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OBJECTIVELY MEASURED EATING BEHAVIORS AND THEIR RELATION TO FOOD INTAKE IN SCHOOL AND HOSPITAL SETTINGS

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OBJECTIVELY MEASURED EATING BEHAVIORS AND THEIR RELATION TO FOOD INTAKE IN SCHOOL AND HOSPITAL SETTINGS

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By

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To my life partner Vasiliki

POPULAR SCIENCE SUMMARY OF THE THESIS

Background

It is of great importance to accurately measure food intake (what and how much we eat and drink) and factors that can affect it since it is related to three great challenges facing humanity: 1) overnutrition/obesity, 2) undernutrition and 3) climate change, as well as their related negative consequences on human health.

Traditional measurements of food intake have mainly been conducted in either a self-report format that relies on the accuracy of human memory, conscious and unconscious expectations about what to answer and people's ability to estimate portion sizes accurately, or measurements with food scales, video cameras and other objective methods in laboratory-bound setups. The self-reported methods have been shown to give inaccurate information about people's energy intake and the laboratory methods have been critiqued for generating results that are not resembling "real life" eating. Therefore, there is a need for objective methods that put less burden on the participants to self-report their food intake accurately, while also being mobile and functional in "real life" situations. Our team, together with collaborators from Greece, Spain, Netherlands, and Germany, made efforts to develop and implement such methods in "real life" settings during three multinational EU-projects.

The purpose of this thesis was to measure and explain differences in food intake in school, hospital and free-living settings by using these methods.

Research approach

Studies in three settings were conducted: 1) a school setting, 2) a hospital setting and 3) a free-living setting. In the school setting, high school students were eating their lunch in their everyday school cafeteria environment. Portable food scales were used to record the weight of the food that was eaten while video cameras were recording the students. Eating behaviors (how a person eats) such as the speed of eating and number of spoonfuls, were annotated in computer software by use of the video recordings. Students were also self-reporting their perceived speed of eating compared to their peers, their fullness before and after the meal, as well as how tasty the food was. The portable food scales and video cameras were used in an additional experiment in the same environment including a subset of the participants. The aim was to compare the energy intake from snacks, during a one-hour work task in a classroom setting, with snacks placed either close to the students (food proximity), or further away from the students so that they needed to stand up and walk to refill with more snacks.

In the hospital setting, a standardized meal was served during normal lunch hours. The purpose was to compare the lunch meal energy intake between groups of early Parkinson's disease patients, advanced Parkinson's disease patients as well as healthy volunteers.

In the free-living setting, we asked school students in Sweden and Greece to download a mobile application developed during one of the EU projects mentioned above. In the application, students self-reported their weight, height and perceived speed of eating in comparison to their peers.

Results

The results showed that eating behaviors (i.e., the speed of eating and number of spoonfuls of food taken during the meal) were the most powerful variables to explain the weight of the food that students consumed during the lunch meal. Self-reported food taste after the lunch meal and the desire to eat before the snack experiment were also powerful explanatory variables for how much students were eating. The self-reported eating rate could be used to divide large groups into slow and fast eaters, but it could not be used to classify an individual's eating rate category accurately. Self-reported fast eating was also related to higher body mass index compared to self-reported slow eating among the students. Putting snack food closer to students resulted in increased energy intake from snacks compared to when the snacks were placed further away from the students. Additionally, advanced Parkinson's disease patients in the hospital study had lower energy intake compared to early Parkinson's disease patients and healthy volunteers, a result that is opposite to what previous self-report studies have shown.

Conclusions

Eating behavior and food proximity interventions might be used to modify the quantity of food intake in both schools and hospitals. Since advanced Parkinson's disease patients were shown to eat less when compared to early Parkinson's disease patients and healthy volunteers, more focus should be given to facilitate balanced energy intake in this patient group and reduce their risk of undernutrition and related health complications. Video cameras and food scales used in this project could be used in larger scale studies that aim to determine the eating behavior of large groups. Future technological innovations (i.e., algorithms based on video and smartwatch data) will allow for automatic detection of eating behaviors, such as the speed of eating and number of spoonfuls taken during a meal in real time. Our team, together with collaborators from Greece, work on the development of such technological tools. Those methodological improvements could be useful for those who need to modify their eating behavior in situations that might be challenging, such as school lunches and other buffet settings.

ABSTRACT

Introduction

The measurement of food intake (what and how much we eat and drink) is of great importance due to its involvement in three great challenges facing humanity: 1) obesity/overnutrition, 2) undernutrition and 3) climate change, as well as their related health consequences. However, measuring food and energy intake in humans is complicated since traditional self-reported methods have systematic bias while traditional objective laboratory methods have generalizability and upscaling issues. Therefore, novel methods to measure food and energy intake in humans have often been requested. A plethora of factors have been associated with variation in food intake in humans. For example, internal behavioral factors such as eating rate, internal disease conditions such as Parkinson's disease (PD) as well as external environmental factors such as food proximity are notable ones. These factors have mainly been investigated by use of the traditional methods listed above.

Aims

The overarching aim with this thesis was to use novel technological tools (i.e., portable food scales and video cameras) to measure and explain variance in food intake and body mass index in school, hospital and free-living settings.

Aims in school setting: To explain variance in food mass intake during school lunch with objectively measured eating behaviors (how a person eats), the proximity to food and subjective appetite measures. To assess the test-retest reliability of objectively measured food mass intake and eating rate during school lunch. To assess the concurrent validity of self-reported eating rate. **Aims in hospital setting:** To compare energy intake among healthy controls, early and advanced PD patients and to investigate the association between clinical features of PD as well as objective eating behaviors with energy intake during a hospital lunch. **Aim in free-living setting:** To distinguish differences in BMI z-scores (BMIz) among self-reported eating rate categories in populations of Swedish and Greek high school students.

Methods

School studies

Settings: The data collection was conducted in the school lunch cafeteria environment at a high school in central area of Stockholm, Sweden. **Study design:** A cross-sectional study design was used to explain variance in food intake and to investigate the association between objectively measured eating rate and food intake. An experimental study design was used to investigate the effects of food proximity and a repeat-measures study design was used to assess the test-retest reliability of objectively measured food mass intake and eating rate. **Participants:** Six high school classes including 187 students were invited to participate in monitored school lunches during 2015-2017. Out of these, 114 unique students provided complete meal data and 103 with a mean (SD) age of 16.7 (0.6) and BMIz of -0.07 (1.05)

were included in the food intake variance analysis. All 114 participants (with a mean (SD) age of 16.5 (0.8) and BMIz 0.04 (1.01)) were included in the association between eating rate and BMIz. Out of the 114 unique participants, 50 students came for a repeated meal and provided complete data for test-retest analyses. **Study procedures:** The lunch study was conducted during normal school lunch hours (11.30-13.00). The students who participated in the snack experiment came back at 15.30 for the one-hour experimental snack session with snack foods, either a) close to the table where they were sitting (proximal condition) or further away from them (distal condition). **Served food:** During school lunches, usual lunch food at the included school (beef/vegetable patties, brown sauce, potatoes, fish, variety of vegetables, water/milk) was served in a buffet-like setting. For the snack experiment, chocolate lentils, crackers and grapes were served ad libitum.

Hospital study

Settings: The data collection was conducted in a dedicated room at the Department of Neurology of the Technical University Dresden (TUD), Germany. **Study design:** A cross-sectional study design was used. **Participants:** 64 participants (n = 23 healthy controls, n = 20 early and n = 21 advanced PD patients) with a mean (SD) age of 62.4 (7.8) and BMI 27.2 (4.3) were included. **Study procedures:** Study participants had a medical evaluation before they ate their lunch meal during normal lunch hours (11.00-15.00). **Served food:** A standardized meal (200g sausages, 400g potato salad, 200g apple mash and 500ml of water) was served to all participants.

Free-living study

Settings: A smartphone application was developed to gather self-reported eating rate and BMIz. **Study design:** A cross-sectional study design was used. **Participants:** Students from multiple high schools in Sweden (n = 748) and Greece (n = 1084) were recruited through school supported actions (n = 1832 in total, mean (SD) age of 15.8 (0.9), BMIz 0.47 (1.41)) that included self-reported measures of weight, height and eating rate. **Study procedures:** Students who chose to participate downloaded the study mobile application and self-reported their data.

Data sources and measurements

In the school and hospital setting, weight and height scales were used to measure participants body weight and height, and food mass and energy intake were measured with portable food scales. Video cameras were used to record the meals and eating behaviors were annotated onto the videos in computer software. In the free-living setting, students self-reported their age, weight, height, and their speed of eating in comparison to others at their own discretion.

Results

Reliability and validity: In the school setting, there was no significant systematic change in mean food mass intake from lunch 1 to lunch 2 (-7.5g, 95% confidence interval: -43.1g to

+28.0g). The intraclass correlation between food mass intake during lunch 1 vs. lunch 2 was 0.74 (95% confidence interval 0.58 to 0.84). There was a significant systematic change in eating rate (g/min) from lunch 1 to lunch 2 (+4.4 g/min, 95% confidence interval: +0.7 g/min to +8.1 g/min). The intraclass correlation between eating rate during lunch 1 vs. lunch 2 was 0.73 (95% confidence interval 0.59 to 0.85).

When comparing the objective eating rate among the three categories of self-reported eating rate (slow, intermediate, and fast), a significant difference between the groups was obtained [$F(2, 111) = 7.104$, $P = 0.001$, partial $\eta^2 = 0.113$]. Bonferroni post hoc comparisons showed that students who self-reported eating slower than others had significantly lower eating rate (-13.7g/min, 95% confidence interval: -22.5g/min to -4.84g/min) compared to students who self-reported eating faster than others. The weighted Kappa value for self-reported eating rate categories versus objectively established eating rate categories was 0.31 ($P < 0.001$).

Main results

School: Eating rate, number of spoonfuls, sex, number of food additions and food taste (explanatory power in that order) were all significant explanatory variables for variance in food mass intake during school lunch, while BMI and change in fullness were not significant (effect size: adjusted R squared = 0.766 for the total model). There was a significant "large" ($R = 0.667$) correlation between objectively measured eating rate and food mass intake during school lunch. When dividing students into tertiles of eating rate (slow, intermediate and fast eaters), a significant difference in food mass intake between the three groups was found [$F(2, 111) = 30.578$, $P < 0.001$, partial $\eta^2 = 0.355$]. Bonferroni post hoc comparisons showed that students in the "slow" objective eating rate tertile were eating 133 grams less food (95% confidence intervals = -210g to -56g) than students in the "intermediate" objective eating rate tertile, and 247 grams less (95% confidence intervals = -324g to -170g) than students in the "fast" eating rate tertile. Students who were participating in the distal snack food condition were eating significantly less energy from snacks than students in the proximal condition (mean difference = -222.7 kcal 95% confidence intervals: -428.3 kcal to -17.2 kcal).

Hospital: Advanced PD patients consumed significantly less energy during lunch compared to both early PD patients (b = -202.7 kcal, 95% confidence interval: -329.2 kcal to -76.2 kcal) and healthy controls (b = -162.1 kcal, 95% confidence interval: -285.7 kcal to -38.4 kcal) when controlling for sex.

Free-living: Self-reported eating rate was found to be a significant explanatory variable for variation in self-reported BMI z-scores [$F(2, 1829) = 9.724$, $P < 0.001$, partial $\eta^2 = 0.011$]. Bonferroni post hoc test showed that students who self-reported eating slower than others had 0.23 units lower BMI z-scores (95% confidence intervals: -0.43 to, -0.03) than students who self-reported intermediate eating rate, and 0.37 units lower (95% confidence intervals: -0.57 to -0.17) than students who self-reported eating faster than others.

Outcome synthesis: Overall, eating behaviors were the most powerful explanatory variables, while desire to eat and food taste were the most powerful self-reported variables for food and energy intake variance when controlling for sex in the included studies. Advanced PD status (hospital study) as well as the food proximity (snack experiment) were also powerful explanatory variables, while PD-related symptomatology as well as self-reported eating rate, hunger, change in fullness and BMI had low or no explanatory power.

Conclusions

Objectively measured single-meal food mass intake and eating rate could be used to rank individuals in comparison to their peers. Subjective eating rate could be used to distinguish groups with slow and fast eating rates in large scale studies but should not be used on an individual level. The outcomes of this thesis suggest that objectively measured eating behaviors and subjective factors such as food taste and desire to eat, as well as the external condition proximity to food, are all powerful explanatory factors for variance in food mass and energy intake and might be potential targets in future interventions that aim to modify food intake. Additionally, advanced PD condition was associated with lower energy intake. Potential interventions mentioned above might be helpful in this patient group to normalize their energy intake and reduce their risk of undernutrition. Furthermore, the results suggest that novel methods that objectively measure eating behaviors could be utilized in larger-scale nutrition research. Further technological developments of these methods could also give real-time feedback on targeted eating behaviors that are related to food intake, thus ultimately reducing the risk of diseases related to over- and undernutrition.

LIST OF SCIENTIFIC PAPERS

I. **Fagerberg P**., Langlet B., Glossner A., Ioakimidis I. Food Intake during School Lunch Is Better Explained by Objectively Measured Eating Behaviors than by Subjectively Rated Food Taste and Fullness: A Cross-Sectional Study. Nutrients. 2019 Mar 12;11(3):597. doi: 10.3390/nu11030597.

II. **Fagerberg P**., Charmandari E., Diou C., Heimeier R., Karavidopoulou Y., Kassari P., Koukoula E., Lekka E., Maglaveras N., Maramis C., Pagkalos I., Papapanagiotou V., Riviou K., Sarafis I., Tragomalou A., Ioakimidis I. Fast Eating Is Associated with Increased BMI among High-School Students. Nutrients. 2021 Mar 9;13(3):880. doi: 10.3390/nu13030880.

III. Langlet B., **Fagerberg P**., Glossner A. and Ioakimidis I.
Objective Quantification of the Food Proximity Effect on Grapes, Chocolate and Cracker Consumption in a Swedish High School. A Temporal Analysis PLoS One. 2017 Aug 10;12(8):e0182172. doi: 10.1371/journal.pone.0182172.

IV. **Fagerberg P**., Klingelhoefer L., Bottai M., Langlet B., Kyritsis K., Rotter E., Reichmann H., Falkenburger B., Delopoulos A., Ioakimidis I. Lower Energy Intake among Advanced vs. Early Parkinson's Disease Patients and Healthy Controls in a Clinical Lunch Setting: A Cross-Sectional Study. Nutrients. 2020 Jul 16;12(7):2109. doi: 10.3390/nu12072109.

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LIST OF ABBREVIATIONS

ANOVA	Analysis of variance
BMI	Body mass index
BMIz	BMI z-scores
cm	Centimeter
DLW	Doubly labeled water
$\eta 2$	Eta Squared
EU	European Union
FFQ	Food frequency questionnaire
g	Grams
IEGS	Internationella Engelska Gymnasiet Södermalm
kcal	Kilocalorie
kg	Kilogram
min	Minute
ml	Milliliter
mm	Millimeter
n	Number
NMS	Non-motor symptoms
PD	Parkinson’s disease
R^2	Coefficient of determination
TUD	Neurology of the Technical University Dresden
vs.	Versus
Wi-Fi	Wireless Fidelity

1 INTRODUCTION

This thesis spans through three European Union (EU) collaborative, interdisciplinary, health/technology research projects, namely: **SPLENDID** (1), **iPrognosis** (2) and **BigO** (3). The **SPLENDID** project aimed at developing tools to guide school students towards healthier eating and physical activity, with the ultimate aim to reduce their risk of developing obesity and eating disorders such anorexia nervosa. The **iPrognosis** project aimed at building detection tests for early Parkinson's disease with the use of novel technological tools. Additionally, the design of interventions to improve Parkinson's disease patients' quality of life was the long-term aim of the project. The **BigO** project aimed at collecting environmental and behavioral "big data" related to obesity development in children. The idea was to build analytical tools that could inform public health authorities in real time about health behaviors in the targeted populations. Together, these three EU projects have shaped the development of this thesis and the papers that have been included.

2 BACKGROUND

2.1 MEASURING FOOD INTAKE

The measurement of food intake (what and how much we eat and drink) is a priority in nutrition science. Today, three of the greatest health-related challenges facing humanity are overnutrition, undernutrition and climate change (4) – all three tied to unbalanced human food consumption (4,5). These challenges have collectively been called "the global syndemic" due to their co-occurrence in time and place as well as their negative impact on human health (4).

Currently, around 2 billion humans suffer from obesity, a multifactorial disease caused by overnutrition, defined as eating more energy from food than the body needs to maintain weight stability over time (6). Overnutrition is mainly driven by the modern food environment, with readily available ultra-processed, highly-palatable and energy-dense fast foods with poor nutritional quality, in combination with sedentary lifestyles (7–10). Obesity is a key risk factor for non-communicable diseases such as cardiovascular disease (11), type 2 diabetes (12), cancer (13), depression (14) as well as early death (12). The related economic costs have been estimated to equal that of smoking, or those of armed violence, war and terrorism added together, or roughly 3% of the global gross domestic product (15). At the same time, the current human behavioral footprint on planetary health has been associated with increased risk of environmental disasters such as drought, wildfires and increased sea levels (4). Interestingly, one of the most important human behavioral footprints on planetary health is the overproduction and overconsumption of food, especially the low quality ultra-processed foods mentioned above (16).

On the other hand, approximately 0.5 billion humans are underweight (5). Underweight is mainly caused by undernutrition, here defined as eating less food, energy, and nutrients than the body needs to be weight stable and function properly over time. These problems are most prevalent in low- and middle-income countries, where the distribution and production of nutritious food can be scarce while a large proportion of people might have inadequate health education and access to good sanitation (5). However, undernutrition also occurs (albeit less frequently) in richer countries. For example, the risk of undernutrition has been estimated to double among elderly and people living with chronic diseases (so called disease-related malnutrition) (17,18). It is even higher among hospitalized patients (18,19) and elderly people who receive municipal health care (20) or live in nursing homes (21). In fact, decreased food intake among hospitalized patients is an important risk factor for early mortality (22) and similar observations have been made in elderly people with BMI < 23 (23). Furthermore, chronic diseases and their treatments can affect eating behaviors such as swallowing and chewing, as well as appetite, digestion and energy expenditure, thus increasing the risk of undernutrition (17). One such disease is the progressive neurodegenerative disorder Parkinson's disease (PD) that has been associated with unintentional weight loss, underweight and in severe cases malnutrition (24,25). To better understand contributing factors to both under- and overnutrition, accurate measurements of food intake are needed.

2.1.1 The gold standard

To be able to evaluate the concurrent validity of a method to measure food and energy intake (i.e., how well it measures "true" intake), a "gold standard" method is needed to compare it to. The most accurate way to do this, although not the most feasible, is to make available a known quantity of food to subjects and then deduce food intake from the leftovers (26–30). Since the common research focus is to estimate food intake over longer time periods, subjects need to live in a controlled environment during the complete study period to reach the highest level of accuracy with this method (26,31,32). This validation method has some important limitations. To begin with, trained staff needs to be constantly vigilant and observe participant's behavior throughout the measurement period. Ideally, subjects should not be aware that they are monitored (i.e., with hidden video surveillance to reduce the risk for protocol deviations), since it might affect their food intake (27). Such approach comes with obvious ethical concerns and this type of environment (i.e., controlled laboratory settings) differs from participants' "real life" environments. Due to this, controlled laboratory style validation studies are scarce.

However, a less burdensome way to estimate energy intake indirectly have been developed and used in validation studies. It is based on the energy balance equation and utilizes the doubly labeled water (DLW) technique, an objective method to measure people's energy expenditure unobtrusively (33). DLW is accurate enough to be used for this purpose (34), as it has been shown to have low systemic bias (35,36) compared to the "gold standard" measurement of energy expenditure respiratory chamber (37). The idea is that if subjects are weight stable (which means that they are in energy balance), then they need to have an average energy intake from food that is very close to the measured energy expenditure obtained from the DLW method. Otherwise, they would gain or lose weight over the study period according to the energy balance equation. Therefore, energy intake can be deduced with high accuracy with this method since most people are expected to be in energy balance during measurement periods of 1-3 weeks (30). Indeed, DLW energy expenditure have been shown to have very low systemic bias vs. the directly observed food intake (kcal) method mentioned above (27). However, it is important to note that some populations, such as the elderly, might lose weight during such short period of time and can therefore result in biased energy intake estimates if body weight changes are not accounted for (38).

Although the above-mentioned method has been used to validate other methods to assess energy intake in humans, it has some important limitations. The main limitation is that DLW is expensive (34). Usually, only small samples of subjects can be included in such studies (39), although bigger scale meta studies do exist (40). Additionally, this indirect method to estimate energy intake cannot show what specific foods a certain individual has been eating. Therefore, other objective biomarker methods have been developed and used that can hint at more specific food choices among participants (41,42). However, these methods are outside the scope of this thesis and will not be further discussed.

2.1.2 Self-reported methods

Traditional methods to measure food, energy and nutrient intake patterns (also called "dietary assessment") in humans have mainly been of a self-reported nature (41). With these methods, subjects are asked to report their consumption of food during a given time interval. These can be retrospective (what was eaten in the past) or prospective (what will be eaten in the future). This means that the accuracy of human memory, conscious and unconscious expectations about what to answer, as well as estimation problems related to portion sizes are all important factors to consider when using these types of methods. The self-reported methods have been suggested as valuable tools to categorize large groups of individuals in crude dietary pattern levels (i.e., low, intermediate and high intake levels) (43).

Food frequency questionnaire (FFQ) is the most common retrospective self-report method used today (44,45). With FFQ, participants are asked to estimate the frequency of consumption of common food items (usually adapted to the food culture of interest (46,47)) during the past year in a questionnaire format. When comparing the energy intake obtained from FFQ vs. DLW energy expenditure, a recent meta-analysis concluded that the FFQ method underestimated energy intake by approximately 30% on a group level (range 24-32% in different studies) (48), and that the correlation between FFQ energy intake and DLW energy expenditure was 0.08-0.34 in the included validation studies.

Another common method to estimate dietary intake in humans is the 24h recall method. With 24h recall, study personnel interviews participants about what food and drinks they have been consumed during the last day (24h). In the same review as cited above (48), 24h recalls had an average underreporting bias for energy intake of 15% (range 6-28% in different validation studies). The correlation between DLW energy expenditure vs. energy intake from a single 24h recall was 0.23-0.36, vs. two 24h recalls 0.26-0.41, and vs. three 24h recalls 0.27-0.42. Like the results obtained from FFQ, these correlations are "trivial'' to "moderate" (49) and indicate that caution is needed when interpreting self-reported energy intake estimations obtained from studies that have utilized these types of methods, both on an individual and on a group level (50).

A common prospective method to measure food intake is dietary records (also called food records (51)) (52). Dietary records has been considered as the “gold standard” self-report method to assess dietary intake since it does not rely on participants memory (52). With this method, participants record all food and beverages they consume in real time during a given period, typically lasting between 3-7 days (or longer). The portion size of each food item is estimated as well as the timepoint for consumption. Stubbs and colleagues found that dietary records (by having participants use digital food scales in a highly controlled environment to measure their food intake, so called weighted dietary records) had a misreporting bias, i.e., underreporting, of approximately 10% vs. covertly measured energy intake (gold standard)(27). The participants in this study were most likely more motivated than the general population since they were willing to live in a “eating suite” for an extended time and record all their food meticulously. The observed bias might therefore have been enhanced if a more representative sample from the general population would be included instead (52). In addition, most individuals do not consume their food in this type of controlled environment, with easy access to weighing scales as well as pen and paper, to register their food consumption all the time. For example, individuals eating lunch in a hectic cafeteria setting or in a restaurant have almost no possibility to weigh all food components that they eat or to write it down before they forget. It could therefore be argued that if the same individuals would have been observed in a “real life” environment, the errors observed in this study would most likely have been exacerbated. Energy intake results obtained from dietary records should therefore be interpreted with caution.

