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OBJECTIVE QUANTIFICATION AND ANALYSIS OF EATING BEHAVIOURS ASSOCIATED WITH OBESITY DEVELOPMENT –

FROM LAB TO REAL-LIFE

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Objective quantification and analysis of eating behaviours associated with obesity development – from lab to real-life

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ABSTRACT

Introduction:

The last four decades have seen a marked increase in childhood and adult obesity prevalence, attributed to an "*obesogenic*" environment. Several genetical, environmental and behavioural factors have been identified that increase the risk of obesity, but treatment outcomes are usually modest and the risk of relapse high. One limitation responsible for these moderate results could be methodological, with researchers questioning both the external validity of eating behaviour measures in the laboratory (*controlled*) and the internal validity of eating behaviour measures in free-living (*real-life*) settings. Technological advances could solve some of these issues, allowing for accurate methods, similar to those used in *controlled* settings, to be used in *real-life*. Deploying accurate methods in both *controlled* and *real-life* settings would in turn enable the estimation of external validity, determining the limits of generalization between settings. In turn enabling the deployment of these methods in settings which allow large scale screening, for early identification of individuals at risk of becoming obese.

Aim:

The overarching aim of the thesis was to: i) evaluate the stability of human eating behaviour and ii) investigate the usability and feasibility of methods developed for *controlled* settings, when deployed in *semi-controlled* and *real-life* settings.

Paper I – Determine if individuals maintain their eating behaviour, in relation to the group, despite experimental manipulations to meal conditions (i.e., unit sizes and serving occasion).

Paper II – Feasibility of employing novel technology for baseline eating behaviour collection in adolescents eating school lunches in a school cafeteria setting (*semi-controlled*).

Paper III – Feasibility of employing novel technology in an experimental manipulation study, to determine the effect of proximity in a *semi-controlled* school setting.

Paper IV – By use of novel technology, examine the maintenance of eating behaviours in adolescents, from *semi-controlled* to *real-life* settings, both at group- and individual-level.

Methods:

Paper I – Three randomised crossover studies, of which two compared eating behaviour across different unit sizes, while one compared eating behaviour between lunch and dinner in healthy young adults. Performed in a *controlled* setting, employing traditional laboratory methods.

Paper II – An observational study of healthy adolescents, performed at lunch in a school cafeteria, employing traditional laboratory methods in a *semi-controlled* setting.

Paper III – A randomised experimental study of healthy adolescents, performed in a *semi-controlled*, comparing the eating behaviour between two groups seated at different proximity to food items.

Paper IV – An observational study on eating behaviour of healthy adolescents, divided into two parts; i) collection of eating behaviour data, performed at lunch in a school cafeteria, using a similar protocol to that of **Paper II** and ii) collection of eating behaviour data by the participants in *real-life* settings, using the same devices as in the *controlled* setting.

Results:

In all papers the distribution of eating behaviour values between individuals were large. In **Paper I**, the largest increase in unit size significantly increased meal duration and chews and while there was a trend for both increased meal duration and number of chews the larger the food unit sizes were, it did not lead to a significant reduction in food intake. Meanwhile, the correlation coefficient of all eating behaviours across all conditions was high (except for number of bites between the largest and smallest food unit size condition). In **Paper II**, male participants ate significantly more, mediated by significantly larger bites. The bite sizes of both men and women were reduced as the meal progressed. In **Paper III**, increased distance to food led to a significant reduction in intake, caused by individuals taking less chocolate. In **Paper IV**, there was no significant difference in eating behaviour characteristics between the *semi-controlled* and *real-life* meals. In addition, the correlation coefficient of food intake and eating rate was high between settings, while the correlation of meal duration was low. Also, on an individual level, 50%, 32% and 27% of the food intake, eating rate and meal duration measures, respectively, from the *semi-controlled* meal fell within the confidence interval of the *real-life* meals. In the *semi-controlled* and *real-life* settings (**Papers II-IV**), the agreement between subjective and objective eating behaviour measures were very low. Meanwhile, in both *semi-controlled* and *real-life* settings the method could be deployed within the time schedule imposed by the school, with high data retention. Also, participants rated the comfortability participating in the *semi-controlled* and *real-life* settings very high and the usability of the system as "*Good*" or higher.

Conclusions:

Human eating behaviour appears stable in comparison to the group when unit size and serving occasion is manipulated in a *controlled* setting and when eating in different settings (*semi-controlled* and *real-life*). Suggesting generalisations can be made between settings and conditions and that risk behaviours may be measured in settings other than *real-life*, at least on group level. However, although individual prediction rates of eating behaviour characteristics from *semi-controlled* setting to *real-life* settings appears higher than subjective ratings, they are still too low for use in the design of tailored interventions. In addition, compared to *controlled* studies, the method allowed recruitment of a younger age group, since it enabled measurements in a different location. The thesis also provides evidence that the employed methods are usable, feasible and acceptable, with high data retention in adolescent users, in *semi-controlled* and *real-life* settings. Methods similar to the ones used in this thesis can provide previously unattainable information (primarily temporal) in settings that are less controlled than the laboratory, such as *semi-controlled* and *real-life*.

LIST OF SCIENTIFIC PAPERS

I. **Langlet B.,** Tang Bach M., Odegi D., Fagerberg P. and 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, 10(7), pii:E880

II. **Langlet B.,** Anvret A., Maramis C., Moulos I., Papapanagiotou V., Diou C., Lekka E., Heimeier R., Delopoulos A. and Ioakimidis I.
Objective Measures of Eating Behaviour in a Swedish High School
Behaviour & Information Technology, 2017, 36(10), 1005-1013

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, 12(8): e0182172.

IV. **Langlet B.,** Fagerberg P., Delopoulos A., Diou C., Maramis C., Maglaveras N., Heimeier R., Anvret A. and Ioakimidis I.
Eating Behaviour of Swedish High-School Students. A Pilot Study Using Novel Methods to Quantify Eating Behaviour in Real-Life
Manuscript

CONTENTS

LIST OF ABBREVIATIONS

Abbreviations are listed in the order they appear in the text.

IMPACT	Innovative use of mobile phones to promote physical activity and nutrition across the lifespan
BMI	Body Mass Index
BC	Before Christ
AD	anno Domini
Diabetes	Type 2 Diabetes Mellitus
DNP	Dinitrophenol
AIM	Automatic Ingestion Monitor
DIMS	Dietary Intake Monitoring System
I	Paper I
II	Paper II
III	Paper III
IV	Paper IV
♀	Female
♂	Male
USB	Universal Serial Bus
PC	Personal Computer
SUS	System Usability Scale
LME	Linear Mixed Effect Model
ANOVA	Analysis of Variance
KS	Kolmogorov-Smirnov test
SD	Standard Deviation
Exp.	Experiment
CI	Confidence Interval
mHealth	Mobile Health
GPS	Global Positioning System

1 BACKGROUND

1.1 OBESITY

1.1.1 Definition and Diagnosis

Obesity is defined as a condition with "*abnormal or excessive fat accumulation that presents a risk to health*" [1]. The diagnosis of obesity and body composition has been conducted using several methods and while the earliest accounts of obesity as a disease was more descriptive, later diagnostic methods include waist circumference, underwater weighing, bio-impedance and dual-energy x-ray absorptiometry [2–4]. By far the most common diagnostic measure is body mass index (BMI), calculated by dividing an individuals' weight by their height squared, kg/m^2, with the threshold for obesity most often set to BMI ≥ 30 kg/m^2 in adults [1]. This method has several known weaknesses, but the low cost and technical requirements are usually considered outweighing its limitations [5].

1.1.2 History

"Those who are constitutionally very fat are more apt to die quickly than those who are thin" – Hippocrates, 400 BC

Our earliest known depictions of obesity are the Venus figurines fashioned during the Upper Palaeolithic age, some dating back 35.000 years [6]. Meanwhile, the first written accounts of obesity are the ones by Hippocrates around 500 BC, who referred to the condition as an excess of flesh (polysarchia) [7]. During classic antiquity morbid obesity was also linked to the increased risk of multiple acute diseases, respiratory diseases and unexpected deaths [8,9]. Later, during the Dark Ages, few discoveries were made in Europe. However, Arabic researchers such as Ibn el Nefis (1207-1288 AD), clarified the association between obesity and respiratory and endocrine disorders, as well as cardiovascular and cerebrovascular accidents [10]. The Early Modern Period saw the reappearance of obesity in Europe in Tobias Venner's Via Recta ad Vitam Longam (1621 AD), which provides an impressive philosophical effort to explain human health as a result of habitat, weather, food types and dietary customs [11]. Despite the knowledge of health risks associated with obesity since antiquity, obesity had always been fashionable, because it signified a life lived in excess [12]. However, around 1850 this view started to change and obesity, or corpulence, was falling out of fashion. One of the first works taking an accusatory tone to obesity and obese individuals was *A Letter on Corpulence Addressed to the Public*, by William Banting, (1863 AD) [13]. Psychosocial models of obesity such as the one developed by Hilde Bruch in the 1940 served to maintain the stigma, by arguing the cause of obesity was overbearing mothers, who in early childhood discouraged the development of self-efficacy [14]. According to the model, this in turn led to escapist behaviour and the substitution of other forms of gratification with overeating. [15].

1.1.3 Prevalence

In adults, the current prevalence of obesity worldwide is nearly three times what it was 1975, rising from 6.4 to 14.9% in women and 3.2 to 10.8% in men, between 1975 and 2014 [16]. In children and adolescents between the ages of 5 and 19, there has been an eight- to nine-fold increase in obesity prevalence, from 0.7 to 5.6% in girls and 0.9 to 7.8% in boys, between 1975 and 2016 [17,18]. Recent trends suggest adult are still gaining weight in most western countries, but that the rise in children's and adolescents' mean BMI may have reached a plateau [16]. Meanwhile, the highest increase in obesity is currently seen in low-income countries, which face a double burden of malnutrition, with a high prevalence of both obesity and undernutrition [19]. Trend projections suggest obesity prevalence will have passed underweight by 2020 [17].

However, in certain countries, such as Sweden, studies have found a decline in childhood obesity. For example, in a cohort study on male participants with a mean age of 8, the obesity prevalence dropped from 10.1 to 9.6%, between 1991 and 2006 [20]. Another study in 10-year olds found a lower obesity prevalence of females participants (3.0% to 2.5%) between 2000 and 2004, while there was only a slight obesity decline in male subjects (-0.1%) [21]. However, other studies have found no such association in children, one instead found an increased obesity prevalence in adolescent boys (17 years old), from 3.6% to 7.3%, between 2004 and 2015 [22]. These findings illustrate the importance of measuring obesity on multiple levels. Even in relatively small areas, such as Stockholm, whose municipal area is estimated at 187 km^2, the difference in childhood (4-year olds) prevalence of overweight between districts varied from 5.1% to 13.5% in 2015 [23], Figure 1.

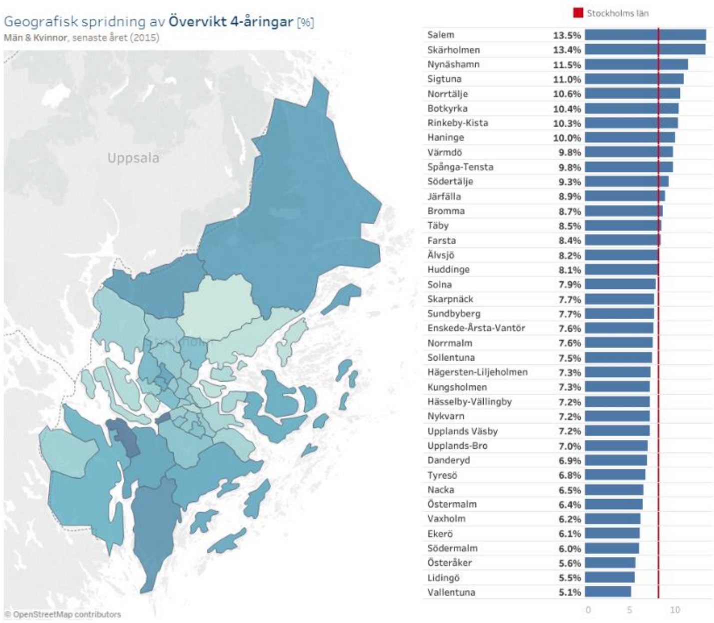

Figure 1. Prevalence of overweight in 4-year old male and female individuals in the municipality of Stockholm, 2015.

1.1.4 Health Complications

As mentioned previously, the connection between obesity and ill health was discovered more than two thousand years ago [24]. Since then, several additional physiological and psychological comorbidities of obesity have been discovered and diseases previously associated exclusively with adults have started appearing in obese children [25,26].

1.1.4.1 Physiological Complications

Three of the most common physiological disorders of obesity are osteoarthritis, type 2 diabetes mellitus (*diabetes*) and coronary heart disease [25]. Osteoarthritis is not deadly, but does lead to nociceptive, inflammatory and neuropathic pain [27]. Meanwhile, coronary heart disease increases the risk of sudden cardiac death [28]. *Diabetes* also increases the prevalence of sudden cardiac death by increasing the risk of cardiovascular disease (of which coronary heart disease is a subcategory) [29]. Additionally, *diabetes* increases the risk of damage, dysfunction and failure of end organs, such as the retina, kidney, nervous system, heart and blood vessels [30,31].

1.1.4.2 Psychological Complications

"Obesity is hardly ever mentioned in the writings of sociologists, and not at all in the literature on social deviance." – Cahnman WJ., 1968

The most common psychological health consequences of obesity are depression and severe depressive symptoms [32]. Which, may at least in part be explained by the social stigma and bullying associated with obesity. Already in the 1960s studies found that obese individuals were more often associated with unfavourable word descriptors [33,34]. Despite the increased prevalence of obesity, more recent studies corroborate these findings [35,36]. In addition to being viewed as a health complication of obesity, some evidence suggest fat stigma and weight discrimination are also risk factors for obesity [37], potentially creating a vicious circle of increased weight gain.

1.1.4.3 Physical and Economical Cost

Currently, overweight and obesity are responsible for more deaths worldwide than underweight, while the associated healthcare costs are higher than that of smoking [38,39]. This has caused organizations, such as the American Medical Association, to categorize obesity as a disease, stressing the importance of early detection and effective prevention and treatment strategies [40]. What makes early detection important is that most studies suggest obese children are likely to maintain their obesity into adulthood [2,41,42]. In addition, in Sweden, a lifetime of obesity has been shown to increase the risk of disability [43] and result in loss of income [44].

1.1.5 Aetiology

"From inhaling the odour of beef the butcher's wife obtains her obesity" - A. Booth, The Builder, 13 July, 1844

The law of conservation of energy states that "*the total energy of an isolated system is constant; energy can be transformed from one form to another, but cannot be created or destroyed.*", which means that the only possible way for a body to accumulate adipose tissue, is for it to expend less energy than it absorbs [45]. Therefore, at a first glance, obesity may seem a very simple disease to counteract by just maintaining an intake below expenditure. However, human metabolism is complex and neither energy expenditure, nor energy intake are ever stable, but constantly change to adapt to internal and external requirements [46]. This fact has caused researchers to investigate the cause of obesity at every conceivable level, from genetic to behavioural.

