prior interval (hours)	-0.046	-1.475	0.140	-0.036	0.032
Place of meal (ref. home)					
work	-0.089	-1.862	0.063	-0.098	0.168
restaurant	0.140	6.386	0.000	0.152	0.409
other	0.026	0.829	0.407	0.028	0.014
R-squared	**0.052**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.071	1.487	0.137	0.048	0.027
Age (years)	-0.018	-0.246	0.806	0.110	-0.016
Sex (M/W)	-0.239	-4.655	0.000	-0.281	0.529
Education level (ref. no training/ current training)					
technical college	-0.009	-0.168	0.867	-0.080	0.006
university	0.049	0.932	0.351	0.093	0.036
Occupation (ref. no job/ retired)[4]					
full time	-0.027	-0.341	0.733	-0.028	0.006
part time/hourly	-0.070	-1.326	0.185	-0.110	0.061
Physical activity (h/week)	0.031	0.700	0.484	0.019	0.005
Smoking status (ref. never smoker)					
current smoker	0.138	1.536	0.124	-0.019	-0.021
former smoker	0.012	1.345	0.179	0.076	0.007
Energy misreporting					
EI/TEE < 0.81	-0.114	-2.319	0.020	-0.165	0.148
EI/TEE > 1.19	0.114	2.853	0.004	0.166	0.149
R-squared	**0.127**				**SUM = 0.94**
LUNCH					
Within level (intake level)					
Week/weekend day (y/n)	0.072	2.894	0.004	0.085	0.153
Season (winter/ summer)	0.011	0.464	0.643	-0.008	-0.002
Special day (y/n)	0.008	0.336	0.737	0.025	0.005
Prior interval (hours)	0.035	1.544	0.122	0.047	0.041
Place of meal (ref. home)					
work	-0.162	-4.552	0.000	-0.170	0.689
restaurant	0.037	1.327	0.185	0.068	0.063
other	-0.049	-1.643	0.100	-0.034	0.042
R-squared	**0.040**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.114	1.364	0.172	0.034	0.011
Age (years)	-0.032	-0.289	0.773	0.233	-0.021
Sex (M/W)	-0.310	-3.108	0.002	-0.346	0.296
Education level (ref. no training/ current training)					

Table S10 continued

Predictor[2]	Beta-weight	t-test	p-value	Correlation	Pratt Index[3]
technical college	-0.092	-1.152	0.250	-0.091	0.023
university	-0.085	-1.003	0.316	-0.012	0.003
Occupation (ref. no job/ retired)[4]					
full time	-0.140	-1.083	0.279	-0.218	0.084
part time/hourly	0.062	0.695	0.487	0.023	0.004
Physical activity (h/week)	0.096	1.511	0.131	0.117	0.031
Smoking status (ref. never smoker)					
current smoker	0.064	0.450	0.653	-0.027	-0.005
former smoker	0.056	0.391	0.696	0.062	0.010
Energy misreporting					
EI/TEE < 0.81	-0.346	-3.606	0.000	-0.416	0.398
EI/TEE > 1.19	0.183	3.082	0.002	0.313	0.158
R-squared	**0.362**				**SUM = 1.0**
AFTERNOON SNACK					
Within level (intake level)					
Week/weekend day (y/n)	0.050	1.900	0.057	0.075	0.046
Season (winter/ summer)	0.025	0.971	0.331	0.022	0.007
Special day (y/n)	0.060	2.047	0.041	0.099	0.072
Prior interval (hours)	0.163	5.929	0.000	0.191	0.380
Place of meal (ref. home)					
work	-0.163	-4.825	0.000	-0.199	0.396
restaurant	0.038	1.544	0.123	0.057	0.026
other	0.058	1.841	0.066	0.097	0.069
R-squared	**0.082**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.103	1.512	0.130	0.002	0.002
Age (years)	-0.061	-0.655	0.512	-0.113	0.058
Sex (M/W)	-0.101	-1.418	0.156	-0.103	0.088
Education level (ref. no training/ current training)					
technical college	0.078	1.102	0.270	0.022	0.015
university	0.022	0.287	0.774	0.033	0.006
Occupation (ref. no job/ retired)[4]					
full time	0.187	1.763	0.078	0.139	0.220
part time/hourly	0.116	1.924	0.054	0.070	0.069
Physical activity (h/week)	0.029	0.479	0.632	-0.020	-0.005
Smoking status (ref. never smoker)					
current smoker	0.028	0.239	0.811	0.033	0.008
former smoker	-0.060	-0.521	0.603	-0.055	0.028
Energy misreporting					
EI/TEE < 0.81	-0.213	-2.916	0.004	-0.188	0.339
EI/TEE > 1.19	0.133	2.057	0.040	0.152	0.171
R-squared	**0.118**				**SUM = 1.0**
DINNER					
Within level (intake level)					
Week/weekend day (y/n)	-0.018	-0.694	0.488	-0.011	0.009
Season (winter/ summer)	0.046	1.892	0.059	0.045	0.099
Special day (y/n)	0.051	1.826	0.068	0.065	0.158
Prior interval (hours)	0.046	1.868	0.062	0.059	0.129