Interestingly, the weighted dietary records method has been one of the most frequently used tools to validate both FFQs and 24h recalls (43). In other words, a method with known systematic bias has been used to validate other methods and the results obtained from such validation studies should be interpreted with caution (27).

Due to the listed limitations with the self-reported methods to measure food and energy intake, most nutrition researchers agree that the “traditional” self-reported measurement tools need to be complemented or replaced by more objective methods to increase accuracy in future research efforts. Improved methods could better inform public health authorities regarding policy decisions (45,50,53–55). Although the development of such methodologies is ongoing, the implementation in “real life” settings is still limited.

2.1.3 Objective methods

To be able to measure short-term food intake during single meals in a precise manner without self-report bias, objective methods in laboratory settings have been developed and used (**Figure 1** for an example) (56,57). In these studies, hidden or visible scales are used to measure the precise meal size as well as the temporal distribution of food intake during meals (56,57).

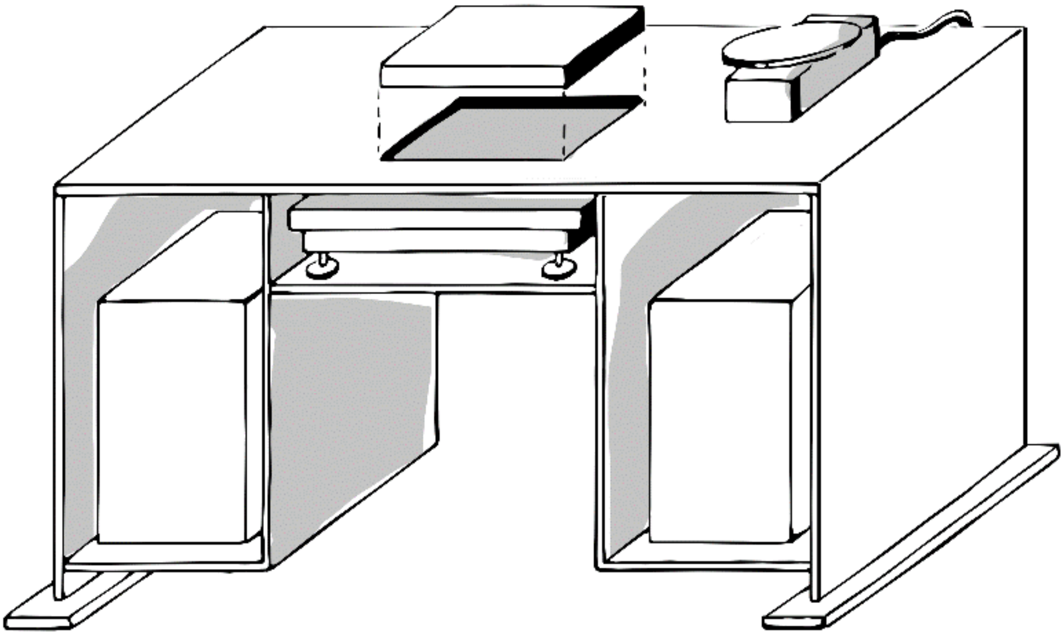


Figure 1. The universal eating monitor, one of the early objective methods to measure food intake during laboratory meals (56). A hidden scale is built into a table and connected to a personal computer. The scale records weight changes from the plate when a person eats, and food mass intake can be objectively recorded in real time. Figure illustration: Elin Fagerberg.

Video recordings can also be added to give detailed description of eating behaviors such as eating rate, number of spoonfuls, chewing and swallowing behaviors that the traditional self-reported methods have not been focusing on (57). These methods are suitable to detect small changes in food intake (both energy intake and food mass intake) and eating behaviors over short time-periods. For example, external manipulations such as changes in food texture (58), social cues (59), portion sizes (60,61), drug ingestion (62), or food of varied energy density (63) and their effects on food intake have been investigated (64–66). Such studies have shown that meal size (both on an individual and a group level) is highly reproducible during a buffet setting (67), as well as during an ad libitum lunch/dinner setting (68,69). Meal size has also been shown to have a “very large” association (r = 0.82) with daily energy intake (70). These observations indicate that a single meal under laboratory conditions could be useful to identify subjects with a tendency towards eating large meal sizes as well as those with small meal sizes (69,70).

It is important to mention that these methods have important limitations. Like the “gold standard” methods, laboratory-based food intake studies are expensive to conduct. Trained staff are needed to collect and supervise the data collection (albeit during a shorter time vs.

the “gold standard” methods), which typically results in small sample sizes vs. FFQ and 24h recall methods (64). Furthermore, if subjects are being aware that their food intake is monitored (i.e., due to ethical reasons/information before the study or by being aware of the external recording equipment), then this can have a suppressive effect on their meal size (71–73). In addition, the method is sensitive to protocol deviations and standardization is needed to reduce the effect of external factors on subject’s food intake (64,65). There is also an ongoing discussion about how well results obtained from laboratory-based studies translate into free living settings (64–66). The short-term nature of these studies can also be criticized for not translating into the longer-term dietary pattern that subjects are exposed to.

Due to these limitations, mobile versions of the laboratory-based tools have been developed to conduct similar research in semi-controlled contexts. One such tool is the Mandometer® food scale that can automatically record food mass intake during meals (74). The Mandometer® measures the weight reduction of the plate during the meal and sends the data to a personal computer (older versions) or to a mobile device such as a smartphone through Wi-Fi connection (latest version, **Figure 2**).

Figure 2. The Mandometer® food scale (74). A portable food scale that is connected to a smartphone application, enabling “real life” data collection. The scale records food mass intake in real time during meals. Figure illustration: Elin Fagerberg.

The Mandometer®, together with video cameras have been tested in school canteen environments (75–77). These methods have allowed for detailed analysis of food mass intake (i.e., the grams of food eaten) (76) and energy intake (78), as well as detailed temporal distribution of food intake among students in a school settings (77,78).

It is important to mention that a range of other objective tools/methods to measure food intake in free living environments have been developed/are under development (79,80). These tools/methods include, but are not limited to, food photography method (81,82), energy balance equations (34) and activity monitors (83), chewing sensors and smartwatches to capture hand to mouth movements (i.e., automatic detection of eating events (84,85)), as well as cameras that capture pictures automatically and analyze them for potential eating events (80). They show promise for future use and might eventually lead to more accurate estimates of food and energy intake than the methods used today. However, most of these tools/methods are still in an early stage of development and have not been validated and deployed on a mass scale successfully yet.

2.1.4 Challenging populations

Some populations are more challenging to conduct research related to food and energy intake in than others. The development of objective unobtrusive methods to measure food and energy intake with high concurrent validity is therefore extra important in research that involves these populations.

2.1.4.1 High BMI

BMI has been identified as an important correlate of energy intake misreporting (48,86). In a meta-analysis of studies that compared self-reported energy intake (from 24h recall and FFQs) vs. DLW, a BMI of 30 was associated with an additional 5-7% misreporting (underreporting) vs. a BMI of 25. An interesting study was conducted among overweight and obese subjects with so called “diet resistance” (defined as having a history of failure to lose weight while self-reporting an energy intake of less than 1200 kcal) (87) and compared self-reported energy intake vs. DLW (adjusted for changes in body composition). The results showed that the participants underreported their energy intake by 47% vs. DLW method. Simple cutoffs (i.e., self-reported energy intake < 1.35 x basal metabolic rate) have been suggested and used in nutrition research (88,89) to exclude such subjects. However, a large degree of bias still remains after removing “misreporters” (17-51% of samples) and the procedure has been discouraged (90).

2.1.4.2 Education level

Education level is also important to mention as it relates to energy intake misreporting. In the above mentioned meta-analysis, having a high school education level was associated with approximately 6-10% increased energy intake misreporting (underreporting) vs. having a collage education level (48). Since obesity is more prevalent in populations with lower education level, studies that have used self-reported energy intake to investigate obesity associations should be interpreted cautiously.

2.1.4.3 Young age

Children and adolescents are more susceptible to misreporting bias compared to adult populations as their cognitive ability is still under development (91–93). These age groups might be extra sensitive to social desirability bias (94) and seem to have a higher demand for short and easy to complete food intake measurements (91,95,96). Indeed, validation studies investigating self-reported vs. DLW energy expenditure in child and adolescent populations have shown that they are prone to both underreport (97–99) and overreport (100) their food intake. As expected, the underreporting phenomenon in these populations also interacts with BMI, i.e., children with obesity (97) and adolescents (98) have greater misreporting vs. overweight and normal weight ones (101).

2.1.4.4 Old age

Another challenging population to measure food intake in is elderly people. Elderly populations have issues with fading memory as well as reduced sight and attention (102–104). They also perceive food intake measurements to be more troublesome to complete compared to younger adults (104). The requirement for easy-to-use methods to record food intake in elderly populations is therefore critical, especially if representative samples are to be included in such studies.

2.1.4.5 Neurodegenerative diseases

Patients with neurodegenerative diseases (i.e., Parkinson's and Alzheimer's Disease) that affect the brain and cognitive abilities are populations that could be considered as “challenging” to conduct nutrition research in. Most food-related studies in these populations have been conducted using self-reported (or caregiver-reported) methods, thus making the interpretation of the obtained results complicated.

2.2 FACTORS ASSOCIATED WITH VARIATION IN FOOD INTAKE

Other than the “obesogenic” modern day food environment, a vast number of factors have also been identified as relevant in determining variation in food intake in humans. These can be broadly categorized in thematic clusters of: food production (nutritional labelling (105), food advertising in children (106)), social psychology (i.e., social facilitation of eating (107,108)), food consumption (portion size (60), energy density (109,110), food variety (111,112)), individual psychology, physiology, individual physical activity and the physical activity environment. See Foresight Obesity System Map for an ambitious systems view of these factors (113). Three of these factors are the focus of this thesis and will be briefly reviewed below.

2.2.1 Eating rate

Fast eating rate has been shown to increase short-term food intake vs. slow eating rate in experimental studies (114). A growing epidemiological literature has also shown that self-reported fast eating rate is associated with increased risk of obesity vs. self-reported slow eating rate (115). Interestingly, eating rate can be considered as: a) an internal behavioral condition, b) external environmental condition, and c) a food related external condition. For example, individuals have different habitual eating rates that tend to be stable in comparison to other individuals from meal to meal, independent of the food that is being served (69). In other words, different individuals might have different levels of risk to overeat in circumstances that facilitate overeating (i.e., buffet settings) due to their habitual eating rate behavior. Eating rate can also be affected by environmental factors such as the time that is available to eat, the eating rate of eating companions as well as peer pressure to be done faster with the meal. Interestingly, different food properties have also been shown to be associated with the speed of eating. Ultra-processed, highly palatable foods have been shown to have faster eating rates vs. unprocessed whole foods that usually need more chewing (116). Liquid foods with fast sensory exposure times, such as soda, have also been shown to have fast eating rates and result in a greater tendency for long-term overconsumption of energy and weight gain (117). Internal behavioral, external environmental and external food conditions all interact to facilitate different levels of eating rate and should therefore be considered together.

Although the literature on eating rate is abundant, no studies have investigated the association between objectively measured eating rate, food intake and BMI among high school students, and no studies have validated self-reported eating rate questionnaires vs. objectively measured eating rate in “real life” settings.

2.2.2 Food proximity

The proximity and availability of food are external environmental conditions that are related to food intake in humans. Food proximity has been categorized as a behaviorally oriented “nudge” (i.e., “any aspect of the choice architecture that alters people’s behavior in a predictable way (1) without forbidding any options or (2) significantly changing their economic incentives” (118)) on consumer behavior. Interestingly, behaviorally targeted nudges have been associated with larger effect sizes ($d = 0.39$, −209 kcal) vs. cognitively ($d = 0.12$, −64 kcal) or affectively ($d = 0.24$, −129 kcal) oriented nudges (118). Furthermore, a recent Cochrane systematic review and meta-analysis suggested that the proximity to food can result in meaningful changes (17-36%) in food and energy intake, with closer food proximity leading to increased energy intake (119). Since most studies have been conducted in laboratory settings (only four were conducted in field settings), studies in “real-world settings” have been requested to improve generalizability of the obtained findings. An interesting setting to investigate the food proximity effect is school. This is a setting that a large proportion of children and adolescents are exposed to throughout their developmental years, and changes that improve children’s habitual food intake in this environment could be meaningful from a public health perspective (120). Research of the effect of food proximity in the school context is therefore needed.

2.2.3 Parkinson's disease

Parkinson's disease (PD) is related to changes in food intake behavior in humans (121). The disease is a progressive neurodegenerative disorder with related motor symptoms such as involuntary rhythmic shaking of the hands and legs (rest tremor), slowness of movement (brady-/hypokinesia), stiff, weak, and inflexible muscles (rigidity) (122,123). Non-motor symptoms (NMS) have also been observed during the PD process. These include (but are not limited to) problems swallowing (dysphagia), constipation, impairments in taste and smell function, and both weight gain and weight loss (in severe cases, malnutrition) are commonly reported NMS among PD patients. More specifically, weight gain has been reported during deep brain stimulation (124) as well as during initiation of dopamine replacement therapy (125), potentially due to compulsive eating induced by the treatments, while weight loss has commonly been observed before the diagnosis of PD as well as in the more advanced stages of PD (25). Weight loss in PD is important since it has been associated with further complications such as nutrient deficiencies, falls, bone fractures, infections as well as reduced quality of life (25).

Since the direct cause of both weight gain and weight loss is energy imbalance (25,126), the energy intake side of the equation (i.e., food and energy intake) is important to investigate further. Unfortunately, most studies related to PD and weight loss have focused on the energy expenditure side of the equation (25). One of the few studies available related to food intake showed that advanced PD patients self-reported higher energy intake (FFQ) compared to normal weight controls while experiencing weight loss (127). The authors therefore argued that the weight loss observed during later stages of PD must be explained by increased energy expenditure, mainly due to their stiff muscles (rigidity), rather than by eating less food. A similar study that used 3-day dietary records came to a similar conclusion (128). However, due to the great uncertainty related to self-reported methods of food and energy intake, especially among elderly populations with neurodegenerative diseases, objective studies are needed to expand this very limited literature and test this hypothesis further.

Furthermore, it is also essential to understand why and how food intake might be affected during PD, and a plethora of explanatory factors have been suggested. Even as early as 1817 James Parkinson himself (who first described the disorder (129)), stated the following in his now classic "Essay on the Shaking Palsy":

"Whilst at meals the fork not being duly directed frequently fails to raise the morsel from the plate: which, when seized, is with much difficulty conveyed to the mouth."…"when the food is conveyed to the mouth, so much are the actions of the muscles of the tongue, pharynx, impeded by impaired action and perpetual agitation, that the food is with difficulty retained in the month until masticated; and then as difficultly swallowed."…"He took very little

nourishment, could chew and swallow no solids, and even found great pain in getting down liquids. Milk was almost his only food"

This quote illustrates the eating difficulties at the different stages of PD, with motor symptoms impairing proper hand-to-mouth movement early in the disease, as well as chewing and swallowing problems impairing the proper eating behavior of solid food later in the disease. Other factors such as impaired smell and taste, cognitive impairments, dementia, constipation, suppression of appetite by anti-parkinsonian drugs, gastrointestinal tract dysfunction, depression, stressors such as death of a spouse, infections, bone fractures, increased energy expenditure due to unconscious muscle contractions, nausea caused by high intakes of levodopa/dopamine agonists, and many more have been suggested to be causing changes in food intake (25,130). However, no objective studies have investigated the association between food intake and PD related symptoms have been conducted.

3 SPECIFIC AIMS

3.1 AIMS IN SCHOOL SETTING

- To explain the variation in food mass intake during school lunches with objectively measured eating behaviors as well as subjective measures of taste and fullness.
- To investigate the association between objectively measured eating rate and food mass intake during school lunch.
- To investigate the effect of food proximity on energy intake from snack foods during a one-hour school task in the classroom context.

3.2 AIMS IN HOSPITAL SETTING

- To compare the energy intake among early and advanced Parkinson's disease patients as well as healthy controls during a standardized lunch.
- To assess eating rate and its relation to food intake among Parkinson's disease patients and healthy controls.
- To assess clinical features of Parkinson's disease and objectively measured eating behaviors among Parkinson's disease patients as well as their relation to variation in energy intake during a hospital lunch.

3.3 AIM IN FREE-LIVING SETTING

- To investigate differences in BMI z-scores among self-reported eating rate categories in populations of Swedish and Greek high school students.

3.4 RELIABILITY AND VALIDITY AIMS IN SCHOOL SETTING

- To assess the test-retest reliability of objectively measured food mass intake and eating behaviors during school lunches.
- To assess the test-retest reliability of objectively measured eating rate during school lunches.
- To assess the concurrent validity of self-reported eating rate vs. objectively measured eating rate on an individual and a group level.

4 MATERIALS AND METHODS

4.1 STUDY SETTINGS

This thesis includes studies conducted in three main settings: a) a school setting (76,78,131), b) a hospital setting (132), and c) a free-living setting (131). The studies were conducted in three countries: Sweden, Germany and Greece.

4.1.1 School

The data collection in school was conducted at Internationella Engelska Gymnasieskolan Södermalm (IEGS), a privately owned high school in central area of Stockholm, Södermalm. The school lunch cafeteria was used to investigate school lunch related aims and a classroom setting was used to investigate snack food proximity aims (see **Figure 3A**).

4.1.2 Hospital

The data collection in hospital took place in a clinical lunch setting at the Department of Neurology of the Technical University Dresden (TUD), Germany. All meals were eaten in a dedicated room at TUD (see **Figure 3B**).

4.1.3 Free-living

A smartphone application was used to investigate free-living aims. In the initial screens of the application, students could self-report their data at their own discretion (see **Figure 3C**).

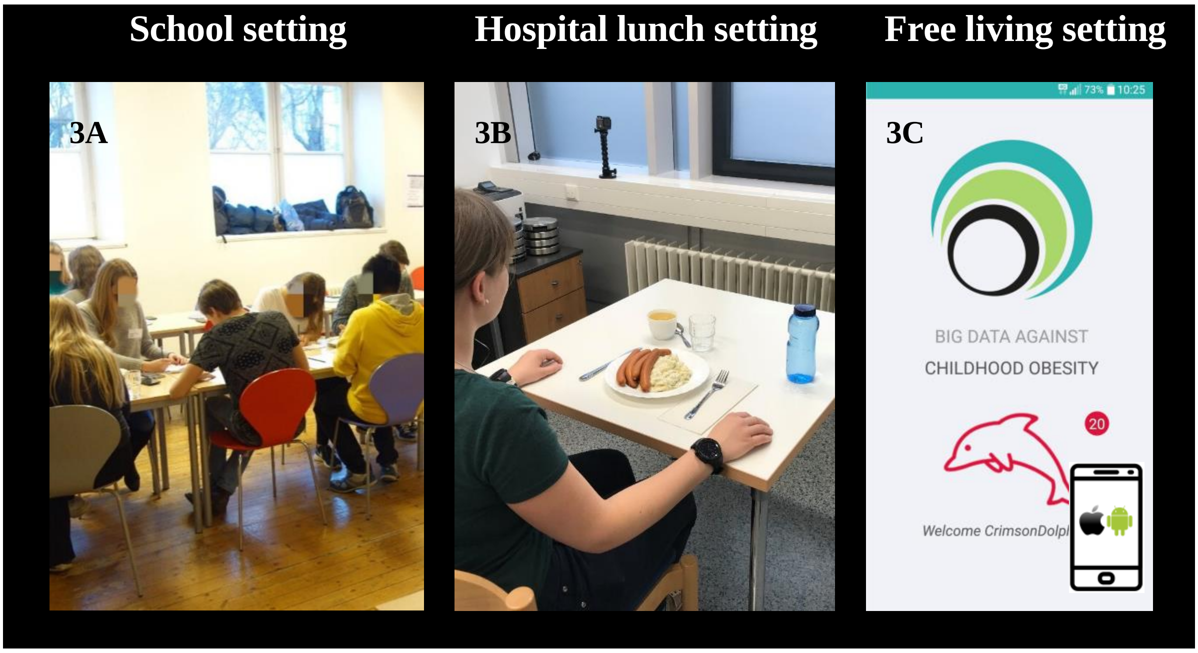


Figure 3A. The school lunch cafeteria environment at IEGS with students filling in questionnaires after eating their lunch in the monitored school setting. **Figure 3B.** The meal setting in the dedicated room at TUD for monitored meals. **Figure 3C.** A screenshot of the BigO mobile phone application.

4.2 STUDY DESIGN

4.2.1 School

A cross-sectional study design was used to: a) explain variation in food mass intake during school lunch, b) investigate the association between objectively measured eating rate and food mass intake, and c) assess the concurrent validity of self-reported eating rate vs. objectively measured eating rate on an individual and a group level. An experimental study design was used to investigate the food proximity effect on snack food intake, while a within-subject, repeat-measure study design was used to investigate the test-retest reliability of food mass intake and eating rate.

4.2.2 Hospital

A cross-sectional study design was used to a) investigate the group level differences in energy intake among early and advanced PD patients as well as healthy controls, b) assess clinical features of PD and objectively measured eating behaviors as well as their relation to variation in energy intake and c) investigate eating rate and its relation to food intake.

4.2.3 Free-living

A cross-sectional study design was used to distinguish differences in BMI z-scores among self-reported eating rate categories in larger populations of Swedish and Greek high school students.

4.3 PARTICIPANTS

4.3.1 School

Monitored school lunches

In total, six high school classes including 187 students at Internationella Engelska Gymnasieskolan Södermalm (IEGS) were invited to participate in monitored school lunches. The recruitment took place during February 2015 (two classes invited), December 2015 (six classes invited, including the 2 from 2015), and April 2017 (six classes invited, same as late 2015). Students were eating monitored school lunches during two days in March 2015 (n = 15 unique participants included for school lunch analysis), December 2015 and February/March 2016 (n = 97 unique participants included for school lunch analysis), and 2017 (n = 2 unique participants included for school lunch analysis).

4.3.1.1 Repeated monitored school lunch

Students who had already participated in a monitored school lunch during early or late 2015 were invited to participate in another monitored lunch meal during February/March 2016. Fifty of the invited students came back for the repeated monitored school lunch.

4.3.1.2 Snack experiment

Students (n = 53) who were going to participate in a monitored school lunch during March 2015 were also invited to the snack experiment (conducted the same day as the school lunch study). Out of these, 41 decided to participate, n = 24 on day 1 (in the distal condition) and n = 17 on day 2 (in the proximal condition).