Genetic research has focused on investigating the effect genes have on behavioural and metabolic functions [47]. There does exists single gene mutations which drastically increase the risk of developing obesity, such as gene defects which disrupt the leptin-melanocortin pathway [48], but as postulated already in the 1960s, it is unlikely that a majority of obesity cases belong to this category [49]. A review in 2005 identified 253 quantitative trait loci in humans associated with obesity [50], an expected amount, since energy intake and regulation are among the most fundamental abilities of an organism for survival. However, it does not appear as if changes in our genome can account for the increase in obesity observed during these last decades [51]. Other suggested metabolic causes to the increased obesity prevalence is reproductive changes (e.g., overweight of mothers and increased maternal age) [52], different gut floras, reduced variability of ambient temperature, smoking cessation and short sleep duration [45]. It needs to be stressed however, that all of these proposed risk factors lack proper evaluation through manipulation studies, randomized control trials and prospective observational studies [53]. Meanwhile, neuroendocrinological models for obesity started emerging in the 1950s, initiated by homeostatic motivation theories which postulated that satiety signals are transmitted via the blood by macronutrients [54,55]. However, the development of brain lesion methods enabled the discovery of the role played by the hypothalamus in satiety signalling. When lesions are made in the ventromedial hypothalamic region, animals initially eat voraciously and gain weight, but after a while reach a stable body weight at a new, elevated level [56]. These findings led to more centralised theories of motivation, such as the "*hypothalamic homeostatic*" and "*set point*" theories, both of which suggest that body weight is kept stable by the response of orexigen and anorexigen signalling molecules to feedback from various tissues (such as adipose tissue, the gastrointestinal tract etc.) [57]. Although very interesting, in real-life, hypothalamic disruption/dysregulation appears rare and therefore not able to account for either the rapid increase or high prevalence of obesity [58].

1.1.5.1 Behavioural Models of Obesity

Many researchers have suggested that the so-called obesity epidemic is merely a response to the living environment having changed to promote obesity, frequently referred to as an "*obesogenic*" environment [59–61]. The reduction of required labour started some 12.000 years ago with the domestication of animals, but around 150 years ago with the industrial (agrarian) revolution human workplace labour has been reduced exponentially and today most jobs are of a sedentary nature. Meanwhile, urban design, public transportation availability, safety and walkability often present barriers for people to engage in healthy lifestyle behaviours [12,62]. In addition, our food environment has seen an increased availability of food stores and restaurants, with increased accessibility to calorie-dense foods and beverages at a reduced price and increased portion size [63–65]. In line with these changes, population based clinical trials have found a connection between obesity and sedentary behaviour, as well as high-calorie food intake [66]. The mentioned reduction in physical activity and increase in availability of energy dense, highly palatable food at low cost is therefore considered a good explanation to the increase in obesity prevalence seen in recent decades [67].

The first models for predicting animal behaviour were developed in the beginning of the 20th century, by JB. Watson, BF. Skinner and I. Pavlov, quantifying the response to various environmental exposures [68–70]. The behaviour models of all three researchers, to various degree attribute animal behaviour to the history of environmental reinforcement. Meanwhile, one of the first behavioural models to describe the difference between obese and normal weight individuals is the externality hypothesis, developed by Stanley Schachter (1968). The hypothesis postulates that for obese individuals "*eating is determined largely by external cues*", while normal weight individuals have a much higher internal control [71]. This hypothesis was challenged in the 1980s and has since been proven hard to reproduce, instead some studies find both obese and normal weight individuals equally vulnerable to external cues [72,73]. An interesting study by Brian Wansink showed a positive association between availability of foods such as candy, cereal, soft drinks, and dried fruit on an individual's kitchen counter and their weight [74]. These findings will likely need to be replicated, since several studies authored by the same researcher have been retracted, shedding doubt on the scientific validity of his work. However, the study protocol emphasizes an interesting venue of research, i.e., "*how environmental components that are modifiable by the individual promote obesity?*". Meanwhile, both studies conducted by Brunstrom et al. [75], and Mars et al., [76] suggest dietary/satiety learning to unknown food types, while studies in children indicate a response to various parental feeding practices [77–80]. Emphasizing a point rarely investigated, which is the change of behaviour over time, similar to the environmental reinforcement theories of early behaviourists. Most of these studies suggest that there is nothing "*wrong*" with the majority of obese individuals, rather than their condition being a learned response to an environment with different requirements than the ones imposed upon humans throughout evolution.

1.1.6 Treatment

Most expert panels consider weight maintenance in children and a weight reduction of 5-10% in adults clinically relevant in obese patients, due to the associated health benefits [81–83]. With these goals in mind, the American Heart Association, American Colleague of Cardiology and The Obesity Society have developed guidelines for the treatment of obesity [84]. These guidelines recommend all overweight individuals (BMI ≥25) a *comprehensive lifestyle intervention,* in addition to this *pharmacotherapy* should be recommended to obese individuals (or BMI ≥27 with ≥1 obesity associated comorbid condition). More severe cases of obesity (BMI ≥40, or BMI ≥35 and ≥1 obesity associated comorbid condition) should be offered *bariatric surgery* [84].

1.1.6.1 Bariatric Surgery

The two most common bariatric surgery procedures for obesity in 2013 were, Roux-en-Y gastric bypass and vertical sleeve gastrectomy [85]. Both procedures usually result in a weight reduction between 25 and 50 kg [86,87], in part mediated by a forced reduction in portion size. However, a Cochrane review concluded that in most randomised control studies on Roux-en-Y gastric bypass and vertical sleeve gastrectomy the rates of adverse events and reoperation are not reported [88]. When reported, adverse events are usually anastomotic leakage, and all-cause mortality, while reoperation rates range from 6.7% to 24% in Roux-en-Y and from 3.3% to 34% in sleeve gastrectomy [88]. In additions, notable long-term negative effects of bariatric surgery are malabsorption and hormonal disturbances leading to, for instance, osteoporosis [89]. On a positive note, the transition in bariatric surgery procedures from open to laparoscopic methods have caused some postsurgical effects, such as abdominal wall hernias and infection to become much rarer [90].

1.1.6.2 Pharmacotherapy

The first pharmacological compound successfully at reducing the body weight of overweight individuals was thyroxine (1893), extracted from sheep glands [91]. In the 1930s dinitrophenol (DNP) was found to promote weight reduction in factory workers, which later led to the successful use of DNP for treating obesity [92]. Just a few years later (1938), after initially being used to treat narcolepsy, amphetamine was established to cause weight reduction and was used successfully for weight reduction [93]. Although successful in promoting weight reduction, variations of thyroxine, DNP, amphetamine, methamphetamine and sibutramine, to name just a few, have been banned for use in obesity treatment, due to their serious adverse effects [91,94]. The only drug allowed by the US Food and Drug Administration for use in obesity treatment between 1990 and 2012 was orlistat. In 2013 four new drugs were added to the list [95] and while these drugs appear safer, users still report higher frequencies of adverse events than placebo and fairly high discontinuation and attrition rates [96]. The history of pharmacology, along with the modest weight reduction in comparison to surgery, have made some researchers question the potential use of drugs as a part in the treatment of obesity [91,97].

1.1.6.3 Comprehensive Lifestyle Intervention

The first treatment recommendations to obesity was the ones by Galen (129 AD), using a combination of dietary management, herbal medicine, bath, massage and exercise [9]. Despite the increased understanding of the aetiology, biology and pathology of obesity, many of the lifestyle treatment methods proposed today are essentially the same as those used 2000 years ago. Although not conclusive, research suggests that *comprehensive lifestyle interventions* are able to promote weight reduction with a low risk of adverse effects in adults [98]. A Cochrane review dividing children into three age groups (0-5, 6-12 and 13-18), concluded that there is strong evidence for the beneficial effects of childhood lifestyle interventions in all age groups, but especially in children between the ages of 6 and 12 [99]. However, due to a large heterogeneity of intervention components, it was not possible to quantify individual effects. In cases where lifestyle interventions have had poor outcome results, two proposed reasons are; i) that they target weak mediators, such as knowledge, awareness and attitudes ii) and that participants have low adherence to the diet and training regime [100,101]. Low adherence could also explain the largest problem for lifestyle interventions, which is weight maintenance, with some studies reporting weight regains of almost 50% at 1-year follow-up [102].

Due to the mentioned complications of bariatric surgery and pharmacotherapy, it would be preferable for interventions to identify and target strong behavioural mediators of obesity and increase adherence. However, the difficulty of achieving weight loss and even larger difficulty of weight maintenance [103–105], as well as the fact that obese children are likely to maintain their obesity into adulthood [106], suggest lifestyle prevention programs are likely more effective in reducing obesity prevalence.

1.1.7 Prevention

Due to the early onset of obesity, prevention strategies should focus on adolescent or younger individuals. In these populations, both surgical and pharmacological treatments are ethically questionable [107,108]. However, based on conditioning theory, these groups are expected to be more susceptible to behavioural training, which in part is strengthened by research [109]. It is estimated that to prevent weight gain in most of the population, a reduction of energy by 100 kcal per day may be enough in behavioural interventions [110]. Several researchers have suggested reaching these goals by altering the environment, for example; building parks, changing the choice architecture in supermarkets and making bicycle/walk friendly environments [61,111]. Implementing these types of preventive measures seem able to affect both physical activity and food selection at group level, but the health response of specific groups has been difficult to evaluate [72,112–114]. However, these environmental prevention methodologies usually require decisions made on district level or higher, leaving individuals in the grace of politicians and policy makers. Parallel to making environmental changes, an individual approach to obesity prevention could improve the self-efficacy of individuals, but may also cause self-blame if unsuccessful [115]. Therefore, targeting only knowledge and awareness, may not be the best solution, since the automatic behaviour displayed by humans suggest they are weak mediators, promoting lower effects than what may be expected by participants [100,116,117]. However, complementing these mediators with real-time feedback and suggestions on how to promote these changes may enable behavioural conditioning (training) [118], improving weight reduction and maintenance. On a side note, while self-control is often considered a positive factor for weight loss and maintenance, restraint theory suggests this may have negative health outcomes on certain individuals [118]. In an ideal situation, both physical activity (energy expenditure) and diet (energy intake) should be included in any obesity prevention programme, since both have been identified as mediators for weight reduction [99,119]. Methodologically however, due to its discreet distribution and less spontaneous nature, eating behaviour appears easier to measure compared to physical activity.

1.2 EATING BEHAVIOUR

Food intake is commonly measured as the cumulative intake of food in discrete units of time, usually minutes, hours or days. In most animals, feeding behaviour is episodic, with one phase called meals, where the predominant activity is feeding and the other phase called inter-meal interval, devoid of feeding behaviour [120]. The unit which food intake is measured in is usually weight (total weight or weight of macronutrients), energy (kcal, kJ) or parts of total (percentage of specific macronutrient) [120]. When the cumulative energy intake and expenditure is estimated it is usually to quantify metabolic adaptation and energy regulation [121]. Meanwhile, when measuring eating behaviours such as food intake, eating rate, oral processing time etc., the purpose is often to identify factors which increase food intake, with the assumption that it will subsequently lead to weight gain. A result of these studies has been the identification of eating behaviours which may serve as indicators for use when identifying individuals at risk of developing obesity, enabling early identification [122,123].

As is the case with several scientific concepts, the boundaries of eating behaviour are not well defined, leading to interpretation difficulties when trying to compare studies. In this thesis eating behaviour refers to what is typically included in studies on the microstructure of eating behaviour, measured during single meals, such as food intake, meal duration and number of bites and chews [124]. In addition, factors on a “macrostructural” level, such as meals per day, energy intake per day etc. will also be included in the definition of eating behaviour [124,125].

1.2.1 Real-life Studies

Due to the lack of accurate measuring techniques, real-life studies have primarily used questionnaires to quantify eating behaviour [126]. For example, the Dutch Eating Behaviour Questionnaire tries to asses an individuals' responsiveness to external and internal cues [127], while 24-hour food recall, diet history and food frequency questionnaires identify the nutrient intake of individuals [128]. Therefore, the most detailed account of eating behaviour in real-life is usually an estimate of time distribution of meals and either portion size or energy intake [129,130]. A review of time of day energy intake, found that there were large differences in the distribution of energy intake across the day between countries [129]. One of the studies included in the review suggest dinner is the main meal (breakfast, lunch and dinner) which contributes the most energy per day for Swedish children, which is similar to findings in US children [131]. Another study on US adults found two peaks where meal events were more common (12:00 and 19:00) and that energy intake at meal events gradually increased across the day [130]. While these observations may be of value in the development of feasible prevention and intervention strategies it is important to acknowledge the underlying assumptions when employing these methods. All questionnaires suffer from the same biases, first and foremost, the assumption that individuals can recall their behaviours, which on several occasions have been proven fallacious [126,132,133]. Secondly, the assumption that individuals are honest to both themselves and researchers, where several incentives have been identified that may prevent an individual from answering questions truthfully [134–136].

"Historical examples abound of stigma interfering with collective responses to diseases ranging from cholera to syphilis. In all of these cases, the social construction of illness incorporated moral judgments about the circumstances in which it was contracted as well as preexisting hostility toward the groups perceived to be most affected by it" – Herek GM., 2003

As such, it is common for self-report methods to result in an underreporting of food and energy intake of at least 20% [137–139]. The magnitude of these biases is also known to differ between groups, with one study finding obese individuals to report approximately 20% lower energy intake than normal-weight individuals, while in truth their energy intake was similar [140]. Finally, human limitations prevent questionnaires to effectively collect microstructural information, such as eating rate, meal duration and oral processing time. This is not to say that questionnaires cannot be useful for categorizing individuals or to understand perceived eating behaviours. However, as with all methods, it is important to acknowledge their limitations, or as Dhurandhar puts it: "*It is time to recognize that even if methods are cheap and convenient, inaccurate scientific methods will lead to inaccurate conclusions.*" [126].

1.2.2 Controlled Studies

Figure 2. The Mandometer®, a device for continuous recording of eating behaviour in humans.

In 1980, Kissileff developed the Universal Eating Monitor, which is essentially a food scale connected to a computer, able to provide weight data at a sampling frequency of 0.25Hz in a laboratory (*controlled*) setting [141]. This provided researchers with detailed temporal information of meals, called microstructural eating behaviour. With this method food weight reduction over the course of a meal is used to create a cumulative intake curve. Later curve fitting studies showed that a second-degree polynomial equation, $y = ax^2+bx+c$, was enough to account for between 96.3% and 99.9% of the variation in single meals [142]. The five parameters included in the polynomial equation correspond to; meal intake (y), meal duration (x), deceleration (a) and initial speed of eating (b), "*c*" in this equation is the amount of food eaten at the start of the meal (0 sec), which is always 0 g [142]. Recording the meal with a video camera and creating an event log of bites and chews, then matching the event log with the weight data series can provide the additional parameters, bite frequency, bite size and chewing frequency [143,144]. Currently, this is done semi-automatically, providing data on meal size, meal duration, initial speed of eating, deceleration, bite size and bite frequency [143]. However, automatic processes relying on algorithms are currently being developed which may enable the use of these devices in real-life environments, on a much larger scale, with higher accuracy [145,146].