Table S10 continued

Predictor[2]	Beta-weight	t-test	p-value	Correlation	Pratt Index[3]
Place of meal (ref. home)					
work	-0.060	-1.917	0.055	-0.063	0.180
restaurant	0.084	2.928	0.003	0.097	0.388
other	-0.025	-0.657	0.511	-0.015	0.018
R-squared	**0.021**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.274	4.973	0.000	0.190	0.151
Age (years)	-0.176	-2.212	0.027	-0.045	0.023
Sex (M/W)	-0.334	-5.978	0.000	-0.420	0.407
Education level (ref. no training/ current training)					
technical college	0.039	0.629	0.529	-0.120	-0.014
university	0.161	2.333	0.020	0.205	0.096
Occupation (ref. no job/ retired)[4]					
full time	0.007	0.089	0.929	0.083	0.002
part time/hourly	0.028	0.504	0.614	-0.005	0.000
Physical activity (h/week)	0.042	0.914	0.361	-0.034	-0.004
Smoking status (ref. never smoker)					
current smoker	-0.047	-0.505	0.613	-0.161	0.022
former smoker	0.000	0.005	0.996	0.151	0.000
Energy misreporting					
EI/TEE < 0.81	-0.250	-4.181	0.000	-0.232	0.168
EI/TEE > 1.19	0.208	4.768	0.000	0.248	0.150
R-squared	**0.345**				**SUM = 1.0**

EI: energy intake; TEE: total energy expenditure
[1] n=682 participants with activity sensor data
[2] for dichotomous variables, the information shown is for the underlined category (reference category not underlined)
[3] might not add up to 100% due to rounding errors from parameter estimates
[4] full time: ≥ 35h/week; part time/hourly: < 35 h/week.

Table S11: Random intercept Multilevel Regression Analysis and Corresponding Pratt for **fat intake** (g/meal); sensitivity analysis adjusting for energy misreporting[1]

Predictor[2]	Beta-weight	t-test	p-value	Correlation	Pratt Index[3]
BREAKFAST					
Within level (intake level)					
Week/weekend day (y/n)	0.131	5.458	0.000	0.147	0.344
Season (winter/ summer)	-0.027	-1.229	0.219	-0.032	0.015
Special day (y/n)	0.017	0.478	0.632	0.066	0.020
Prior interval (hours)	0.026	0.868	0.385	0.038	0.018
Place of meal (ref. home)					
work	-0.116	-2.465	0.014	-0.128	0.265
restaurant	0.130	4.829	0.000	0.142	0.330
other	0.015	0.372	0.710	0.015	0.004
R-squared	**0.056**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	-0.010	-0.217	0.828	-0.042	0.003
Age (years)	0.015	0.233	0.816	0.085	0.008
Sex (M/W)	-0.303	-6.464	0.000	-0.306	0.591
Education level (ref. no training/ current training)					
technical college	-0.015	-0.315	0.753	-0.026	0.002
university	-0.094	-1.817	0.069	-0.025	0.015
Occupation (ref. no job/ retired)[4]					
full time	0.058	0.814	0.416	-0.016	-0.006
part time/hourly	0.048	1.083	0.279	-0.016	-0.005
Physical activity (h/week)	0.064	1.448	0.147	0.042	0.017
Smoking status (ref. never smoker)					
current smoker	0.082	0.937	0.349	-0.025	-0.013
former smoker	0.044	0.503	0.615	0.040	0.011
Energy misreporting					
EI/TEE < 0.81	-0.114	-2.308	0.021	-0.187	0.136
EI/TEE > 1.19	0.160	4.499	0.000	0.238	0.243
R-squared	**0.157**				**SUM = 1.0**
LUNCH					
Within level (intake level)					
Week/weekend day (y/n)	0.068	2.893	0.004	0.075	0.268
Season (winter/ summer)	0.028	1.109	0.267	0.012	0.018
Special day (y/n)	0.036	1.535	0.125	0.046	0.087
Prior interval (hours)	0.045	1.944	0.052	0.053	0.126
Place of meal (ref. home)					
work	-0.079	-2.070	0.038	-0.087	0.362
restaurant	0.027	1.023	0.306	0.051	0.072
other	-0.043	-1.457	0.145	-0.028	0.063
R-squared	**0.019**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.066	0.858	0.391	-0.009	-0.002
Age (years)	0.116	1.044	0.296	0.338	0.110
Sex (M/W)	-0.250	-2.505	0.012	-0.296	0.208
Education level (ref. no training/ current training)					