4.3.2 Hospital

Subjects who participated in the hospital-based lunch study were a) healthy controls, b) early PD patients, and c) advanced PD patients. All PD patients were recruited from the in- and outpatient clinics of the Department of Neurology, at the University Hospital of Dresden, Germany. Approximately 600 patients with PD diagnosis were screened based on their health records, and in accordance with the inclusion/exclusion criteria, around 150 PD patients and 150 healthy persons were approached in person. 41 PD patients (n=20 early and n=21 advanced PD patients) and 23 controls agreed to enroll in the study. Among the control subjects, six were partners of the included PD patients, while the remaining healthy controls were recruited through the promotion and advertisement of the study by flyers spread at TUD, newspaper announcements and study description at the research webpage of TUD.

4.3.3 Free-living

Students from multiple high schools in Sweden (n = 748) and Greece (n = 1084) were recruited by teachers through school supported actions from March 2018 until the end of 2019. The data collection included self-reported measures of weight, height and eating rate. The Swedish high schools were IEGS (n = 613) in Stockholm and NTI gymnasiet (n = 135) in Uppsala. The Greek high schools were Ellinogermaniki Agogi high school (n = 230) in Athens, Ekpaideutiria Mpakogianni (n = 111) in Larissa and 16 public and private high schools in Thessaloniki (n = 439). Students (n = 304) who participated in a multidisciplinary intervention program for the management of overweight and obesity (at the outpatient childhood overweight and obesity clinic, First Department of Pediatrics “Aghia Sofia” Children’s’ Hospital, in Athens) were also recruited.

4.3.4 Inclusion/exclusion criteria

4.3.4.1 School and free-living

For the studies in school and free-living settings, the recruitment of students was conducted in a non-discriminatory fashion, meaning that no more inclusion/exclusion criteria were applied than: a) being part of the included schools, b) be willing to take part in the study procedures and c) providing informed consent.

4.3.4.2 Hospital

For the hospital study, strict inclusion and exclusion criteria were used. PD patients with dementia and other forms of PD than idiopathic PD were excluded. Patients who had: a) received more advanced treatments (i.e., duodopa pump or deep brain stimulation), b) any contraindication to oral food intake (i.e., allergy to the food served), c) other disease that causes dysphagia (i.e., throat cancer), d) endocrine or malignant disease, e) acute major depression, or f) other diseases that could have a major impact on body composition and/or food intake during the five years before the current study were also excluded.

4.4 STUDY PROCEDURES

4.4.1 School

4.4.1.1 Monitored school lunches

In the morning of the experiment day, students came to a dedicated classroom for the experiment at IEGS where their weight and height were recorded by the responsible researchers. Later, students came to the school lunch canteen at either 11.30 or 12.30 (one class per time slot). The time duration for each meal was 25 minutes since this was the scheduled time for lunch according to school curriculum for the included classes. Students were serving themselves in a buffet-like setting. The lunchroom is part of the usual school canteen environment at IEGS, but it was available only for the study participants during the day of the experiment and the school lunch studies. At the lunch table, students were eating their food on a Mandometer® (portable food scale), and video cameras (five cameras were placed in different corners of the room to give a complete view of the tables where the students were eating) were recording the lunchroom environment as well as the buffet table. Students were eating their food together with their peers and could talk freely while eating. They could also take extra food from the buffet table when/if they wanted more food. Responsible researchers were available if any issues occurred. Students who completed a monitored school lunch received one cinema ticket as a compensation for their participation.

4.4.1.2 Snack experiment

The snack experiment was conducted during two separate days. During both days, students arrived at the dedicated classroom for the experiment at IEGS approximately three hours after eating a monitored school lunch (15.30, described above). Students were told that they were going to participate in a one-hour groupwork task. Like in the school lunch study, they were monitored by video cameras. During the first experiment day, snack foods were placed in a separate room approximately 6 meters away from where the students were sitting (distal snack condition, **Figure 4A**). Students needed to stand up from the table and walk to the snack station to pick up snacks in this condition. During the second experimental day, the snack foods were placed near each table where students were sitting during the work task (proximal snack condition, **Figure 4B**). In this setup, students could reach the snacks without needing to walk away from the table. In both conditions, snacks were served ad libitum in large food containers.

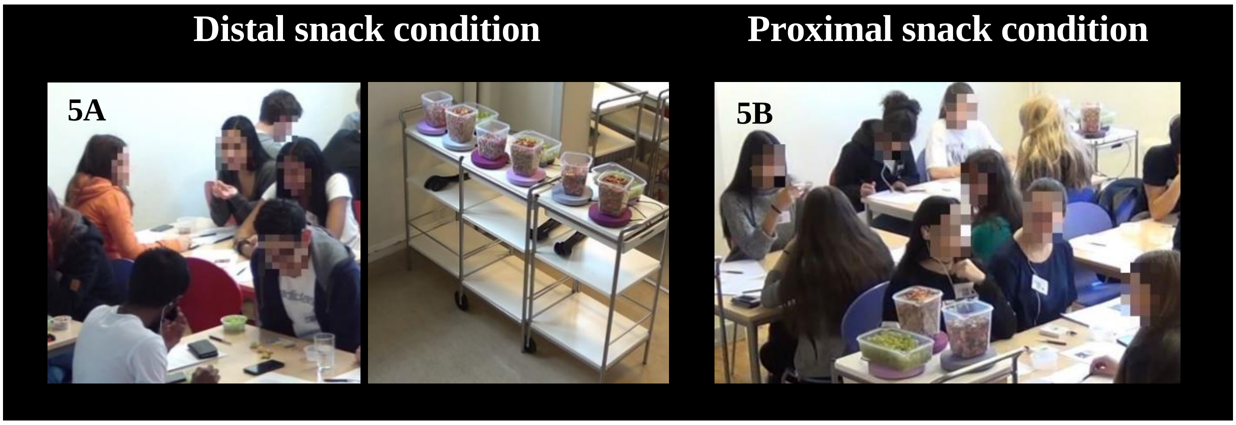


Figure 4A. Students who came to the first snack experiment got served snacks in a separate room approximately 6 meters away from the table (distal snack condition) where they were doing the school task. **Figure 4B.** Students who came the second day were served snacks at the table where they were doing their school task (proximal snack condition).

4.4.2 Hospital

Study participants arrived at the Department of Neurology of the Technical University Dresden where they met with a neurologist. First, they had a medical evaluation based on investigations of normal bodily effort covering a medical history, questionnaires and scales about motor and non-motor symptoms of PD (**Figure 5A**). Participants' weight and height were also measured by research staff by use of weight and height scales. After the medical evaluation, the participants were served a standardized meal in a quiet room in the department of neurology around usual lunch period (11.00-15.00) (**Figure 5B**). Participants could drink water freely before/during/after the meal. The meal was recorded by video cameras and the responsible researcher weighed the plate with food before and after the meal, without participants' awareness. The meal was not time limited. Participants used a phone placed on the meal table to call the responsible researcher when they were finished with their meal.

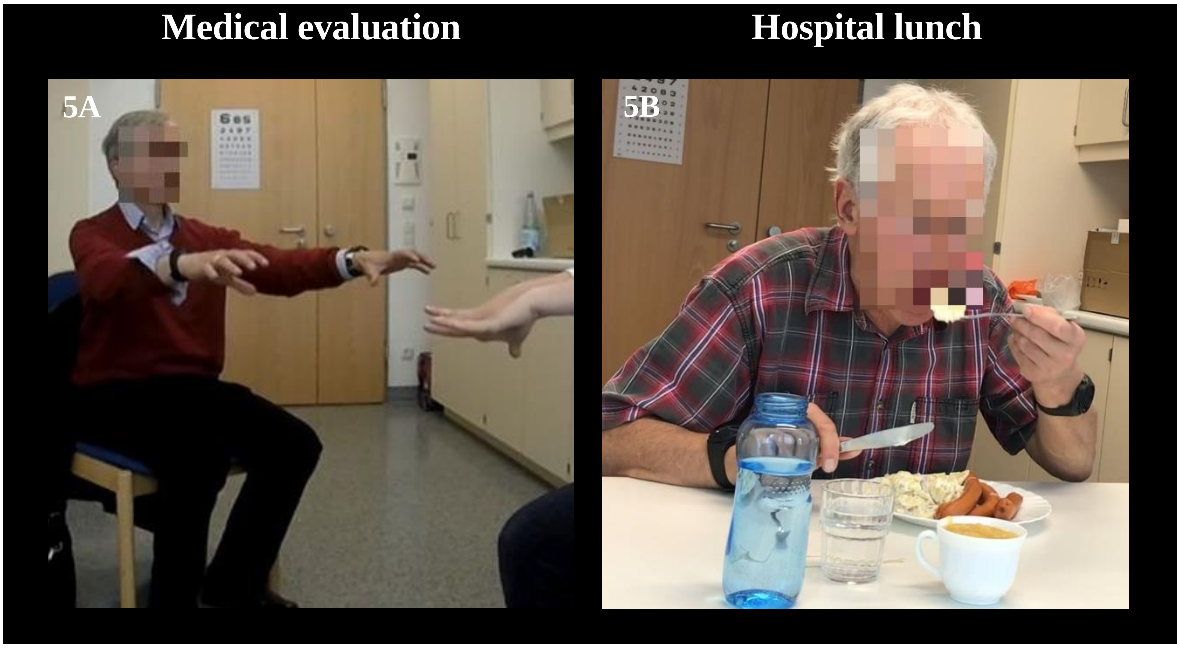


Figure 5A. Medical evaluation of a study participant in the hospital study. **Figure 5B.** Study participant eating the standardized meal.

4.4.3 Free-living

Students who chose to participate in the free-living study downloaded the study mobile application (myBigO application) at Google Play store (for android devices) or App Store (apple devices). In the initial registration screens of the application, students could self-report their age, weight, height and their speed of eating in comparison to others.

4.5 SERVED FOOD

4.5.1 School lunch

The students who participated in monitored school lunch meals were served food in a buffet-like meal setting (**Figure 6A**). This is the usual meal setting in Swedish schools. The available foods in the buffet were potatoes, beef patties, celery patties, fish (pollock), cream sauce, vegetables (such as sliced carrots, cucumber, lettuce, sprouts, olives), crisp bread, cottage cheese and jam. The same foods were ordered, from the usual school catering company, in all instances of the school lunches (2015, 2016 and 2017). Additionally, water, crisp breads and milk were available ad libitum to the students.

4.5.2 School snacking session

During the school snack session, three types of snack food items were available ad libitum: 1) green seedless grapes, 2) chocolate lentils and 3) rice crackers (see **Figure 6B**). The idea behind serving these three snack food items was to include snacks of different energy densities, sensory properties as well as satisfying different snack food preferences among the participating students.

4.5.3 Hospital lunch

In the hospital lunch setting, the PD patients and the healthy controls were all served the same type of food in a standardized way (see **Figure 6C**). This meal included: 200g of pre-heated sausages (solid food), 400g cold potato salad (semi-solid food) and 200g of apple puree (soft food). The idea behind the inclusion of these foods was to serve foods of different food textures (solid, semi-solid and soft), as well as to serve “a typical German lunch meal” that would suit the food preferences of a broad range of potential participants. Furthermore, all subjects were served a bottle of 500ml of water that they could drink freely from before/during/after the meal.

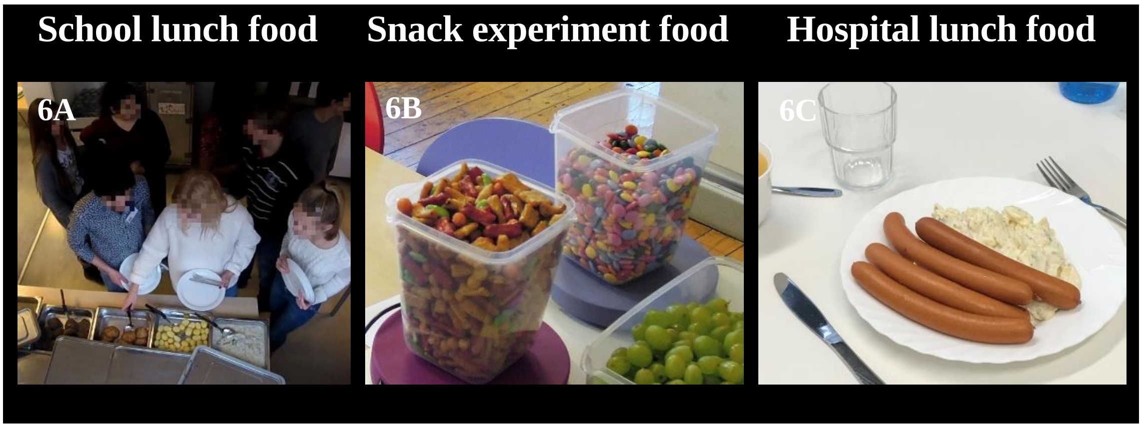


Figure 6A. Students taking food at the school lunch buffet. **Figure 6B.** The snack food items that were served during the snack food experiment. To the left, rice crackers, in the middle upper box chocolate lentils and in the bottom right corner green seedless grapes. **Figure 6C.** The standardized meal (200g sausages, 400g potato salad and 200g of apple mash as well as 500ml of water) that was served to all included participants in the hospital lunch study.

4.6 DATA SOURCES AND MEASUREMENTS

The types of measurement methods/tools used in the studies included in this thesis are summarized in **Table 1**.

Table 1. Types of measurement methods, the outcome data that emerged from using these measurements, as well as the setting that they were used in.

Type of measurement method	Outcome data	Setting
Weight and height scales	Objective body weight, height, BMI, and BMI z-scores.	School & hospital
Mandometer®/food scale	Objective food mass intake and eating rate	School & hospital
MyBigO mobile application	Self-reported body weight, body height, BMI, and BMI z-scores.	Free-living
VAS scale in paper format	Subjective eating rate category	School
GoPRO video cameras + The Observer XT video annotation software	Annotation of eating behaviors on video recordings of the meals: a) meal duration (meal start and meal stop), b) food additions, c) spoonfuls. These annotations enabled calculation of objective eating rate.	School & hospital
Neurologist conducting medical evaluation	Upper extremity tremor, brady-/hypokinesia, dysphagia	Hospital

BMI = Body mass index

VAS = visual analog scale

4.6.1 Weight and height scales

The weight and the height of all subjects that participated in the school and hospital meals were recorded objectively by researchers with the use of weight and height scales. The obtained weight and height data were later used to calculate the participants BMI (and BMI z-scores in the school setting).

4.6.2 Food scales

To measure the objective food mass intake in both school and hospital lunch context, digital portable food scales were used. The weight of the plate with food on as well as the weight of the plate with leftovers on after the meal were recorded. By subtracting the weight of the plate with leftovers on (after the meal plate weight) from the weight of the plate with food on (before the meal plate weight), total meal food mass intake in grams could be calculated. Water and milk intake were not quantified in the school lunch setting.

In the snack food experiment, each snack component (chocolate lenses, rice crackers and seedless grapes) was placed on a separate food scale, allowing recording of food component snack selection. By subtracting each individual's snack leftovers, the total snack food intake (grams) could be calculated. By use of the energy content (kcal per 100g) listed on the packages of the chocolates and crackers and the database livsmedelsdatabasen (133) for the grapes, total snack food energy intake (kcal) during the snack experiment could be calculated (by multiplying the kcal per gram snack food with the grams eaten of each specific snack food).

During the hospital lunch, the meal was standardized with the same weight of potato salad (400g), sausages (200g sausages) and apple mash (200g) for all participants. By weighing each individual food component leftover, subtracting that value from the original portion and multiplying that value with the kcal content listed on the packages of each food component, total energy intake during the meal from each food could be calculated.

4.6.3 MyBigO mobile application

Students who participated in the large-scale eating rate investigation could self-report their weight, height, age, and sex in a mobile phone application (MyBigO). These data were used to calculate the subjective BMI and BMI z-scores of each participating student. Additionally, students also reported their subjective eating rate category in this application by selecting one of five options: "Much slower than others", "Slower than others", "Similar to others", "Faster than others" or "Much faster than others". Students who self-reported eating "Much slower than others" and "Slower than others" were categorized into the eating rate category "Slow eater" and those reporting eating "Faster than others" or "Much faster than others" were categorized as "Fast eater". Students reporting eating "Similar to others" were labeled as "intermediate". Similar categorization scheme has been used in previous studies on self-reported eating rate (115).

4.6.4 VAS scale

During the school lunch, students were asked to self-report their fullness before and after the meal, as well as how the food tasted (see **Figure 7**). The scale was 10 cm long and the dot given as an answer was later measured with a ruler and transformed into a value ranging from 0 (0mm) to 100 (100mm).

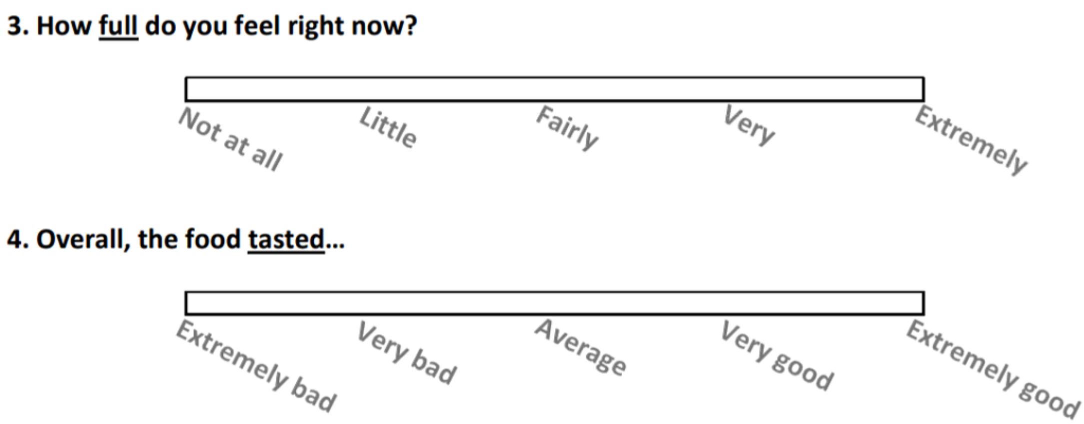


Figure 7. The questionnaire that was used to assess fullness and food taste among the participating students.

Students’ subjective eating rate category was also self-reported on a questionnaire in paper format in the school lunch study. Similar eating rate categories as mentioned above (in the MyBigO application section) were used.

4.6.5 GoPRO video cameras & The Observer XT annotation software

To assess objective eating behaviors in both the school and hospital lunch meal contexts, video recordings of each meal were used. Later, the videos were loaded into the computer software “The Observer XT” and eating behaviors were annotated (see **Figure 8**). Meal duration (meal start and meal stop), food additions and number spoonfuls were all recorded with this method.

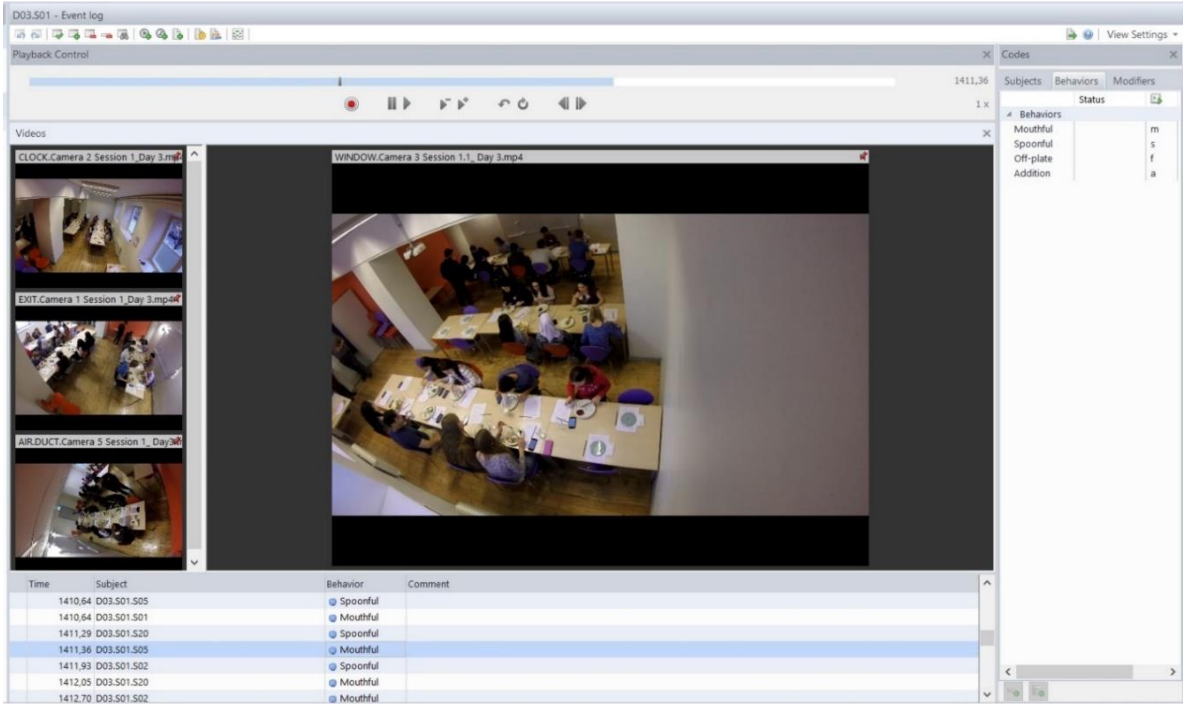


Figure 8. Screenshot of the Observer XT software while annotating eating behaviors for the school lunch study.

4.7 STATISTICAL METHODS

Table 2 shows the statistical models that were used in the outcome analyses included in this thesis.

Table 2. Overview of the statistical models used to in the included analyses in this thesis.

Analysis	Statistical model
School	
Explaining variation in food mass intake	Multiple linear regression
Eating rate and its relation to food intake	Pearson correlation
Food proximity and its relation to food and energy intake (experimental)	T-test
Hospital	
Parkinson's disease and its relation to food and energy intake	Multiple linear regression
Clinical features of Parkinson's disease and their relation for energy intake	Multiple linear regression
Eating rate and its relation to food intake in Parkinson's disease	Pearson correlation
Reliability and validity	
Reliability of objective food mass intake and eating rate	Systematic change in the mean, intra-class correlation, typical error of measurement
Concurrent validity of self-reported eating rate vs. objectively measured eating rate on an individual level	Cohen weighted Kappa
Concurrent validity of self-reported eating rate vs. objectively measured eating rate on a group level	One way ANOVA
Free living	
Eating rate vs. BMI z-scores	One way ANOVA

BMI = Body mass index

ANOVA = Analysis of variance

4.7.1 School setting analyses

Multiple linear regression was used to explain the variance in food mass intake during school lunch. Food intake in grams was used as the dependent (response) variable while eating rate (grams eaten/minute), number of spoonfuls, number of food additions, sex, food taste, change in fullness (after meal fullness – before meal fullness) and BMI as independent (explanatory) variables. Independent sample t-test was used to investigate the group difference in energy intake between the two snack conditions and multiple linear regression was used for effect size comparison.

4.7.2 Hospital setting analyses

Multiple linear regression was used to explain variation in the dependent variable single lunch energy intake (kcal). The three groups (healthy controls, early PD patients and advanced PD patients) were coded as three binary variables for each subject. The group variables were tested with the potential confounding variables: sex, age, height, and bodyweight in the primary outcome model. Sex had a significant effect on the primary outcome model and was included to control for confounding. Age, bodyweight and height did not affect the primary outcome model and were therefore excluded. Additionally, outliers were excluded based on having a Cook's distance >4/n. Pearson correlation analysis was conducted in each of the included groups between objective eating rate (grams/minute) and food mass intake (grams).