Traditionally, due to technological limitations, the detailed analysis of eating behaviour during single meals, i.e., microstructural eating behaviour, has taken place in *controlled* environments, which also have enabled researchers to control for sources of variance [147,148]. Studies conducted in *controlled* environments, on both solid and semi-solid meals, have found that most individuals maintain their eating behaviour rank in the group in test-retest conditions (R^2 >0.75) [122,149–151]. There is also some evidence that individuals respond similarly when energy density and texture are manipulated (R^2 >0.75) [152]. Meanwhile, a plethora of external cues have been identified to modify human eating behaviour at group level. For instance, lowering the effort of acquiring food by placing it closer or making it more accessible/visible in other ways seem to increase intake [153–155]. Increasing the size of food packages, plates and cutlery seem to have similar effects [156–158], perhaps partly through visual cues [159]. Also, increasing the number of dining companions [160,161] or the food variation in buffet like settings [162] appear to increase food intake. Meanwhile, some of the internal cues which can affect food intake is a person's appetite sensation [163,164] and emotional state [165,166]. The most prominent internal cues affecting food intake appears to be portion size and eating rate [167,168]. Many of the *controlled* studies suggest what researchers have called a "*mindless*" [116] or "*automatic*" [100] eating in humans, where cognitive faculties have a minimal influence on food selection and ingestion [169]. Which means that, if an individual learns to eat in a way that puts him/her at risk of obesity it may be very difficult to alter this behaviour later.

However, *controlled* studies often disregard real-life constraints known to affect eating behaviour [147], which can limit their real-life applications [148]. Several *controlled* studies disregard the monetary cost and physical effort of acquiring food in real-life, by providing *ad libitum* quantities of both meal and snack-related food items to subjects [147]. In addition, most laboratory meals are served when it is convenient for the researcher and the subject, usually at lunch time during weekdays, disregarding the effect work and social schedules have on eating behaviour [147,170]. For example, a study changing vending machine prices, showed the effectiveness of monetary cost by reducing the price of low-fat snacks by 10%, 25% and 50%, which resulted in a 9%, 39% and 93% increase in purchase of these food items, respectively [171]. Similarly, in a school setting increasing the proximity of candy by 10 meters, and thereby increasing the physical cost of acquiring food, reduced intake of carrot slices by almost 75% [155]. Regarding meal scheduling, real-life studies employing questionnaires usually find energy and food intake differences between lunch and dinner meals [129]. For example, Sjöberg et al., found a 59% higher energy intake in dinners compared to lunches, perhaps caused by a food item selection difference [131]. Previous studies have found subjective eating rate to be a good predictor of objective eating rate in *controlled* settings [172,173]. However, one study found that the same was not the case for real-life meals [172], which may be a result of work and social schedule differences. Studies also indicate a difference in energy intake and timing of meals between weekdays and weekends, with less "*healthful*" food consumption and a reduced time window for meals during weekends [130,174]. These findings may cast doubt on the value of *controlled* studies. However, since evolution has provided humans with the tools to eat almost anywhere, laboratory studies should not be disregarded as useless [175]. What is important is to identify which real-life settings are comparable to laboratory settings.

1.2.3 Technological Advances

With advances in sensory technology the field of human behavioural nutrition has seen an influx of new methods with the potential to quantify eating behaviour in real-life conditions [176–180]. Most of these measuring techniques rely on algorithms to provide an inferential measure of the value of interest. That is to say that, while the primary goal is to measure a factor associated with the risk of obesity, such as portion size and eating rate, most of the time, the devices measure other factors which correlates with these risk factors.

1.2.3.1 Novel Technology

Open-air mics have been shown able to provide data on the sound of food processing, while in-ear mics can capture the sound of temporo-mandibular join movements during mastication [181,182], a fact used to estimate chews, food type and food volume. A piezoelectric strain gauge placed below the outer ear can provide data on the resistance produced during mastication, which has been used to quantify number of chews and chew force [181]. Capacitance measurements can provide data on the timing of bites and number of bites [183]. In addition, the use of meal photographs to quantify portion size, nutrient composition, eating rate and in which setting the food is eaten have met with various degrees of success [176,184,185]. These devices appear promising for trying to measure human eating behaviour in real-life settings [186], but they rely on algorithm corrected, inferential data. Methods reliant on algorithms may only be valid under certain circumstances, for example, the wireframe measurements used by one of the photograph methods may be less accurate for certain food shapes [176]. Meanwhile, a Bluetooth connected scale has been shown to provide accurate non-inferential measurements of food intake and meal duration across meals [187]. However, this method requires the user to initiate recording, which may increase user bias. Either by users selectively recording certain meals due to social desirability or forgetting to record less planned meals. Identifying the limitation of these devices is important, as a first step, to determine what data can be reliably collected in laboratory and real-life settings [188]. It will also enable the combination of several sensors to

Figure 3. Device developed for use in detection of eating in the SPLENDID EU project.

get a fuller picture of human behaviour, as has been done with the Automatic Ingestion Monitor (AIM), Dietary Intake Monitoring System (DIMS) and eButton [176,185,189].

Before this technology can be used reliably, both the usability and the feasibility need to be evaluated in the setting in which they are intended to be used. If the intended group is not willing to use the technology, the accuracy of the method becomes irrelevant. Meanwhile, different settings may impose different obstacles for technology, making data collection unfeasible. Once technology has been adjusted to the requirements imposed by the user and the environment it will enable quantification of human eating behaviour at a level previously impossible [146,190].

2 HYPOTHESIS AND AIM

2.1 HYPOTHESIS

Past research has provided evidence that human eating behaviour (e.g., food intake, meal duration, number of bites and chews) during meals is stable under traditional laboratory test-retest conditions. However, limited information exists on the stability of these behaviours when external factors are manipulated in the laboratory and when the behaviours are studied in less controlled conditions. The overarching hypothesis of the current work is that humans (young adults and adolescents) maintain their eating behaviour rank within the group during meals, despite group level changes in their overall eating behaviour caused by varying meal conditions.

2.2 AIMS

The overarching aim of this thesis was two-fold:

I) To test the scientific hypothesis that, despite changes in eating behaviour characteristics elicited by variations in external factors across meals, healthy, humans maintain their eating behaviour rank within the group (i.e., relative reliability).

II) To evaluate the feasibility, usability and acceptability of traditional laboratory methods for the quantification of human eating bahaviour, modified for use in a *semi-controlled* and free-living *real-life* settings.

2.3 SCOPE OF THE INCLUDED PAPERS

Paper I tested the hypothesis that healthy, young adult females maintain their eating behaviour characteristics, in relation to the group, despite experimental manipulations to meal conditions (i.e., unit sizes and serving occasion). The study employed traditional microstructural eating behaviour methodologies in a laboratory (*controlled*) setting.

Paper II is a descriptive study, where the aim was to collect detailed information on meal-related eating behaviour characteristics of adolescents eating school lunches in their everyday school cafeteria (*semi-controlled*) setting. The study utilized frequently used laboratory methods for quantifying eating behaviour in single subjects, modified to enable their use on multiple subjects in a *semi-controlled* setting. Evaluating the feasibility and usability of these methods in this setting. Additionally, the paper compared eating behaviour in the *semi-controlled* setting with similar measurements collected in a *controlled* setting, from healthy female young adults, eating identical foods.

Paper III returned to the *semi-controlled* school setting. This paper employed previously developed methodologies (**Paper II**) to test the effect of snack proximity on the eating behaviour of adolescent students during a predefined work-task. Thus, this paper experimentally tested a previously identified external factor affecting food intake, in a challenging measurement environment, for a population not previously described. This work improved upon the previously deployed methodologies for synchronous analysis of group eating behaviours, adding the potential of behavioural analysis across longer periods of time. The novel methodological approach was used to experimentally test, for the first time, the hypothesis that food proximity increases energy intake by affecting the distribution of servings across time.

Paper IV tested the hypothesis that healthy adolescents maintain their eating behaviour across *semi-controlled* and *real-life* settings, both at group- and individual-level. The feasibility and usability of a method improved, based on information from **Papers II-III**, was also evaluated in both settings. Additionally, the proposed methodologies were used for the first time to provide a detailed group-level comparison of the longitudinal distribution of meals and snacks between weekdays and weekends.

3 MATERIALS AND METHODS

A detailed description of individual papers is available in the publications and manuscripts section of this work. Additionally, traditional laboratory methods for single meal (microstructural) analysis of eating behaviours, such as the one used in **Paper I**, have already been described in the background section of the thesis (§1.2.2). Instead, this section will focus on the comparison of the materials and methods among studies, as the employed methodologies transitioned from *controlled* (laboratory), to *semi-controlled* (school cafeteria) to *real-life* (free-living) settings.

3.1 RECRUITMENT

Healthy subjects were recruited for all presented papers, with the main health criteria being a normal body mass index. The recruitment for **Paper I** and the *controlled* setting of **Paper II** was conducted close to Karolinska Institutet, including only young adult females. Meanwhile, the recruitment for **Papers III** and **IV**, as well as the *semi-controlled* setting in **Paper II** was conducted in a high-school located in central Stockholm, Sweden, including adolescents of both sexes. It is important to note that the same participants attended the *semi-controlled* experiment of **Papers II** and **III**.

Table 1. Subject characteristics of each paper.

	I	II	III	IV
Subjects	♀ BMI 18-28 Young adults [a]	♀♂ BMI 18-28 Adolescents [b] Young adults [a]	♀♂ BMI 18-28 Adolescents [b]	♀♂ BMI 18-28 Adolescents [b]

[a] 18-35 years of age, [b] 15-18 years of age.

3.2 PROTOCOL

In accordance with the thesis aim, the quantification of eating behaviour gradually transitioned from *controlled*, to *semi-controlled*, to *real-life* settings in **Papers I-IV**. Thus, **Paper I** was conducted in a *controlled* setting, employing an experimental design. **Paper II** was divided into two parts, with the first one conducted in a *controlled* setting and the second conducted in a *semi-controlled* setting, employing an observational design. **Paper III** was conducted in a *semi-controlled* setting, employing an experimental design. Meanwhile, **Paper IV** was divided into two parts, with the first one conducted in a *semi-controlled* setting and the second conducted in a *real-life* setting, using an observational study design for both parts.

Table 2. Study protocol of each paper.

I	II	III	IV
Controlled	*Controlled*	*Semi-controlled*	*Semi-controlled*
			
	Semi-controlled		*Real-life*
			

Additional pictures of the respective research setting can be found in the published papers.

3.3 FOOD

In all papers except **Paper III**, subjects were allowed to eat "*at one's pleasure*" (*ad libitum*), regarding food volume and meal duration. Meanwhile, in **Paper III** the format was different to a regular school meal, with participants allowed to eat as much as they wanted, but within a pre-set duration of 60 minutes. The available selection of food types at each meal occasion increased across the studies; from one in the *controlled* setting, to three in the *semi-controlled* setting, to a free choice of food in the *real-life* setting.

Table 3. Food types of each paper.

I			II & IV	III
Experiment I	Experiment II	Experiment III		
Ad-libitum	*Ad-libitum*	*Ad-libitum*	*Ad-libitum* *, [a]	*60 minutes*
				
				
				

** Only the semi-controlled condition in **Paper IV** used the displayed food types, [a] Due to selection differences between subjects only examples of the meals including the three main dish components are displayed. Additional pictures of the respective food types can be found in the published papers.*

3.4 DEVICES

The weight of the ingested food in all papers was quantified by use of the Mandometer® [179], a medical device, consisting of a food scale, for weight measurement, integrated with an electronic device, for data-collection (e.g., a smartphone). The Mandometer® allows for continuous weight measures at a recording frequency of 1Hz. In parallel, video cameras were used to quantify additional eating behaviours (e.g., number of bites, chews and buffet servings). In the *controlled* setting (**Paper I** and part of **Paper II**) every meal was recorded by one video camera. In the *semi-controlled* setting (**Papers II**, **III** and part of **Paper IV**) the recording field of each video camera was set to capture approximately 15 individuals, with overlapping fields to ensure video data was available from at least two different angles for each subject. No video cameras were used in the *real-life* setting of **Paper IV**.

Table 4. Devices used in each paper.

	I	II	III	IV
Devices used	Video camera Mandometer®	Video camera Mandometer®	Video camera Mandometer®	Video camera* Mandometer®

Video cameras were only used in the controlled setting of* ***Paper IV*.

3.5 DATA COLLECTION

The system of **Paper I-III** used a small computer for data storage and only allowed transfer manually via USB connection to a PC. **Paper IV** used a smartphone, with an accompanying application, enabling direct data transfer via Wi-Fi to a database. The application in **Paper IV** allowed for real-time registering of main meals and snacks, providing a time-stamp for each registered event (Figure 4). Apart from providing the time of the meal, participants could choose to self-report meals, providing only the meal type (i.e., breakfast, lunch, dinner or snack), or to record the meal using the Mandometer® (Figure 5). Mandometer® supported recording was available for all meal types, except snacks, providing the same information as self-reports, as well as data on food intake and meal duration.

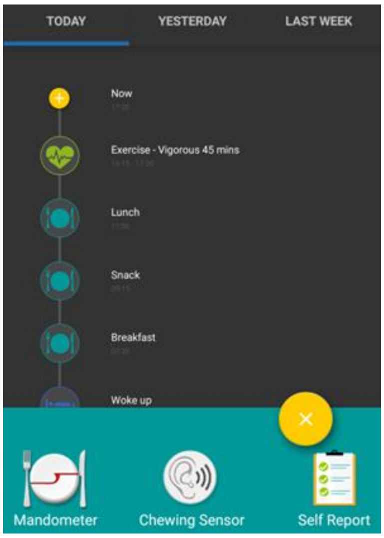

Figure 4. Main menu for recording and reporting meals in the real-life setting of ***Paper IV***.

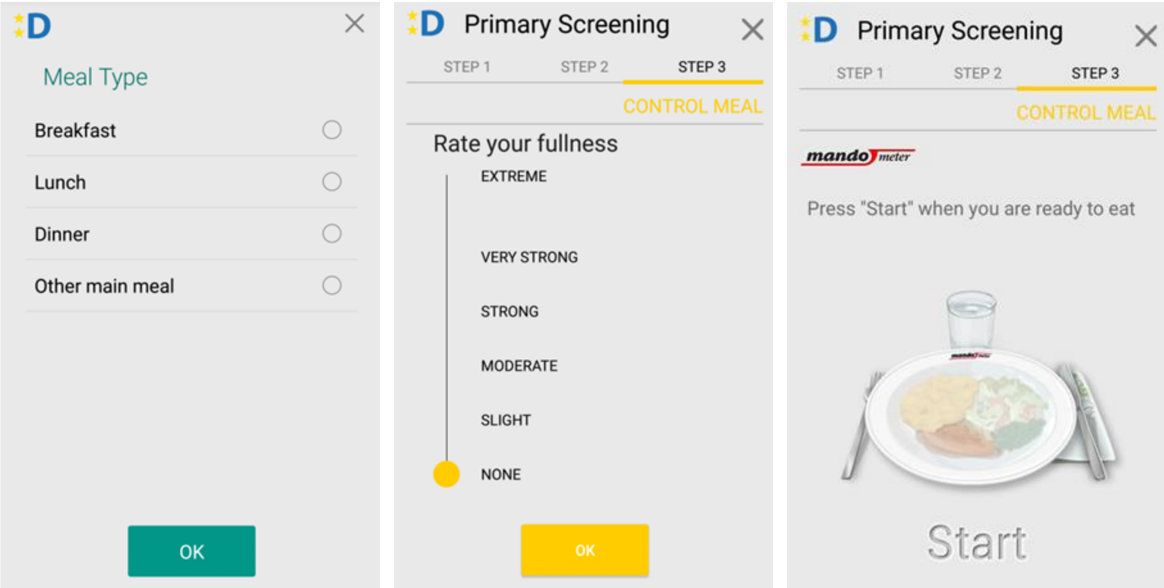

Figure 5. From left to right is shown the chronological order of recording a main meal using the system. Starting with the main meal type, followed by a satiety rating, after which the meal was initiated. Once the meal was terminated an identical satiety question appeared. When self-reporting, only the left-most figure was displayed to the user (with the additional option to choose "snack").

