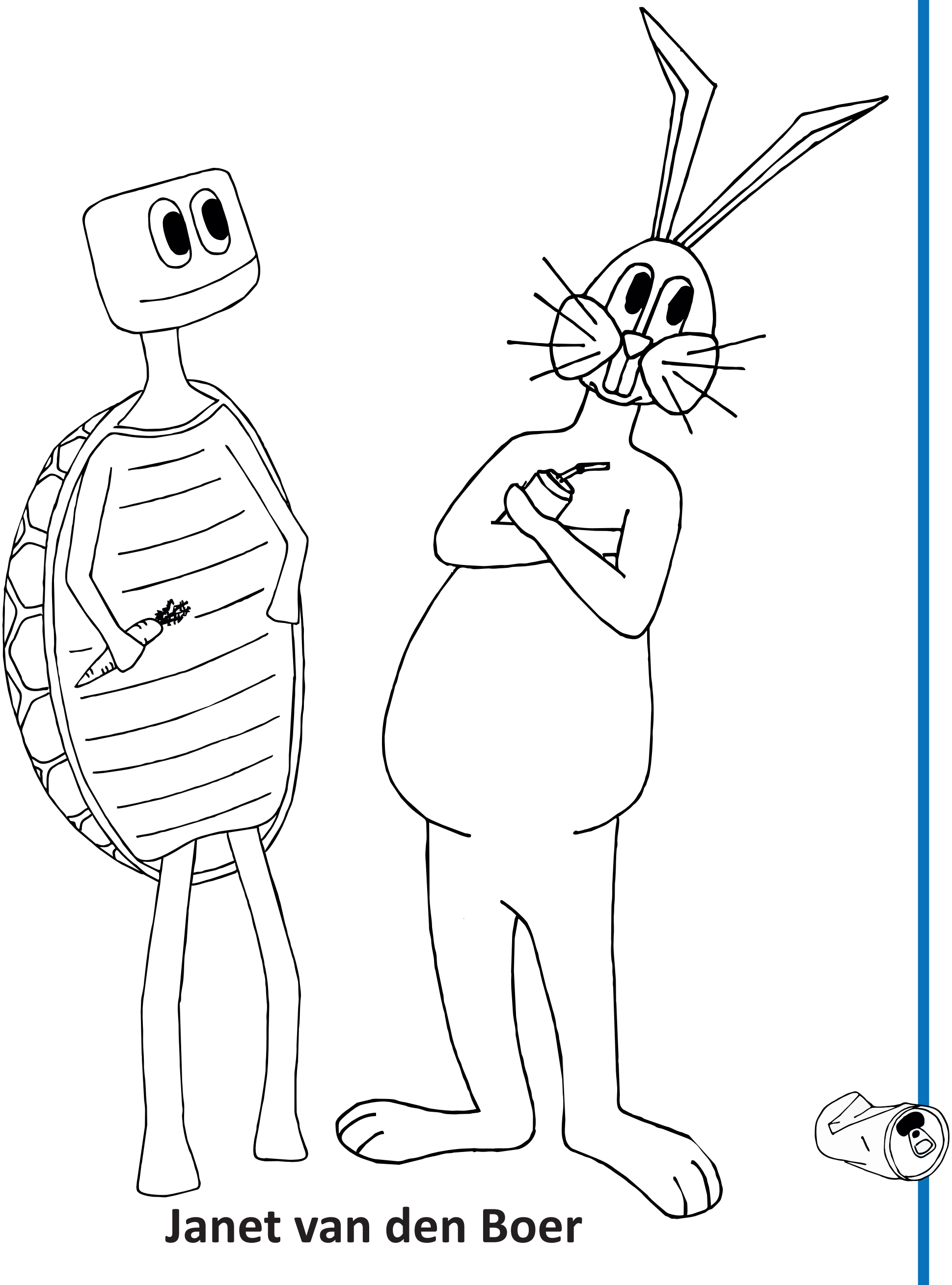
SLOW DOWN!

Exploring opportunities for reducing eating rate



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This research was conducted under the auspices of the Graduate School VLAG (Advanced studies in Food Technologies, Agrobiotechnology, Nutrition and Health Sciences.

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Exploring opportunities for reducing eating rate

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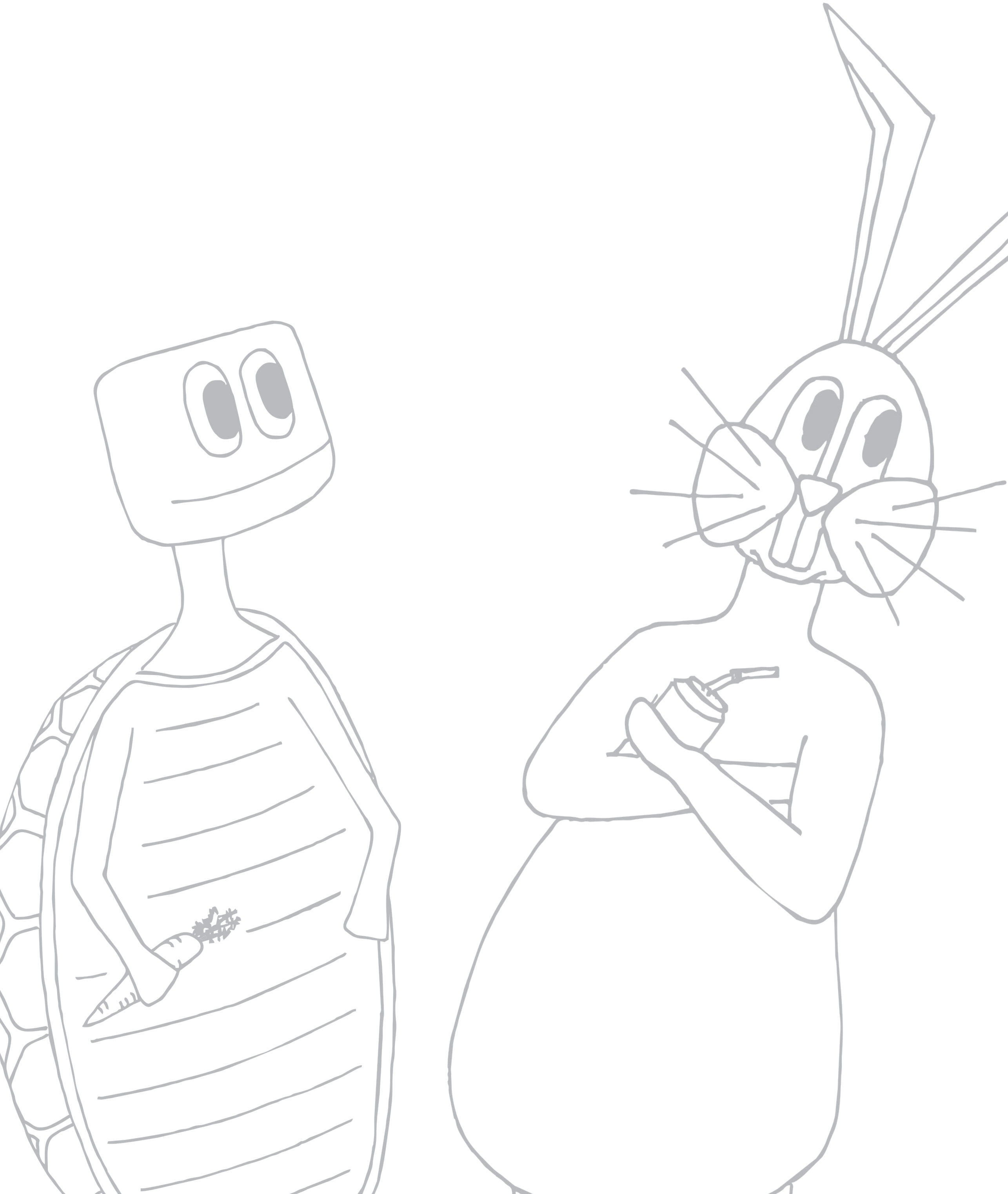
Thesis
submitted in fulfilment of the requirements for the degree of doctor
at Wageningen University
by authority of the Rector Magnificus,
Prof. Dr A.P.J. Mol,
in the presence of the
Thesis Committee appointed by the Academic Board
to be defended in public
on Monday 9 April 2018
at 4 p.m. in the Aula.

Janet van den Boer
“SLOW DOWN! Exploring opportunities for reducing eating rate”,
190 pages.