4.7.3 Free-living setting analyses

One way ANOVA analysis was used for all statistical tests that were used to distinguish differences in BMI z-scores among self-reported eating rate categories (slow, intermediate, and fast) in the larger populations of Swedish and Greek high school students and to estimate its relation to BMI z-scores. Bonferroni post hoc tests were conducted to assess specific group level differences when the overall ANOVA model was significant.

4.7.4 Reliability and validity analyses

Cohen's Weighted Kappa analysis was used to investigate the agreement between self-reported vs. objective eating rate categories. Systematic change in the mean, intra-class correlation and the typical error of measurement were used to assess the test-retest reliability of food mass intake and eating rate between the two lunches (134).

4.7.5 Effect sizes

The variance explained in the dependent variable was examined by adjusted R squared in all regression models as well as partial eta squared in all ANOVA models. For correlation analyses, a correlation coefficient of 0.0-0.1 was interpreted as "trivial", 0.1-0.3 "small", 0.3-0.5 "moderate", 0.5-0.7 "large", 0.7-0.9 "very large" and 0.9-1 as "nearly perfect". For categorical agreement analyses, a Cohen's weighted Kappa value of 0–0.20 was interpreted as "No agreement", 0.21–0.39 "Minimal agreement", 0.40–0.59 "Weak agreement", 0.60–0.79 "Moderate agreement", 0.80–0.90 "Strong agreement", and above 0.9-1 as "Almost perfect agreement".

IBM SPSS statistical software version 25-27 was used for all statistical tests in studies 1-3 and $P < 0.05$ was used as the threshold for statistical significance in all analyses.

5 RESULTS

5.1 DESCRIPTIVE STATISTICS

In **Table 3**, the descriptive statistics for all the included samples in this thesis are shown.

Table 3. Descriptive statistics of the samples of participants that were included in the different analyses included in the thesis.

	Explaining variation in food mass intake[a]	Eating rate and its relation to food intake[b]	Eating rate vs. BMI z-scores (association)[b]	Food proximity and its relation to food and energy intake (experimental)[c]	Parkinson's disease and its relation to food and energy intake[d]	Reliability and validity of objective eating rate and food intake[a, b]
Subjects, n	103	114	1832	41	64	50
Context	School	School	Free-living	School	Hospital	School
Age, y	16.7 ± 0.6	16.5 ± 0.8	15.8 ± 0.9	16.8 ± 0.4	62.4 ± 7.8	16.7 ± 0.6
Females (%)	59 (57%)	67 (58.8%)	937 (51.1%)	22 (53.7%)	29 (45.3%)	29 (58.0%)
Weight	61.8 ± 12.1	62.0 ± 11.7	66.6 ± 18.0	62.2 ± 10.1	80.8 ± 14.5	61.8 ± 11.8
Height	170.3 ± 9.5	170.1 ± 9.8	169.9 ± 10.1	170.9 ± 9.7	172.1 ± 9.6	168.7 ± 8.9
BMI	21.2 ± 3.2	21.4 ± 3.1	23.1 ± 6.0	21.2 ± 2.5	27.2 ± 4.3	23.1 ± 6.0
BMIz	-0.07 ± 1.05	0.04 ± 1.01	0.47 ± 1.41	0.01 ± 0.79	-0.07 ± 1.05	0.08 ± 1.04

Presented numbers are mean ± standard deviation if otherwise not specified.

BMI = Body mass index

5.2 RELIABILITY AND VALIDITY RESULTS

5.2.1 Test-retest reliability results for objective food intake

5.2.1.1 Food intake lunch 1 vs. lunch 2

There was no significant systematic change in mean food mass intake from lunch 1 to lunch 2 (-7.5g, 95% confidence interval: -43.1g to +28.0g). The intraclass correlation between food mass intake during lunch 1 vs. lunch 2 was 0.74 (95% confidence interval 0.58 to 0.84), while the typical error of measurement was 88.5g (95% confidence interval: 73.9 to 110.3) or expressed as a coefficient of variation 26.1% (95% confidence interval: 21.4% to 33.5%). See **Figure 9A** and **9B.**

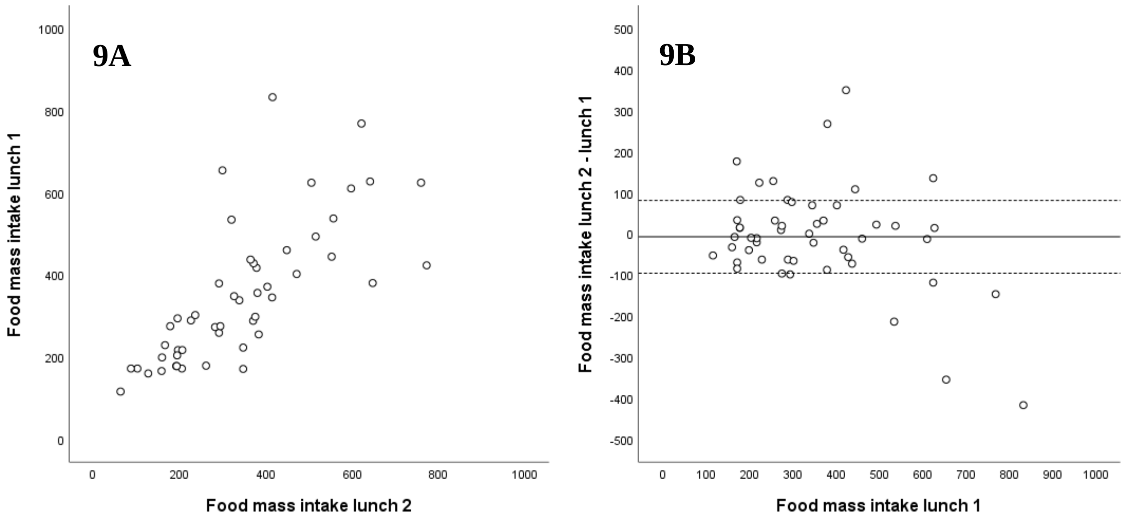


Figure 9A. Scatter plot illustrating the association between food intake (grams) during lunch 1 vs. lunch 2 among the 50 students who came for repeated meals. **Figure 9B.** Scatter plot illustrating the systematic change in mean (bold line), the typical error of measurement (striped lines), as well as the individual level changes in food intake (grams) from lunch 1 to lunch 2.

5.2.2 Test-retest reliability results for objective eating rate

5.2.2.1 Eating rate lunch 1 vs. lunch 2

There was a significant systematic change in eating rate (g/min) from lunch 1 to lunch 2 (+4.4 g/min, 95% confidence interval: +0.7 g/min to +8.1 g/min). The intraclass correlation between eating rate during lunch 1 vs. lunch 2 was 0.73 (95% confidence interval 0.59 to 0.85), while the typical error of measurement was 9.1 g/min (95% confidence interval: 7.6 to 11.4) or expressed as a coefficient of variation: 24.9% (95% confidence interval: 20.4% to 31.9%). See **Figure 10A** and **10B.**

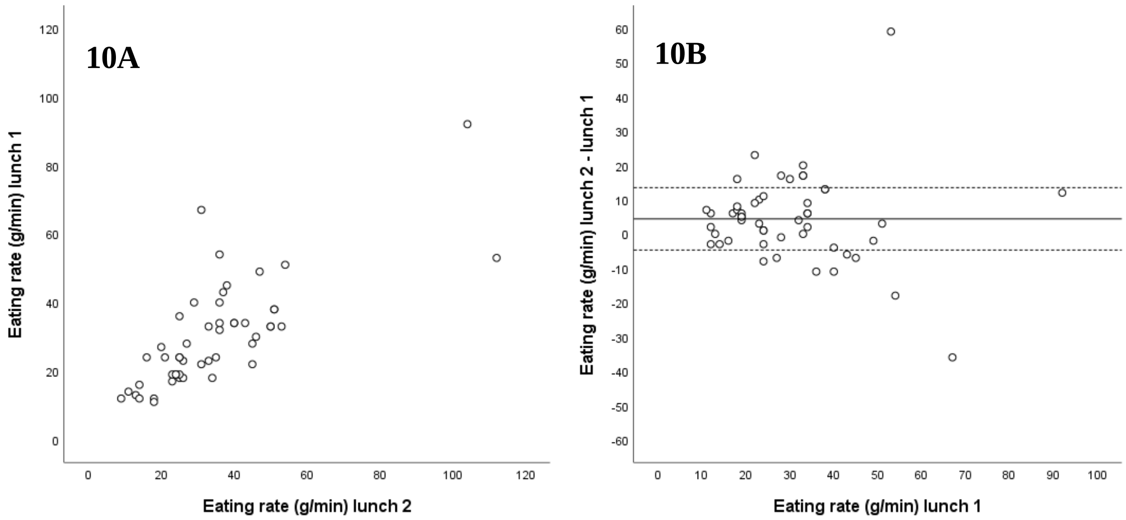


Figure 10A. Scatter plot illustrating the association between eating rate (grams/minute) during lunch 1 vs. lunch 2 among the 50 students who came for repeated meals. **Figure 10B.** Scatter plot illustrating the systematic change in mean (bold line), the typical error of measurement (striped lines), as well as the individual level changes in eating rate (grams/minute) from lunch 1 to lunch 2.

5.2.3 Concurrent validity results for subjective eating rate

5.2.3.1 Objective eating rate within subjective eating rate categories

When comparing the objective eating rate among the three categories of self-reported eating rate (slow, intermediate, and fast), a significant difference between the groups was obtained by the main effects ANOVA analysis [$F(2, 111) = 7.104$, $P = 0.001$, partial $\eta^2 = 0.113$]. Bonferroni post hoc comparisons showed that students who self-reported eating slower than others had significantly slower eating rate (-13.7g/min, 95% confidence interval: -22.5g/min to -4.84g/min; P = 0.001) vs. students who self-reported eating faster than others. However, there were no significant differences in objective eating rate between students who self-reported eating slower than others vs. intermediate, or between students who self-reported eating intermediate vs. those reported eating faster than others (**Figure 11**).

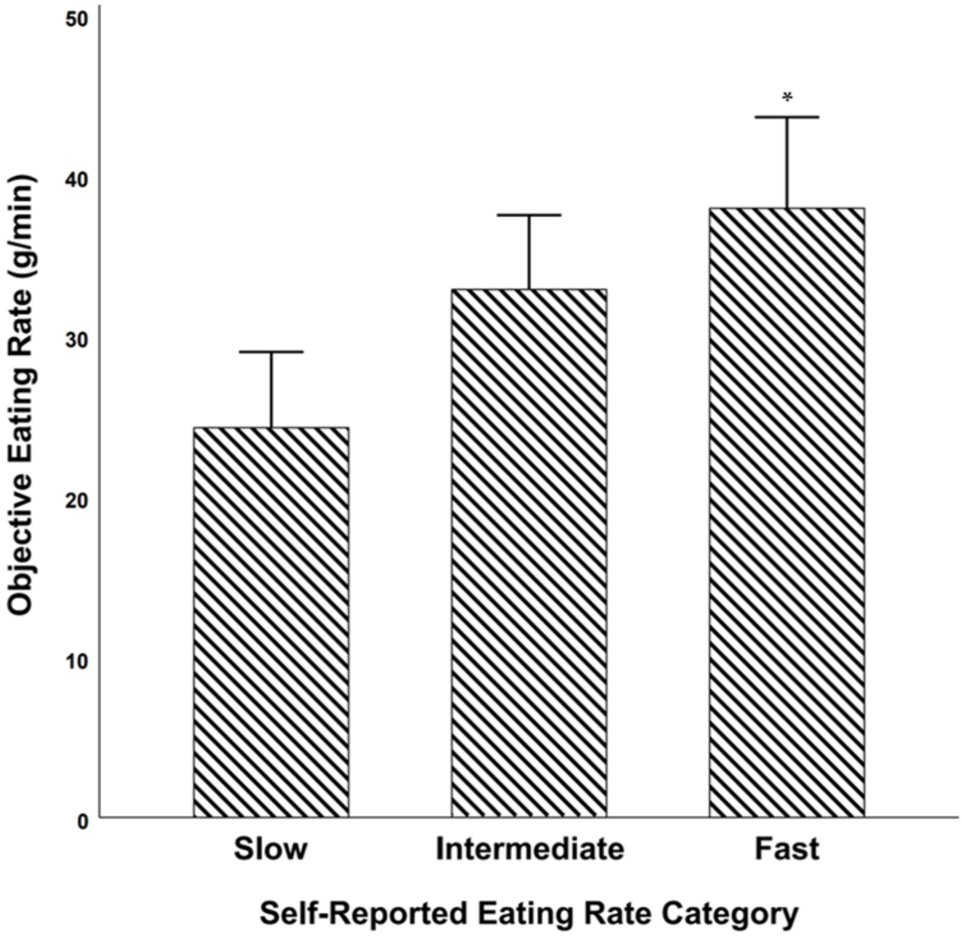


Figure 11. Objective eating rate among the three groups of self-reported eating rate (slow, intermediate and fast). * = significant difference in objective eating rate vs. the group of slow self-reported students. Error bars represent 95% confidence intervals.

5.2.3.2 Subjective vs. objective eating rate categories

The weighted Kappa value for self-reported eating rate categories vs. objectively established eating rate categories was 0.31 ($P < 0.001$). The number of students who self-reported their eating rate category similar to/different from the objectively established eating rate category can be seen in **Figure 12.**

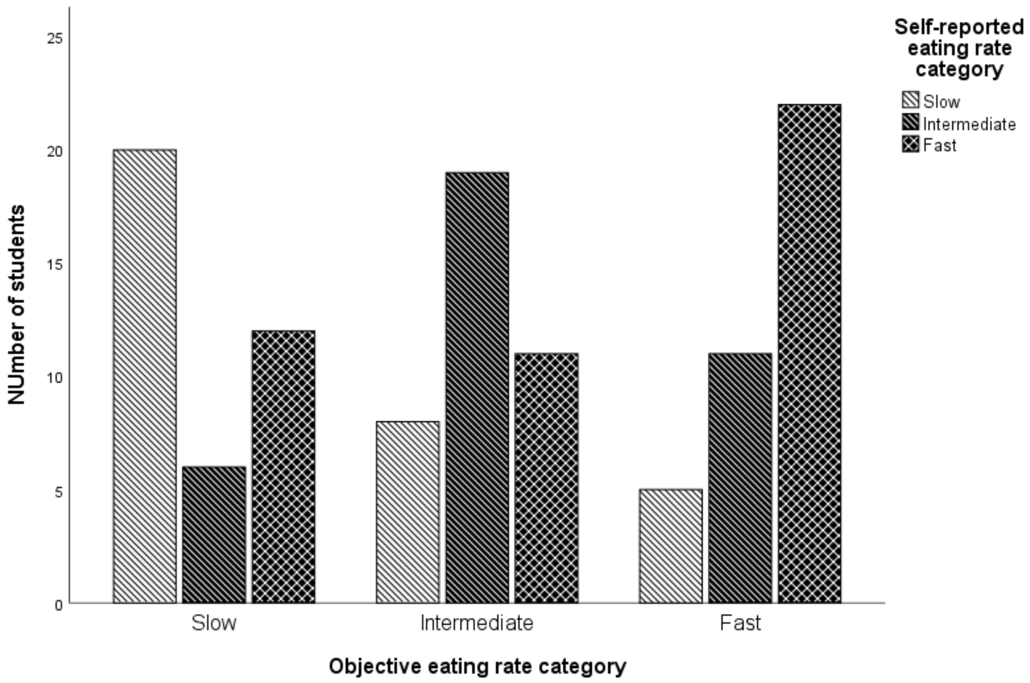


Figure 12. Graph illustrating the number of subjects who self-reported their eating rate category similar to/different from the objectively established eating rate category.

5.3 MAIN RESULTS

5.3.1 School

5.3.1.1 Explaining variation in food mass intake

Table 4 shows the hierarchy of explanatory variables associated with variation in food mass intake during school lunch. The total model could explain ~77% of the variance in food mass intake (Adjusted $R^2 = 0.766$) and eating rate (g/min) was the most powerful significant explanatory variable followed by number of spoonfuls, sex, number of food additions, food taste, BMI and change in fullness (in that order).

Table 4. Multiple linear regression model showing the hierarchy of explanatory variables for variation in food mass intake during school lunch.

Explanatory variables	***Standardized B***	***p***
Eating rate (g/minute)	0.54	< 0.001
Number of spoonfuls	0.43	< 0.001
Sex	0.17	0.003
Number of food additions	0.16	0.003
Food taste	0.12	0.033
BMI	0.09	0.084
Change in fullness	0.00	0.954

Model was significant, $p < 0.001$, adjusted R2 = 0.766.

Standardized B = standardized b coefficients

p = the probability value

Change in fullness = fullness after the lunch meal – fullness before the lunch meal.

g = gram

5.3.1.2 Eating rate and its relation to food intake

There was a significant "large" (R = 0.667) correlation between objectively measured eating rate and food mass intake during school lunch (see **Figure 13**).

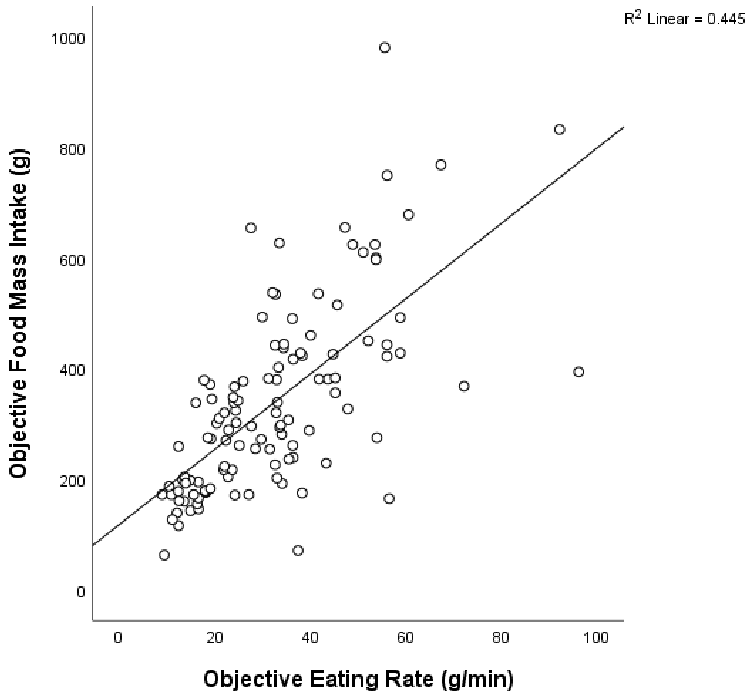


Figure 13. The relationship between objective food mass intake vs. objective eating rate during school lunch.

When dividing students into tertiles of eating rate (slow, intermediate and fast eaters), there was also a significant difference in food mass intake between the three groups [$F(2, 111) = 30.578$, partial $\eta 2 = 0.355$] (**Figure 14)**. Bonferroni post hoc comparisons showed that students in the "slow" objective eating rate tertile were eating 133 grams less food (95% confidence intervals = -210g to -56g) vs. students in the "intermediate" objective eating rate tertile, and 247 grams less (95% confidence intervals = -324g to -170g) than students in the "fast" eating rate tertile. Furthermore, students in the "intermediate" eating rate tertile were eating 114g less (95% confidence intervals = -191g to -37g) vs. students in the "fast" eating rate tertile. Similar observations were found among both females [$F(2, 64) = 14.653$, $P = 0.000$] and males [$F(2, 44) = 11.964$, $P = 0.001$], when analyzed separately.

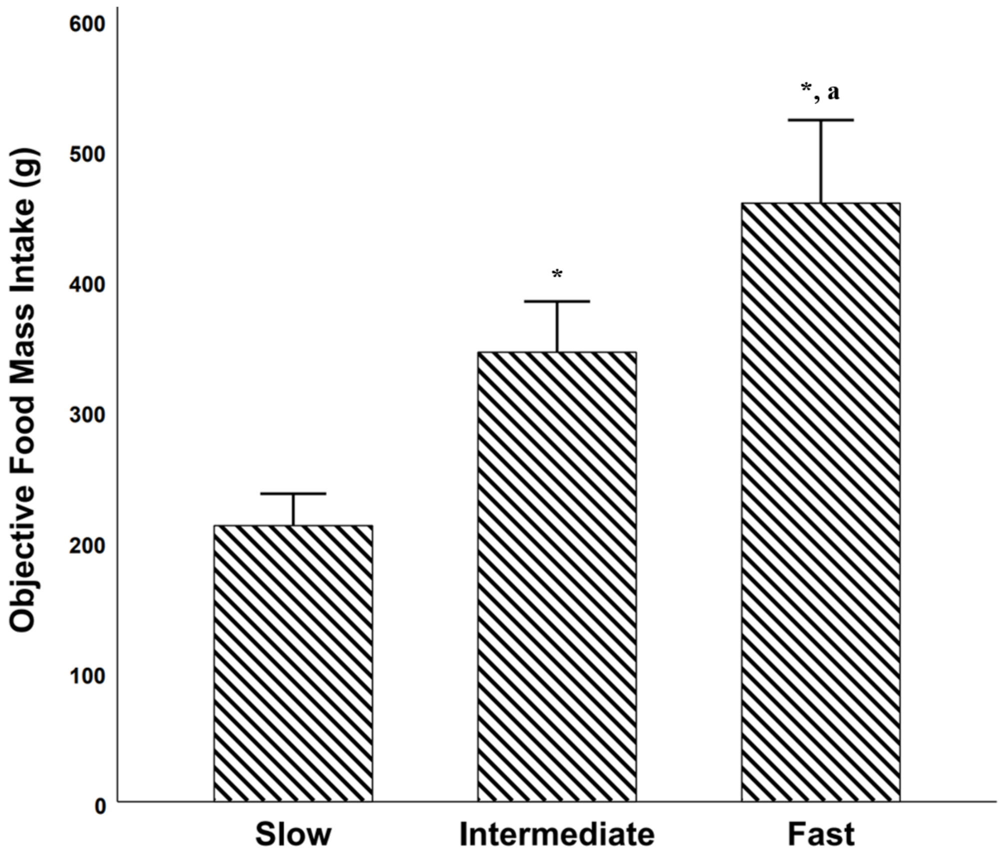


Figure 14. Average objective food mass intake among the three tertiles of eating rate during school lunch. Error bars represent 95% confidence intervals. * = significant difference vs. Slow. a = significant difference vs. intermediate.

5.3.1.3 Food proximity and its relation to food and energy intake

Students who were participating in the distal snack food condition were eating significantly less energy from snacks vs. students in the proximal condition (mean difference = -222.7 kcal 95% confidence intervals: -428.3 kcal to -17.2 kcal), **Figure 15**.