3.6 AVAILABLE DATA

The study protocol of **Paper I** enabled collection of food intake, meal duration, additions and numbers of bites and chews, in accordance with a previously developed laboratory methodology [143]. With the camera positioned further away in **Paper II**, **III** and the *semi-controlled* setting of **Paper IV**, chewing data could not be reliably collected, which is why they are not part of the outcome analysis in these papers. Similarly, since no video data were available in the *real-life* setting of **Paper IV**, the number of bites and chews could not be reliably collected. In all the papers the deployed methods enabled the collection of self-rated pre-meal fullness, as well as post-meal fullness and food liking (meal questions). In **Papers II-IV** subjects self-rated their perceived levels of food intake and eating rate in relation to their peers (perceived eating). As mentioned in individual papers, the meal-related questionnaires were used to identify inconsistencies in appetite, not as outcome variables. In addition, in the *semi-controlled* and *real-life* settings (**Papers II-IV**), the comfortability of the participants during the studies and the perceived usability of the deployed methods were measured using the System Usability Scale; SUS [191]. A tool frequently used to collect a user's subjective rating of product usability.

Table 5. Collected data in each paper.

	I	II	III	IV
Objective	Food intake Meal duration Additions Bites Chews	Food intake Meal duration Additions Bites	Food intake Meal duration Additions Bites	Food intake Meal duration Additions
Subjective	Meal questions	Meal questions SUS Perceived eating	Meal questions SUS Perceived eating	Meal questions SUS Perceived eating

3.7 DATA HANDLING & ANALYSIS

For **Papers I-III** the devices had no Wi-Fi connection, therefore both Mandometer® and video data was transferred manually to computers. With minor formatting the food intake and meal duration could be extracted from the raw Mandometer® files, while the video data was used to create an event log based on behaviours relevant for each paper (e.g., number of chews and bites in **Paper I**). In the *real-life* setting of **Paper IV**, the deployed measurement system enabled real-time data transfer to a server, supporting automatic algorithm correction of the recorded meals. The algorithm-corrected recordings were then visually inspected by a researcher, in order to remove obvious mistakes made by the users and recordings that were not meals.

To confirm that the assumption of normality was fulfilled all papers used one normality test and two visual representations of the data distribution (Shapiro-Wilk test, Q-Q plot and residual vs. fitted value plot). T-tests (either dependent or independent, based on the specifics of each comparison) were employed to evaluate significant group differences between two conditions in all papers. Meanwhile, to evaluate significant group differences between three or more conditions linear mixed effect model (LME) was used in **Paper I** and analysis of variance (ANOVA) was used in **Paper II**. To test whether individuals maintained their rank within the group, **Papers I** and **IV** used Pearson correlation coefficients. In **Papers II-IV**, to evaluate the agreement between subjective and objective measures of food intake and eating rate Cohen's kappa was used. A Kolmogorov-Smirnoff (KS) test was used to determine if there was a significant temporal difference between servings of the two conditions of **Paper III**. Finally, **Paper IV** employed a chi-square test to determine if there was a significant difference between observed and expected record and report frequencies.

Table 6. Data handling and analysis in each paper.

	I	II	III	IV
Data formatting	Manual	Manual	Manual	Automatic / Manual
Data analysis	Normality test T-test LME Correlation	Normality test T-test Cohen's kappa ANOVA	Normality test T-test Cohen's kappa KS test	Normality test T-test Cohen's kappa Chi-square Correlation

4 RESULTS

This section focuses on the combined results of subjective and objective food intake and eating rate measures, across the included papers of this thesis. The presented graphs and tables combine results across papers, starting with subject characteristics and group level values of eating behaviour. Afterwards, the main findings of individual papers are presented. Followed by comparisons between objective and subjective, self-reported responses of eating behaviour, adding information beyond those presented in the included papers. Finally, the measures of the perceived fullness pre-and post- meal, food liking, comfort, system usability and feasibility are presented. For a more detailed account of the study results of individual papers, the reader is referred to the corresponding paper, at the end of this thesis.

4.1 SUBJECTS

The mean age of the samples in the *controlled* setting was higher, compared to the *semi-controlled* and *real-life* samples, due to the differences in the recruitment process described in §3.1. Meanwhile, the mean BMIs of the participant groups were similar across all the included studies (Table 7). The sample size of individual papers was not large enough to enable statistical testing of differences across papers.

Table 7. Subject characteristics.

	Age (yrs.)	BMI (kg/m2)	Sex (%♀)
Paper I			
Experiment 1 (n = 19)	22.5 (1.8)	21.1 (1.6)	100%
Experiment 2 (n = 18)	25.9 (4.7)	22.5 (2.2)	100%
Experiment 3 (n = 28)	24.4 (2.7)	22.5 (2.0)	100%
Paper II			
Controlled (n = 10)	22.5 (1.7)	21.5 (2.1)	100%
Semi-controlled (n = 41)	16.7 (0.4)	21.2 (2.5)	54%
Paper III			
Proximal (n = 17)	16.8 (0.3)	21.7 (2.6)	53%
Distal (n = 24)	16.6 (0.4)	20.9 (2.4)	54%
Paper IV			
Semi-controlled & *Real-life* (n = 24)	16.8 (0.7)	21.9 (4.1)	71%

Values are expressed as mean (SD), if not otherwise specified.

4.2 FOOD INTAKE

The food intake distribution across individuals in the sample of each papers was large, with the highest food intake being at least twice as high as the lowest in all papers (Figure 6).

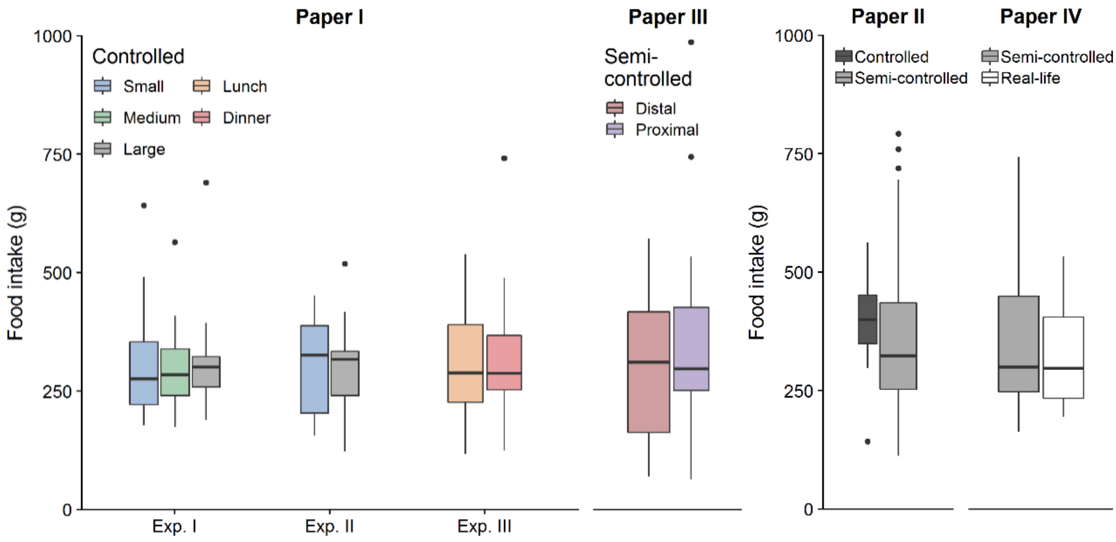

*Figure 6. Boxplots displaying the food intake distribution of each participant group, with box widths relative to the number of subjects in the respective condition of each paper. Left: The controlled (**Paper I**) and semi-controlled (**Paper III**) experimental papers, with individual boxes displaying experimental conditions. Right: The observational papers (**Papers II and IV**), with individual boxes displaying the research setting.*

4.3 EATING RATE

Except in **Paper III**, the eating rate distribution across individuals in the sample of each paper was large, with the highest eating rate being at least twice as high as the lowest in all papers (Figure 7).

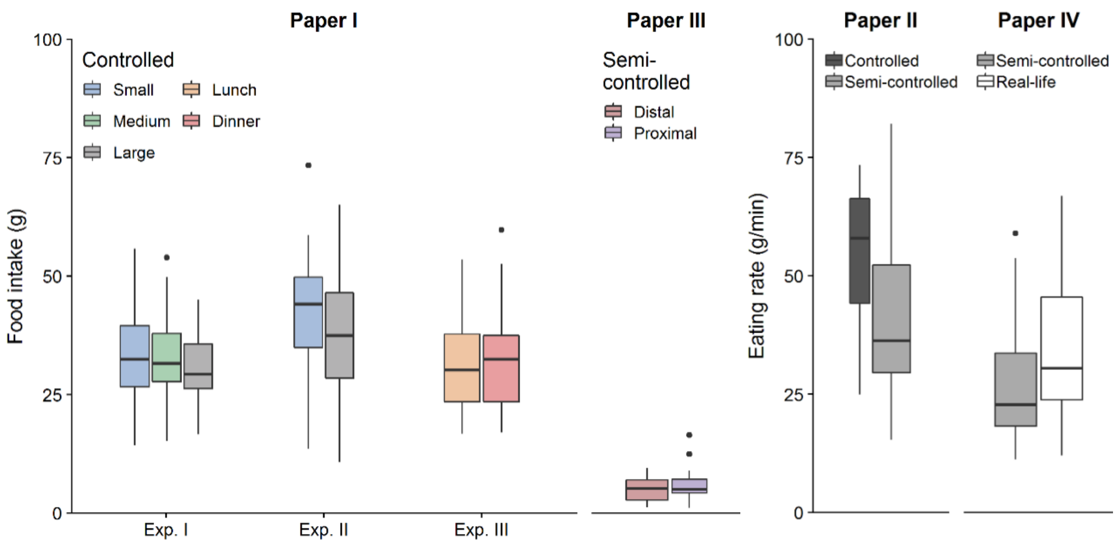

*Figure 7. Boxplots displaying the eating rate distribution of each participant group, with box widths relative to the number of subjects in the respective condition of each paper. Left: The controlled (**Paper I**) and semi-controlled (**Paper III**) experimental papers, with individual boxes displaying experimental conditions. Right: The observational papers (**Papers II and IV**), with individual boxes displaying the research setting.*

4.4 MAIN FINDINGS

4.4.1 Paper I

In experiment III of **Paper I**, where serving occasion was manipulated, no significant difference was observed between lunch and dinner in any of the measured eating behaviour characteristics (food intake, meal duration, eating rate, number of bites and chews). Meanwhile, in experiments I and II, where unit size was manipulated, the number of chews between the large and small unit size condition exceeded the threshold set for significance. However, meal duration was only significantly different between the large and small unit size condition in exp. II.

*Table 8. P-values from significance tests between conditions in **Paper I**.*

	Experiment I		Experiment II	Experiment III
	Small vs Medium	Small vs Large	Small vs Large	Lunch vs Dinner
Food intake, g	0.950	0.900	0.562	0.819
Meal duration, min	0.804	0.107	0.046*	0.651
Bites, n	0.999	0.132	0.918	0.766
Chews, n	0.120	0.018*	0.027*	0.799

*Values are p-values ranging from 0 to 1, * Show values below the threshold set for significance (0.05)*

4.4.2 Paper II

In **Paper II**, men displayed a significantly higher food intake (49%) and took significantly larger bites (22%). Meanwhile, the bite sizes of both male and female participants gradually reduced as the meals progressed. Compared to the *controlled* setting, the time spent away from the table (i.e., making food additions) was longer in the *semi-controlled* setting.

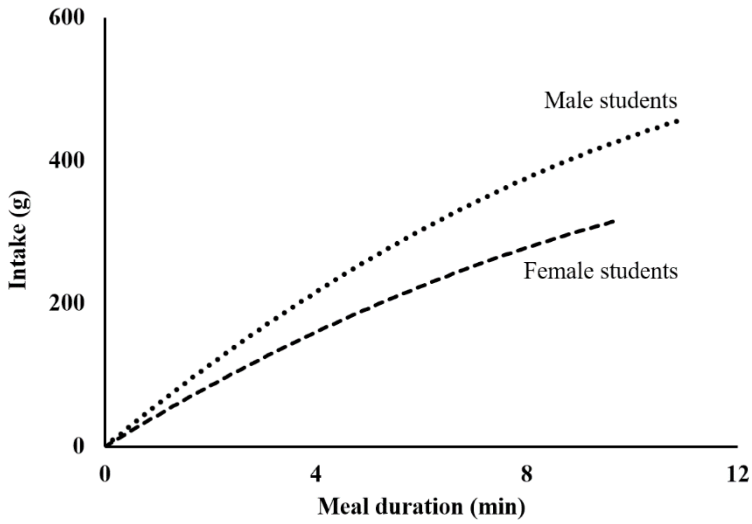

*Figure 8. The average eating style projection of male and female participants in the semi-controlled setting of **Paper II**.*

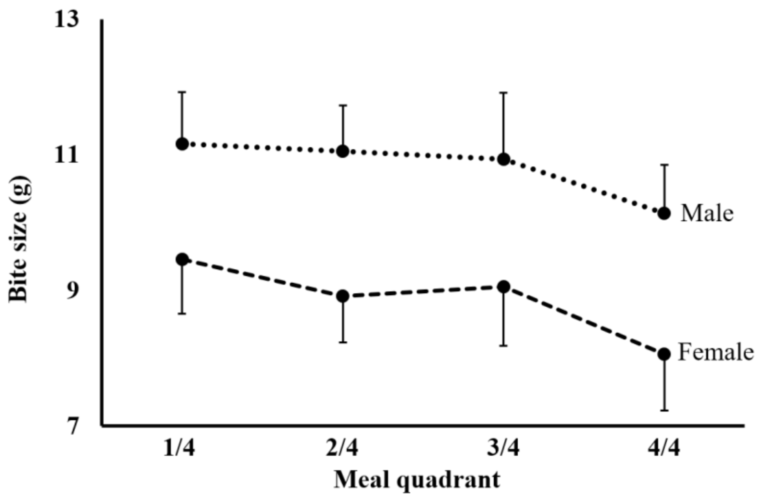

Figure 9. Visual representation of the bite size changes as meals progress for male and female participants in the semi-controlled setting of ***Paper II****.*

4.4.3 Paper III

In **Paper III**, increasing the distance from the sitting positions of the participants to the serving location of snacks by around six meters reduced the energy intake (kcal) by 31%, but did not reduce the food intake (g). On a group level, the reduced energy intake in the distal condition was due to a significantly lower intake of chocolate. In addition, the reduced intake of chocolate in the distal condition was in part caused by more individuals (primarily women) not selecting chocolate. Also, participants served themselves grapes and crackers significantly more often in the proximal condition. Meanwhile, the serving sizes of chocolate was significantly larger in the proximal condition. Temporally, the proximal and distal condition was initiated by a similar burst of food intake, after which the temporal distribution of servings in the distal condition became significantly less homogenously distributed than in the proximal condition.