PhD thesis, Wageningen University, Wageningen, the Netherlands (2018)
With references, with summaries in English and Dutch

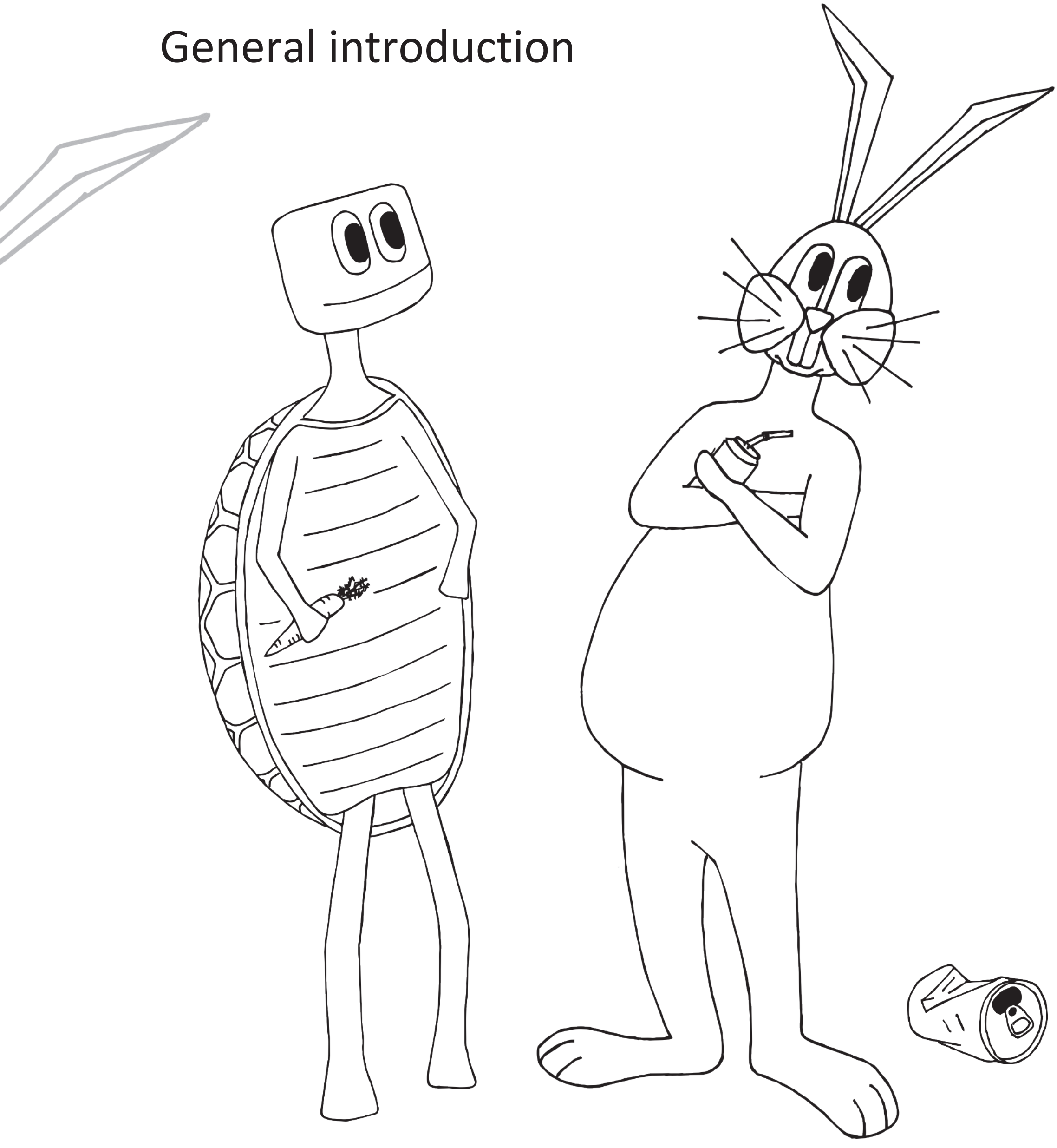
ISBN: 978-94-6343-254-2
DOI: 10.18174/440689

Content



Chapter 1

General introduction



Relevance of eating rate

Obesity has reached epidemic proportions in many countries around the world [1]. At first glance, the solution for the obesity epidemic seems to be simple. Overweight and obese people just need to reduce energy intake below energy expenditure [2,3]. This, however, is easier said than done. It seems that our biology is more effective at preventing weight loss, than at preventing weight gain [2]. Moreover, we are currently living an obesogenic environment: i.e. an environment that promotes a positive energy balance [4-7]. The latest numbers show that worldwide over 1.9 billion adults were overweight and over 650 million adults were obese in 2016 [1]. These numbers demonstrate that people are having difficulties with limiting energy intake to match energy expenditure. Therefore strategies to make controlling energy intake easier and more enjoyable need to be identified, as pointed out by the World Health Organization [8].

We may help people to better control their energy intake by lowering eating rate, i.e. the amount of food consumed per unit of time. Already a long time ago eating rate has attracted attention for its potential role in preventing and treating obesity [9]. Slower eating is expected to reduce food intake and consequently body weight; when calories pass quickly through the oral cavity they do not bring about an adequate satiety response [10-14]. Oro-sensory exposure plays a major role in this; if food spends more time in the mouth this induces a stronger cephalic phase response which contributes to satiety [15,14,11,16,13,17].

Extensive research has shown that food intake can be reduced by lowering eating rate. A review by Robinson et al. [18] shows that experimental studies have consistently found that people eat less when eating rate is reduced. Moreover, it seems that this is not compensated in subsequent meals [19-21]. Furthermore, literature suggests that eating rate can affect long-term energy intake and BMI [22-26]. This makes lowering eating rate a promising strategy for reducing energy intake and eventually body weight.

Possible approaches for lowering eating rate

A wide range of options exist for lowering eating rate. There are those that target the person: i.e. directly target a person’s eating behavior. There are those that target the food: i.e. indirectly affect a person’s eating behavior by changing the food consumed. Finally, it might also be possible to lower eating rate through the eating environment: i.e. indirectly affect a person’s eating behavior by changing the direct environment of a person eating. Figure 1 provides an overview of the different levels at which eating rate can be targeted.

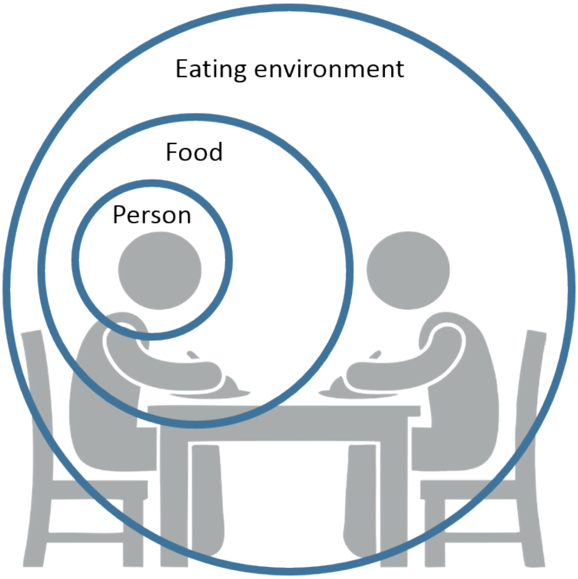


Figure 1 Different levels from which eating rate can be targeted: i.e. the person, the food and the eating environment

Below it is described in more detail how the person, food and eating environment affect eating rate and how we can use that to lower eating rate.

Person

Eating rate is a personal characteristic: i.e. some people tend to eat faster than others and vice versa [27-30]. Moreover, findings from a twin study suggests that eating rate has a heritable component [31,32]. Differences in sucking vigor, which shows parallels with eating rate, have been observed in infants as young as 2-4 weeks old [33-35]. In adults, eating rate is consistently found be a personal characteristic [27-30]. It seems that fast eaters are not more efficient in orally processing foods, but that they are swallowing a bolus that is less broken down [28].

Eating rate, being a personal characteristic, can potentially affect long-term energy intake and weight status. Several studies already investigated whether personal eating rate is associated with BMI. In general, these studies confirm that there is a positive association, although the results are not conclusive [22,26,31,36,34,35]. Several laboratory studies investigated whether weight status is associated with personal eating rate in adults [37,38,36,39,40]. Most of them found a positive association, the inverse association was not found. Furthermore, there are several cross-sectional studies, predominantly performed in Asian populations, that have investigated whether (self-reported) eating rate is associated with energy intake and BMI. The results indicate that a higher self-reported eating rate is associated with a higher long-term energy intake and a higher BMI [41,42,22,37,43]. Further research is needed to confirm the generalizability of these findings to other populations, and to confirm a causal relation between personal eating rate, energy intake and weight status.