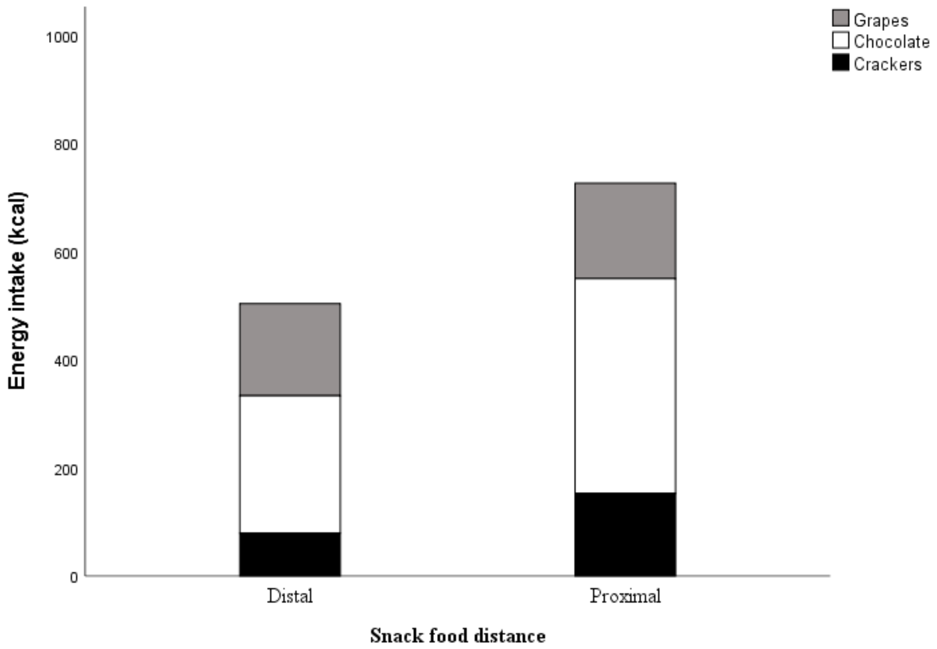
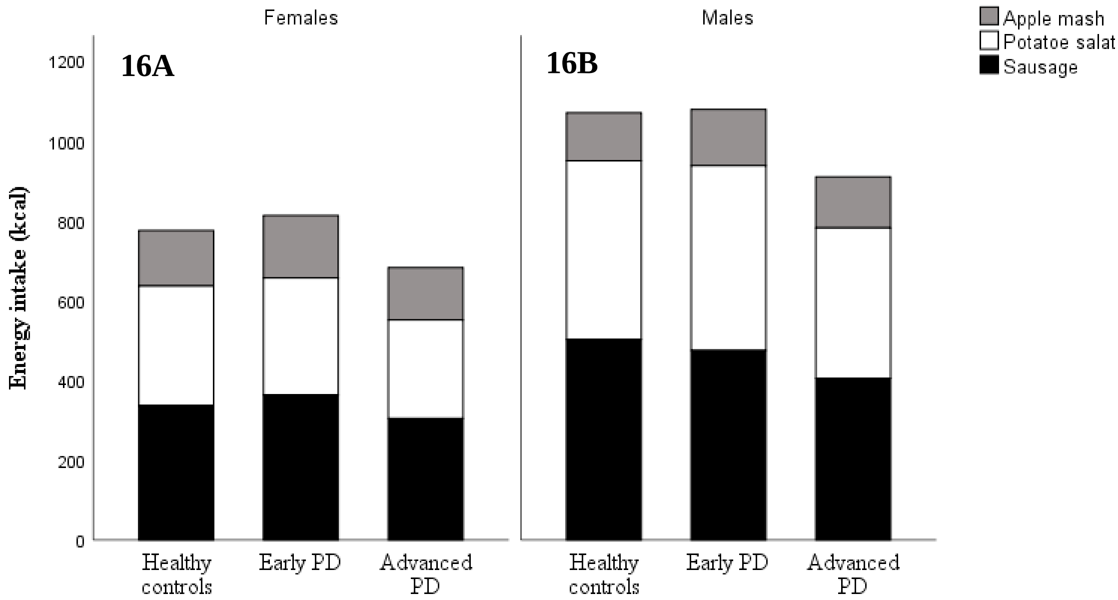


Figure 15. The energy intake among student participating in the distal and proximal snack conditions.

5.3.2 Hospital

5.3.2.1 Parkinson's disease and its relation to food and energy intake

In the hospital lunch setting, multiple linear regression models showed that advanced PD patients consumed significantly less energy during lunch vs. both early PD patients (b = -202.7 kcal, 95% confidence interval: -329.2 kcal to -76.2 kcal) and healthy controls (b = -162.1 kcal, 95% confidence interval: -285.7 kcal to -38.4 kcal) when controlling for sex (**Figure 16A** and **Figure 16B**).



Figures 16A and 16B. Average energy intake among female (**16A**) and male (**16B**) healthy controls, early and advanced PD patients.

5.3.2.2 Eating rate and its relation to food intake among PD patients

There was a significant "moderate" correlation (r = 0.401, p = 0.001) between objective eating rate and food mass intake in the total sample of participants in the hospital study (**Figure 17**).

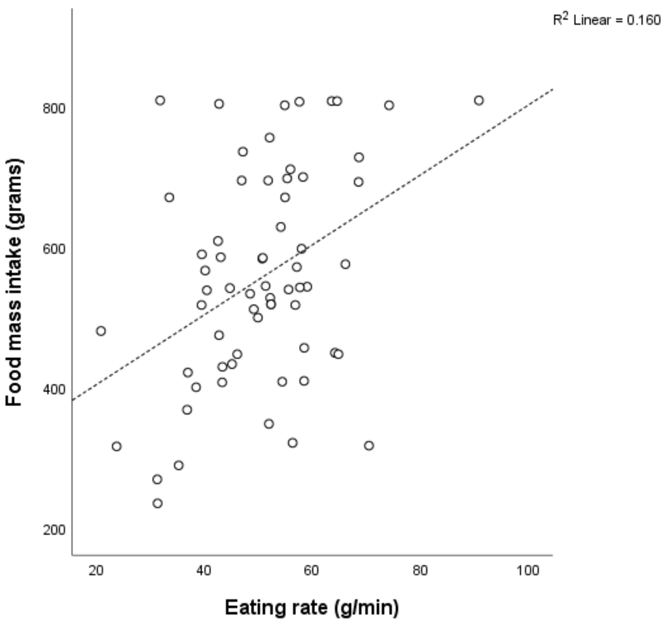
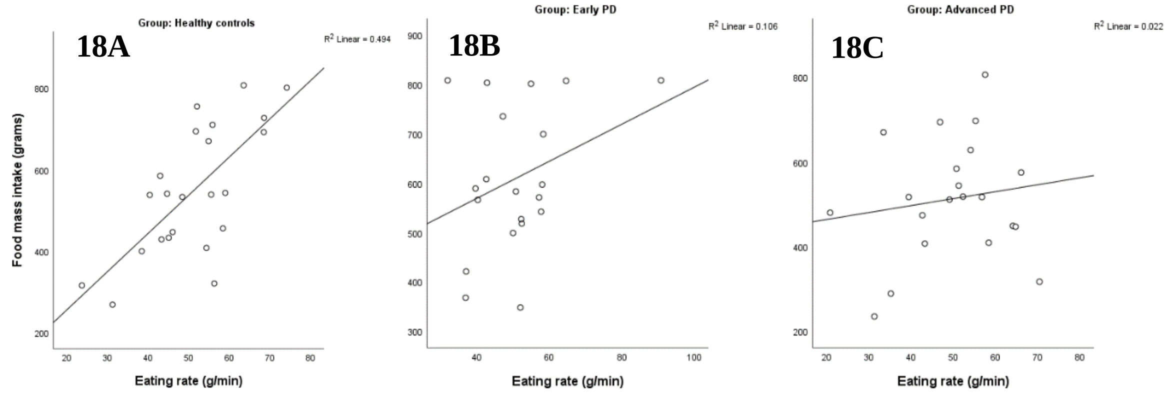


Figure 17. Scatter plot illustrating the correlation between food mass intake (grams) and eating rate (grams/minute) in the total study sample in the hospital study.

However, when analyzing the three groups separately, the correlation between eating rate and food mass intake was “very large” among the healthy controls (r = 0.703, p = 0.000, **Figure 18A**), while the correlations among early (“moderate” correlation, r = 0.326, p = 0.161, **Figure 18B**) and advanced PD patients (“small” correlation, r = 0.148, p = 0.523, **Figure 18C**) were weaker and not significant.



Figures 18A-18C. Scatter plots illustrating the associations between food mass intake (grams) vs. eating rate (grams/min) among healthy controls (**18A**), early PD patients (**18B**) and advanced PD patients (**18C**) included in the hospital study.

5.3.3 Free-living

5.3.3.1 Subjective eating rate vs. BMI z-scores

In the larger sample of students who self-reported their eating rate, self-reported eating rate was found to be a significant explanatory variable for variation in self-reported BMI z-scores [$F(2, 1829) = 9.724$, $P<0.001$, partial $\eta^2 = 0.011$]. Bonferroni post hoc test showed that students who self-reported eating slower than others had 0.23 units lower BMI z-score (95% confidence intervals: -0.43 to, -0.03; P = 0.021) vs. students who self-reported intermediate eating rate, and 0.37 units lower (95% confidence intervals: -0.57 to -0.17; P < 0.001) vs. students who self-reported eating faster than others (**Figure 19**).

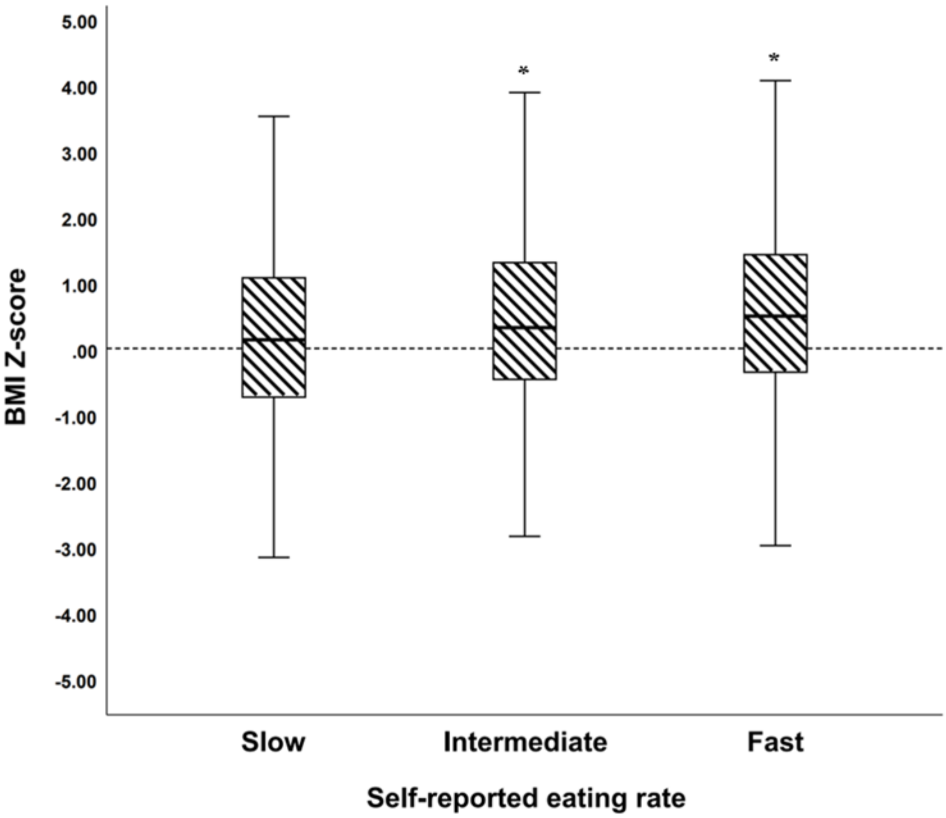
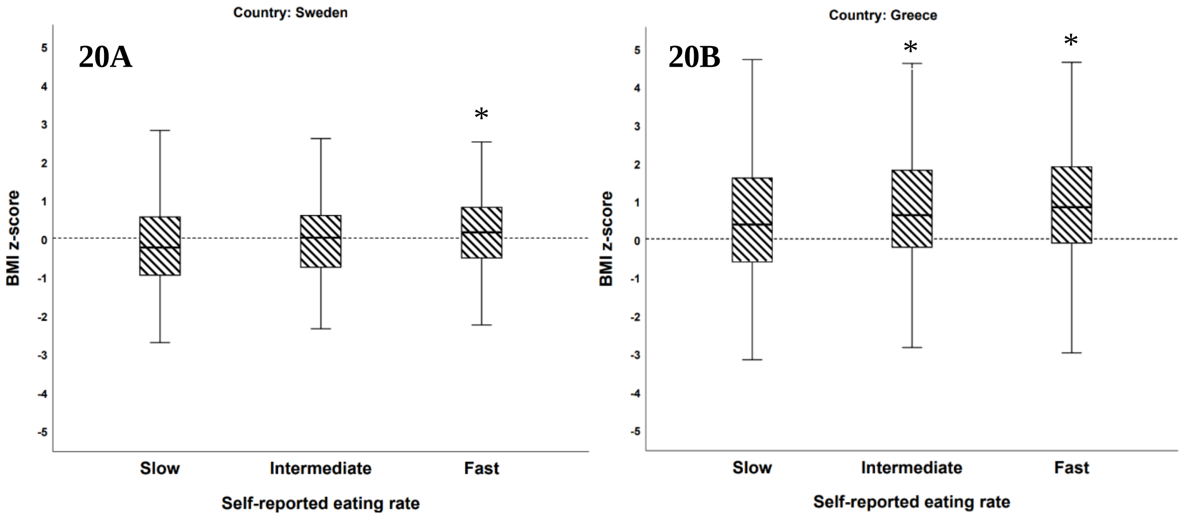


Figure 19. Boxplots illustrating BMI z-scores among the three groups of self-reported eating rate (slow, intermediate, and fast). * = significantly higher BMI z-score vs. slow self-reported eating rate group.

Similar results were obtained when dividing the total sample of students into Swedish (n = 748) and Greek students (n = 1084), [Swedish students: $F(2, 745) = 5.955$, $P = 0.003$, partial $\eta^2 = 0.012$; Greek students: $F(2, 1081) = 6.533$, $P = 0.002$, partial $\eta^2 = 0.016$].

Bonferroni post hoc tests showed that Swedish students with "slow" self-reported eating rate had 0.36 units lower BMI z-scores vs. Swedish fast eating rate students (95% confidence interval: -0.61 to -0.10; P = 0.003). Furthermore, Greek students with slow self-reported eating rate had 0.29 units lower BMI z-scores vs. Greek students with intermediate eating rate (95% confidence interval: -0.57 to, -0.02; P= 0.032), and 0.41 units lower vs. Greek students with fast eating rate (95% confidence interval: -0.69 to -0.14; P = 0.001).

There was no significant difference between Swedish students who self-reported eating slower than others vs. intermediate, as well as Greek students self-reporting intermediate eating rate vs. eating faster than others (**Figures 20A and 20B**).



Figures 20A and 20B. BMI z-scores among the three groups of self-reported eating rate (slow, intermediate, and fast), among Swedish (n = 748, **Figure 20A**) and Greek (n = 1084, **Figure 20B**) students.

When comparing the BMI z-scores among the three groups of self-reported eating rate (slow, intermediate and fast) among the clinical sample of Greek high school students, there were no significant group level differences.

5.3.4 Outcome synthesis

Table 5 summarizes the explanatory variables for food intake variation included in the studies in a hierarchical structure, based on the explanatory power of each variable (with sex added as a confounder in each model).

Table 5. Explanatory power of variables included in this thesis for variation in food intake[1,2].

Variable	Increase in adjusted R Square
Number of spoonfuls (hospital lunch)	0.31
Number of snack servings (snack)	0.29
Eating rate (g/min, school lunch)	0.23
Number of spoonfuls (school lunch)	0.19
Objectively measured fast eater (school lunch)	0.19
Desire to eat before the snack experiment (snack)	0.13
Food taste (school lunch)	0.12
Food additions (school lunch)	0.11
Eating rate (g/min, hospital lunch)	0.11
Food proximity (snack)	0.09
Advanced PD diagnosis (hospital lunch)	0.06
Levodopa dose[3] (hospital lunch)	0.03
Dysphagia (hospital lunch)	0.03
Height (school lunch)	0.02
Upper extremity tremor (hospital lunch)	0.02
Change in fullness (school lunch)	0.01
Self-reported fast eater (school lunch)	0
Subjective taste problems (hospital lunch)	0
Upper extremity brady-/hypokinesia (hospital lunch)	0
Height (hospital lunch)	0
Subjective smell problem (hospital lunch)	0
BMI[4] (school lunch)	0
BMI[4] (hospital lunch)	-0.01
Upper extremity rigidity (hospital lunch)	-0.01
Hunger before the snack experiment (snack)	-0.01

[1]Food mass intake (g) was used as the dependent variable for the explanatory variables gathered during the school lunch, while energy intake (kcal) was used as the dependent variable for the variables in the snack food proximity experiment and in the hospital lunch study.

[2] The increase in adjusted R squared is compared to only including the confounding variable sex in the model.

[3]mg/kg/day

[4]BMI = Body mass index

6 DISCUSSION

6.1 FEASIBILITY

The studies presented in this thesis support that objective measures of short-term food intake are feasible to use outside the laboratory environment where they traditionally have been implemented. More specifically, food scales and cameras can be used to record meal-related eating behaviors, both in school lunch cafeteria environments (76,77) as well as in hospital lunch environments (132). These objective methods could add important information related to how people eat in such contexts in addition to being more accurate for the assessment of short-term food intake (both energy and food mass intake), in comparison to the traditional self-reported methodologies. Furthermore, the methods used can show accurate, detailed estimations of energy intake from specific food components (78,132) – as it has previously been shown in laboratory settings. Therefore, the methods used could partly solve the problem of biased self-reported energy intake estimations (50), at least on a meal-to-meal basis in semi-controlled settings. These objective methods are ideal to use in experimental studies with short-term energy intake as the primary outcome. It could be argued that, when enough resources are available, the objective methods used in this thesis should replace traditional methods of dietary assessment in school and hospital lunch settings when the research question targets lunch meal energy intake. These methods could also be utilized to validate the traditional methodologies in such environments – i.e., self-reported methods to investigate hospital lunch intake among PD patients (i.e., as used in (127)) or the school lunch intake among students (i.e., as used in (135)).

6.2 GENERALIZABILITY

Some might argue that the generalizability of single-meal energy intake measurements is limited to the single-meal context. This question can be partly addressed by use of a publicly available dataset (136). The data were collected by Kevin Hall and colleagues during a four-week long, inpatient, randomized controlled cross-over trial to assess the effects of an ultra-processed diet on energy intake and body weight changes vs. an unprocessed diet (9). In this study, food intake was carefully measured by the researchers during the whole study period, thus estimating the energy intake with high accuracy (gold standard method). The dataset includes more than 2000 meals and snacks collected from the included subjects. Energy intake during a single lunch meal is a good predictor of total daily energy intake in this dataset. In fact, single-lunch meal energy intake (from the first meal on the ultra-processed diet) can explain approximately 90% of the actual two-week energy intake variation on the ultra-processed diet (R^2 = 0.86, Pearson correlation = 0.93, see **Figure 21A**). In other words, the results suggest that by measuring the energy intake during a single lunch, it is possible to rank individuals in a group regarding how much they will eat during the upcoming two-week period in a controlled context. Interestingly, single-lunch meal energy intake could also explain ~30% of the variance in weight gain that occurred on the ultra-processed diet in this study (R^2 = 0.289, Pearson correlation = 0.538, see **Figure 21B**). This highlights the utility of experimental single-meal measurements to predict sensitivity of weight gain on "weight promoting" diets. However, it is important to mention that the activity level of each participant was held constant in this study, and real-world heterogeneity in physical activity level between subjects might have affected these outcomes (137).

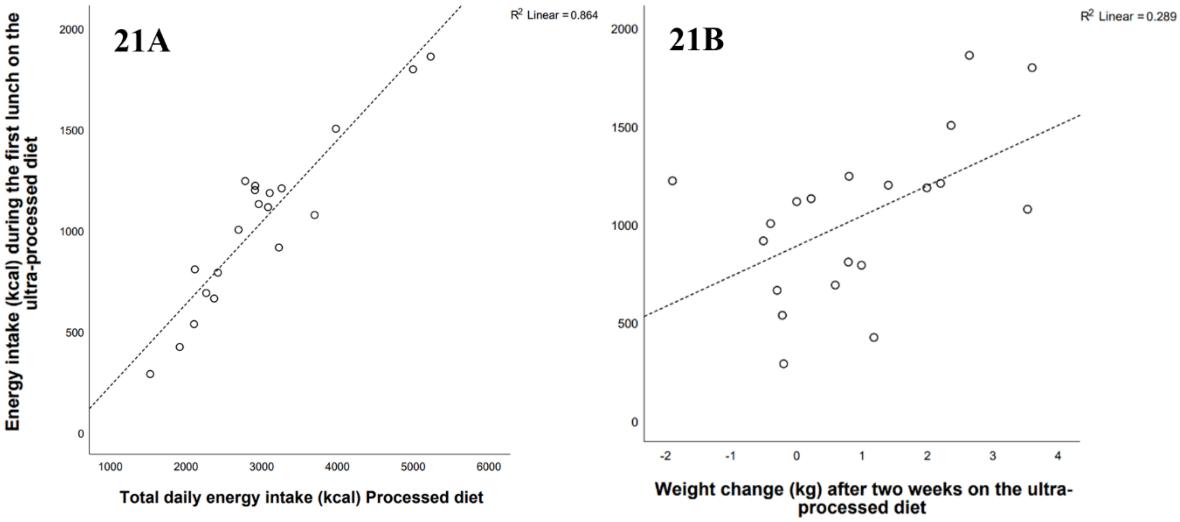


Figure 21A. Scatterplot showing the strong relation between the energy intake during a single lunch meal on an ultra-processed diet vs. the total daily energy intake for the whole two-week period on the ultra-processed diet. **Figure 21B**. Scatterplot showing the relationship between the energy intake during a single lunch meal on an ultra-processed diet vs. weight change after the two weeks of being exposed to an ultra-processed diet. Data collected by Kevin Hall and his colleagues (9).

Our team has shown that the food mass intake during a single school lunch meal was enough to rank students' free living food mass intake ($R^2 = 0.83$), further suggesting that the generalizability of objectively measured single meals is appropriate (138). This should be contrasted with the current literature showing that self-reported energy intake, by use of FFQ or 24h recalls, can only explain between 0-18% ($R^2 = 0.00$-0.18) of "real-world" energy intake variation during a two-week period (48). That is why the objective methods used in this thesis are suggested as better alternatives vs. the traditional self-reported methods if energy intake variation is the main outcome of interest in nutrition studies. The results also suggest that single-meal study designs might be proper to use when attempting to rank participants according to their total daily energy intake.