Table S11 continued

Predictor[2]	Beta-weight	t-test	p-value	Correlation	Pratt Index[3]
technical college	-0.080	-1.011	0.312	-0.065	0.015
university	-0.085	-1.070	0.285	-0.033	0.008
Occupation (ref. no job/ retired)[4]					
full time	-0.090	-0.714	0.475	-0.262	0.066
part time/hourly	0.028	0.354	0.724	-0.038	-0.003
Physical activity (h/week)	0.098	1.323	0.186	0.148	0.041
Smoking status (ref. never smoker)					
current smoker	0.026	0.205	0.838	0.012	0.001
former smoker	-0.001	-0.010	0.992	0.019	0.000
Energy misreporting					
EI/TEE < 0.81	-0.340	-3.720	0.000	-0.437	0.417
EI/TEE > 1.19	0.156	2.669	0.008	0.302	0.132
R-squared	**0.356**				**SUM = 1.0**
AFTERNOON SNACK					
Within level (intake level)					
Week/weekend day (y/n)	0.068	2.480	0.013	0.098	0.077
Season (winter/ summer)	-0.009	-0.351	0.725	-0.012	0.001
Special day (y/n)	0.043	1.438	0.151	0.091	0.045
Prior interval (hours)	0.150	5.669	0.000	0.176	0.303
Place of meal (ref. home)					
work	-0.173	-4.781	0.000	-0.212	0.422
restaurant	0.070	2.739	0.006	0.089	0.072
other	0.071	2.603	0.009	0.103	0.084
R-squared	**0.087**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.066	0.966	0.334	-0.030	-0.012
Age (years)	-0.100	-1.179	0.238	-0.025	0.015
Sex (M/W)	-0.219	-3.283	0.001	-0.195	0.256
Education level (ref. no training/ current training)					
technical college	0.042	0.660	0.509	0.028	0.007
university	-0.041	-0.587	0.557	-0.029	0.007
Occupation (ref. no job/ retired)[4]					
full time	0.039	0.391	0.696	0.021	0.005
part time/hourly	0.076	1.491	0.136	0.055	0.025
Physical activity (h/week)	0.058	1.093	0.275	0.029	0.010
Smoking status (ref. never smoker)					
current smoker	-0.074	-0.809	0.418	0.039	-0.017
former smoker	-0.200	-2.237	0.025	-0.099	0.119
Energy misreporting					
EI/TEE < 0.81	-0.206	-2.968	0.003	-0.231	0.285
EI/TEE > 1.19	0.192	4.241	0.000	0.258	0.297
R-squared	**0.167**				**SUM = 1.0**
DINNER					
Within level (intake level)					
Week/weekend day (y/n)	-0.049	-1.937	0.053	-0.045	0.105
Season (winter/ summer)	0.052	2.151	0.031	0.052	0.129
Special day (y/n)	0.036	1.498	0.134	0.040	0.069

Table S11 continued

Predictor[2]	Beta-weight	t-test	p-value	Correlation	Pratt Index[3]
Prior interval (hours)	0.039	1.593	0.111	0.051	0.095
Place of meal (ref. home)					
work	-0.082	-1.754	0.079	-0.081	0.316
restaurant	0.060	2.758	0.006	0.068	0.194
other	-0.047	-1.441	0.150	-0.038	0.085
R-squared	**0.021**				**SUM = 1.0**
Between level (participant level)					
BMI (kg/m^2)	0.217	4.273	0.000	0.117	0.067
Age (years)	-0.057	-0.779	0.436	0.112	-0.017
Sex (M/W)	-0.335	-5.886	0.000	-0.417	0.368
Education level (ref. no training/ current training)					
technical college	-0.042	-0.675	0.500	-0.122	0.013
university	0.028	0.434	0.664	0.103	0.008
Occupation (ref. no job/ retired)[4]					
full time	-0.033	-0.422	0.673	-0.081	0.007
part time/hourly	0.110	2.023	0.043	0.057	0.017
Physical activity (h/week)	0.043	0.973	0.331	0.017	0.002
Smoking status (ref. never smoker)					
current smoker	-0.055	-0.554	0.580	-0.121	0.018
former smoker	-0.024	-0.247	0.805	0.111	-0.007
Energy misreporting					
EI/TEE < 0.81	-0.341	-5.677	0.000	-0.372	0.334
EI/TEE > 1.19	0.224	5.807	0.000	0.322	0.190
R-squared	**0.380**				**SUM = 1.0**