Research has shown that is possible to reduce a person's eating rate and thereby food intake on short-term [18]. Several experimental studies have altered a person's eating rate, either through verbal instructions or prompts from electronic devices, which affected meal intake in the expected direction [18]. Furthermore, some intervention studies investigated whether eating rate could be reduced over a longer period, and thereby also reduce long-term energy intake and body weight [9,44,45]. The interventions consisted of either advice on lowering eating rate or a device that provided assistance with lowering eating rate. Overall the results of these studies are positive. Although the participants that merely received advice were not able to maintain a lower eating rate over time [9]. It, therefore, would be particularly interesting to explore the potential of the devices further.

Food

The oral processing of some foods is more time consuming than that of others. As a result the type of food consumed affects eating rate [46-48]. How long it takes to process a food mainly depends on the degree of structure that needs to be broken down and the degree of lubrication needed before a food is safe to swallow [46-48]. For example, beverages, which have no structure that needs to be broken down and do not need any lubrication, can be readily swallowed and are consumed quickly [48,47,49]. While tough dry meat requires a considerable amount of chewing and lubrication before it is safe to be swallowed and is therefore consumed more slowly [46,47].

Experimental studies have consistently shown that meal intake (g), and thereby energy intake (kcal), can be reduced by replacing a food with a slower alternative (i.e. lower food-specific eating rate) [18,50,47,19,15]. Moreover, research suggests that the consumption of slower foods can reduce long-term energy intake and eventually body weight. Studies have shown that if the energy intake of a single meal is reduced by lowering food-specific eating rate, people do not compensate for it during the remainder of the day [19-21]. Furthermore, intervention studies suggest that the consumption of caloric beverages, which have a high food-specific eating rate [47], contribute to weight gain

[23,24,11]. Moreover, a positive association between the consumption of caloric beverages and BMI has been found [25,24].

To date no intervention studies have been performed that can confirm whether long-term energy intake can be lowered through the consumption of slower foods. We need to get more insight into the current situation first. The availability of slow and fast foods in the diet is still unknown. There are some studies that describe the food-specific eating rate of commonly consumed foods, but the foods described do not represent of a whole diet [51,52,46,47]. Furthermore, it is unknown to what extent the population already eats slow foods.

Eating environment

Literature has shown that the eating environment can affect eating behavior [53-55]. It, for example, has been repeatedly shown that people adjust their intake to that of their eating companion; i.e. eat more when their eating companion eats more and vice versa [56-58]. To our knowledge, however, only little is known about the effect of the eating environment on eating rate. There is research that has shown that people eat faster when they hear fast tempo music, compared to slow tempo music [59,60]. Moreover, people ate faster hearing both the fast and slow tempo music compared to hearing no music [59]. Furthermore, observational research by Hermans et al. [61] indicates that people copy the act of taking a bite from their eating companion. This could affect eating rate. When a person copies the bites of an eating companion, bite frequency—and therefore eating rate—will depend on the bite frequency of the eating companion. This, however, warrants further investigation.

This thesis

As described above, it is now well-established from a variety of experimental studies that short-term energy intake can be reduced by lowering eating rate. Furthermore, results from observational studies have shown that eating rate is positively associated with long-term energy intake and weight status. At this moment, however, evidence from randomized controlled trials confirming a causal relation between eating rate, long-term energy intake and weight status is lacking. This evidence is needed before eating rate can be included in official recommendations and guidelines [62].

In order to perform such a randomized controlled trial we first need to identify an effective approach for lowering long-term eating rate, that would be successful at lowering long-term energy intake and body weight. Hence, the aim of the current thesis was to explore the opportunities for lowering long-term eating rate and their potential to reduce long-term energy intake and body weight.

Chapter 2 and 3 provide more insight into the potential of lowering eating rate, and thereby energy intake and body weight, by targeting the **person**. In Chapter 2 it is investigated whether eating rate is a stable personal characteristic and whether it is associated with long-term energy intake and BMI. In Chapter 3 we explored the feasibility of developing a tool that may be used to alter eating rate.

Chapter 4 and 5 investigate the opportunities for lowering eating rate, and thereby energy intake and body weight, through the **food**. In Chapter 4 we mapped the availability of slow and fast foods in the Dutch diet. In Chapter 5 we investigated to what extent the Dutch population already eats slow foods and explored whether this is associated with long-term energy intake and BMI.

Chapter 6 explores the potential of lowering eating rate, and thereby energy intake and body weight, through the **eating environment**. It describes an experiment that tested whether a person’s bite frequency (i.e. number of bites per minute), and therefore eating rate, is affected by the bite frequency of an eating companion, and whether this has an effect on food intake.

Finally, in **Chapter 7** the findings of the above mentioned studies are discussed, and directions for future research and implications for weight management are provided.

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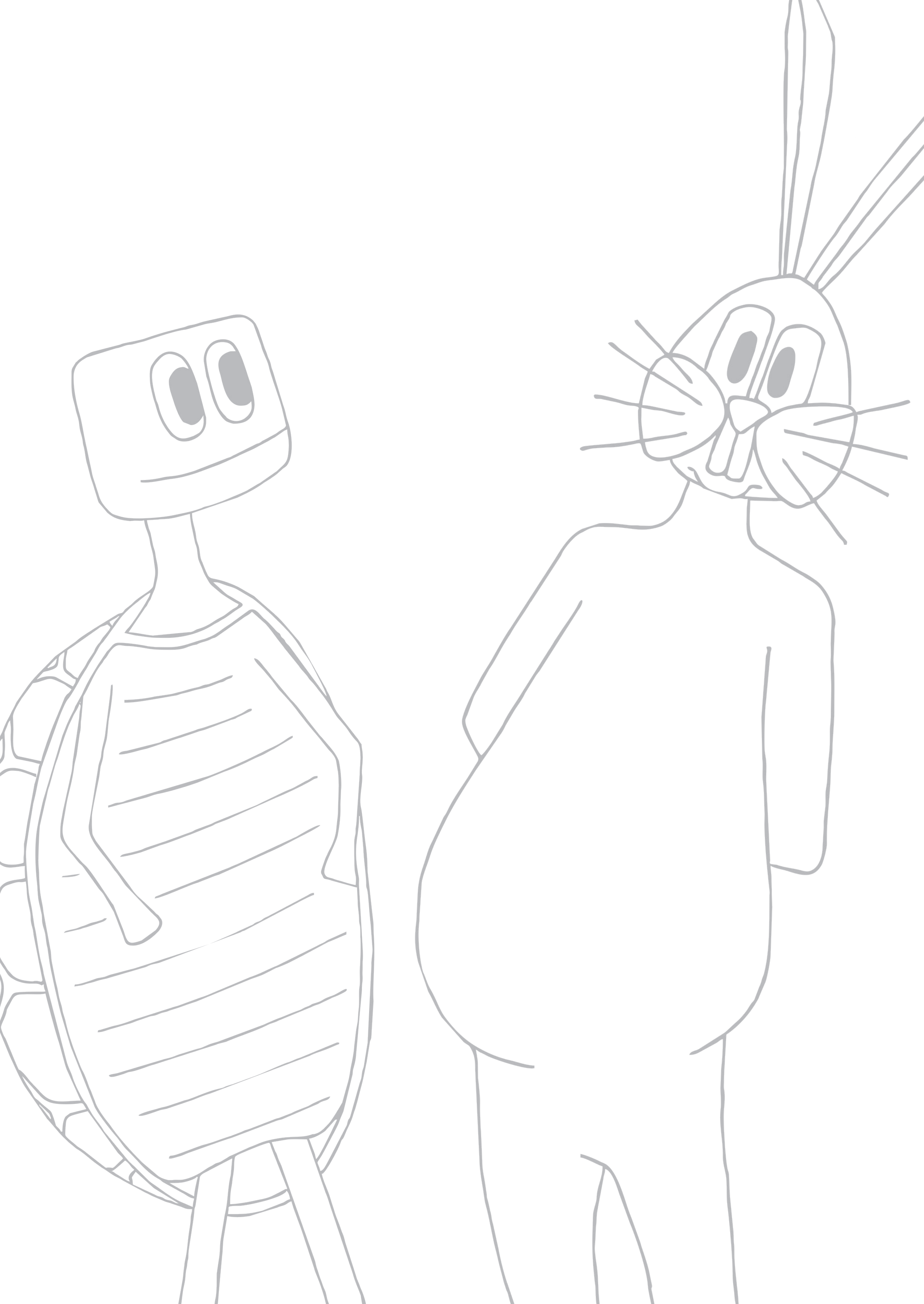
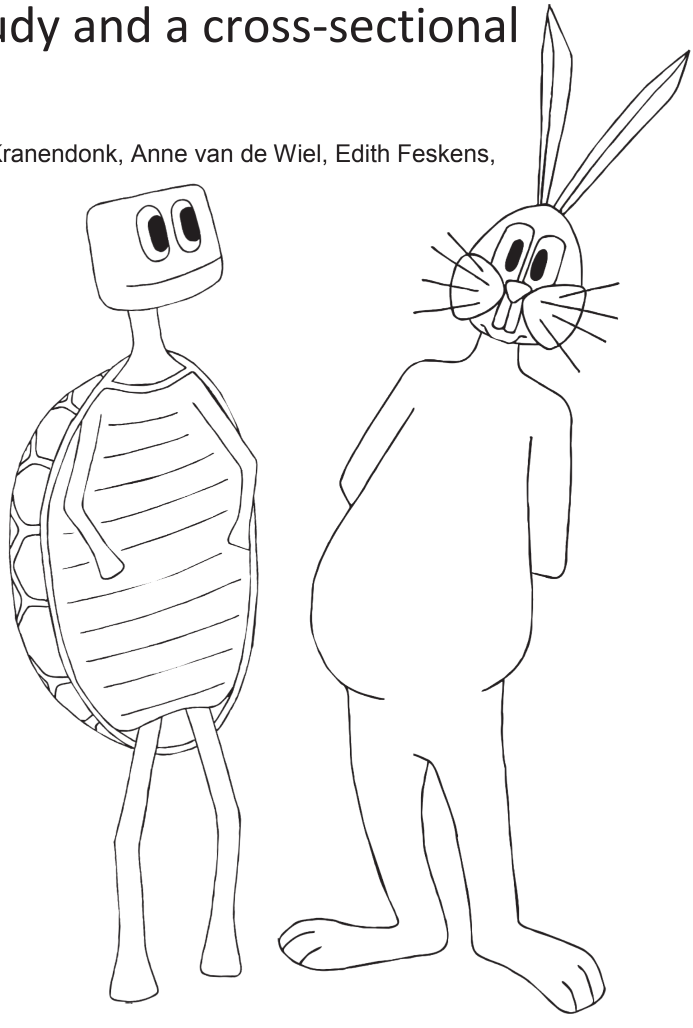
Chapter 1