6.3 EXPLAINING VARIATION IN FOOD INTAKE

6.3.1 Eating rate

Eating rate was the most powerful explanatory variable for variation in food mass intake during school lunch. This finding suggests that interventions that aim to modify eating rate in school lunch settings would potentially have meaningful effects on student's overall food intake. Indeed, a plethora of epidemiological studies has confirmed such positive association between self-reported eating rate and risk of obesity (115). Furthermore, experimental studies have shown increased food intake due to fast eating rate vs. slow eating rate in laboratory conditions (114). A randomized controlled trial that used a computer feedback system to slow down eating rate among young people with overweight showed weight loss benefits vs. the usual weight loss treatment (139). A simple intervention to improve the eating rate among students could be to ensure that enough time is available for school lunch (140). For example, a school intervention that either increases the time available to eat lunch or schedules recess before/after lunch could have positive impact on students eating rate, energy intake and food choices and should be investigated further (140). Furthermore, the importance of eating rate for food intake regulation indicates that novel technological tools which help the user to slow down their speed of eating, could be valuable for weight loss. It also suggests that school policies that facilitate proper eating conditions (i.e., enough time to eat lunch without needing to eat fast) could help student populations towards more balanced food intake. Interestingly, in the hospital setting, the association between eating rate and food intake was reduced in early PD (R = 0.3) and advanced PD (R = 0.1) vs. healthy controls (R = 0.7). Although our study was not powered for such analysis, the results suggest that future studies in PD patients should investigate the eating rate among PD patients further. Changes in eating rate during the PD process (i.e., in an early and in an advanced stage) vs. a healthy population might be a novel behavioral marker for PD development.

6.3.2 Number of spoonfuls

An interesting finding was the importance of number of spoonfuls in explaining variation in single-meal food and energy intake (both in the school lunch setting (76) and in the hospital lunch setting (132)). Based on this finding, number of spoonfuls could be a behavioral target in nutritional interventions which aim to limit food intake in certain contexts, for example young patients with obesity. A smartwatch (141) (or a smart fork as used in (142)) could be utilized to provide feedback when the meal should be terminated based on a pre-decided number of spoonfuls. Such feedback could also be valuable in other challenging situations, like when eating out in buffet settings, where food is abundant and external cues might be needed to reduce the effect of ad libitum food availability and variation, as well as the social facilitation of eating, on food intake (59,143–145). Another case might be PD patients who lose weight unintentionally, due to reduced food intake caused by their disease condition (25). Feedback from technological devices regarding the number of spoonfuls needed during a meal might facilitate increased food intake and help them reach energy balance more easily (132).

The measurement of spoonfuls could also be used to regulate the speed of eating. For instance, in a busy context such as a school lunch cafeteria environment, feedback from a technological tool that could measure spoonfuls in real time (i.e., a smartwatch with such functionality), could facilitate slower eating and thus lower food intake unobtrusively. This might be valuable to people who tend to eat quickly in environments where food is available ad libitum (i.e., buffet settings and school lunch cafeteria environments) and who are therefore prone to eat more than what was willfully planned for.

Future technological developments that can automatically count number of spoonfuls in real time during meals would be valuable. One such effort is the development of the automatic “bite” (i.e., spoonful) counter "Rapid Automatic Bite Detection" (RABiD), **Figure 22** (146).

Figure 22. Visual illustration of skeletal extraction for algorithm estimations of number of spoonfuls during a meal by an early version of the bite/spoonful counting algorithm "Rapid Automatic Bite Detection".

RABiD is an algorithm that was developed to detect bites (spoonfuls with food going to the mouth) based on skeletal features extracted from videos of people eating meals. RABiD has shown excellent agreement vs. researcher annotators for number of spoonfuls during a meal (R = 0.91-0.96 depending on the food that was served) as well as the absolute meal duration (R = 0.99-1.0) on both an individual and on a group level. RABiD has also been trained on the hospital dataset included in this thesis with similar results for automatic estimation of number of spoonfuls (**Figure 23**).

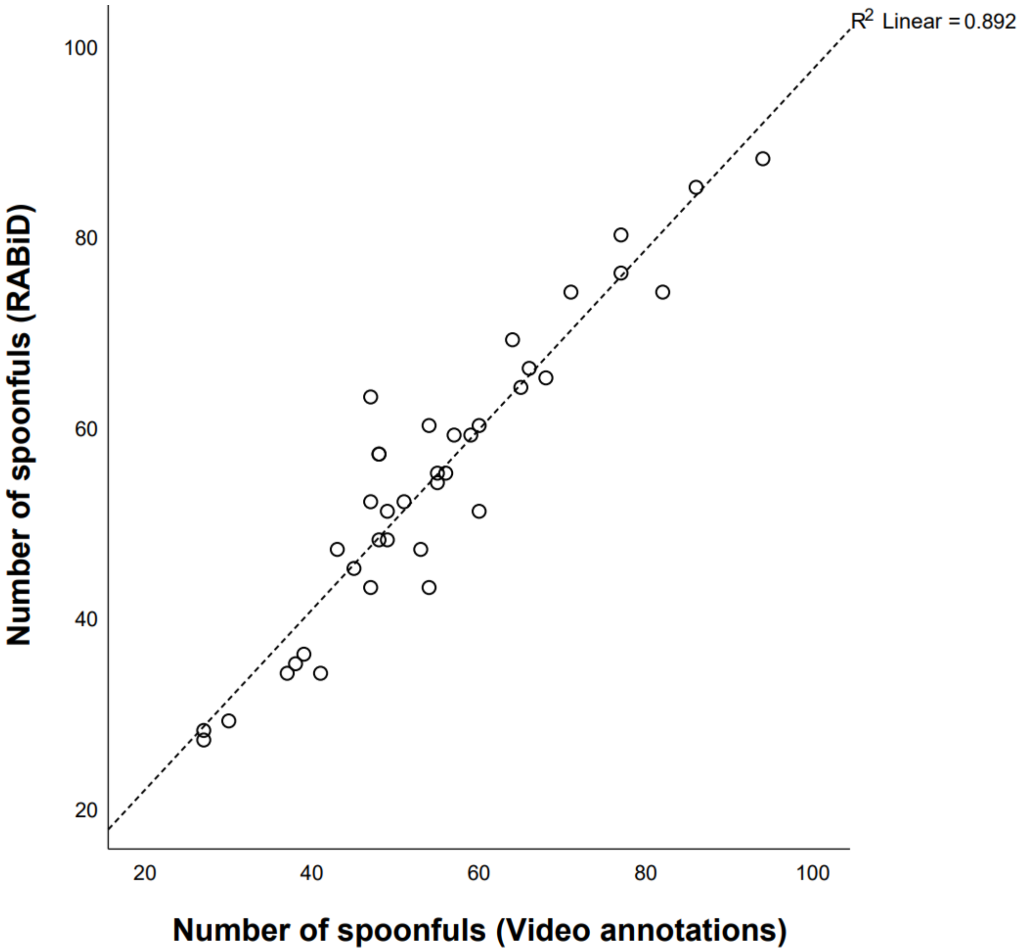


Figure 23. Scatterplot illustrating the strong correlation between the video annotated number of spoonfuls (gold standard) vs. RABiD number of spoonfuls for the included PD patients in the hospital study. Publication pending.

Today, RABiD needs to run offline with previously collected meal videos to annotate the temporal distribution of bites during a meal. However, with advances in computing technology, such algorithms could run "real time" on future generations of smartphones, thus enabling real time feedback on spoonful eating behavior to the user. They might be able to count bites in real time without needing to share personal data (i.e., video recordings) outside one's own smartphone. The camera input could be automatically processed (extraction of spoonfuls) inside the smartphone without personal data leaving the smartphone device. For example, feedback on bite speed (bites/min) as well the absolute number of bites would be helpful in buffet settings among people how need to limit their food intake in such contexts (59,143–145).

Other novel technological tools have also been developed to detect spoonfuls automatically. One such method is an algorithm that automatically detects bites (spoonfuls going to the mouth) based on sensor signals collected from commercially available smartwatches (141). This method has also been used by our collaborators to measure plate-to-mouth hand movement duration during meals among the PD patients who participated in the hospital study in this thesis (141).

6.3.3 Food proximity

The results obtained in the proximity experiment (78) were in line with previous studies that have investigated the proximity effect (147–151), with an effect size similar to the overall effect size of all food proximity studies conducted so far (119). The snack study presented in this thesis is one of the few food proximity studies that have been conducted in a “real life” setting (119) and with objective measurements such as food scales and video cameras. Most other studies have either been conducted in laboratory settings (i.e., (149,152)) or researchers have manually counted food intake in real time during the experiment (148). Interestingly, the proximity effect on energy intake in our study seemed to be caused by increased consumption of ultra-processed snack alternatives (crackers: Proximity condition unstandardized B = 73 kcal, and chocolates: Proximity condition unstandardized B = 143 kcal), but not for the unprocessed snack alternative (grapes: Proximity condition unstandardized B = 6 kcal). A study conducted at a local child care center in a large gymnasium showed that both unprocessed (carrot sticks) and ultra-processed (crackers) snack intake was increased the closer children were sitting to the snack food (148). Similar observations were made in a laboratory kitchen setting among college students (147). Both carrot and apple intake were increased in the proximal condition vs. the more distal condition in that study.

6.3.4 Parkinson’s disease

Our results showed that advanced PD patients had lower energy intake during lunch vs. both early PD patients and healthy controls when controlling for sex. This contrasts with an Italian study that used a FFQ to assess energy intake (127). The study showed that advanced PD patients reported higher energy intake vs. healthy controls, although they were losing weight. Our results are also in contrast to those observed in a Swedish study that used 3-day food records (128). This study found that PD patients who lost weight after 1 year follow-up had increased their energy intake (year 1 vs. year 2) while PD patients without weight loss had decreased their energy intake. A later publication by the same research group showed that weight loss was associated with eating difficulties and a preference for soft food (153). This finding is consistent with our results showing that the advanced PD patients were eating less sausages (solid food) vs. healthy controls and that their lower energy intake could be explained partly by their perceived eating difficulties (132). Furthermore, a study conducted in Belgium that used 2-day food records, found that PD patients had similar energy intake as the general population (154). The observed energy intake among the PD patients in the Belgian study was similar to the energy intake observed in the Italian study (154).

Since all the findings mentioned above relied on self-reported methodologies, it is reasonable to explain the difference in our study vs. previous studies based on this methodological difference. The self-reported methods have been shown to give biased results related to energy intake in the normal population (48,50). Furthermore, the PD patients included in the above-mentioned studies were elderly subjects who suffer from a neurological disorder that might interfere with their ability to self-report accurately. Interestingly, PD patients with cognitive decline were shown to experience more severe weight loss vs. those without cognitive decline (155), suggesting that the self-reported energy intake estimations collected in these studies should be interpreted with great caution. Additionally, cultural differences might be present. More studies are needed to better investigate this discrepancy between our study and the studies using self-reported methodologies.

6.3.5 Food availability

In the hospital lunch setting, the participants were served a relatively large portion size (800g food mass consisting of 200g sausages, 400g potato salad, 200g apple mash) with food that have a high energy density (> 2 kcal/g of food) while in the school lunch buffet, as well as in the school proximity snack study, students could serve themselves in a buffet like setting with food of varying energy density. Interestingly, although advanced PD patients were eating less energy during lunch vs. early PD patients and healthy controls on a group level, they were still eating a large quantity of calories during their lunch. For example, the Advanced PD male participants had an average estimated energy expenditure ~2200 kcal (calculation based on Harris Benedict Equation, male gender, light activity, age 64, weight 85.8kg, height 178cm) and in the current study they ate 911kcal (~40% of their estimated energy expenditure) during the lunch meal. This suggest that serving large portions with high energy density to weight losing PD patients might reduce their risk of unintentional weight loss. However, the foods served in the hospital study were all ultra-processed food with poor nutritional quality (156). This type of food has been associated with negative health consequences (i.e., cardiovascular disease, cerebrovascular disease, depression and all-cause mortality (157,158)) in epidemiological studies, perhaps independent of their association with weight gain and obesity. Potential interventions that aim to better balance PD patients' energy intake should use unprocessed foods with high energy density instead.

6.3.6 Sex / gender

Sex (and/or gender) was a powerful explanatory variable for variation in food and energy intake in all settings (R^2 = 0.20 in the snack setting, 0.22 in the school lunch setting, and 0.24 in the hospital lunch setting), with males eating more than females. This was expected based on previous literature on sex differences in short term food intake (70,77). It shows that it is important to account for sex/gender effects when analyzing differences in food intake within/between groups. For example, if a study is conducted to investigate effects of an intervention on food mass or energy intake, the groups of comparison should ideally have the same proportion of males/females to account for this confounder. Alternatively, sex should be added as a confounding variable in multivariate models to control for this expected confounding effect on food and energy intake. If a large sample size is available, another option would be to stratify the sample into two groups (males and females) and do the outcome analyses in both groups instead of the overall population.

The association between sex and food intake can be explained by that men have more fat free mass (FFM) than women on a group level (of the same age), and FFM has been shown to be a powerful explanatory variable for food intake (70,137). Furthermore, men are on average taller than women and height is also associated with food intake (159). In our school lunch dataset, height seems to have a similar explanatory power ($R^2 = 0.17$) as sex ($R^2 = 0.22$) on food mass intake, but when combining both variables in a multivariate regression model, little extra explanatory power is added vs. only adding sex to the model ($R^2 = 0.25$).

The effect of sex/gender can also be explained by cultural expectations on boys vs. girls (160,161). For example, boys are expected to eat more food during public meals with mixed groups of peers vs. girls (160). Thus, cultural expectations related to gender identity might also partly explain the observed difference in food intake between men and women in our studies (161).

6.3.7 Subjective taste

In the school lunch setting, subjective food taste (reported after the lunch meal) was the most powerful subjective variable to explain variance in food mass intake. This is in line with an earlier study that showed that post-meal taste rating was positively correlated with food mass intake of a standardized meal (banana-colada frozen yogurt drink) in a laboratory setting (162). Interestingly, pre-meal taste rating was negatively correlated with food mass intake during the meal in that study. Unfortunately, we did not collect pre meal taste rating, so a comparison is not possible. Other studies have manipulated taste ratings (i.e., palatability) by adulteration (i.e., by adding spices such as cumin (162) or salt (163) to food) with mixed effects on food intake.

6.4 LIMITATIONS

Although the methods used in this thesis were shown to be feasible to use in the described school and hospital contexts, it is important to mention that larger scale implementation would require resources (both equipment and study personnel) far exceeding those needed when conducting research with FFQ questionnaires, as an example. School or hospital personnel needs to be involved and such investigations require a large commitment from all included parties to enable reliable data collection across a larger population of schools and hospitals. It would also be challenging to implement the current objective methods in schools that have less resources for projects like this vs. IEGS, since part of the school cafeteria environment needs to be dedicated for the data collection during the days of the experiment and school schedules need to be adjusted. It is therefore important to weigh the benefits of using these objective methods vs. the traditional self-reported methods. With that said, if valid and reliable results are of major importance, as well as the ability to capture eating behaviors such as eating rate and number of spoonfuls in “real life” settings, then investments should be made to use the current objective methods instead of the traditional self-reported methods in school and hospital settings.

For the school study, the specific food component selection and consumption was not measured, and energy intake from the meal could therefore not be calculated. Since the foods that were served (i.e., beef patties, potatoes, a variety of vegetables, brown sauce etc.) have varying energy densities (kcal/gram of food), the food mass intake during school lunch might not have corresponded to the actual energy intake. Future studies should measure the consumption of each individual food component (as was done in the snack and hospital lunch studies) to get a more meaningful outcome variable (i.e., kcal intake) vs. food mass intake. With that said in the school lunch setting, eating behavior variables such as eating rate and number of spoonfuls were shown to have similar explanatory power to those variables in the hospital lunch study when energy intake was used as the dependent variable. The generalization of the results obtained from the conducted regression models might therefore still be valid. Furthermore, the liquid intake was not measured in the school lunch study. Since students could drink water and milk freely, their food intake might have been affected by how much they were drinking (164). Milk also contains energy and variation in milk intake would have affected the total meal energy intake among the students (164). Future studies should quantify liquid intake carefully to account for this limitation. Although acute exercise/physical activity does not seem to have a major impact on subsequent energy intake (30,165–167), longer-term (>1 week) physical activity level will influence habitual food intake in most people (30,168–170). Future studies should measure the habitual physical activity level of the participants and use this as a confounder in the regression models when explaining variance in food intake. Additionally, the school included in the current lunch study has high entry grade requirements and can be seen as a school with students of high socioeconomic status. Therefore, future studies should expand the inclusion of schools to also involve those with lower socioeconomic status students to get a better view of food intake among students in the general population. Additionally, the sample included in the school lunch study had a low proportion of students (14%) classified as overweight and obese according to WHO cut-offs (171). For comparison, a representative sample of Swedish second year high-school students had 25% prevalence of overweight and obesity according to IOTF cut-offs (172). Since the use of WHO cut-offs results in a higher proportion of subjects classified as overweight/obese vs. IOTF cut-offs (173), the representativeness of our sample to the general high-school student population in Sweden can be questioned. One of the key devices used in this thesis, the Mandometer®, is owned by a company, and its availability is limited to researchers that are approved to use it by the company. The larger scale implementation with this device in nutrition research is dependent on the willingness of this company to support such research.

For the snack experiment, the serving of snacks during a school task in a classroom setting is not common practice in Swedish schools. Perhaps the one-hour work task could better resemble non-supervised group tasks done outside of scheduled lectures. The one-hour timeframe might not be fully predictive of energy consumption from snack if the food proximity exposure would be sustained for a longer time frame. It would be interesting to conduct repeated measures of snack food proximity effects. Furthermore, the students who participated in the two conditions were randomized based on what class they were belonging to. This was due to school schedule that could not be changed at the time of conducting the study. Future research should instead randomize participants on an individual level into 1) snacks proximal, 2) distal, or 1) snacks distal, 2) snacks proximal in a within-subject design.

For the hospital study, the main limitation was the unbalanced proportion of males-females in the included groups of early and advanced PD patients as well as healthy controls. However, the recruitment of male healthy controls of similar age and BMI was limited as well as the recruitment of female PD patients (PD is more common in males (174)). Although we controlled for sex in our models, future studies should better balance sex proportions in the groups that are included to reduce the impact of this confounder. The sample size (n=64) was limited to the primary outcome analysis (differences in energy intake among the included groups of participants) and larger scale studies are needed to confirm our findings as well as to investigate the explanatory power of disease related symptoms on food intake variation with proper power. Our cross-sectional study design limits the implications of the observed results. It would be interesting to examine whether the observed lower energy intake would increase the risk for long-term weight loss and malnutrition with a prospective study design. The strict inclusion/exclusion criteria resulted in a sample of PD patients with mild PD symptomatology and younger age than a more general PD population (174). The results might have differed if patients with advanced PD treatments such as duodopa pumps and deep brain stimulation as well as patients with severe dysphagia had been included. Furthermore, the meals were eaten in isolation, and might not resemble how most PD patients eat normally, especially since they were eating in front of two video cameras as well as having two smartwatches strapped to their wrists while eating.

For the free-living study, a relatively large sample size was achieved in both Greece and Sweden. However, the schools do not represent the overall school populations in Greece and Sweden. The weight, height, and age were all self-reported by the students to calculate BMIz scores and might have resulted in some bias among students with higher BMI (175).

6.5 ETHICAL CONSIDERATIONS

This thesis involves recruitment of participants from two main populations: 1) school students, and 2) PD patients. In the school and free-living settings, included students were between 15-18 years of age. The recruitment process was conducted in a non-discriminative fashion, since all students in the invited schools could participate independently of their BMI, gender, or nationality. In the hospital setting, PD patients were recruited by neurologists at Dresden University hospital. In this study, strict inclusion/exclusion criteria were used to a) balance the age and other confounding variables between the three included groups: a) advanced PD patients, b) early PD patients as well as c) healthy controls.

From a legal point of view, our research has been reviewed and approved by an ethical review board in Sweden (in the case of the Parkinson’s study, a German ethical approval is given as well). The included research participants and their legal guardians (in the cases of participants who are younger than 15 years) have been given information about the aim of the research, the methods used, potential risks, and the responsible researchers. Participants were giving their assent to participate. The participants were also informed that they could withdraw their assent and stop their participation whenever they wanted, without the need to give the reason why.

From an ethical point of view, it should be mentioned that since the participating students were between 15-18 years of age, it is very important that ethical principles such as “autonomy”, “to not harm” and “anonymity” are adhered to as well as to make sure that the obtained results can be used to “do something beneficial to society” (in the current context students in the same age range as the included research participants). This is also true for the participating PD patients who are in an older age range and who might be extra vulnerable due to their neurodegenerative health condition. More specifically, there is a risk for perceived stigmatization among the students and the PD patients regarding their personal health behaviors (i.e., how fast they eat, their BMI, potential problems handling the food while eating etc.), especially if this information would be accessible to a potential “third party”. Due to this reason, all sensitive personal data have been coded in a sense that it is not possible to connect personal data to other “health data” – i.e., BMI, speed of eating, and medication use (PD patients), without the use of a “decoding key” together with the data files. The data and the decoding keys are stored in encrypted hard drives behind locked doors on password protected computers. This is also true for all video recordings of the participants. These safety measures should reduce the risk of personal data being in the hands of a third party sufficiently.

Another ethical consideration is related to the communication of information to high school students by teachers in the included school. Since the teachers could be considered as authorities, the autonomy principle of the participating students might be challenged. This could also be true for the PD patients with their doctors being in a similar authority position, i.e., if the teachers (or doctors in the case of PD patients) put some form of pressure on the students to participate. Some students might perceive their participation as a form of obligatory task to receive “good” grades. In the case of PD patients, they might perceive that their access to proper care and treatment could be affected. It could be argued that the above-mentioned risks are worthwhile to take since the future value of the research (i.e., development of novel objective methods to measure food intake in special populations such as students and PD patients) motivates the implementation of the studies and it is possible to argue that it would be unethical to not conduct such research efforts.

The studies presented in this thesis were all conducted according to the ethical principles outlined in The Declaration of Helsinki. Involved researchers informed the participants that they could withdraw their participation whenever they wanted to, without giving the reason. This information was given after the teachers presented the project to the students. This supports that the autonomy of the students was better respected. The same was also true for the PD patients. Another important argument for conducting our studies is that several other studies have been done (same school, same method, and same researchers) without complications, which further indicates that the procedures were well accepted. In our studies, there were no cases of students who reported perceived stigmatization or who wanted to quit their participation. These studies have all been approved by different ethical review boards (i.e., there have been different review board members during each ethical vetting). This indicates that these studies follow ethical principles and adhere to the Swedish laws related to research.

There are some additional ethical challenges to consider when scaling up the methodologies used in the studies presented in this thesis. The use of video cameras to record eating behavior in semi-controlled contexts such as the school lunch cafeteria could lead to recordings of students who did not want to participate in the experiment (i.e., if a student who did not consent to participate in the experiment enters the cafeteria environment while the video recordings are ongoing). Since consent is needed to gather sensitive personal data such as recordings of how people eat (including their face being visible while they are eating), proper control of the environment by the responsible researchers is needed if video cameras are to be used in such studies. In other words, the upscaling of similar studies to a larger number of schools would require proper training of the responsible researchers at each school site. With that said, it could be argued that the benefits of doing studies in semi-controlled environments such as the school lunch context still outweighs the above-mentioned drawbacks. Therefore, well-prepared, professionally conducted large-scale investigations of eating behavior in naturalistic and semi-controlled environments should be encouraged. With advances in computing technologies and mobile technological equipment such as smartphones, video analysis could be conducted in real-time while people are eating (see section “points of perspective”).