EI: energy intake; TEE: total energy expenditure
[1] n=682 participants with activity sensor data
[2] for dichotomous variables, the information shown is for the underlined category (reference category not underlined)
[3] might not add up to 100% due to rounding errors from parameter estimates
[4] full time: ≥ 35h/week; part time/hourly: < 35 h/week.

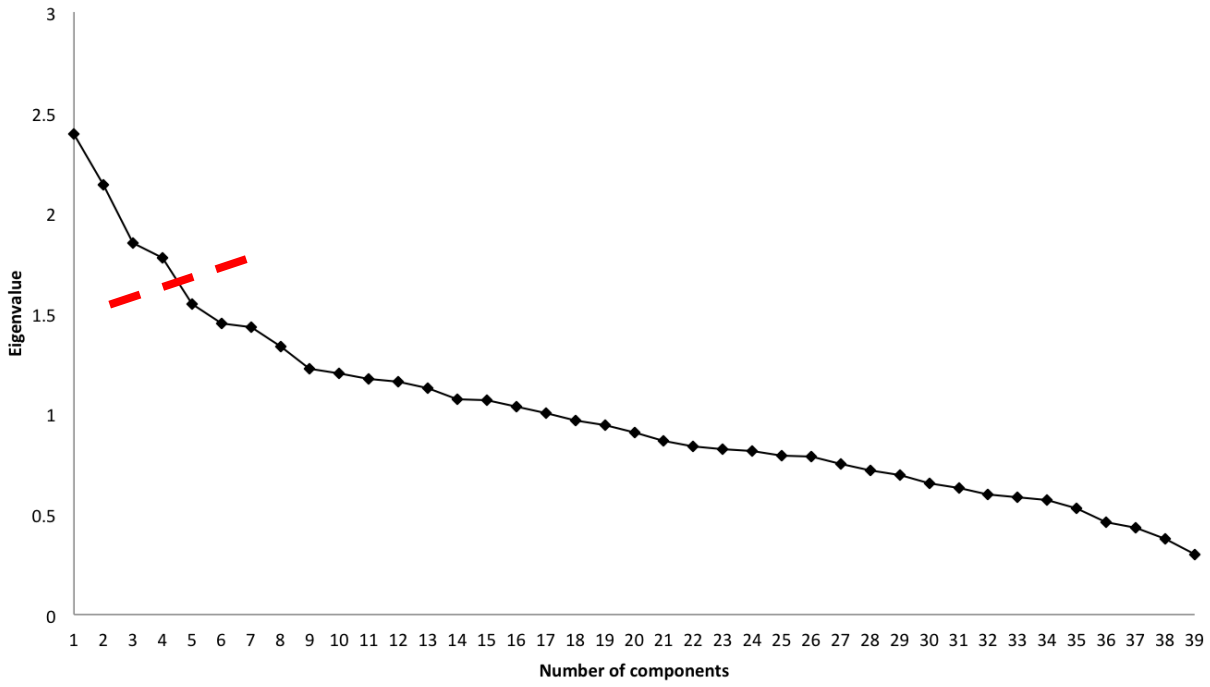

Figure S1: Scree plot for the PCA-derived habitual dietary patterns. The dotted line indicates cut-off for the retained components.

Relevant Publications

Part of the research contained within this doctoral thesis has been published as:

> Carolina Schwedhelm, Khalid Iqbal, Sven Knüppel, Lukas Schwingshackl, Heiner Boeing; Contribution to the understanding of how principal component analysis–derived dietary patterns emerge from habitual data on food consumption, *The American Journal of Clinical Nutrition*, Volume 107, Issue 2, 1 February 2018, Pages 227–235. DOI: https://doi.org/10.1093/ajcn/nqx027

> Carolina Schwedhelm, Sven Knüppel, Lukas Schwinshackl, Heiner Boeing, Khalid Iqbal; Meal and habitual dietary networks identified through Semiparametric Gaussian Copula Graphical Models in a German adult population, *PLOS ONE*, Volume 13, Issue 8, 24 August 2018. DOI: https://doi.org/10.1371/journal.pone.0202936

and any reprinted material has been appropriately cited as such.