Chapter 2

Self-reported eating rate is associated with weight status in a Dutch population: A validation study and a cross-sectional study

Janet van den Boer, Jentina Kranendonk, Anne van de Wiel, Edith Feskens, Anouk Geelen, Monica Mars



Published in: International Journal of Behavioral Nutrition and Physical Activity, 2017. 14(1): p.121, doi: 10.1186/s12966-017-0580-1

Abstract

Observational studies performed in Asian populations suggest that eating rate is related to BMI. This paper investigates the association between self-reported eating rate (SRER) and body mass index (BMI) in a Dutch population, after having validated SRER against actual eating rate. Two studies were performed; a validation and a cross-sectional study. In the validation study SRER (i.e. 'slow', 'average', or 'fast') was obtained from 57 participants (men/women=16/41, age: 22.6±2.8 yrs., BMI: 22.1±2.8 kg/m^2) and in these participants actual eating rate was measured for three food products. Using analysis of variance the association between SRER and actual eating rate was studied. The association between SRER and BMI was investigated in cross-sectional data from the NQplus cohort (i.e. 1,473 Dutch adults; men/women=741/732, age: 54.6±11.7 yrs., BMI: 25.9±4.0 kg/m^2) using (multiple) linear regression analysis. In the validation study actual eating rate increased proportionally with SRER (for all three food products *P*<0.01). In the cross-sectional study SRER was positively associated with BMI in both men and women (*P*=0.03 and *P*<0.001, respectively). Self-reported fast-eating women had a 1.13 kg/m^2 (95% CI 0.43, 1.84) higher BMI compared to average-speed-eating women, after adjusting for confounders. This was not the case in men; self-reported fast-eating men had a 0.29 kg/m^2 (95% CI -0.22, 0.80) higher BMI compared to average-speed-eating men, after adjusting for confounders. These studies show that self-reported eating rate reflects actual eating rate on a group-level, and that a high self-reported eating rate is associated with a higher BMI in this Dutch population.

Background

Eating rate, the amount of food consumed per unit of time, has attracted attention for its potential role in preventing and treating obesity [1]. Slower eating is expected to reduce food intake and consequently body weight. Calories that pass quickly through the oral cavity go largely undetected and do not bring about an adequate satiety response, resulting in an increased intake [2]. Moreover, eating rate is a personal characteristic – some people tend to eat faster than others, or vice versa [3-5] – and eating rate could therefore affect long-term energy intake and consequently body weight. A recent meta-analysis has shown that the amount of food eaten can be altered by (experimentally) manipulating eating rate [6]. Furthermore, research indicates that eating rate might affect long-term energy intake and weight status [1,7-9].

The relation between (self-reported) eating rate, energy intake and BMI has been studied in a number of cross-sectional studies, predominantly Asian. The results in general indicate that a higher self-reported eating rate (SRER) is associated with a higher long-term energy intake, though the results are not conclusive [10,11]. Furthermore, a recent study by Fogel et al. [12] showed that the actual eating rate of Singaporean children was positively associated with BMI. Regarding adults, a recent review and meta-analysis by Ohkuma et al. [7] showed that self-reported fast eaters were more likely to be overweight (BMI≥25 kg/m^2) compared to self-reported slow eaters; All studies reported a positive association between eating rate and weight status, although there was a large variation in magnitude of the association. In addition, positive associations have been found between SRER and weight gain in longitudinal studies [13,14]. For example, Tanihara et al. [13] found that male office workers who reported to be fast eaters on average gained 1.9 kg over a period of 8 years while the other male office workers only gained 0.7 kg on average.

This research consistently showed that SRER is associated with energy intake and BMI, but the generalizability of these findings is questionable. The studies in this field of research are limited to Asian populations, predominantly Japanese. To date only Leong et al. [15] investigated the association between SRER and BMI in a non-Asian population (i.e. New Zealand). This study, however, only included women, relied on self-reported data for height and weight, and did not collect data on energy intake. More research is needed to see if similar (positive) associations between SRER, energy intake and BMI exist in non-Asian populations, despite differences in diet, habits and ethnicity [7].

Furthermore, data on the validity of self-reported eating rate is limited [10,16-18]. To our knowledge only Petty et al. [18] validated SRER against actual eating rate (g/min). They showed that, on a group-level, actual eating rate increased with increasing SRER-categories (i.e. slow, medium and fast). They, however, only validated SRER for one food product (i.e. pasta), and they did not address how well SRER reflects the actual eating rate of individuals.

Hence we aimed to validate self-reported eating rate and investigate its relation with energy intake and objectively assessed weight status in Dutch men and women. First we conducted a laboratory study validating self-reported eating rate in three foods varying in structure, after which we analyzed self-reported eating rate and different measures of weight status (i.e. BMI, waist circumference and body fat percentage) in a large, Dutch cohort study (i.e. NQplus [19]).

Methods and materials

Study 1: Validation SRER

Study population and design

Students were recruited through posters at university buildings and student housing in Wageningen. Students who did not like the food products offered were excluded from participation. In total 64 students participated. Seven of them were excluded from the analyses; six because of a technical error and one because of mobile phone usage during the test session.

SRER and actual eating rate were obtained from participants during a single visit to the university in October-November 2013. This allowed for comparison between SRER and actual eating rate within persons. Participants were told that the aim of the study was to pilot test lunch products for another study.

Procedure

Participants were instructed not to eat anything in the two hours prior to their lunch at the university. First they filled out a questionnaire on their eating behavior which included a question on eating rate: "How would you describe your eating rate compared with others? 'Very slow', 'slow', 'average', 'fast' or 'very fast'?". This question was based on previous research [15,10]. Subsequently the participants received three lunch products: first a soft bun with cheese, then apple, and finally vanilla custard. Serving sizes differed between participants. The total lunch offered represented a normal lunch in terms of energy content; i.e. 20% of the daily energy requirement of the individual participants, which was estimated using the Schofield equation while assuming a moderate physical activity level [20,21]. Participants pressed the spacebar of the laptop in front of them with the first bite of a product and again when they swallowed the last bite. The time between pressing the spacebars was recorded, which represents the time spent eating. Intake was measured by weighing the products prior to and after consumption. Actual eating rate was determined by dividing the intake in grams by the time spent eating in minutes for each product separately.

Furthermore, before the consumption of each product and at the end participants rated their level of satiety using visual analogue scales (0-100mm); Feelings of hunger (Not at all-Extremely), fullness (Not at all-Extremely), satiety (Not at all-Extremely), desire to eat (Very weak-Very strong) and prospective consumption (Nothing at all-A very large amount) were rated [22]. Overall satiety scores were calculated by extracting the average of the scores for hunger, desire to eat and prospective consumption from the average of the scores for fullness and satiation [22]. Moreover, after the consumption of each product participants indicated how much they liked the product (1, Dislike very much – 5 Like very much).