4.4.4 Paper IV

In **Paper IV**, there was no significant difference in food intake, meal duration or eating rate between the *semi-controlled* setting and the mean value of *real-life* meals, with p-values adjusted for multiple comparison. However, using unadjusted p-values, the food intake was significantly higher in the *semi-controlled*, than in the *real-life* setting (mean difference: 43.3g, 95% CI 7.3 to 79.3, $p = 0.027$).

In **Paper IV,** a confidence interval was created for each individual, from the eating behaviour characteristic of all their recorded *real-life* meals. For food intake, in 50% of all cases the single *semi-controlled* meal was within the confidence interval of the *real-life* meals, Figure 10. Meanwhile, for eating rate and meal duration, in 32% and 27% of all cases the single *semi-controlled* meal was within the confidence interval of the *real-life* meals, respectively.

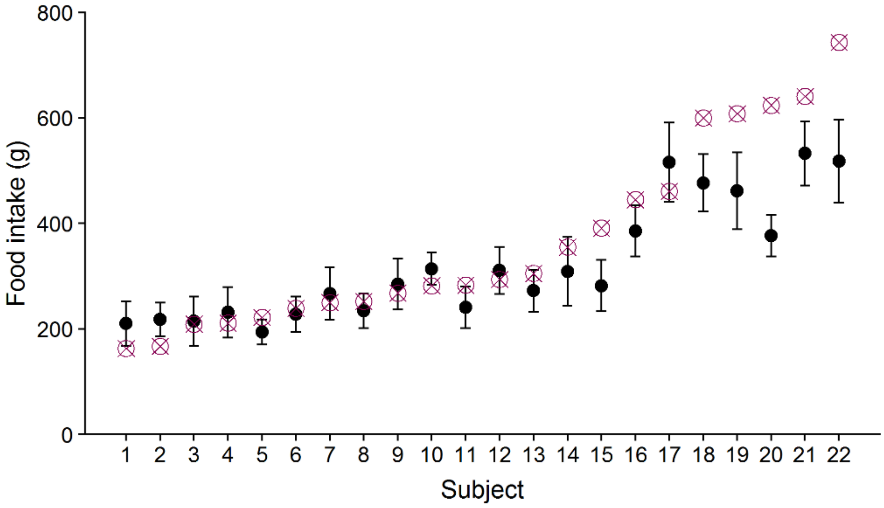

*Figure 10.The food intake confidence interval of real-life meals compared with the food intake at the semi-controlled meal, with individual subjects on the x-axis in **Paper IV**.*

When analysing the time distribution of meals, according to the median value of main meals, breakfasts, lunches and dinners were eaten earlier during weekdays, compared to weekends. The difference in breakfast and lunch meals between weekdays and weekends was much larger (2.95 and 3.05 hours, respectively) than the difference in dinners (0.23 hours).

4.5 AGREEMENT BETWEEN SUBJECTIVE AND OBJECTIVE EATING BEHAVIOURS

The self-reported answer to the question "*How much do you eat compared to others?*" was rated on a 5-point Likert scale, with the word selectors; "*Much less*", "*Less*", "*Average*", "*More*" and "*Much more*". Meanwhile, the objective range of each category was calculated based on the difference between the lowest and highest value of the sample and divided into five categories, for comparison with the subjective scores (i.e., from "*Much less*" to "*Much more*"). This resulted in food intake ranges larger than 100g in the *semi-controlled* setting, while the range was 70g in the *real-life* setting.

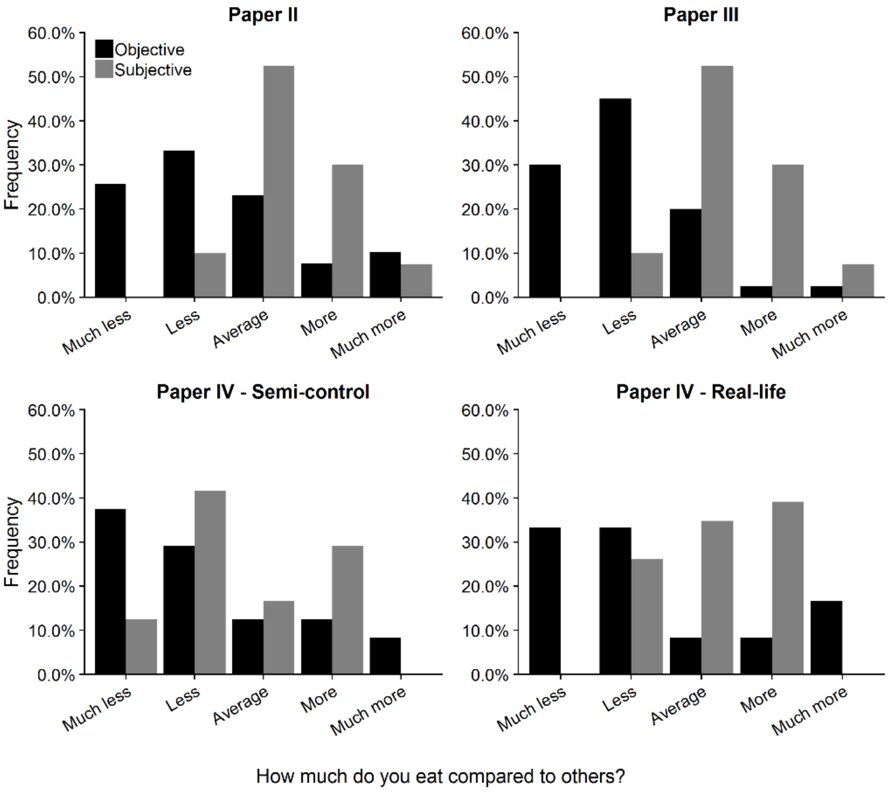

*Figure 11. Frequency distribution of subjectively and objectively measured food intake in **Papers II-IV**.*

Dividing the data in this way resulted in a very low agreement between the subjective rating and objective recording, which can be seen on group level by a kurtosis of subjective ratings and right skewness of objective measures. More specifically, the agreement was "*slight*" in both **Paper II** (25.6%, κ <0.2) and **Paper III** (7.5%, κ <0.2). Similarly, the agreement was "*slight*" in both the *semi-controlled* (25.0%, κ <0.2) and *real-life* (8.7%, κ <0.2) setting of **Paper IV**.

Similar to food intake, the self-rated answer to the question "*How fast do you eat compared to others?*" was rated on a 5-point Likert scale, with the word selectors; "*Much slower*", "*Slower*", "*Average*", "*Faster*" and "*Much faster*". Meanwhile, the objective range of each category was calculated based on the difference between the lowest and highest value of the sample and divided into five categories, for comparison with the subjective scores. This resulted in eating rate ranges close to 10g/min in **Papers II** and **IV**, while the range was 1.5g/min in **Paper III**, due to the pre-determined 60-minute duration of the study protocol.

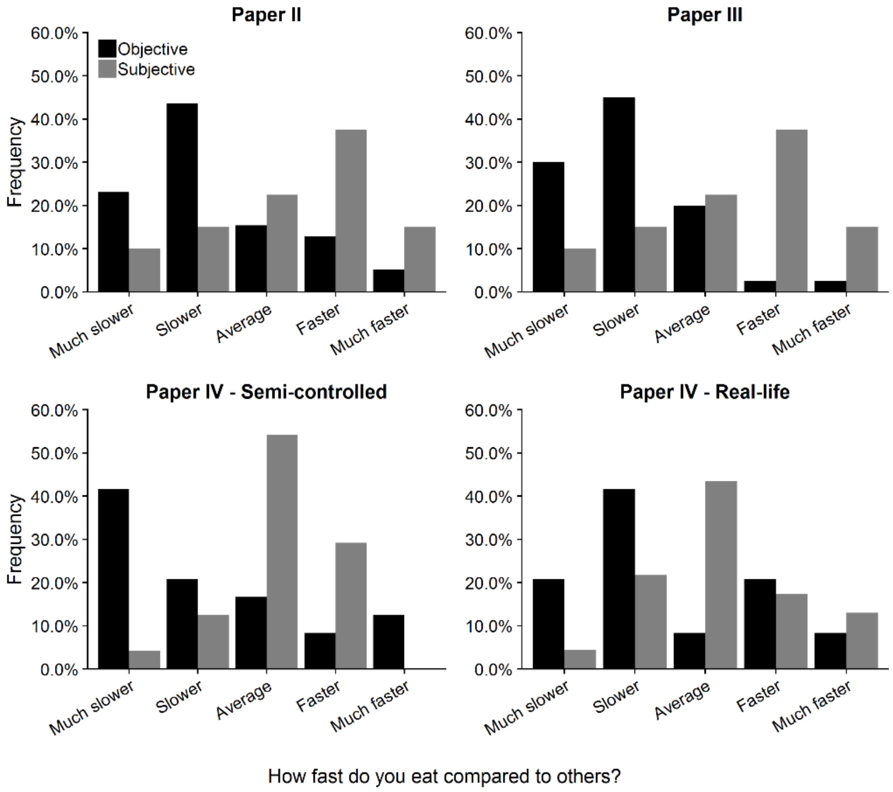

Figure 12. Frequency distribution of subjectively and objectively measured eating rate in ***Papers II-IV****.*

The division resulted in a low agreement between the subjective rating and objective recording, just as in the food intake measures on group level the objective eating rate was right skewed. More specifically, the agreement was "*slight*" in both **Paper II** (15.4%, κ <0.2) and **Paper III** (15.0%, κ <0.2). Similarly, the agreement was "*slight*" in both the *semi-controlled* (29.2.0%, κ <0.2) and *real-life* (30.4%, κ <0.2) setting of **Paper IV**.

4.6 EATING BEHAVIOUR CORRELATION BETWEEN CONDITIONS

Of the measured eating behaviours (food intake, meal duration, eating rate, bites and chews), only the correlation coefficient of bites between the small and large unit size condition of experiment II, in **Paper I**, was below the threshold set for high (R^2 ≥0.75). Similarly, the correlation coefficient of food intake between the *semi-controlled* setting and the mean value of all *real-life* meals of **Paper IV** was very high (R^2 ≥0.90) and the correlation coefficient of eating rate was high (R^2 ≥0.75). Meanwhile, the correlation of meal duration between the *semi-controlled* setting and the mean value of all *real-life* meals in **Paper IV** was low (R^2 ≥0.50).

*Table 9. Pearson correlation coefficient (R^2) of meal duration, food intake, bites and chews in all experiments of **Paper I**.*

		Food intake	Meal duration	Eating rate	Bites	Chews
Paper I						
Exp. I	- Small vs. Medium	0.78	0.81	0.88	0.85	0.78
	- Small vs. Large	0.90	0.82	0.89	0.76	0.80
Exp. II	- Small vs. Large	0.81	0.98	0.94	0.60	0.94
Exp. III	- Lunch vs. Dinner	0.79	0.90	0.89	0.86	0.91
Paper IV						
Semi-controlled vs. *Real-life*		0.91	0.49	0.77	-	-

Values are expressed as R^2

4.7 PRE- AND POST-MEAL APPETITE

Although not a major part of the thesis, subjective appetite ratings were measured in all papers. Fullness was significantly increased from the start of the meal to the end in *controlled* and *semi-controlled* conditions. In addition, food taste/liking was rated between 47.4 and 67.9 across papers.

		Δ Fullness (0-100)	Food liking (0-100)
Paper I			
Experiment I	- Small	70.3 (25.4)	54.6 (21.6)
	- Medium	69.3 (22.0)	58.3 (12.5)
	- Large	75.7 (22.4)	56.8 (20.9)
Experiment II	- Small	47.6 (27.2)	47.4 (21.4)
	- Large	48.6 (26.6)	48.1 (19.1)
Experiment III	- Lunch	66.4 (19.3)	67.8 (17.8)
	- Dinner	64.4 (17.7)	62.9 (22.1)
Paper II			
Controlled		65.9 (25.1)	53.7 (24.9)
Semi-controlled		43.2 (26.8)	52.8 (11.4)
Paper III			
Proximal		30.2 (25.3)	-
Distal		30.7 (27.7)	-
Paper IV			
Semi-controlled		41.5 (22.8)	51.6 (15.9)

Values are expressed as mean (SD).

4.8 COMFORT AND SYSTEM USABILITY

On average, participants rated themselves feeling "*comfortable*" (score = 7) in the setting in all *semi-controlled* and *real-life* papers (**Papers II-IV**). The first iteration of the system, used in the *semi-controlled* setting of **Papers II** and **III,** received a grade B, "*Good*" rating (68-80.3) using the SUS. Meanwhile, the second iteration of the system, used for both settings of **Paper IV,** received a grade A, "*Excellent*" rating (>80.3) in the *semi-controlled* setting and grade B, "*Good*" in the *real-life* setting.

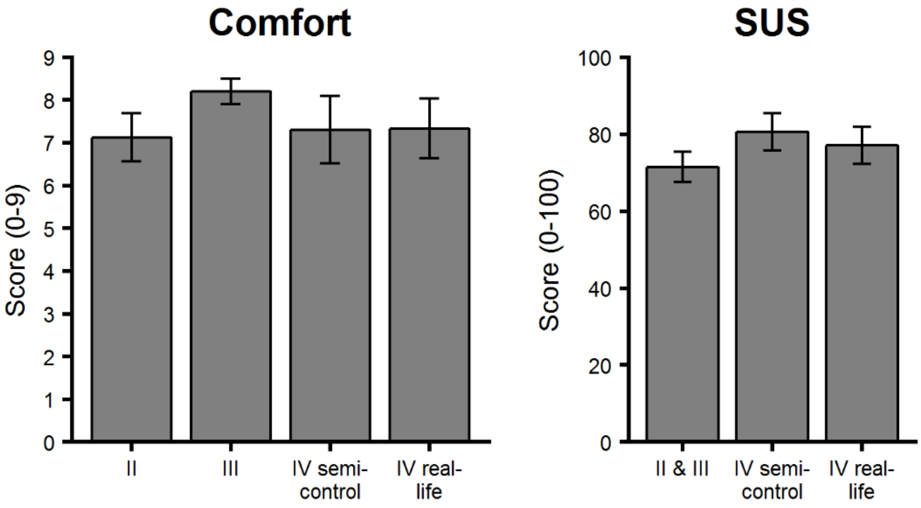

Figure 13. Left: Mean value (CI) of comfort ratings between "Not at all comfortable" (0), to "Very comfortable" (9) on a 9-point Likert scale. Right: Mean value (CI) of SUS score, derived from the 10 items of the SUS questionnaire.