7 CONCLUSIONS

- Objectively measured single-meal food intake and eating rate could be used to rank individuals in comparison to their peers.
- Subjective eating rate could be used to distinguish groups with slow and fast eating rates in large scale studies but should not be used on an individual level.
- Objectively measured eating behaviors (number of spoonfuls, eating rate, number of food additions/servings), the subjective factors food taste and desire to eat, as well as the external condition proximity to food are all powerful explanatory factors for variance in food intake and might be potential targets in future interventions that aim to modify food intake.
- The internal disease condition advanced PD was associated with lower food intake and potential interventions mentioned above might be helpful in this patient group to normalize their food intake and reduce their risk of undernutrition.
- Further technological developments of these methods could give real-time feedback on targeted eating behaviors that are related to food intake, that might help reduce the risk of diseases related to over- and undernutrition.

8 POINTS OF PERSPECTIVE

8.1.1 Next steps after the school lunch study

An interesting extension of the school lunch study presented in this thesis is to expand the used protocol in more schools other than Internationnella Engelska Gymnasieskolan Södermalm (IEGS). IEGS is a high school located in central Stockholm area (the capital of Sweden) and can be considered as a school with relatively high socio-economic status (SES). The level of entry grades to IEGS programs are very high and the school is privately owned. Therefore, it would be interesting to involve more schools, preferably located in lower socio-economic districts in Stockholm, as well as in other cities in Sweden. A concrete example would be to include high schools in the district Skärholmen since it is a district with a high proportion of childhood obesity rates as well as being inhabited with people of low SES (176,177). Our team has shown that the proportion of advertisements for ultra-processed food is higher in the low SES area Skärholmen vs. the high SES area Östermalm in Stockholm (176). Studies in areas with lower socioeconomic status are valuable to reduce health inequality related to lifestyle vs. higher SES areas.

Furthermore, additional school lunch studies could be expanded in other cities in Sweden as well, having as long-term goal to examine a representative sample of the whole school population of Sweden to track school lunches on a national level. Prospective yearly follow-up studies could also be done to track high school students' dietary habits in a more objective manner. Such efforts would be of substantial value from a public health perspective, since dietary intake of school children is heavily influenced by what and how much they eat during school lunches. This information could be an important tool to use to inform public health policies related to school lunches (178).

Such studies could also be utilized in a climate impact context. Our objective food intake assessment methods could be used to track food waste - both on an individual level as well as on a group/school level. Estimations of total school food waste at different stages of school lunches (i.e., during preparation as well as during/after consumption) could be assessed objectively and food waste interventions could be better planned based on this data. For example, various changes in the school lunch buffet setting could be investigated in randomized controlled studies to inform schools how to best set up their canteen environment to reduce food waste and improve students' nutritional intake.

8.1.2 Next steps after the school snack proximity study

A possible next research step would be to expand the experimental protocol from a snacking situation (perhaps not so common during school hours) to the school lunch context (occurs every day among students in Sweden). In this way, questions could be answered about the effects of food proximity on students' total lunch food intake (total food mass eaten and their energy intake during lunch) as well as their food choices, when placing the food buffet close (i.e., proximal condition/high effort condition, 1-2m away from students) vs. placing it in a separate room (i.e., distal condition/high effort condition). The outcome of such a study could give meaningful information about how to better set up school canteen environments (140).

It would also be interesting to look deeper into students' food choices (i.e., amount of vegetables consumed vs. the amount of main dish consumed, similar to the analysis in (179)) as well as drink choices (i.e. amount of water or milk consumed). Experimental studies could later change environmental cues/conditions that "nudge" students into better food choices (118,180). A concrete example could be an experiment that manipulates food proximity and investigates its effect on fruit and vegetable intake (foods that are recommended from a public health point of view). Examining the proximity of fruit and vegetable location in relation to students' eating location could give worthy insights on students' fruit and vegetable intake (140). If proximity would have a positive effect, it could serve as an important intervention in the school lunch cafeteria context to promote more healthy food choices among students. Such experimental studies, if properly powered, could have real-world implications for how the school cafeteria buffet environment is set up and might have meaningful effects on students' overall dietary intakes. If expanded to a larger number of schools in Sweden, it could also have a positive public health effect in the long run.

As mentioned in the section of "next steps after the school lunch study", an interesting aspect of school lunch proximity intervention would be to investigate the effects on food waste and the climate footprint of the school. For example, a relevant hypothesis to examine would be that of food being served in a distal condition from students. If food is served more distal to students (i.e., in a separate room), they might take more food on their plates when they serve themselves (since it will take a considerable effort to add more food later) thus the risk of food waste might therefore increase as well. Since food waste is an important topic for schools (as well as for society at large, especially regarding its climate impact), it would be a valuable addition to the food proximity literature that has mainly been related to its health impacts until now.

8.1.3 Next steps after the hospital meal study

Since our study was not powered to conduct further analyses other than the primary outcome of group level differences in energy intake, the next step would be to reproduce our initial results in a larger scale study. Such study would preferably be conducted in more clinics and perhaps also in other countries. It is important to mention that strict exclusion criteria were applied in our study and the observed group level differences would most likely be greater if more severe cases of PD patients would have been included.

Since our initial results suggest that upper extremity tremor seems to be an important mediator of lower energy intake among advanced PD patients (132), it would be interesting to record repeated meals among high tremor PD patients at different time points during the day (i.e., when tremor is usually high in the day vs. when tremor is usually low in the day). Energy intake during these distinct time points could then be correlated to severity of tremor symptoms and compared to the energy intake among a group of healthy controls. If tremor would be shown to be an important mediator of lower food intake in such studies, interventions could be carried out with the aim to educate advanced PD patients when in the day it would be most suitable to place large meals to increase their total daily energy intake (of course also dependent on PD medication schedule). Randomized controlled intervention studies could also be carried out to test drugs or other forms of tremor therapies to assess if such interventions could have a normalizing effect on PD patient's overall energy intake and energy balance.

Prospective studies would be needed to investigate if energy intake during a controlled hospital lunch is predictive of long-term weight loss and malnutrition among advanced PD patients. If that would be the case, a logical extension of our initial testing protocol might be used in a clinical setting to assess PD patients who are at greater risk for weight loss and malnutrition. It could aid the clinician to better screen for PD patients that might need extra nutritional care during treatment.

Lastly, the methodology used in our study might also be used to assess PD patients at risk of weight gain and obesity. For example, patients who undergo deep brain stimulation and who start dopamine replacement therapy (excluded in the current analysis) often gain weight on a group level. Our test protocol could preferably be used to assess eating behavior changes that might occur during and after treatment in these groups of PD patients. The long-term aim would be to capture individuals at risk and help them reduce unhealthy weight gain and development of obesity during this stage of PD.

8.1.4 Next steps after the free-living study

Since it was shown that self-reported eating rate could be used as a proxy for group level objective eating rate, a next step would be to include a similar questionnaire in larger scale studies. Such studies should include multiple schools in different cities (and districts/municipalities within the cities) in Sweden, since the questionnaire does not add much cost to the current survey methodologies that are utilized by Swedish agencies, and the adoption might therefore be appropriate (i.e., (172)). Examples would be the Swedish population-based survey "Riksmaten ungdom" (172) or "Skolbarns hälsovanor" that is conducted by the Swedish Food Agency and The Public Health Agency of Sweden (181) respectively. They could include self-reported eating rate in future population-based surveys. Such inclusion would add another dimension (eating behavior) to these surveys. Differences in proportion of students with fast self-reported eating rate between schools could be investigated. Such investigations could facilitate school-based interventions, to reduce the speed of eating among students, through elongation of the scheduled lunch breaks in schools with a high proportion of students with fast eating rate. Such surveys could be included in population-based research in other countries around the world as well.

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10 REFERENCES

1. Splendid [Internet]. [cited 2018 Nov 21]. Available from: https://splendid-program.eu/.

2. Home - i-PROGNOSIS [Internet]. [cited 2018 Dec 11]. Available from: http://www.i-prognosis.eu/.

3. BigO [Internet]. [cited 2018 Feb 21]. Available from: https://bigoprogram.eu/.

4. Swinburn BA, Kraak VI, Allender S, Atkins VJ, Baker PI, Bogard JR, et al. The Global Syndemic of Obesity, Undernutrition, and Climate Change: The Lancet Commission report. Lancet Lond Engl. 2019 23;393(10173):791–846.

5. WHO | Double burden of malnutrition [Internet]. WHO. [cited 2018 Dec 14]. Available from: http://www.who.int/nutrition/double-burden-malnutrition/en/.

6. Hill JO, Wyatt HR, Peters JC. Energy Balance and Obesity. Circulation. 2012 Jul;126(1):126–32.

7. Stuckler D, McKee M, Ebrahim S, Basu S. Manufacturing epidemics: the role of global producers in increased consumption of unhealthy commodities including processed foods, alcohol, and tobacco. PLoS Med. 2012;9(6):e1001235.

8. Hall KD. Did the food environment cause the obesity epidemic? Obes Silver Spring Md. 2018 Jan;26(1):11–3.

9. Hall KD, Ayuketah A, Brychta R, Cai H, Cassimatis T, Chen KY, et al. Ultra-Processed Diets Cause Excess Calorie Intake and Weight Gain: An Inpatient Randomized Controlled Trial of Ad Libitum Food Intake. Cell Metab. 2019 Jul;30(1):67-77.e3.

10. Romieu I, Dossus L, Barquera S, Blottière HM, Franks PW, Gunter M, et al. Energy balance and obesity: what are the main drivers? Cancer Causes Control CCC. 2017 Mar;28(3):247–58.

11. Riaz H, Khan MS, Siddiqi TJ, Usman MS, Shah N, Goyal A, et al. Association Between Obesity and Cardiovascular Outcomes: A Systematic Review and Meta-analysis of Mendelian Randomization Studies. JAMA Netw Open. 2018 Nov;1(7):e183788–e183788.

12. Bhaskaran K, dos-Santos-Silva I, Leon DA, Douglas IJ, Smeeth L. Association of BMI with overall and cause-specific mortality: a population-based cohort study of 3·6 million adults in the UK. Lancet Diabetes Endocrinol. 2018 Dec;6(12):944–53.

13. Bhaskaran K, Douglas I, Forbes H, dos-Santos-Silva I, Leon DA, Smeeth L. Body-mass index and risk of 22 specific cancers: a population-based cohort study of 5·24 million UK adults. Lancet Lond Engl. 2014 Aug;384(9945):755–65.

14. Luppino FS, de Wit LM, Bouvy PF, Stijnen T, Cuijpers P, Penninx BWJH, et al. Overweight, obesity, and depression: a systematic review and meta-analysis of longitudinal studies. Arch Gen Psychiatry. 2010 Mar;67(3):220–9.

15. How the world could better fight obesity | McKinsey [Internet]. [cited 2019 May 17]. Available from: https://www.mckinsey.com/industries/healthcare-systems-and-services/our-insights/how-the-world-could-better-fight-obesity.

16. Hadjikakou M. Trimming the excess: environmental impacts of discretionary food consumption in Australia. Ecol Econ. 2017 Jan;131:119–28.

17. Saunders J, Smith T. Malnutrition: causes and consequences. Clin Med. 2010 Dec;10(6):624–7.

18. Norman K, Pichard C, Lochs H, Pirlich M. Prognostic impact of disease-related malnutrition. Clin Nutr Edinb Scotl. 2008 Feb;27(1):5–15.

19. Barker LA, Gout BS, Crowe TC. Hospital malnutrition: prevalence, identification and impact on patients and the healthcare system. Int J Environ Res Public Health. 2011 Feb;8(2):514–27.

20. Neziraj M, Hellman P, Kumlien C, Andersson M, Axelsson M. Prevalence of risk for pressure ulcers, malnutrition, poor oral health and falls - a register study among older persons receiving municipal health care in southern Sweden. BMC Geriatr. 2021 Apr 21;21(1):265.

21. Suominen M, Muurinen S, Routasalo P, Soini H, Suur-Uski I, Peiponen A, et al. Malnutrition and associated factors among aged residents in all nursing homes in Helsinki. Eur J Clin Nutr. 2005 Apr;59(4):578–83.

22. Hiesmayr M, Schindler K, Pernicka E, Schuh C, Schoeniger-Hekele A, Bauer P, et al. Decreased food intake is a risk factor for mortality in hospitalised patients: the NutritionDay survey 2006. Clin Nutr Edinb Scotl. 2009 Oct;28(5):484–91.

23. Winter JE, MacInnis RJ, Wattanapenpaiboon N, Nowson CA. BMI and all-cause mortality in older adults: a meta-analysis. Am J Clin Nutr. 2014 Apr;99(4):875–90.

24. Sheard JM, Ash S, Silburn PA, Kerr GK. Prevalence of malnutrition in Parkinson's disease: a systematic review. Nutr Rev. 2011 Sep;69(9):520–32.

25. Ma K, Xiong N, Shen Y, Han C, Liu L, Zhang G, et al. Weight Loss and Malnutrition in Patients with Parkinson's Disease: Current Knowledge and Future Prospects. Front Aging Neurosci. 2018;10:1.

26. The Biology of Human Starvation II [Internet]. University of Minnesota Press. [cited 2021 May 10]. Available from: https://www.upress.umn.edu/book-division/books/the-biology-of-human-starvation-ii

27. Stubbs RJ, O'Reilly LM, Whybrow S, Fuller Z, Johnstone AM, Livingstone MBE, et al. Measuring the difference between actual and reported food intakes in the context of energy balance under laboratory conditions. Br J Nutr. 2014 Jun;111(11):2032–43.

28. Garden L, Clark H, Whybrow S, Stubbs RJ. Is misreporting of dietary intake by weighed food records or 24-hour recalls food specific? Eur J Clin Nutr. 2018;72(7):1026–34.

29. Whybrow S, Stubbs RJ, Johnstone AM, O'Reilly LM, Fuller Z, Livingstone MBE, et al. Plausible self-reported dietary intakes in a residential facility are not necessarily reliable. Eur J Clin Nutr. 2016 Jan;70(1):130–5.

30. Edholm OG, Fletcher JG, Widdowson EM, Mccance RA. The energy expenditure and food intake of individual men. Br J Nutr. 1955;9(3):286–300.

31. Kalm LM, Semba RD. They Starved So That Others Be Better Fed: Remembering Ancel Keys and the Minnesota Experiment. J Nutr. 2005 Jun;135(6):1347–52.

32. The Biology of Human Starvation [Internet]. University of Minnesota Press. [cited 2021 May 10]. Available from: https://www.upress.umn.edu/book-division/books/the-biology-of-human-starvation.

33. Westerterp KR. Doubly labelled water assessment of energy expenditure: principle, practice, and promise. Eur J Appl Physiol. 2017;117(7):1277–85.

34. Ravelli MN, Schoeller DA. An objective measure of energy intake using the principle of energy balance. Int J Obes. 2021 Apr;45(4):725–32.

35. Ravussin E, Harper IT, Rising R, Bogardus C. Energy expenditure by doubly labeled water: validation in lean and obese subjects. Am J Physiol. 1991 Sep;261(3 Pt 1):E402-409.

36. Schoeller DA, Ravussin E, Schutz Y, Acheson KJ, Baertschi P, Jéquier E. Energy expenditure by doubly labeled water: validation in humans and proposed calculation. Am J Physiol. 1986 May;250(5):R823-830.

37. Aulick LH, Arnhold H, Hander EH, Mason AD. A new open and closed respiration chamber. Q J Exp Physiol Camb Engl. 1983 Jul;68(3):351–7.

38. Shahar DR, Yu B, Houston DK, Kritchevsky SB, Newman AB, Sellmeyer DE, et al. Misreporting of energy intake in the elderly using doubly labeled water to measure total energy expenditure and weight change. J Am Coll Nutr. 2010 Feb;29(1):14–24.

39. Bhutani S, Racine N, Shriver T, Schoeller DA. Special Considerations for Measuring Energy Expenditure with Doubly Labeled Water under Atypical Conditions. J Obes Weight Loss Ther. 2015 Jul;5(Suppl 5).

40. Black AE, Coward WA, Cole TJ, Prentice AM. Human energy expenditure in affluent societies: an analysis of 574 doubly-labelled water measurements. Eur J Clin Nutr. 1996 Feb;50(2):72–92.

41. Johnson RK. Dietary Intake—How Do We Measure What People Are Really Eating? Obes Res. 2002;10(S11):63S-68S.

42. Dragsted LO, Gao Q, Scalbert A, Vergères G, Kolehmainen M, Manach C, et al. Validation of biomarkers of food intake—critical assessment of candidate biomarkers. Genes Nutr. 2018 May;13(1):14.

43. Block G. A review of validations of dietary assessment methods. Am J Epidemiol. 1982 Apr;115(4):492–505.

44. Pérez Rodrigo C, Aranceta J, Salvador G, Varela-Moreiras G. Food frequency questionnaires. Nutr Hosp. 2015 Feb 26;31 Suppl 3:49–56.

45. Katz DL, Rhee LQ, Katz CS, Aronson DL, Frank GC, Gardner CD, et al. Dietary assessment can be based on pattern recognition rather than recall. Med Hypotheses. 2020 Feb 26;140:109644.

46. Teufel NI. Development of culturally competent food-frequency questionnaires. Am J Clin Nutr. 1997 Apr;65(4 Suppl):1173S-1178S.

47. Shim J-S, Oh K, Kim HC. Dietary assessment methods in epidemiologic studies. Epidemiol Health. 2014 Jul;36:e2014009.

48. Freedman LS, Commins JM, Moler JE, Arab L, Baer DJ, Kipnis V, et al. Pooled results from 5 validation studies of dietary self-report instruments using recovery biomarkers for energy and protein intake. Am J Epidemiol. 2014 Jul;180(2):172–88.

49. New View of Statistics: Effect Magnitudes [Internet]. [cited 2018 Dec 20]. Available from: https://www.sportsci.org/resource/stats/effectmag.html.

50. Dhurandhar NV, Schoeller D, Brown AW, Heymsfield SB, Thomas D, Sørensen TIA, et al. Energy balance measurement: when something is not better than nothing. Int J Obes 2005. 2015 Jul;39(7):1109–13.

51. Gibson RS. Principles of Nutritional Assessment. Oxford University Press; 2005. 930 p.

52. Satija A, Yu E, Willett WC, Hu FB. Understanding nutritional epidemiology and its role in policy. Adv Nutr Bethesda Md. 2015 Jan;6(1):5–18.

53. Hu FB, Willett WC. Current and Future Landscape of Nutritional Epidemiologic Research. JAMA. 2018 Nov 27;320(20):2073–4.

54. Satija A, Yu E, Willett WC, Hu FB. Objective measures are complementary to, rather than a replacement for, self-reported methods. Int J Obes 2005. 2015 Jul;39(7):1179.

55. Satija A, Stampfer MJ, Rimm EB, Willett W, Hu FB. Perspective: Are Large, Simple Trials the Solution for Nutrition Research? Adv Nutr Bethesda Md. 2018 Jul;9(4):378–87.

56. Kissileff HR, Klingsberg G, Van Itallie TB. Universal eating monitor for continuous recording of solid or liquid consumption in man. Am J Physiol. 1980 Jan;238(1):R14-22.

57. Ioakimidis I, Zandian M, Eriksson-Marklund L, Bergh C, Grigoriadis A, Södersten P. Description of chewing and food intake over the course of a meal. Physiol Behav. 2011 Oct;104(5):761–9.

58. Forde CG, van Kuijk N, Thaler T, de Graaf C, Martin N. Texture and savoury taste influences on food intake in a realistic hot lunch time meal. Appetite. 2013 Jan;60(1):180–6.

59. Ruddock HK, Brunstrom JM, Vartanian LR, Higgs S. A systematic review and meta-analysis of the social facilitation of eating. Am J Clin Nutr. 2019 Oct;110(4):842–61.

60. Hollands GJ, Shemilt I, Marteau TM, Jebb SA, Lewis HB, Wei Y, et al. Portion, package or tableware size for changing selection and consumption of food, alcohol and tobacco. Cochrane Database Syst Rev. 2015 Sep;2015(9):CD011045.

61. Rolls BJ, Morris EL, Roe LS. Portion size of food affects energy intake in normal-weight and overweight men and women. Am J Clin Nutr. 2002 Dec;76(6):1207–13.

62. Barkeling B, Elfhag K, Rooth P, Rössner S. Short-term effects of sibutramine (Reductil) on appetite and eating behaviour and the long-term therapeutic outcome. Int J Obes Relat Metab Disord J Int Assoc Study Obes. 2003 Jun;27(6):693–700.

63. Rolls BJ, Bell EA, Castellanos VH, Chow M, Pelkman CL, Thorwart ML. Energy density but not fat content of foods affected energy intake in lean and obese women. Am J Clin Nutr. 1999 May;69(5):863–71.

64. Robinson E, Bevelander KE, Field M, Jones A. Methodological and reporting quality in laboratory studies of human eating behavior. Appetite. 2018 Jun;125:486–91.

65. Stubbs RJ, Finlayson GS. Improving laboratory studies of human eating behaviour: Energy balance and real-world considerations. Appetite. 2018 Nov;130:334–5.

66. Hetherington MM, Rolls BJ. Favouring more rigour when investigating human eating behaviour is like supporting motherhood and apple pie: A response to Robinson, Bevelander, Field, and Jones (2018). Appetite. 2018 Nov;130:330–3.

67. Arvaniti K, Richard D, Tremblay A. Reproducibility of energy and macronutrient intake and related substrate oxidation rates in a buffet-type meal. Br J Nutr. 2000 May;83(5):489–95.

68. Gregersen NT, Flint A, Bitz C, Blundell JE, Raben A, Astrup A. Reproducibility and power of ad libitum energy intake assessed by repeated single meals. Am J Clin Nutr. 2008 May;87(5):1277–81.

69. Langlet B, Tang Bach M, Odegi D, Fagerberg P, Ioakimidis I. The Effect of Food Unit Sizes and Meal Serving Occasions on Eating Behaviour Characteristics: Within Person Randomised Crossover Studies on Healthy Women. Nutrients. 2018 Jul;10(7):880.

70. Caudwell P, Finlayson G, Gibbons C, Hopkins M, King N, Näslund E, et al. Resting metabolic rate is associated with hunger, self-determined meal size, and daily energy intake and may represent a marker for appetite. Am J Clin Nutr. 2013 Jan;97(1):7–14.

71. Robinson E, Hardman CA, Halford JCG, Jones A. Eating under observation: a systematic review and meta-analysis of the effect that heightened awareness of observation has on laboratory measured energy intake. Am J Clin Nutr. 2015 Aug;102(2):324–37.

72. Robinson E, Kersbergen I, Brunstrom JM, Field M. I’m watching you. Awareness that food consumption is being monitored is a demand characteristic in eating-behaviour experiments. Appetite. 2014 Dec;83:19–25.

73. Robinson E, Proctor M, Oldham M, Masic U. The effect of heightened awareness of observation on consumption of a multi-item laboratory test meal in females. Physiol Behav. 2016 Sep;163:129–35.

74. Esfandiari M, Papapanagiotou V, Diou C, Zandian M, Nolstam J, Södersten P, et al. Control of Eating Behavior Using a Novel Feedback System. J Vis Exp. 2018 May 8;(135):57432.

75. Zandian M, Ioakimidis I, Bergström J, Brodin U, Bergh C, Leon M, et al. Children eat their school lunch too quickly: an exploratory study of the effect on food intake. BMC Public Health. 2012 May;12:351.