Study 2: Association between SRER and weight status

Study population and design

This study investigates data from NQplus, an ongoing cohort study designed to: validate a newly developed FFQ, start a reference database for nutrition research and study associations between diet and intermediate health outcomes [19,23]. The cohort consists of adults (20-70 years old) randomly selected from households in Wageningen, Renkum, Ede, Arnhem and Veenendaal. Participants were recruited via letters and emails between May 2011 and March 2013. In total 2,048 people were included. SRER was available for 1,642 participants; The other participants either did not answer the eating rate question, or dropped out before receiving the question. Finally, 1,473 participants were included in the analyses, as other data (i.e. data on age, smoking, education level, emotional eating, restraint eating, and/or external eating) was missing for 169 out of the 1,642 participants with SRER.

Since registration the participants received a number of questionnaires (which twice included the eating rate question). Additionally, anthropometric measurements were taken. The collected data was used for the cross-sectional analysis of the association between SRER and weight status.

Online questionnaires

General characteristics

At baseline participants reported their highest completed education, which was categorized into three groups; low (i.e. no education, primary education, lower or preparatory vocational education, or lower general secondary education), medium (i.e. intermediate vocational education or apprenticeship, or higher general secondary education or pre-university secondary education) and high (i.e. higher vocational education or university). Additionally, the participants completed a semi-quantitative food frequency questionnaire (FFQ) on last month's intake which was used to calculate average daily energy intake. This FFQ has been found to be valid to assess mean energy intake in large samples and for ranking individuals [24].

Furthermore, the participants received the ‘Dutch Eating Behavior Questionnaire’ (DEBQ) [25]. The DEBQ contains 33 items; 13 items reflect emotional eating, ten items reflect external eating and ten items reflect restrained eating. Average scores were calculated to obtain sub scores for emotional, external and restrained eating. Usual physical activity was assessed using two questionnaires: i.e. the ‘Activity Questionnaire for Adults and Adolescents’ (AQUAA) for sedentary activity [26], and the ‘Short questionnaire to assess health-enhancing physical activity’ (SQUASH) for moderate-to-vigorous activity [27]. Both sedentary and moderate-to-vigorous activity were determined in minutes per week, and were converted to hours per week for the analyses.

Self-reported eating rate

Participants twice received a questionnaire that included the eating rate question (see validation study). The median time in between was 12.1 months. In the analyses we used the SRER off the first time the participants answered the eating rate-question. SRER-data from the second time the participants answered the eating rate-question was only used to test repeatability.

Anthropometrics

Anthropometric measurements were performed twice. The median time in between was 12.9 months. Height was measured, without footwear, to the nearest 0.1 cm using a stadiometer (SECA, Hamburg, Germany). Weight was measured to the nearest 0.1 kg using a digital scale (SECA, Hamburg, Germany), after taking of footwear and heavy clothes and removing heavy items from the pockets. Waist circumference was measured between the lowest rib and the iliac crest to the nearest 0.5 cm using a non-elastic flexible tape (SECA, Hamburg, Germany), after removing thick clothes from that area. This measurement was performed twice and the average of those measurements was used for analyses. Finally, body fat percentage was measured using a DEXA-scan (Lunar Prodigy Advance; GE Healthcare, Madison, Wisconsin, United States).

For the current analyses we used the anthropometric data of the visit closest to the first time the eating rate-question was answered. On average there were 165 (±91) days between answering the eating rate-question for the first time and the anthropometric measurements.

Statistical analyses

SPSS (IBM SPSS Statistics, Version 20, IBM Corporation, Armonk, NY, USA) was used for the statistical analyses. Means and standard deviations are given, unless stated otherwise. *P*-values of <0.05 were considered statistically significant. Normality was judged by visual inspection using QQplots; all data were normally distributed.

SRER was split into three categories for the analyses, as in both studies only few participants reported to be a very slow or very fast eater; The 'very slow' category was combined with the 'slow'-category and the 'fast' category with the 'very fast'-category.

<u>Study 1: Validation SRER</u>

By means of analysis of variance it was investigated whether there was a linear trend between SRER and actual eating rate. Post-hoc analyses (Gabriel's procedure) were performed to identify differences in actual eating rate between SRER-categories. To investigate how well SRER reflects the actual eating rate of individuals, the level of agreement between SRER and tertiles of actual eating rate was determined by calculating kappa (κ) (i.e. chance-corrected proportional agreement) [28].

Furthermore, correlation analyses were performed to investigate the association between the eating rate of the lunch products, between eating rate and liking, and between eating rate and satiety. Independent t-tests were performed to investigate whether eating rate differed between men and women.

<u>Study 2: Association between SRER and weight status</u>

Data were analyzed for the total population and for men and women separately, as both eating rate and BMI are sex-dependent [29,30]. Kappa (κ) was calculated to assess the level of agreement between answers of participants that answered the eating rate-question on two separate occasions [28]. One-way analyses of variance, independent samples T-tests and chi-square tests were performed to check whether the participant characteristics (e.g. weight status and intake) differed between males and females and between the SRER-categories. Linear regression analysis was performed to investigate whether there was a linear trend between the SRER-categories and participant characteristics.

Furthermore, multiple linear regression analyses were performed to investigate the association between SRER and BMI with adjustment for potential confounders. First a crude model was tested with two dummy variables of SRER; one for comparing fast with average eating rate, one for comparing slow with average eating rate. In a second model age, smoking and education level were added. In the third and main model DEBQ-scores (i.e. emotional, restrained and external eating) were added. In an additional model, 'Model X', energy intake, moderate-to-vigorous activity and sedentary activity were added to the main model. Suspected under reporters of energy intake (i.e. reported energy intake / calculated basal metabolic rate < 1.35 [31]) were excluded. Due to the exclusion of suspected under reporters and missing data 'Model X' is based on a small subset of the total sample, and is therefore not considered to be the main model. Furthermore, it was investigated whether there was a linear trend between the SRER-categories and BMI in the different models by replacing the dummy variables with the categorical variable for SRER.

Finally, odds ratios for overweight (i.e. BMI ≥ 25kg/m^2) were determined for self-reported fast eaters (compared to self-reported slow plus average-speed eaters) by means of logistic regression analyses, taking into account potential confounders (i.e. age, smoking, education level, emotional eating, restrained eating and external eating).

Results

Study 1: Validation SRER

In total 57 (men/women=16/41) participants (22.6±2.8 years old, self-reported BMI of 22.1±2.8 kg/m^2) were included. Eleven participants reported to be a slow eater (i.e. very slow (n=1) or slow (n=10)), 27 participants reported to be an average speed eater, and 19 participants reported to be a fast eater (i.e. fast (n=18) or very fast (n=1)). Eating rate (g/min) increased proportionally with SRER for all three lunch products (bread with cheese $F(1, 51)=10.45$, $P<0.01$; apple $F(1, 43)=12.79$, $P<0.01$; vanilla custard $F(1, 49)=13.12$, $P<0.01$) (Figure 1). Post-hoc analyses showed that eating rate was significantly higher in self-reported fast eaters compared to self-reported slow and average-speed eaters, but did not differ between self-reported slow and average-speed eaters.

The level of agreement between SRER and actual eating rate-tertiles was fair; for all three lunch products a κ-value of 0.25 was found [28]. Within all lunch products actual eating rate-tertiles corresponded with SRER in 50% of the cases, while in about 10% of the cases the actual eating rate-quartiles and SRER showed the opposite; e.g. indicated to be a slow eater, while actual eating rate was in the highest tertile.

Furthermore, how fast participants consumed one lunch product was correlated with how fast they ate the other lunch products (bread with cheese x apple, r=.54 P<0.001; bread with cheese x vanilla custard, r=.50 P<0.001; apple x vanilla custard, r=.69 P<0.001). Liking was correlated with eating rate in vanilla custard (r=.37, P<0.01), but not in bread with cheese (r=-.02, P=0.90) and apple (r=.16, P=.28). Moreover, eating rate was not associated with the satiety score at the start of consumption for all three lunch products (bread with cheese, r=-.13 P=0.37; apple, r=.07 P=0.66; vanilla custard, r=-.12 P=0.41). Finally, men ate all three lunch products faster than women (bread with cheese t(52)=-4.84, P<0.001; apple t(44)=-6.22, P<0.001, vanilla custard t(50)=-4.65, P<0.001).

Study 2: Association between SRER and weight status

Data from 741 men and 732 women is included in the main analyses (Table 1). On average, men were 57.5±10.6 years old and had a BMI of 26.4±3.5 kg/m^2 whereas women were 51.8±12.0 years old and had a BMI of 25.3±4.4 kg/m^2. Collectively, ages ranged from 21.7-77.0 yrs. old and BMI from 16.8-57.6 kg/m^2 for the two groups.