4.9 FEASIBILITY

In **Papers II** and **IV** the *semi-controlled* protocol was executed within the 25-minute timeframe of a regular school-lunch and in **Paper III** the protocol was executed within the 60-minute pre-determined time of the experimental protocol. The data retention rate was 97% in **Paper II**, 100% in **Paper III** and 92% in **Paper IV**. No adverse events were reported to researchers during the experiments of **Papers II-IV**, nor were adverse events reported to school personnel after the experiments. During the first week in the *real-life* setting of **Paper IV**, 70% of all the expected main meals were recorded or reported, increasing to 76% during the second week of system use. With recordings being more frequent during lunch (54%) and dinner (65%), while reporting was more frequent during breakfasts (78%).

5 DISCUSSION

This section presents each paper in order, first providing a rationale for its inclusion in this thesis, followed by a discussion of the results of each paper compared with past literature, as well as their relation to the aim of the thesis. Finally, the strengths, the limitations and some ethical considerations related to the papers are presented.

Overall, to evaluate the value of eating behaviours as risk indicators for the development of obesity and their use as potential targets in prevention and intervention programs, requires:

- Understanding of eating behaviour in real-life and how it compares to more controlled settings where eating behaviour is expected to be less varied.
- Knowledge of the acceptability, usability and reliability of methods for quantifying eating behaviour in *real-life*.

5.1 PAPER I: CONTROLLED SETTING

As mentioned in the introduction, it is known that environmental cues and food properties can influence eating behaviour at a group level [192–195]. Additionally, in *controlled* settings, individuals have been shown to maintain their eating behaviour rank in the group when exposed to similar conditions on multiple occasions (test-retest) [122,149–152]. However, in real-life, variations in macronutrient composition, texture and cutlery are just a few examples which put different requirements on humans eating behaviour. Currently few studies have explored if individuals maintain their eating behaviour rank in relation to the group across different environmental cues and food properties [152]. Such studies are needed as a first step of investigating the generalisability across conditions in *controlled* studies, required for the development of predictive models of eating behaviour on an individual level.

To evaluate the stability of human eating behaviour in a *controlled* setting, **Paper I** investigated the effect of increasing the food unit size of meal components (unit size) and eating a standardised meal at either lunch or dinner (serving occasion). While both of the experimental conditions were tested in a *controlled* environment, they directly refer to meal parameters which vary across real-life meals.

Past studies suggest that increasing the unit size of food items lead to a subsequent increase in oral processing time [196]. In connection with these findings, there appears to be a correlation between increased oral processing time and increased meal duration, which in turn, results in a reduced food intake during meals [197,198]. However, manipulating unit size has had different results on food intake [199–201]. Meanwhile, studies investigating the health effects of serving occasion, suggest irregular meals and late meals may be a risk of obesity [202,203]. *Controlled* studies which employ a protocol with breakfast, lunch and dinner meals generally use different foods [204], or present a buffet of foods to select from [205]. This is due to the difference of the research question to the one posed in **Paper I**, but also correspond to normal diurnal human eating preferences, where food types are usually varied. Meanwhile, epidemiological studies have found a higher energy intake at dinner compared to lunch in Swedish children and adolescents, while these patterns may vary greatly between countries both in children and adults [129,131,206]. Epidemiological studies also suggest an association between time-of-day energy intake and obesity on a global level [129].

In **Paper I** (and the rest of the included papers in this thesis, see §4.2), the distribution of food intake and eating rate across individuals, belonging to otherwise "*homogenous*" participants groups, was large. This finding is not novel, as it has been repeated in several *controlled* studies of human eating behaviour [143,207]. However, the finding suggest that it should be fairly easy to identify individuals at risk of becoming obese, assuming that these eating behaviours are strong predictors of obesity. This of course requires that an individual's eating behaviour is stable, in relation to the group, across external and internal conditions.

The manipulation of unit size and serving occasion induced lower than expected eating behaviour differences, with no manipulation leading to a significantly increased or decreased food intake. In line with previous oral processing studies [196], the larger unit size condition of both experiment I and II resulted in significantly higher number of chews compared to the small condition. Although there was a trend for increased unit size leading to a longer meal duration, there was only a significant difference in meal duration between the small and large condition of experiment II. Contrary to the hypothesis, the increased meal duration did not lead to a significant reduction in food intake. However, it is possible that further increasing unit size would eventually reduce food intake. Similar to how increasing the unit size caused a significant increase in number of chews in both experiments, but only an increased meal duration in the experiment where the difference in unit size was the largest (experiment II). Previous unit size manipulation studies have had mixed results, where it seems that providing regular meals [201], similar to this paper, or healthy snacks [208] in various sizes don't seem to increase food intake. Meanwhile, increasing the size of unhealthy snacks appear to increase intake [200,209,210], attributed by researchers to either "*unit bias*" [199] or a "*segmentation effect*" [200].

Meanwhile, manipulating the serving occasion of identical foods in **Paper I**, caused only slight group level differences in all eating behaviour characteristics, far from reaching the significance threshold. The reason for the discrepancy between these results and epidemiological findings [206] are likely two-fold. Firstly, epidemiological studies suggest that food item selection is different between lunch and dinner, with the potential of eating behaviours being different as a response to food properties. Secondly, lunches and dinners are likely ingested in different environments, with the possibility of eating behaviour being different as a result of all associated environmental cues.

The correlation coefficients between conditions of **Paper I** suggest that individuals maintain their eating behaviour characteristic rank in the group despite changes in unit size and serving occasion ($R^2 \geq 0.75$), except for number of bites in Experiment II. It is also interesting to note that the two highest correlation coefficients ($R^2 = 0.98$ and 0.94) were measured in the eating behaviour characteristics that were significantly changed by the food unit size manipulation in experiment II. The reason that the correlation was not as high in number of bites in experiment

II compared to all other coefficients ($R^2 = 0.60$), could be due to individuals having different strategies of food handling when the food required cutting, compared to when it did not. Except for the number of bites, these findings are in line with previous test-retest studies, in which both solid and semi-solid foods have displayed high R^2-values [122,149–152]. They are also corroborated by a study in which energy density and food texture was manipulated [152]. These findings strengthen the hypothesis of the thesis that, irrespective of if environmental cues or food properties induce group level changes to eating behaviour or not, individuals maintain their eating behaviour rank, in relation to the group.

The ratings of food liking seem to confirm that the presented eating behaviour measurements were not affected by serving food that was too bland or palatable. Similarly, the self-rated reduction in satiety, from pre- to post-meal, suggest that the experimental meals were acceptable by the participants. In addition, we did not find anyone eating in the absence of hunger, which is a known confounder in eating behaviour experiments [211,212].

Overall, the findings of **Paper I** suggest that single meal measurements can not only be used with high accuracy to predict an individuals' eating behaviour in relation to the group in identical conditions, but may also be used to predict eating behaviour ranks across different conditions. For example, an individual identified as a faster than average eater ("*fast eater*") under one condition is likely to be a "*fast eater*" under other conditions too. Assuming individuals at risk of developing obesity respond similarly to these manipulations, this means that a standardized single meal protocol could be sufficient to detect individuals at risk of developing obesity, based on their eating behaviour. However, the *controlled* setting and methods do not allow for large scale screening of vulnerable target groups.

5.2 PAPERS II & III: SEMI-CONTROLLED SETTING

Compared to *controlled* (laboratory) studies that have already produced accurate measures of human behaviour across single meals for almost four decades [141], measuring eating behaviours in less controlled environments is usually done by use of self-report methods such as meal habit or food recall questionnaires [126]. However, methods tied to the *controlled* setting usually result in convenience samples, for example due to the location of the equipment and the schedule of participants and researchers [147,148]. As a result, most eating behaviour studies have been conducted using adult participant samples. Nowadays, smaller mobile devices allow studies to be conducted in less controlled environments, enabling the recruitment of younger populations, more relevant when studying obesity related risk behaviours [107,108]. In these age ranges school lunches are of specific interest, since a method which allows reliable quantification in this setting would allow the deployment of large-scale screening programs. Such a method would also enable studying the influence environment has on selection and food intake in more realistic environments, i.e., the school cafeteria. However, this setting poses additional challenges, one of which is the requirement to measure multiple individuals within a narrow timespan.

Papers II and **III** evaluated the feasibility and usability of laboratory-based methodologies, deployed in a *semi-controlled* school-cafeteria setting. **Paper II** examined the baseline behaviours of students during a school lunch meal. In addition, a sample of young adults eating the same food in a laboratory setting was used for comparison of eating behaviour characteristics. In **Paper III**, the system was used to quantify the behaviour difference in food intake resulting from experimentally manipulating the proximity of snack stations to the participants, during a work assignment. In addition, **Paper III** explored the possibility of using a limited number of devices to quantify the eating behaviour of several subjects across a longer period of time.

In the past, due to methodological limitations, most studies of school meals have focused on simple measurements, such as meal duration [213,214]. Recently, a study employed laboratory methods to quantify a younger age group (12-15 yrs.) in a school lunch setting, similar to the protocol employed in **Paper II** [215]. In the younger age group male participants had a higher food intake compared to females, while the meal duration increased in all participants when they ate a meal alone. Meanwhile, little is known about the microstructural meal characteristics of adolescents in a school environment. Regarding food proximity, previous studies in both school [153] and office [155] settings suggest that increasing the distance to food reduces the food intake. Similar to observational studies, methodological limitations have resulted in studies only providing subjective estimates of serving sizes and no temporal information in experimental studies [153,155].

The method employed in **Papers II-III** (and **Paper IV**) enabled transition to a high-school environment, resulting in the recruitment of adolescent individuals, which are more relevant in the search for risk factors of obesity and the development of successful prevention strategies. The more homogenous distribution of male and female students in the classes in the high-school also allowed the recruitment of both sexes in **Papers II-III**.

Paper II found a significantly larger food intake in male compared to female participants, primarily caused by significantly larger bite sizes. Meanwhile, the number of bites were similar between sexes. This finding is in line with previous findings of younger participants in a school lunch setting [215] and older participants in laboratory environments [151,216]. **Paper II** also illustrates the detail at which eating behaviour can be analysed using currently developed methods. For instance, temporal measurements allowed the finding that bite sizes were reduced across the meal in both male and female participants. Meanwhile, **Paper III** found that a more distal position of snacks led to a lower energy intake, caused by a reduced ingestion of chocolate, similar to previous studies [153,155]. In addition, **Paper III** provided an underlying cause of the increased intake. While the group intake was comparable during the first five minutes between the two conditions, the participants consumed more energy in the proximal condition as time progressed. Temporal measurements also allowed the identification of a significant difference in serving distribution, where servings in the proximal condition were more homogenously distributed, Figure 14.

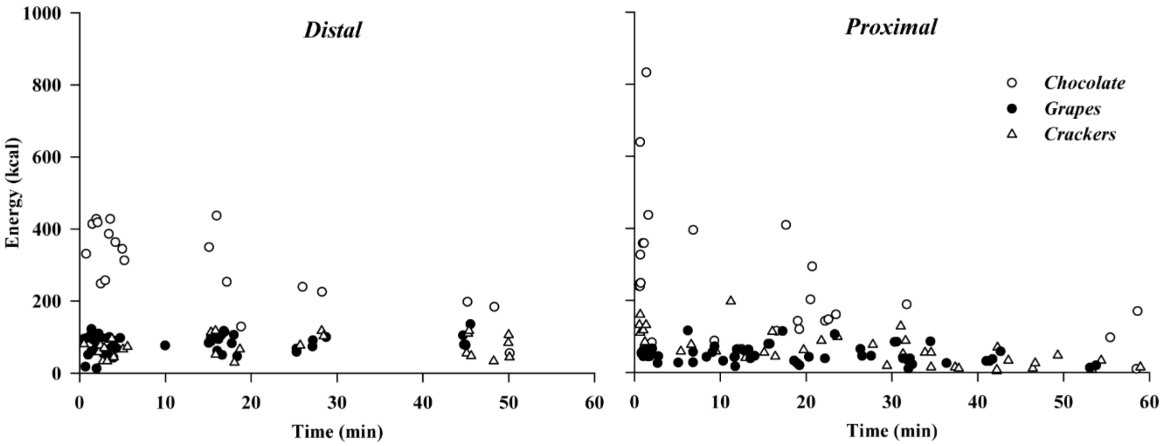

Figure 14. Temporal distribution of serving events. The time point and energy load for each serving event of grapes, chocolate and crackers, in each condition.

When comparing the perceived food intake and eating rate with the objective distribution of these eating behaviours (§4.5), both **Papers II** and **III** found that the subjective measures were poor predictors of their respective objective measure (**Paper IV** had similar findings). In general, the participants perceived that they ate more and faster compared to their peers, at least in the tested settings. In disagreement with these results, a study in a *controlled* environment found that self-reported eating rate correspond well with objectively measured eating rate [216]. However, another study found that subjective eating rate corresponds to objective eating rate in *controlled* settings, but not to real-life settings, which would account for the discrepancy [172].

Similar to **Paper I**, the average rating of food liking and reduction of fullness across the meal (§4.7) in **Papers II** and **III** (and **Paper IV**), although crude, create some confidence that the recorded eating behaviours were reliable. Meanwhile, the self-rated comfortability score increases our confidence that the participants' eating behaviours were not influenced by the observer effect (i.e., adjusting ones behaviour as a result of being observed by either a person or device) [217,218]. When the participants evaluated the interfaces of the devices that were used they received a "*Good*" rating on the SUS, which puts the system above the 50th percentile of evaluated systems. This is usually considered "*acceptable*" for use in the setting in which it has been tested [191].

Concerning data retention and handling, both **Papers II** and **III** managed to keep a high data retention rate (97 and 100%, respectively), in spite of the time restrictions. The methods of **Paper II** allowed for the concurrent measurement of at least 21 participants, within a time-period of 25 minutes during school lunch, compared to 4 concurrent participants within a time-period of 35 minutes of a previous study [215]. Similarly, the methods of **Paper III** allowed the concurrent measurement of at least 21 participants, within a pre-determined 60-minute time period. While comparable numbers have been produced by others in *semi-controlled* settings, past studies have not been able to provide temporal measures of food intake [153,155].

In conclusion, **Paper II** provides evidence that the employed methods and technology can reliably be used for large-scale screening purposes to quantify human eating behaviour, during school-lunches, with minor behavioural changes caused by the employed methods. Meanwhile, **Paper III** provides evidence that experimental laboratory protocols can be deployed with a high data retention rate in *semi-controlled* environments. In addition, with slight modification, the methods of **Paper III** could be used to enable large scale quantification of food selection in *semi-controlled* settings. Using one device to track the food selection of multiple individuals, as opposed to the traditional way of using one device to track the food intake of one individual. Providing a flexible and cheap alternative to other systems targeting such behaviours [219].

5.3 PAPER IV: REAL-LIFE SETTING

Measuring meal-related behaviours, in any target group, in a real-life setting is arguably the biggest challenge, but also very valuable in the effort to evaluate individual eating behaviours, working towards individualised prevention or intervention programs. As stated before, some researchers have suggested that eating behaviours displayed in *controlled* setting may not correspond to the ones expressed in *real-life* [147]. It is clear that naturalistic settings add numerous variables which closely affect an individual's natural eating behaviour, which are not present in *controlled* or *semi-controlled* settings. Now that methods are available which may be able to measure eating behaviour in both *controlled* and *real-life* settings, finally the relationship between these settings may be clarified. Providing an understanding of which laboratory studies are generalizable to which *real-life* settings.