76. Fagerberg P, Langlet B, Glossner A, Ioakimidis I. Food Intake during School Lunch Is Better Explained by Objectively Measured Eating Behaviors than by Subjectively Rated Food Taste and Fullness: A Cross-Sectional Study. Nutrients. 2019 Mar;11(3).

77. Langlet B, Anvret A, Maramis C, Moulos I, Papapanagiotou V, Diou C, et al. Objective measures of eating behaviour in a Swedish high school. Behav Inf Technol. 2017 Oct;36(10):1005–13.

78. Langlet B, Fagerberg P, Glossner A, Ioakimidis I. Objective quantification of the food proximity effect on grapes, chocolate and cracker consumption in a Swedish high school. A temporal analysis. PLOS ONE. 2017 Aug;12(8):e0182172.

79. McClung HL, Ptomey LT, Shook RP, Aggarwal A, Gorczyca AM, Sazonov ES, et al. Dietary Intake and Physical Activity Assessment: Current Tools, Techniques, and Technologies for Use in Adult Populations. Am J Prev Med. 2018;55(4):e93–104.

80. Archundia Herrera MC, Chan CB. Narrative Review of New Methods for Assessing Food and Energy Intake. Nutrients. 2018 Aug;10(8):1064.

81. Delisle Nyström C, Forsum E, Henriksson H, Trolle-Lagerros Y, Larsson C, Maddison R, et al. A Mobile Phone Based Method to Assess Energy and Food Intake in Young Children: A Validation Study against the Doubly Labelled Water Method and 24 h Dietary Recalls. Nutrients. 2016 Jan;8(1):50.

82. Gemming L, Utter J, Ni Mhurchu C. Image-assisted dietary assessment: a systematic review of the evidence. J Acad Nutr Diet. 2015 Jan;115(1):64–77.

83. Shook RP, Hand GA, O'Connor DP, Thomas DM, Hurley TG, Hébert JR, et al. Energy Intake Derived from an Energy Balance Equation, Validated Activity Monitors, and Dual X-Ray Absorptiometry Can Provide Acceptable Caloric Intake Data among Young Adults. J Nutr. 2018 Mar;148(3):490–6.

84. Kyritsis K, Fagerberg P, Ioakimidis I, Chaudhuri KR, Reichmann H, Klingelhoefer L, et al. Assessment of real life eating difficulties in Parkinson's disease patients by measuring plate to mouth movement elongation with inertial sensors. Sci Rep. 2021 Jan;11(1):1632.

85. Kyritsis K, Diou C, Delopoulos A. Detecting Meals In the Wild Using the Inertial Data of a Typical Smartwatch. In: 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 2019. p. 4229–32.

86. Heitmann BL, Lissner L. Dietary underreporting by obese individuals--is it specific or non-specific? BMJ. 1995 Oct;311(7011):986–9.

87. Lichtman SW, Pisarska K, Berman ER, Pestone M, Dowling H, Offenbacher E, et al. Discrepancy between self-reported and actual caloric intake and exercise in obese subjects. N Engl J Med. 1992 Dec;327(27):1893–8.

88. Goldberg GR, Black AE, Jebb SA, Cole TJ, Murgatroyd PR, Coward WA, et al. Critical evaluation of energy intake data using fundamental principles of energy physiology: 1. Derivation of cut-off limits to identify under-recording. Eur J Clin Nutr. 1991 Dec;45(12):569–81.

89. Black AE. Critical evaluation of energy intake using the Goldberg cut-off for energy intake:basal metabolic rate. A practical guide to its calculation, use and limitations. Int J Obes Relat Metab Disord J Int Assoc Study Obes. 2000 Sep;24(9):1119–30.

90. Ejima K, Brown AW, Schoeller DA, Heymsfield SB, Nelson EJ, Allison DB. Does exclusion of extreme reporters of energy intake (the 'Goldberg cutoffs') reliably reduce or eliminate bias in nutrition studies? Analysis with illustrative associations of energy intake with health outcomes. Am J Clin Nutr. 2019 Nov;110(5):1231–9.

91. Livingstone MBE, Robson PJ, Wallace JMW. Issues in dietary intake assessment of children and adolescents. Br J Nutr. 2004 Oct;92 Suppl 2:S213-222.

92. Burrows TL, Martin RJ, Collins CE. A systematic review of the validity of dietary assessment methods in children when compared with the method of doubly labeled water. J Am Diet Assoc. 2010 Oct;110(10):1501–10.

93. Forrestal SG. Energy intake misreporting among children and adolescents: a literature review: Energy intake misreporting among children and adolescents. Matern Child Nutr. 2011 Apr;7(2):112–27.

94. Grimm P. Social Desirability Bias. In: Wiley International Encyclopedia of Marketing [Internet]. American Cancer Society; 2010 [cited 2019 Oct 29]. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1002/9781444316568.wiem02057.

95. Livingstone MB, Robson PJ. Measurement of dietary intake in children. Proc Nutr Soc. 2000 May;59(2):279–93.

96. Rockett HRH, Berkey CS, Colditz GA. Evaluation of dietary assessment instruments in adolescents. Curr Opin Clin Nutr Metab Care. 2003 Sep;6(5):557–62.

97. Waling MU, Larsson CL. Energy Intake of Swedish Overweight and Obese Children Is Underestimated Using a Diet History Interview. J Nutr. 2009 Mar;139(3):522–7.

98. Bratteby LE, Sandhagen B, Fan H, Enghardt H, Samuelson G. Total energy expenditure and physical activity as assessed by the doubly labeled water method in Swedish adolescents in whom energy intake was underestimated by 7-d diet records. Am J Clin Nutr. 1998 May;67(5):905–11.

99. Bandini LG, Schoeller DA, Cyr HN, Dietz WH. Validity of reported energy intake in obese and nonobese adolescents. Am J Clin Nutr. 1990 Sep;52(3):421–5.

100. Livingstone MB, Prentice AM, Coward WA, Strain JJ, Black AE, Davies PS, et al. Validation of estimates of energy intake by weighed dietary record and diet history in children and adolescents. Am J Clin Nutr. 1992 Jul;56(1):29–35.

101. Fisher JO, Johnson RK, Lindquist C, Birch LL, Goran MI. Influence of body composition on the accuracy of reported energy intake in children. Obes Res. 2000 Nov;8(8):597–603.

102. van Staveren WA, de Groot LC, Blauw YH, van der Wielen RP. Assessing diets of elderly people: problems and approaches. Am J Clin Nutr. 1994;59(1 Suppl):221S-223S.

103. McNeill G, Winter J, Jia X. Diet and cognitive function in later life: a challenge for nutrition epidemiology. Eur J Clin Nutr. 2009 Feb;63 Suppl 1:S33-37.

104. Kelsey JL, O'Brien LA, Grisso JA, Hoffman S. Issues in carrying out epidemiologic research in the elderly. Am J Epidemiol. 1989 Nov;130(5):857–66.

105. Crockett RA, King SE, Marteau TM, Prevost AT, Bignardi G, Roberts NW, et al. Nutritional labelling for healthier food or non-alcoholic drink purchasing and consumption. Cochrane Database Syst Rev. 2018 Feb;2(2):CD009315.

106. Boyland EJ, Nolan S, Kelly B, Tudur-Smith C, Jones A, Halford JC, et al. Advertising as a cue to consume: a systematic review and meta-analysis of the effects of acute exposure to unhealthy food and nonalcoholic beverage advertising on intake in children and adults. Am J Clin Nutr. 2016 Feb;103(2):519–33.

107. Herman CP. The social facilitation of eating. A review. Appetite. 2015 Mar;86:61–73.

108. Christakis NA, Fowler JH. The Spread of Obesity in a Large Social Network over 32 Years. N Engl J Med. 2007 Jul;357(4):370–9.

109. Karl JP, Roberts SB. Energy density, energy intake, and body weight regulation in adults. Adv Nutr Bethesda Md. 2014 Nov;5(6):835–50.

110. Rouhani MH, Haghighatdoost F, Surkan PJ, Azadbakht L. Associations between dietary energy density and obesity: A systematic review and meta-analysis of observational studies. Nutr Burbank Los Angel Cty Calif. 2016 Oct;32(10):1037–47.

111. Roe LS, Meengs JS, Birch LL, Rolls BJ. Serving a variety of vegetables and fruit as a snack increased intake in preschool children123. Am J Clin Nutr. 2013 Sep;98(3):693–9.

112. Johnson F, Wardle J. Variety, palatability, and obesity. Adv Nutr Bethesda Md. 2014 Nov;5(6):851–9.

113. Reducing obesity: future choices [Internet]. GOV.UK. [cited 2021 Apr 6]. Available from: https://www.gov.uk/government/publications/reducing-obesity-future-choices.

114. Robinson E, Almiron-Roig E, Rutters F, de Graaf C, Forde CG, Tudur Smith C, et al. A systematic review and meta-analysis examining the effect of eating rate on energy intake and hunger. Am J Clin Nutr. 2014 Jul;100(1):123–51.

115. Ohkuma T, Hirakawa Y, Nakamura U, Kiyohara Y, Kitazono T, Ninomiya T. Association between eating rate and obesity: a systematic review and meta-analysis. Int J Obes 2005. 2015 Nov;39(11):1589–96.

116. Forde CG, Mars M, de Graaf K. Ultra-Processing or Oral Processing? A Role for Energy Density and Eating Rate in Moderating Energy Intake from Processed Foods. Curr Dev Nutr. 2020 Mar;4(3):nzaa019.

117. de Graaf C. Why liquid energy results in overconsumption. Proc Nutr Soc. 2011 May;70(2):162–70.

118. Cadario R, Chandon P. Which Healthy Eating Nudges Work Best? A Meta-Analysis of Field Experiments. Mark Sci. 2019 Jul 19;39(3):465–86.

119. Hollands GJ, Carter P, Anwer S, King SE, Jebb SA, Ogilvie D, et al. Altering the availability or proximity of food, alcohol, and tobacco products to change their selection and consumption. Cochrane Database Syst Rev. 2019 Sep;9(9):CD012573.

120. Driessen CE, Cameron AJ, Thornton LE, Lai SK, Barnett LM. Effect of changes to the school food environment on eating behaviours and/or body weight in children: a systematic review. Obes Rev Off J Int Assoc Study Obes. 2014 Dec;15(12):968–82.

121. Aiello M, Eleopra R, Rumiati RI. Body weight and food intake in Parkinson’s disease. A review of the association to non-motor symptoms. Appetite. 2015 Jan;84:204–11.

122. Jankovic J. Parkinson’s disease: clinical features and diagnosis. J Neurol Neurosurg Psychiatry. 2008 Apr;79(4):368–76.

123. Postuma RB, Berg D, Stern M, Poewe W, Olanow CW, Oertel W, et al. MDS clinical diagnostic criteria for Parkinson’s disease. Mov Disord Off J Mov Disord Soc. 2015 Oct;30(12):1591–601.

124. Steinhardt J, Münte TF, Schmid SM, Wilms B, Brüggemann N. A systematic review of body mass gain after deep brain stimulation of the subthalamic nucleus in patients with Parkinson’s disease. Obes Rev. 2020 Feb;21(2):e12955.

125. Kistner A, Lhommée E, Krack P. Mechanisms of Body Weight Fluctuations in Parkinson’s Disease. Front Neurol. 2014 Jun;5:84.

126. Hall KD, Sacks G, Chandramohan D, Chow CC, Wang YC, Gortmaker SL, et al. Quantification of the effect of energy imbalance on bodyweight. Lancet Lond Engl. 2011 Aug;378(9793):826–37.

127. Barichella M, Cereda E, Cassani E, Pinelli G, Iorio L, Ferri V, et al. Dietary habits and neurological features of Parkinson’s disease patients: Implications for practice. Clin Nutr Edinb Scotl. 2017 Aug;36(4):1054–61.

128. Lorefät B, Ganowiak W, Wissing U, Granérus A-K, Unosson M. Food habits and intake of nutrients in elderly patients with Parkinson’s disease. Gerontology. 2006;52(3):160–8.

129. Parkinson J. An essay on the shaking palsy. 1817. J Neuropsychiatry Clin Neurosci. 2002;14(2):223–36; discussion 222.

130. Chen H, Zhang SM, Hernán MA, Willett WC, Ascherio A. Weight loss in Parkinson’s disease. Ann Neurol. 2003;53(5):676–9.

131. Fagerberg P, Charmandari E, Diou C, Heimeier R, Karavidopoulou Y, Kassari P, et al. Fast Eating Is Associated with Increased BMI among High-School Students. Nutrients. 2021 Mar;13(3).

132. Fagerberg P, Klingelhoefer L, Bottai M, Langlet B, Kyritsis K, Rotter E, et al. Lower Energy Intake among Advanced vs. Early Parkinson's Disease Patients and Healthy Controls in a Clinical Lunch Setting: A Cross-Sectional Study. Nutrients. 2020 Jul;12(7).

133. Sök näringsinnehåll - Livsmedelsverket [Internet]. [cited 2021 May 6]. Available from: https://www7.slv.se/SokNaringsinnehall.

134. Spreadsheets for analysis of validity and reliability [Internet]. [cited 2018 Dec 10]. Available from: http://www.sportsci.org/2015/ValidRely.htm.

135. Osowski CP, Lindroos AK, Barbieri HE, Becker W. The contribution of school meals to energy and nutrient intake of Swedish children in relation to dietary guidelines. Food Nutr Res. 2015 Oct;59:27563.

136. Hall KD. Effect of Ultra Processed versus Unprocessed Diets on Energy Intake. 2019 Apr 29 [cited 2021 Apr 9]; Available from: https://osf.io/rx6vm/.

137. Blundell JE, Caudwell P, Gibbons C, Hopkins M, Naslund E, King N, et al. Role of resting metabolic rate and energy expenditure in hunger and appetite control: a new formulation. Dis Model Mech. 2012 Sep;5(5):608–13.

138. Langlet B, Fagerberg P, Delopoulos A, Papapanagiotou V, Diou C, Maramis C, et al. Predicting Real-Life Eating Behaviours Using Single School Lunches in Adolescents. Nutrients. 2019 Mar;11(3):672.

139. Ford AL, Bergh C, Södersten P, Sabin MA, Hollinghurst S, Hunt LP, et al. Treatment of childhood obesity by retraining eating behaviour: randomised controlled trial. BMJ. 2009 Jan;340:b5388.

140. Kessler HS. Simple interventions to improve healthy eating behaviors in the school cafeteria. Nutr Rev. 2016 Mar;74(3):198–209.

141. Kyritsis K, Diou C, Delopoulos A. Modeling Wrist Micromovements to Measure In-Meal Eating Behavior From Inertial Sensor Data. IEEE J Biomed Health Inform. 2019;23(6):2325–34.

142. Hermsen S, Mars M, Higgs S, Frost JH, Hermans RCJ. Effects of eating with an augmented fork with vibrotactile feedback on eating rate and body weight: a randomized controlled trial. Int J Behav Nutr Phys Act. 2019 Oct;16(1):90.

143. Stubbs RJ, Johnstone AM, Mazlan N, Mbaiwa SE, Ferris S. Effect of altering the variety of sensorially distinct foods, of the same macronutrient content, on food intake and body weight in men. Eur J Clin Nutr. 2001 Jan;55(1):19–28.

144. Temple NJ, Nowrouzi B. Buffets and obesity. Clin Nutr Edinb Scotl. 2013 Aug;32(4):664–5.

145. Stunkard A, Mazer A. Smorgasbord and obesity. Psychosom Med. 1978 Mar;40(2):173–5.

146. Konstantinidis D, Dimitropoulos K, Langlet B, Daras P, Ioakimidis I. Validation of a Deep Learning System for the Full Automation of Bite and Meal Duration Analysis of Experimental Meal Videos. Nutrients. 2020 Jan;12(1).

147. Privitera GJ, Creary HE. Proximity and Visibility of Fruits and Vegetables Influence Intake in a Kitchen Setting Among College Students. Environ Behav. 2013 Oct;45(7):876–86.

148. Musher-Eizenman DR, Young KM, Laurene K, Galliger C, Hauser J, Wagner Oehlhof M. Children's sensitivity to external food cues: how distance to serving bowl influences children's consumption. Health Educ Behav Off Publ Soc Public Health Educ. 2010 Apr;37(2):186–92.

149. Maas J, de Ridder DTD, de Vet E, de Wit JBF. Do distant foods decrease intake? The effect of food accessibility on consumption. Psychol Health. 2012 Oct;27 Suppl 2:59–73.

150. Painter JE, Wansink B, Hieggelke JB. How visibility and convenience influence candy consumption. Appetite. 2002 Jun;38(3):237–8.

151. Privitera GJ, Zuraikat FM. Proximity of foods in a competitive food environment influences consumption of a low calorie and a high calorie food. Appetite. 2014 May;76:175–9.

152. Hunter JA, Hollands GJ, Pilling M, Marteau TM. Impact of proximity of healthier versus less healthy foods on intake: A lab-based experiment. Appetite. 2019 Feb;133:147–55.

153. Lorefält B, Granérus A-K, Unosson M. Avoidance of solid food in weight losing older patients with Parkinson's disease. J Clin Nurs. 2006 Nov;15(11):1404–12.

154. Baert F, Matthys C, Mellaerts R, Lemaître D, Vlaemynck G, Foulon V. Dietary Intake of Parkinson's Disease Patients. Front Nutr. 2020 Jul;7:105.

155. Lorefält B, Ganowiak W, Pålhagen S, Toss G, Unosson M, Granérus A-K. Factors of importance for weight loss in elderly patients with Parkinson's disease. Acta Neurol Scand. 2004 Sep;110(3):180–7.

156. Monteiro CA, Cannon G, Levy RB, Moubarac J-C, Louzada ML, Rauber F, et al. Ultra-processed foods: what they are and how to identify them. Public Health Nutr. 2019 Apr;22(5):936–41.

157. Costa CS, Del-Ponte B, Assunção MCF, Santos IS. Consumption of ultra-processed foods and body fat during childhood and adolescence: a systematic review. Public Health Nutr. 2018 Jan;21(1):148–59.

158. Chen X, Zhang Z, Yang H, Qiu P, Wang H, Wang F, et al. Consumption of ultra-processed foods and health outcomes: a systematic review of epidemiological studies. Nutr J. 2020 Aug 20;19(1):86.

159. Eckhardt CL, Suchindran C, Gordon-Larsen P, Adair LS. The association between diet and height in the postinfancy period changes with age and socioeconomic status in Filipino youths. J Nutr. 2005 Sep;135(9):2192–8.

160. Brindal E, Wilson C, Mohr P, Wittert G. Eating in groups: Do multiple social influences affect intake in a fast-food restaurant? J Health Psychol. 2015 May;20(5):483–9.

161. Higgs S, Thomas J. Social influences on eating. Curr Opin Behav Sci. 2016 Jun;9:1–6.

162. Bobroff EM, Kissileff HR. Effects of changes in palatability on food intake and the cumulative food intake curve in man. Appetite. 1986 Mar;7(1):85–96.

163. Bolhuis DP, Lakemond CMM, de Wijk RA, Luning PA, de Graaf C. Effect of salt intensity on ad libitum intake of tomato soup similar in palatability and on salt preference after consumption. Chem Senses. 2010 Nov;35(9):789–99.

164. Daniels MC, Popkin BM. The impact of water intake on energy intake and weight status: a systematic review. Nutr Rev. 2010 Sep;68(9):505–21.

165. Schubert MM, Desbrow B, Sabapathy S, Leveritt M. Acute exercise and subsequent energy intake. A meta-analysis. Appetite. 2013 Apr;63:92–104.

166. Blundell JE, King NA. Effects of exercise on appetite control: loose coupling between energy expenditure and energy intake. Int J Obes Relat Metab Disord J Int Assoc Study Obes. 1998 Aug;22 Suppl 2:S22-29.

167. Stubbs RJ, Sepp A, Hughes DA, Johnstone AM, Horgan GW, King N, et al. The effect of graded levels of exercise on energy intake and balance in free-living men, consuming their normal diet. Eur J Clin Nutr. 2002 Feb;56(2):129–40.

168. Westerterp KR. Physical activity, food intake, and body weight regulation: insights from doubly labeled water studies. Nutr Rev. 2010 Mar;68(3):148–54.

169. Stubbs RJ, Hughes DA, Johnstone AM, Whybrow S, Horgan GW, King N, et al. Rate and extent of compensatory changes in energy intake and expenditure in response to altered exercise and diet composition in humans. Am J Physiol Regul Integr Comp Physiol. 2004 Feb;286(2):R350-358.

170. Beaulieu K, Blundell JE, van Baak MA, Battista F, Busetto L, Carraça EV, et al. Effect of exercise training interventions on energy intake and appetite control in adults with overweight or obesity: A systematic review and meta-analysis. Obes Rev Off J Int Assoc Study Obes. 2021 May;e13251.

171. Growth reference 5-19 years - BMI-for-age (5-19 years) [Internet]. [cited 2021 May 23]. Available from: https://www.who.int/tools/growth-reference-data-for-5to19-years/indicators/bmi-for-age.

172. Livsmedelsverket [Internet]. [cited 2021 Mar 29]. Available from: https://www.livsmedelsverket.se/matvanor-halsa--miljo/matvanor---undersokningar/riksmaten-ungdom.

173. Gómez-Campos R, David Langer R, de Fátima Guimarães R, Contiero San Martini M, Cossio-Bolaños M, de Arruda M, et al. Accuracy of Body Mass Index Cutoffs for Classifying Obesity in Chilean Children and Adolescents. Int J Environ Res Public Health. 2016 May;13(5):472.

174. Tysnes O-B, Storstein A. Epidemiology of Parkinson's disease. J Neural Transm Vienna Austria 1996. 2017;124(8):901–5.

175. Olfert MD, Barr ML, Charlier CM, Famodu OA, Zhou W, Mathews AE, et al. Self-Reported vs. Measured Height, Weight, and BMI in Young Adults. Int J Environ Res Public Health. 2018 Oct;15(10):2216.

176. Fagerberg P, Langlet B, Oravsky A, Sandborg J, Löf M, Ioakimidis I. Ultra-processed food advertisements dominate the food advertising landscape in two Stockholm areas with low vs high socioeconomic status. Is it time for regulatory action? BMC Public Health. 2019 Dec;19(1):1717.

177. Barnhälsovårdsrapporter | Vårdgivarguiden [Internet]. [cited 2019 May 17]. Available from: https://www.vardgivarguiden.se/behandlingsstod/bvc/barnhalsovardsrapporter/.

178. Eustachio Colombo P, Patterson E, Elinder LS, Lindroos AK. The importance of school lunches to the overall dietary intake of children in Sweden: a nationally representative study. Public Health Nutr. 23(10):1705–15.

179. Kongsbak I, Skov LR, Nielsen BK, Ahlmann FK, Schaldemose H, Atkinson L, et al. Increasing fruit and vegetable intake among male university students in an ad libitum buffet setting: A choice architectural nudge intervention. Food Qual Prefer. 2016 Apr;49:183–8.

180. Nudge | Yale University Press [Internet]. [cited 2021 Apr 20]. Available from: https://yalebooks.yale.edu/book/9780300122237/nudge.

181. Skolbarns hälsovanor — Folkhälsomyndigheten [Internet]. [cited 2021 May 23]. Available from: http://www.folkhalsomyndigheten.se/folkhalsorapportering-statistik/om-vara-datainsamlingar/skolbarns-halsovanor/.