Table 1 Characteristics of the men and women participating in NQplus

	Men			Women			*P*
	n	Mean	SD	n	Mean	SD	
Age (yrs.)	741	57.5	10.6	732	51.8	12.0	<0.001*
Height (cm)	741	180.4	6.8	732	168.6	6.3	<0.001*
Weight (kg)	741	86.0	12.8	732	71.8	13.2	<0.001*
BMI (kg/m^2)	741	26.4	3.5	732	25.3	4.4	<0.001*
Waist circumference (cm)	737	96.9	10.7	731	85.8	11.6	<0.001*
Body fat percentage (%)	683	24.7	6.6	613	34.9	7.7	<0.001*
Energy intake (MJ/day)	691	9.5	2.6	654	7.8	2.1	<0.001*
Energy intake (MJ/day) ‡	288	11.7	2.1	296	9.4	1.6	<0.001*
Emotional eating score	741	1.94	0.65	732	2.28	0.74	<0.001*
Restrained eating score	741	2.87	0.73	732	3.13	0.68	<0.001*
External eating score	741	2.70	0.43	732	2.71	0.45	0.48*
Moderate-to-vigorous activity (hours/week)	696	33.9	18.5	666	35.3	16.9	0.13*
Sedentary activity (hours/week)	696	36.6	21.0	666	36.4	34.0	0.90*
		n	%		n	%	
Prevalence of overweight§		460	62.1		322	44.0	<0.001†
Prevalence of obesity		118	15.9		91	12.4	0.06†
Self-reported eating rate							<0.001†
Very slow		5	0.7		13	1.8	
Slow		54	7.3		104	14.2	
Average		315	42.5		408	55.7	
Fast		316	42.6		183	25.0	
Very fast		51	6.9		24	3.3	
Education level¶							0.58†
Low		111	15.0		122	16.7	
Medium		217	29.3		219	29.9	
High		413	55.7		391	53.4	
Smoking status							0.07†
Non-smoker		664	89.6		676	92.3	
Smoker		77	10.4		56	7.7	

* Independent samples T-test; † Chi-square test; ‡ Suspected under reporters (i.e. reported energy intake / calculated basal metabolic rate < 1.35) excluded; § BMI ≥25kg/m^2; BMI ≥30kg/m^2 ; ¶ Education level: low (i.e. no education, primary education, lower or preparatory vocational education, or lower general secondary education), medium (i.e. intermediate vocational education or apprenticeship, or higher general secondary education or pre-university secondary education) and high (i.e. higher vocational education or university)

Table 1 shows the prevalence of all five SRER-categories in men and women. The SRER-categories were distributed differently for men and women (chi-square, *P*<0.001); compared to women, men more often reported to be fast eaters. Furthermore, 931 participants (men/women=458/473) answered the eating rate question twice (Table 2). A κ-value of 0.64 was found for the level of agreement between the answers to both questions.

Table 2 Frequency of self-reported eating rate-categories (SRER) in participants that answered the eating rate question twice*

		SRER second time				
		Very slow	Slow	Average	Fast	Very fast
SRER first time	Very slow	13	3	0	0	0
	Slow	5	87	23	2	0
	Average	0	36	367	58	0
	Fast	1	0	49	226	18
	Very fast	0	0	2	18	23

* κ-value = 0.64

Table 3 and 4 show the characteristics of the participants by SRER-category (i.e. slow, average, fast). A positive linear association was found between BMI and SRER-category in both men (r=.08, *P*=0.03) and women (r=.16, *P*<0.001). Also waist circumference and body fat percentage showed a positive association with SRER in women (waist circumference r=.10, *P*<0.01; body fat percentage r=.14, *P*<0.001), but not in men (waist circumference r=.01, *P*=0.74; body fat percentage r=.01, *P*=0.71). In addition SRER was positively associated with moderate-to-vigorous activity, restrained eating and external eating in men, and positively associated with emotional, restrained and external eating in women.

Table 3 Characteristics (mean±SD) of the participants by self-reported eating rate-category, within the total population and in men and women separately

	Self-reported eating rate									*P*	*P*
	Slow			Average			Fast			ANOVA	linear trend
	n	mean	SD	n	mean	SD	n	mean	SD		
Total											
Age (yrs.)	176	53.0	13.1	723	55.1	11.0	574	54.6	12.1	0.11	.42
BMI (kg/m^2)	176	24.8	4.1	723	25.5	4.0	574	26.6	3.9	<0.001	<0.001
Waist circumference (cm)	175	88.2	13.1	721	90.4	12.3	572	93.6	12.2	<0.001	<0.001
Body fat percentage (%)	145	29.9	9.0	647	30.2	8.6	504	28.6	8.8	0.01	0.01
Energy intake (MJ/day)	158	8.4	2.3	662	8.5	2.4	525	8.9	2.7	<0.01	<0.01
Energy intake (MJ/day) *	75	9.9	1.8	300	10.2	2.0	209	11.3	2.4	<0.001	<0.001
Emotional eating	176	2.13	0.69	723	2.06	0.71	574	2.17	0.73	0.02	0.09
Restrained eating	176	2.86	0.79	723	3.01	0.72	574	3.03	0.69	0.03	0.03
External eating	176	2.61	0.48	723	2.67	0.42	574	2.78	0.43	<0.001	<0.001
Moderate-to-vigorous activity (h/day)	164	35.4	19.5	663	33.8	17.0	535	35.4	18.0	0.24	0.53
Sedentary activity (h/day)	164	37.6	35.0	663	35.5	29.0	534	37.4	24.4	0.45	0.68
Men											
Age (yrs.)	59	57.9	10.7	315	58.2	10.0	367	56.7	11.1	0.16	0.10
BMI (kg/m^2)	59	25.7	3.9	315	26.3	3.4	367	26.7	3.5	0.09	0.03
Waist circumference (cm)	58	96.1	10.9	314	97.0	10.7	365	96.9	10.7	0.82	0.74
Body fat percentage (%)	52	23.8	6.9	294	24.9	6.8	337	24.7	6.4	0.56	0.71
Energy intake (MJ/day)	54	10.0	2.4	295	9.3	2.5	342	9.5	2.8	0.25	0.89
Energy intake (MJ/day) *	27	11.5	1.6	125	11.4	2.0	136	12.0	2.2	0.04	0.03
Emotional eating	59	2.01	0.68	315	1.85	0.61	367	2.01	0.67	<0.01	0.053
Restrained eating	59	2.65	0.79	315	2.84	0.75	367	2.92	0.69	0.02	<0.01
External eating	59	2.62	0.48	315	2.64	0.42	367	2.76	0.43	0.001	<0.001
Moderate-to-vigorous activity (h/day)	57	31.5	19.0	298	32.6	17.8	341	35.4	18.9	0.10	0.04
Sedentary activity (h/day)	57	37.6	19.4	298	35.0	18.8	341	37.8	22.9	0.23	0.30
Women											
Age (yrs.)	117	50.6	13.5	408	52.7	11.1	207	50.8	12.9	0.09	0.75
BMI (kg/m^2)	117	24.4	4.2	408	25.0	4.3	207	26.4	4.6	<0.001	<0.001
Waist circumference (cm)	117	84.2	12.4	407	85.3	10.9	207	87.6	12.3	0.02	<0.01
Body fat percentage (%)	93	33.2	8.3	353	34.6	7.4	167	36.5	7.7	<0.01	<0.001
Energy intake (MJ/day)	104	7.6	1.8	367	7.8	2.0	183	7.8	2.3	0.58	0.39
Energy intake (MJ/day) *	48	9.0	1.1	175	9.4	1.5	73	9.8	1.9	0.02	<0.01
Emotional eating	117	2.19	0.69	408	2.22	0.73	207	2.45	0.74	0.001	<0.001
Restrained eating	117	2.97	0.77	408	3.4	0.66	207	3.21	0.65	<0.01	<0.001
External eating	117	2.60	0.48	408	2.69	0.43	207	2.82	0.44	<0.001	<0.001
Moderate-to-vigorous activity (h/day)	107	37.5	19.5	365	34.7	16.4	194	35.3	16.4	0.31	0.41
Sedentary activity (h/day)	107	37.7	41.1	365	35.9	35.2	193	36.6	27.0	0.90	0.87

* Suspected under reporters (i.e. reported energy intake / calculated basal metabolic rate < 1.35) excluded

Table 4 Frequency of participant characteristics by self-reported eating rate-category, within the total population and in men and women separately