In order to investigate the *real-life* usability of a system for quantifying eating behaviour, **Paper IV** deployed a system, developed based on feedback from **Papers II** and **III**, in *real-life* settings. The system allowed the participants to register meals in the system in two different ways: i) to self-report meals, providing data on meal time and type (snack, breakfast, lunch and dinner) and ii) to self-record meals, providing the same data as in meal-reporting, with the addition of the recordings of food intake and meal duration. It should be emphasized that the selected method was not developed for the precise calculation of daily energy intake for the participating students, but rather as a more reliable method of collecting eating behaviour characteristics in *real-life*. In addition, the paper evaluated the type of data that could be collected, as well as the feasibility of using such a system in *real-life*. Finally, **Paper IV** used the *semi-controlled* meal of each individual to predict their food intake and meal duration in *real-life* meals.

Several mHealth methods have been able to provide information on various parts of human eating behaviour in a laboratory setting and a few mHealth methods targeting mediators such as knowledge and awareness have been employed in real-life settings [220]. To date no study has measured the response difference in eating behaviour between *semi-controlled* and *real-life* studies, or estimated prediction rates of *real-life* eating behaviour from one *semi-controlled* meal.

In **Paper IV**, the first challenge was the validity of the registering frequency of meals in the system in *real-life*, either in the format of *reported* or *recorded* meals. Obviously, the lack of reliable alternative methods to be used as "*gold-standard*" prevents the precise calculation of the validity of the deployed method. In this case, traditional self-reporting techniques, like the food-diaries and food-behaviour questionnaires were not regarded as appropriate validation tools, due to their associated measurement biases [138,221,222]. Instead, the reliability of the produced dataset was assessed through the analysis of the registered meals in comparison to the meals expected to be recorded by the target participants during the monitoring period. Hence, in order to calculate the meal registering frequency, the maximum expected registering frequency was set to three main meals per day (breakfast, lunch and dinner) for each day in the monitoring period. The registration frequency of snacks was not calculated, since the maximum expected registration frequency of snacks could not be estimated reliably. Based on these assumptions, the reported registration ratio of 73% for the main meals during the period of system use, should be regarded as promising, especially if one considers that 27% of the "*missing*" meals include both non-reported and skipped meals (i.e., meals that the participants never consumed). Overall, the observed registration frequency of meals can be considered a valid starting point for the development and optimisation of similar methods in the future, in this study it resulted in an average of 15.3 main meals registered per individual, per week, of which 7.5 were self-recorded.

The fact that the registering frequency of the main meals increased from week one to week two (from 70% to 76%), shows that a familiarization period or a longer teaching session with researchers might be required in the future. Regarding the difference between recordings and reports among different main meal types, the most important observation was that breakfasts were less likely to be self-recorded. This might be due to the fact that food items consumed at breakfast were; i) not appropriate to eat on the measuring device, ii) consumed under time-pressure, or iii) were bought and eaten on the go. Since the deployed methodologies cannot be used to answer this question, future investigation on this point is warranted. Irrespective of the underlying reason, the low recording frequency of breakfasts led to only 63% of subjects having breakfast data on food intake and meal duration. Therefore, the planned comparisons between the *semi-controlled* and *real-life* meals might be more relevant for evaluating the relationship between *semi-controlled* lunches and the recorded *real-life* lunches and dinners.

Interestingly, the distribution of food intake and eating rate measures across individuals in the *real-life* meals seem to be comparable to the distribution of values in the monitored meals in all the *semi-controlled* and *controlled* settings across the included studies. This finding is surprising, since the expected distribution in the *real-life* settings was expected to be wider, due to the variation of the external meal conditions. This raises the question of how well the *controlled* and *semi-controlled* setting accomplish the task of reducing measurement error and if the recruited groups of participants in the *controlled* and *semi-controlled* studies can truly be called "*homogenous*" in regards to eating behaviour.

In **Paper IV**, after adjusting for multiple comparisons, there was no significant difference in objectively measured food intake, eating rate or meal duration between the *semi-controlled* meal and the mean value of all *real-life* meals. These results do not strengthen the assertion that there is a difference in eating behaviour between *controlled* and *real-life* settings.

However, the unadjusted p-value of food intake was below 0.05, with meals eaten in the *real-life* setting being significantly smaller. If we accept the unadjusted p-value the findings are similar to a study conducted in a school lunch setting, where an *ad libitum* condition promoted longer meal duration and lower food intake, compared to the regular school lunch, which was 35 minutes long [215]. The similarity to the results of **Paper IV** is that when the meal duration is not enforced (assumed to be the case in the *real-life* setting), food intake is lower. However, more studies are required to clarify the relationship between *controlled*, *semi-controlled* and *real-life* studies. Another explanation for the difference between settings is the heteroscedasticity between the *semi-controlled* and *real-life* setting, with a high difference between the *semi-controlled* and *real-life* condition of the five individuals with the highest food intake (§4.4.4, the five individuals on the right side of the plot). The apparent difference in some individuals between conditions warrants care when identifying and potentially excluding outliers, that respond differently to *real-life* settings. Interestingly, it should be noted that "*outlier*" individuals were predominantly males (4/5), but the sample size does not allow for a proper statistical comparison between sexes.

Similar to the findings of **Papers II** and **III**, on a group level subjective food intake and eating rate was higher than the objective food intake and eating rate in **Paper IV**, leading to a very low agreement between subjective and objective measures of food intake and eating rate.

The high correlation of food intake and eating rate in **Paper IV** corroborates the findings of previous test-retest studies and of **Paper I** [122,149,152]. The high correlation of food intake and eating rate of **Paper IV** was unexpected, since all main meals (breakfast, lunch and dinner) were included in the analysis. This suggests that measuring an individual's food intake rank may not require using only certain main meals (e.g., dinner). Meanwhile, the low correlation in meal duration suggests that it is more varied within the group, perhaps more affected by external factors and may require subdivision to increase correlation.

Concerning the correlation of food intake and eating rate, most participants seem to maintain their rank in the group between the *semi-controlled* and *real-life* setting. In contrast, meal duration seems to be less stable across the group, with the real-life measurements not correlating strongly with those in the *semi-controlled* meals. However, it is important to note that the *real-life* value was based on the mean value of all recorded meals, which in theory has brought the value closer to a statistically true value of a *real-life* meal.

In an effort to evaluate the predictive power of single *semi-controlled* meals, the eating behaviour value was compared with the confidence intervals of all the self-recorded *real-life* main meals. These results show that the current methodology is not sensitive enough to provide absolute measures of an individual's eating behaviour. However, the food intake prediction is higher between the objective measures in the *semi-controlled* and *real-life* setting, compared to the subjective comparison in all *semi-controlled* settings (**Papers II-IV**) and the *real-life* setting of **Paper IV** (§4.4.4). The prediction rate could potentially be improved by increasing the number of *semi-controlled* meals measured, reducing the measurement error, or by increasing the number of *real-life* meals measured, which would also enable part-predictions for different food types (e.g., breakfast, lunch and dinner) and sex-specific predictions.

The *real-life* method did not allow participants to rate their liking of the food. It is possible that when left to select food for themselves, participants opted for more palatable foods, potentially altering their eating behaviour. However, the current method did not enable such an analysis.

The same environment was used in the *semi-controlled* setting of **Papers II-IV**, which may explain why the self-rated comfortability score of **Paper II-IV**, although not part of a validated questionnaire, were similar. Suggesting that if individuals were affected as a result of the protocol at least the exposure and response was similar. In addition, the SUS score in the *semi-controlled* setting was higher in **Paper IV**, than it was in **Paper II** and **III**. Putting the rating above the 75^{th} percentile. In addition, in the *real-life* setting of **Paper IV** the system was rated similar in usability to that of **Papers II** and **III**, which were conducted in a more controlled environment. Both results indicate a successful improvement of the system from **Paper II** and **III**, to **Paper IV** and hopefully a lower risk of system use altering an individual's eating behaviour.

On a descriptive level, **Paper IV** reveals that it is common for Swedish adolescents to eat their breakfast and lunch later during weekends compared to school-days. These findings are corroborated in a study on adults, where the first caloric intake occurred earlier during workdays, while timing of the last meal was similar between work days and weekends [130]. One possible cause of the difference in breakfast and lunch between weekdays and weekends could be the restrictions imposed by school/work schedule during weekdays. The effects of meal timing on health has been difficult to determine, in part due to differences in definitions and methodological limitations [223]. In some cases, intermittent fasting appears to reduce body weight [224], perhaps by reducing the total number of meals ingested. In other studies, breakfast-skipping appears to increase the risk of obesity and type 2 diabetes [225–228]. The current system provides a reliable method which can provide accurate measures of the meal timing, hopefully removing one of the obstacles for determining the health effects of meal timing. Similar analyses can also be performed in other systems supporting real-time meal-registration, such as in cases of meal-picture collection platforms, which are currently widely deployed for lifestyle monitoring (see Figure 15 for example).

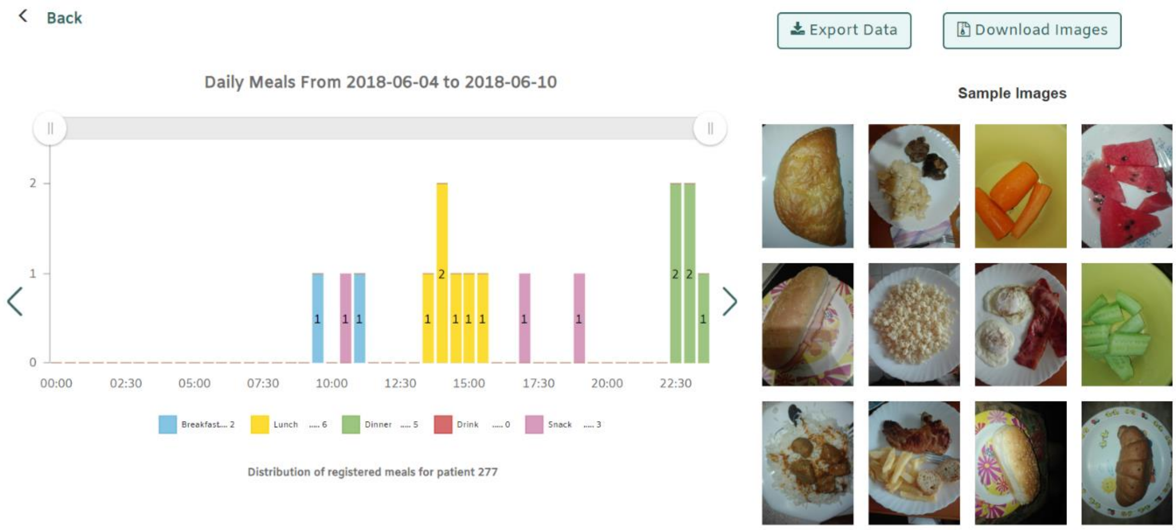

Figure 15. An example of temporal daily meal analysis currently deployed in the BigO system, using the meta-data of the user-uploaded pictures to plot meals across a week for an obese patient (14 years old).

In conclusion, the findings of **Paper IV** suggest that the method is mature enough to be deployed in a much larger scale, which will increase statistical power. In addition, measurements in *semi-controlled* settings appear able to identify individuals who have a high food intake and eating rate in *real-life*, compared to the group. However, it seems the employed method is unable to identify groups of individuals that differ in regards to meal duration. Similarly, with prediction rates 50% or lower in food intake, eating rate and meal duration, the current method is not mature enough to provide individual recommendations, for use in preventions and interventions protocols.

5.4 STRENGTHS AND LIMITATIONS

The main strengths of all papers were a device which enabled reliable continuous recording of weight removed from the plate, which in all video recorded sessions (*controlled* and *semi-controlled*) was equivalent to food intake. This setting also enabled the temporal analysis of behaviour in **Papers II** and **III**. In the *semi-controlled* settings of **Paper II-IV** participants were able to eat their meal in their regular school lunch setting, following their regular schedule, having a selection of foods commonly served in the cafeteria. In addition, all papers used an app which allowed easy recording of each meal. In the *real-life* environment the app also allowed self-reporting and self-recording to be made in real-time (not relying on recall). Less homogenous samples usually lead to larger ranges of the values of interest, which in turn can increase correlation coefficients, therefore the homogenous sample is considered a strength in **Papers I** and **IV**. In addition, although some data was lost due to equipment mishandling and software issues, there was no missing data as a result of dropouts, enabling missing data to be viewed as a random occurrence (an assumption required when using certain statistical analyses).

As mentioned previously, the controlled nature of the study protocol in **Paper I** could be considered both a strength and a weakness, controlling for several known confounders. The protocol ensures the observed effects were a result of the experimental manipulations, but the analyses outcomes might not be generalizable in less controlled environments. In addition, **Paper I** only included young adult women, due to the difficulty of recruiting younger age groups and men for the laboratory setting. Limitations of the *semi-controlled* and *real-life* settings (**Papers II-IV**) was the small sample size, which was primarily a result of the novelty of the methods (low number of available devices). Serving sizes were only quantifiable in **Paper I**, due to the developed app not being able to quantify serving sizes in a buffet or restaurant setting, where the servings do not occur at the table. In addition, less controlled environments resulted in a decline in the number of eating behaviours that could be reliably measured (i.e., no measures of chews in *semi-controlled* environments and no measures of chews and bites in the *real-life* setting). Due to the lack of video data in the *real-life* setting of **Paper IV** we cannot be sure the weight removed from the device equals food intake. This is not expected to be a problem in healthy populations, but may cause problems in unhealthy populations, where there may be a stigma related to food intake, as is the case with obesity [36,229]. In **Paper IV**, another limitation is the measure of compliance. The assumption was that individuals eat one breakfast, one lunch and one dinner per day, although we know from meal habit questionnaires and epidemiological studies that it is common for this group to skip meals. However, currently there is no consensus on the measurement method or definition of meal-skipping, resulting in large differences between studies (5 to 83%) [230]. In a study using similar methods as **Paper IV** a randomly timed notification asked participants if they had a meal within the last 30 minutes. Compliance was then calculated by comparing random timed notification results with the self-reported meals [130]. In addition, for all papers only normal weight adolescents and young adults were recruited. Future studies should endeavour to measure these same behaviours in younger, as well as overweight and obese populations. Similarly, the samples in **Papers II-IV** included less male than female participants, based on the distribution of the sexes in the monitored school.

5.5 ETHICAL CONSIDERATIONS

As is required by all human research conducted in Sweden, the studies of all papers were conducted in accordance to the ethical principles mentioned in the Declaration of Helsinki and the ethical vetting was approved by the regional ethical review board in Stockholm, Sweden.

Before data was collected all adult participants (18 yrs. or older) signed written consent forms. In studies involving adolescent participants (15-18), for participants under the age of 18, both the participant and his/her legal guardians signed written consent forms.