	Self-reported eating rate						P
	Slow		Average		Fast		chi-square
	n	%	n	%	n	%	test
Total*							
Prevalence of overweight§	75	42.6	354	49.0	353	61.5	<0.01
Prevalence of obesity	18	10.2	89	12.3	102	17.8	<0.01
Prevalence of smoking	19	10.8	56	7.7	58	10.1	0.23
Education level¶							0.19
Low	29	16.5	126	17.4	78	13.6	
Medium	44	25.0	220	30.4	172	30.0	
High	103	58.5	377	52.1	324	56.4	
Men†							
Prevalence of overweight§	29	49.2	196	62.2	235	64.0	0.09
Prevalence of obesity	6	10.2	48	15.2	64	17.4	0.33
Prevalence of smoking	6	10.2	31	9.8	40	10.9	0.71
Education level¶							0.37
Low	12	20.3	52	16.5	47	12.8	
Medium	13	22.0	92	29.2	112	30.5	
High	34	57.6	171	54.3	208	56.7	
Women‡							
Prevalence of overweight§	46	39.3	158	38.7	118	57.0	<0.001
Prevalence of obesity	12	10.3	41	10.0	38	18.4	0.01
Prevalence of smoking	13	11.1	25	6.1	18	8.7	0.16
Education level¶							0.46
Low	17	14.5	74	18.1	31	15.0	
Medium	31	26.5	128	31.4	60	29.0	
High	69	59.0	206	50.5	116	56.0	

* Slow, n=176; Average, n=723; Fast, n=574

† Slow, n=59; Average, n=315; Fast, n=367

‡ Slow, n=117; Average, n=408; Fast, n=207

§ BMI ≥25kg/m^2

BMI ≥30kg/m^2

¶ Education level: low (i.e. no education, primary education, lower or preparatory vocational education, or lower general secondary education), medium (i.e. intermediate vocational education or apprenticeship, or higher general secondary education or pre-university secondary education) and high (i.e. higher vocational education or university)

In both men and women SRER was not associated with energy intake before excluding participants suspected of under reporting energy intake (Table 3). In total, 754 participants (men/women=399/355) were identified as underreporting their energy intake. After excluding these participants SRER was positively associated with energy intake in men (r=.13, *P*=0.03 (n=296)) and women (r=.17, *P*<0.01 (n=288)). In turn, energy intake was positively associated with BMI in men and women after excluding suspected under reporters and adjusting for sedentary and moderate-to-vigorous activity; regression coefficients were 0.28 kg/m^2 /MJ (95% CI: 0.12, 0.44) for men and 0.55 kg/m^2 /MJ (95% CI: 0.30, 0.79) for women (men/women=273/281).

Model 3 in Table 5 shows the associations between SRER-categories and BMI after adjusting for age, smoking, education level, emotional eating, restrained eating, and external eating. BMI was 1.13 kg/m^2 higher in self-reported fast-eating women compared to self-reported average-speed-eating women. The BMI of self-reported slow-eating women was not significantly different from that of self-reported average-speed-eating women. In men the BMI of both self-reported slow- and fast-eaters was not significantly different from that of self-reported average-speed-eaters. The relation between SRER and BMI was not significantly different between men and women (interaction effect in multiple linear regression: P=0.06). Furthermore, when energy intake, moderate-to-vigorous activity and sedentary activity were added to the main model, the results remained similar (men/women=273/281) (Table 5, Model X).

Finally, self-reported fast eaters were at higher risk to be overweight (i.e. BMI ≥ 25kg/m^2) compared to the other participants (i.e. self-reported average- plus slow-speed eaters) with an adjusted odds ratio of 1.73 (95% CI: 1.38, 2.17). Within women this adjusted odds ratio was 2.05 (95% CI: 1.44, 2.91), while within men this was 1.13 (95% CI: 0.82, 1.56). These odds ratios were not significantly different for men and women (interaction effect in logistic regression: P=0.09).

Table 5 Association between self-reported eating rate (SRER) and BMI within the total population and in men and women separately according to multiple linear regression analysis and linear trend analyses

Independent variables	Model 1*		Model 2†		Model 3‡		Model X§	
	Partial regression coefficient	95 % CI or *P*	Partial regression coefficient	95 % CI or *P*	Partial regression coefficient	95 % CI or *P*	Partial regression coefficient	95 % CI or *P*
Total		(n=1473)		(n=1473)		(n=1473)		(n=554)
SRER-categories								
Slow	-0.69	(-1.35, -0.03)	-0.57	(-1.22, 0.08)	-0.48	(-1.11, 0.15)	-0.47	(-1.20, 0.27)
Average	0.00	(reference)	0.00	(reference)	0.00	(reference)	0.00	(reference)
Fast	1.03	(0.59, 1.47)	1.09	(0.66, 1.52)	0.90	(0.48, 1.32)	0.58	(0.05, 1.10)
Linear trend		<0.001		<0.001		<0.001		<0.01
Men		(n=741)		(n=741)		(n=741)		(n=273)
SRER-categories								
Slow	-0.57	(-1.55, 0.41)	-0.56	(-1.51, 0.40)	-0.47	(-1.40, 0.47)	-0.42	(-1.49, 0.65)
Average	0.00	(reference)	0.00	(reference)	0.00	(reference)	0.00	(reference)
Fast	0.40	(-0.14, 0.93)	0.51	(-0.001, 1.03)	0.29	(-0.22, 0.80)	0.28	(-0.38, 0.94)
Linear trend		0.03		<0.01		0.08		0.18
Women		(n=732)		(n=732)		(n=732)		(n=281)
SRER-categories								
Slow	-0.56	(-1.46, 0.34)	-0.44	(-1.34, 0.45)	-0.24	(-1.11, 0.63)	-0.34	(-1.36, 0.67)
Average	0.00	(reference)	0.00	(reference)	0.00	(reference)	0.00	(reference)
Fast	1.40	(0.67, 2.14)	1.51	(0.78, 2.23)	1.13	(0.43, 1.84)	0.71	(-0.15, 1.56)
Linear trend		<0.001		<0.001		<0.01		0.06

* Crude model; † Crude model with age, smoking and level of education; ‡ Crude model with age, smoking, level of education, emotional eating, restrained eating and external eating; § Crude model with age, smoking, level of education, emotional eating, restrained eating, external eating, energy intake, moderate-to-vigorous activity and sedentary activity (excl. suspected under reporters of energy intake; i.e. reported energy intake / calculated basal metabolic rate < 1.35)

Discussion

In these studies self-reported eating rate was validated against actual eating rate, and the association between self-reported eating rate (SRER) and weight status was investigated in a Dutch population. The validation study confirmed that self-reported eating rate was positively associated with actual eating rate. The cross-sectional data from the NQplus cohort showed that self-reported eating rate was positively associated with BMI among both men and women. After adjusting for confounders self-reported eating rate remained significantly associated with BMI in women; fast eaters had on average a 1.13 kg/m^2 higher BMI compared to average-speed eaters. In men this relation was no longer significant after adjusting for confounders; nonetheless, the direction of the association was still in the expected direction. Overall, self-reported fast eaters were more likely to be overweight compared to self-reported non-fast eaters.

These findings are in line with previous studies investigating the association between SRER and weight status. In the current study the adjusted odds ratio for being overweight, comparing self-reported fast eaters to non-fast eaters, was 1.73 (95% CI: 1.38, 2.17); where Ohkuma et al. [7] found a pooled odds ratio of 2.15 (95% CI, 1.84-2.51) in their meta-analysis. This shows that previous findings from Asian populations may translate to non-Asian populations. The current study was the first to investigate this association in a non-Asian population that included men and objectively measured height, weight, waist circumference and body fat percentage.

Eating rate is expected to affect weight status via energy intake. If people eat fast, calories pass through the oral cavity quickly, are not sensed and do not bring about an adequate satiety response, resulting in an increased intake [32-36]. The current findings are in line with this. After excluding suspected under reporters, energy intake was positively associated with BMI. More importantly, energy intake was positively associated with SRER. Previous studies also found positive relations between energy intake and SRER, although not always statistically significant. More accurate measurements of energy intake might reveal stronger relations between energy intake, SRER and BMI. The problem with dietary assessment methods is that the measurement error depends on BMI; overweight people are more likely to underreport energy intake [24]. Excluding under-reporters does not completely resolve this issue.

Furthermore, the validation study confirms that on a group level self-reported eating rate reflects actual eating rate in young adults. Actual eating rate increased proportionally with SRER-categories, and like Petty et al. [18], we found that actual eating rate was significantly higher in self-reported fast eaters compared to self-reported slow and average-speed eaters. We assumed that these findings will also translate to older adults, as eating rate appears to be a stable personal characteristic [3-5]. Moreover, we did not find an association between SRER and age in the cross-sectional study.