We did expect the adolescent population to be able to understand the potential risks and burdens of participation. However, due to the type of information that can be collected and the novelty of the methods used we wanted to ensure the protocol and methods were accepted by both participants and their parents. As mentioned earlier the development of small sensors presents a great opportunity for researchers to quantify human behaviours previously unattainable. But, with all this information available it becomes crucial to ensure the protection of individuals to prevent discrimination. The Information Communication Technology field may require just as much care when it comes to an individual’s integrity as does genetics [134,135]. In genetics, researchers recently found that based on a partial DNA sequence of the Y-chromosome, age, and U.S. state of residence it is possible to identify a man [231]. It is difficult to foresee what information will be available to researchers with the development of deep learning algorithms. Already, collecting an individual's geo-location (GPS), acceleration (accelerometer), torque (gyroscope), orientation (magnetometer), etc. can provide a lot of information which may not be directly obvious to the user. Therefore, in **Paper IV**, care was given to turn off all unnecessary features, such as GPS, in the *real-life* setting. In addition, in all papers, to ensure confidentiality, a key file was created which coupled the name of each participant with a serial number. This file and information which could cause identification of a participant (e.g., personal number) was stored locally on an external hard-drive, disconnected from any network. Another risk of system use is stigmatization, either if left out or included. To reduce this risk, recruitment was done per class, with all participants eligible for participation. However, this becomes an even more valid concern if these systems are intended for use in intervention and prevention studies, where the use of the device is an immediately identifier of the disease or disorder.

6 CONCLUSIONS

This section starts with a view on what methodological steps should be taken in order to improve measures and generate more reliable conclusions, for each setting described in the thesis, after which the potential value of each setting is described. Ending with a section discussing the future outlook of the field.

6.1 CONTROLLED

In this thesis the value of *controlled* (laboratory) meals have been discussed, when doing so it is important to make a distinction between two similar claims:

1. *"The laboratory is an artificial environment where certain parts of human eating behaviour cannot be studied*". The suggestion has been to refocus the study of human eating behaviour to real people, eating real foods in real environments [148], but as Kissileff HR., points out: "*Humans eat in almost every conceivable situation in which they find themselves*" [175], which leads us to the next claim.
2. *"Certain experimental manipulations employed in the laboratory are unlikely to ever occur in real-life"*. This is a valid concern, since of course there is reason to question the value of exposing an individual to equipment, foods and environmental cues that are not present in the individuals day to day environment. In line with the previous argument, it is therefore important to evaluate which study protocols are generalizable to which settings. For example, *ad libitum* laboratory conditions, as the one used in **Paper I**, may be similar to buffet settings, as the ones used in **Paper II** and the *semi-controlled* part of **Paper IV**.

Before these relationships have been properly analysed, the risk of making to broad generalizations from laboratory findings will prevail.

Another important point which needs to be addressed, not only in *controlled* settings, but in the field of behavioural nutrition as a whole, is the conflict of definitions. The overlap in definition of some food properties and human eating behaviours with a lack of taxonomy, may result in misinterpretation of the type of exposure that elicits a specific response. An example of where this can become a risk is the unit size condition in **Paper I**. Here, if smaller and smaller particles are created, eventually the texture may change from solid to semi-solid. Similarly, experimentally manipulating eating rate in some experiments have led to increased portion sizes, which is a potential confounder, since both eating rate and portion size are considered risk factors for obesity. Therefore, proper distinctions between frequently used words are required, to not make mistakes when designing study protocols or when making interpretations of the results. Another factor that would require some standardization is the methods employed in this field, with meta studies commenting on the heterogeneity of methods [167].

A fairly new and interesting line of inquiry is that of individual response. Most statistical methods compare differences at group level, which is reflected by the experimental protocol. However, due to the varying results of behavioural interventions, some researchers have argued the benefit of intervention and prevention strategies tailored to individuals [232]. Providing the data upon which to base these tailored interventions require an understanding of individual variation. Here, behavioural nutrition could probably benefit from adopting practices used in sports performance studies to quantify the precision of measurements and individual response to exposures [233]. Currently, if at all reported, most studies evaluating individual response in behavioural nutrition do so using correlation, which measures the reproducibility of rank order of subjects on retests. However, to properly evaluate the stability of eating behaviour would also require the measurement error in these studies, to get the measurement of variation within each subject. This in turn, requires multiple measurements of each condition, which would provide measurement error ranges for each individual in each condition, enabling the identification of individual response [234,235], depicted in Figure 16.

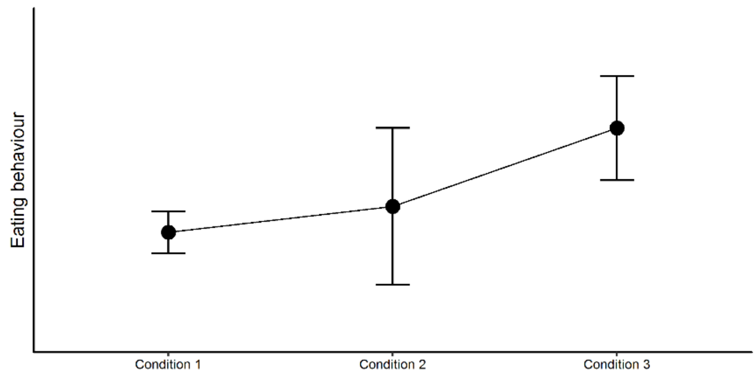

Figure 16. Theoretical depiction of an individual's response with measurement error, resulting from multiple measured of each condition.

Most of the above-mentioned problems are present in less controlled settings as well. Meanwhile, *controlled* studies remain the most accurate and reliable way of measuring the response of experimental manipulations, as opposed to studying them in *semi-controlled* or *real-life* settings. In addition, research protocols allowing individual response quantification could provide a "*pure*" response measure for the design of behavioural predictive models. A difficult, if not impossible, feat to accomplish in less controlled settings with the technology available today.

6.2 SEMI-CONTROLLED

In the current thesis *semi-controlled* settings, refers to the school lunch area, with the presence of recording apparatuses and researchers. This environment may not provide the strong control of confounders that the *controlled* settings does, or the relevance of measuring *real-life* behaviours. However, it does provide a unique opportunity for baseline data collection and screening on a large scale. The deployment of a baseline protocol, as was done in **Paper II** and the *semi-controlled* setting of **Paper IV**, appears to be acceptable by the adolescent population and provide a high data retention rate, only requiring availability of more devices to enable large scale screening. In addition, while the automatic algorithms provided data on food intake and meal duration, improving it further could enable quantification of number of bites and additions. Meanwhile, before putting individuals on intervention or prevention protocols based on screening using the system of the thesis, the method requires proper measures of sensitivity and specificity, to estimate the risk of misclassification. Enabling the creation of likelihood ratios, which could provide an estimate of clinical relevance for screening [236].

Although the current thesis only evaluated the feasibility of baseline collection in a high-school cafeteria, the method could easily be modified for use in pre-school lunch areas, work place cafeterias and restaurants, depending on the research question. Regarding screening, although the focus of this paper was obesity, screening protocols could also easily be adjusted to identify individuals at risk of other diseases or disorders related to food, such as anorexia and bulimia.

6.3 REAL-LIFE

Although it is enticing to expeditiously employ the methods used in the current thesis for prevention and intervention purposes. Several limitations to the system may need to be addressed to reduce the risk of measurement bias. First and foremost, the system should be improved to allow measurement of portion size in main meals and the recording of snacks, as well as improve the recording frequency of breakfasts. Once this has been accomplished it is important to perform proper validation (i.e., use methods in parallel) of these methods (real time *report* and *record*), comparing them with recall methods (e.g., 7-day food record and meal habit questionnaire), as well as automatic recording (e.g., eButton and Automatic Ingestion Monitor). In parallel with validation studies, it makes sense to conduct reliability studies both across methods and settings, it would be of interest to include several measures per individual in the *controlled*, *semi-controlled* and *real-life* setting. This would enable an estimation of how much the *controlled* setting actually reduces the measurement error and if the exposure to the *real-life* setting elicits a different response than does the *controlled* setting. The current assumption is that when moving from a more controlled to a less controlled setting; the measurement error is increased, while the mean (true) value is maintained within the individual, depicted in Figure 17.

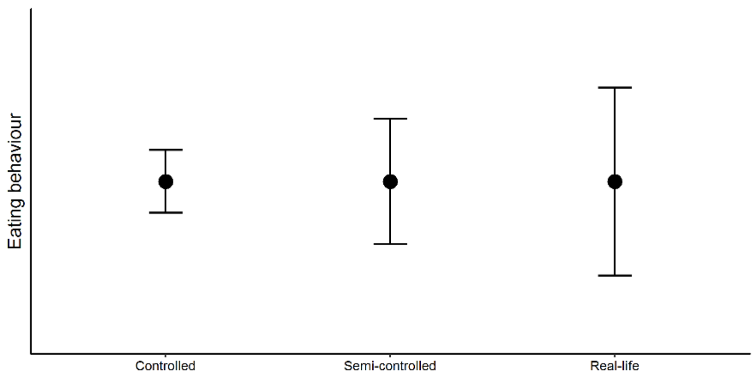

Figure 17. Assumption of confidence interval and mean value in the transition from controlled to real-life setting.

Since sensors able to measure new environmental variables are constantly being developed, the system likely to provide the most accurate information of a person's exposures and eating behaviour is one including several sensors. By focusing on the strengths of each sensor, prioritizing direct measures and using inferential measures as backup, a more complete picture of an individuals can be provided. For instance, if you have the weight measurement, controlling for individuals throwing away food could be done by accurate measures of chewing. Similar to how, in physical activity research, photoplethysmography and skin conductance have been used to measure compliance, while accelerometer and gyroscope sensors estimate the physical activity intensity and type, respectively.

Once the process of combining sensors identified to have a high validity and reliability when measuring certain eating behaviour parameters in the intended setting and designing a protocol which promotes low attrition rates and high compliance from the intended user group. The result is expected to be a system which enables quantification of human eating behaviour in previously inaccessible environments. It is also expected to improve the accuracy of the measurements made in environments where other methods have previously been employed.

6.4 FUTURE OUTLOOK

Future studies, employing the current system, or an improved version, should aim to include other groups, such as children, elderly and obese, as well as individuals of different socioeconomic groups. In Sweden another vulnerable group is children not attending high-school, where almost one fourth of individuals are obese according to a recent Swedish report [237]. Since the school setting is not available in this group, it presents an additional obstacle of identifying appropriate *semi-controlled* settings for large scale screening.

Potential strengths of using technology to quantify eating behaviour which warrant further investigation are:

- If technology can promote lower attrition rates than using questionnaires and other methods of self-report, due to the ease of use and the availability of the equipment. For example, almost all adolescents today own a Smartphone. Ensuring at least that they carry the registering/recording device (Smartphone) with them, while paper based questionnaires can be forgotten.
- If providing real-time feedback can enable a person to alter their behaviour in time, instead of reminding them that they have failed to follow the protocol, which is done in non-real-time approaches. This in turn could enable conditioning and retraining, employing a more behaviouristic approach to obesity prevention and intervention protocols.
- How adding additional sensors can provide more information on the environment as well as the eating behaviour. Systems like the one developed by Sazonov et al., could measure chews and swallows. Cameras such as the one used by the eButton, could identify the food environment, food type and potentially quantify food volume. Meanwhile, light and heat sensors could provide data on the environmental ambiance.
- How machine learning (and deep learning) can find patterns not obvious to human observers, enabling the identification of previously unknown risk factors. For example, a typical machine learning protocol would start with participant labelling their data, as was done in the current thesis (i.e., breakfast, lunch, dinner and snack). The labelled data would then be used to create a machine learning program able to identify the meal

type of other individuals who display similar behaviours as the ones used in the labelled data.

As was mentioned in the introduction, advances in technology are usually blamed for the cause of the obesity epidemic, by reducing physical activity, while providing an excess of food with high energy density. However, technology and sensors, similar to the ones used in this thesis, can hopefully be the solution to the problem of obesity. Providing accurate, easy to use measurement methods that can be used over long periods of time. Enabling not only the identification of differences between obese and normal weight individuals, but providing feedback in real-time, facilitating adjustments to behaviours when they happen, not afterwards.

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9 FIGURE REFERENCES AND ATTRIBUTIONS

Figure 1. Prevalence of overweight in 4-year old in the municipality of Stockholm.

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Figure 2. The Mandometer®

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Figure 3. Device developed for use in detection of eating.

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Table 2. Study protocol

Images for **Paper III**, are reprinted from:
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, 12(8): e0182172. Available from: https://doi.org/10.1371/journal.pone.0182172. Licensed under Creative Commons Attribution cc-by 4.0.

Table 3. Food type

Images from **Paper I** are reprinted from:
Langlet B., Tang Bach M., Odegi D., Fagerberg P. and 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, 10(7), pii:E880. Available from: https://www.mdpi.com/2072-6643/10/7/880. Licensed under Creative Commons Attribution cc-by 4.0.

Figure 4. Main Menu of the Mobile Application for Recording and Reporting Meals in **Paper IV.**

Own work by the PhD student.

Figure 5. Meal Recording of the Mobile Application in **Paper IV**.

Own work by the PhD student.

Figure 6. Boxplots displaying the food intake distribution of all papers in the thesis.

Own work by the PhD student.

Figure 7. Boxplots displaying the eating rate distribution of all papers in the thesis.

Own work by the PhD student.

Figure 8. Eating style projection of participants in the semi-controlled setting of **Paper II**.

Langlet B., Anvret A., Maramis C., Moulos I., Papapanagiotou V., Diou C., Lekka E., Heimeier R., Delopoulos A. and Ioakimidis I. Objective Measures of Eating Behaviour in a Swedish High School. *Behaviour & Information Technology*, 2017, 36(10), 1005-1013. Available from: https://doi.org/10.1080/0144929X.2017.1322146. Reprinted with permission from Taylor & Francis Journals Helpdesk

Figure 9. Bite size changes across the meal of participants in the semi-controlled setting of **Paper II**.

Langlet B., Anvret A., Maramis C., Moulos I., Papapanagiotou V., Diou C., Lekka E., Heimeier R., Delopoulos A. and Ioakimidis I. Objective Measures of Eating Behaviour in a Swedish High School. *Behaviour & Information Technology*, 2017, 36(10), 1005-1013. Available from: https://doi.org/10.1080/0144929X.2017.1322146. Reprinted with permission from Taylor & Francis Journals Helpdesk

Figure 10. Food intake confidence interval of real-life meals compared with the food intake at the semi-controlled meal of **Paper IV**.

Own work by the PhD student.

Figure 11. Frequency distribution of subjectively and objectively measured food intake in **Papers II-IV**.

Own work by the PhD student.

Figure 12. Frequency distribution of subjectively and objectively measured eating rate in **Papers II-IV**.

Own work by the PhD student.

Figure 13. Bar plot of Comfort and SUS ratings in **Papers II-IV**.

Own work by the PhD student.

Figure 14. Temporal distribution of serving events in **Paper 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, 12(8): e0182172. Available from: https://doi.org/10.1371/journal.pone.0182172. Licensed under Creative Commons Attribution cc-by 4.0.

Figure 15. Example of temporal daily meal analysis deployed in the BigO system.

Work by Ioannis Ioakeimidis.

Figure 16. Depiction of individual response with measurement error.

Own work by the PhD student.

Figure 17. Assumption of confidence interval and mean value in the transition from controlled to real-life setting.

Own work by the PhD student.