However, when examining the results of the validation study at the individual level, only half of the participants correctly classified themselves according to their actual eating rate. The kappa-values showed that after correcting for chance the remaining agreement between SRER and tertiles of actual eating rate was only 25%, which is considered 'fair' [28]. As such, SRER might not be a good measure for actual eating rate at the individual level. In the cross-sectional study, however, SRER was used as a measure of eating rate on a group-level. Furthermore, this imperfect agreement between SRER and actual eating rate might mean that the results of the cross-sectional analysis underestimate the true association between eating rate and BMI.

Different explanations exist for the agreement between SRER and actual eating rate being only fair. First, people might not be aware of their eating rate, although this does not seem to be the case. There is good agreement between the answers of people that answered the eating rate question twice, which shows that they have a fixed image of their eating rate. Second, people might interpret eating rate differently than scientists. Third, people are limited to their own observations to evaluate their eating rate and that of others. People do not monitor their eating rate like scientists would: i.e. using a stopwatch and kitchen scale. So how do they answer the eating rate-question? They, for example, could base their answer on how long it takes them to finish one portion or the length of their meals. Finally, they could use different people as a reference.

More intervention studies are needed to investigate if there is a causal relation between (self-reported) eating rate and BMI, and whether this is mediated by long-term energy intake. Based on evidence from experimental studies, these intervention studies should focus on increasing oral sensory exposure time. Some interventions targeting eating rate have already been examined. Spiegel et al. [1] included advice on reducing eating rate in a weight loss program. Participants successfully reduced eating rate, which resulted in weight loss. However, the slower eating rate was not maintained over time. McGee et al. [8] performed a four-month intervention with an 'oral volume restriction device'. This device was worn in the upper palate during a meal, which reduced bite size and thereby eating rate. Participants that used the device most lost more weight. Further advancements could be made by using new technologies, which offer useful tools for both monitoring and altering eating rate. The SPLENDID-system and 10SFork constitute examples of such new technologies [37,38]. Both provide real-time feedback on eating rate. Usage of such technologies seems to be the logical next step for future research.

Conclusions

The two current studies showed that 1) self-reported eating rate reflects actual eating rate on a group-level, but not at the individual level, and 2) that self-reported fast eating is associated with a higher BMI in a Dutch, adult population, although this association was more pronounced in women. Lowering eating rate might be a promising strategy in tackling obesity. However, first more empirical evidence is needed to confirm the causal relationship between (self-reported) eating rate and BMI, and to show the effectiveness of interventions targeting eating rate.

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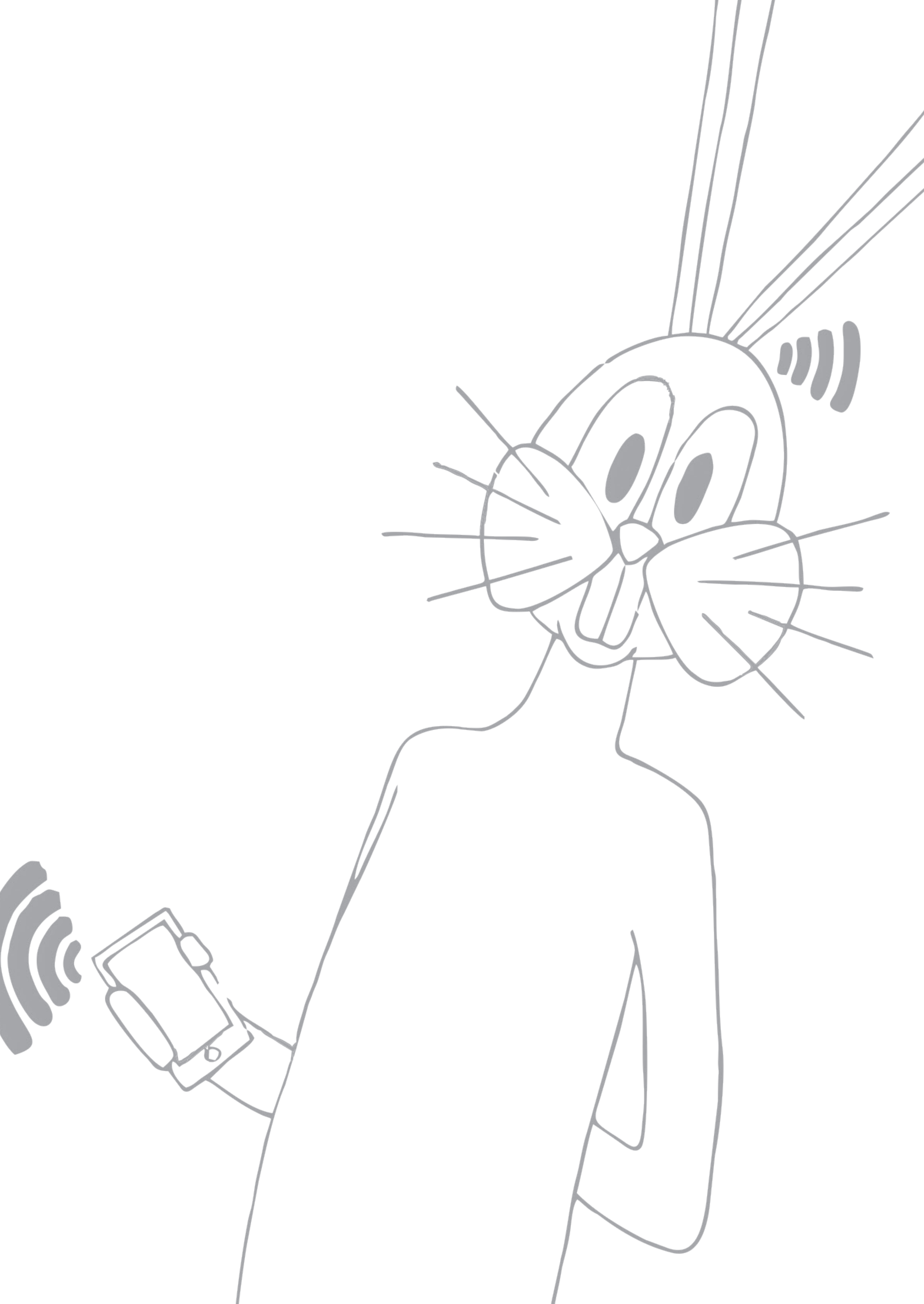

Chapter 3

The user-informed development of the SPLENDID eating detection sensor

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In preparation

Abstract

The available methods for monitoring food intake—which for a great part rely on self-report—often provide biased and incomplete data. Currently, no good technological solutions are available. Hence, the SPLENDID eating detection sensor (i.e. an ear-worn device) was developed to enable complete and objective measurements of eating events. The technical performance of this device has been described before. To date, literature is lacking a description of how such a device is perceived and experienced by potential users. The current paper describes how potential users perceived and experienced the SPLENDID eating detection sensor during the different stages of its development. Potential users evaluated the eating detection sensor at different stages of its development: 1) At the start twelve health professionals (e.g.dieticians or personal trainers) were interviewed and a focus group was held with five potential end-users (m/w=0/5, age: 22±2 yrs., BMI: 22.5±1.9 kg/m2) to find out about their thoughts on the concept of the eating detection sensor. 2) Preliminary prototypes of the eating detection sensor were tested in a laboratory setting where 23 participants (m/w=13/10, age: 23±3 yrs., BMI: 22.6±3 kg/m2) reported their experiences. 3) The first wearable version of the eating detection sensor was tested in a semi-controlled study where 22 young, overweight adults (m/w=3/19, age: 23±2 yrs., BMI: 28.0±2.3 kg/m) used the sensor on two days and reported their experiences. 4) The final version of the sensor was tested in a 4-week feasibility study by 20 young, overweight adults (m/w=4/16, age: 25±2 yrs., BMI: 28.8±2.8 kg/m2) who reported their experiences. Most individuals were enthusiastic about the concept across the different stages of development. It, however, was stressed multiple times that it is critical that the device is discreet and comfortable to wear for a longer period of time. The experiences of the potential users with the eating detection sensor show that some participants would like the sensor to be less noticeable, but that especially the wearer comfort of the device needs to be further improved. In the final study, the eating detection sensor received a grade of 3.7 for wearer comfort, on a scale of 1 to 10. Moreover, experienced discomfort was the main reason for wearing the eating detection sensor less than two hours a day. The participants reported to have used the eating detection sensor on, on average, 19 out of 28 days. The SPLENDID eating detection sensor is a promising new device that can facilitate the collection of reliable food intake data, as shown by its technical potential, which has been described before. Potential users are enthusiastic, but in order to be successful the wearer comfort and discreetness of the device need to be improved.

Introduction

Background

The available methods for monitoring food intake—which for a great part rely on self-report—often provide biased and incomplete data [1-5]. Depending on the exact method used they require people to eat consciously, to be knowledgeable on what they eat, to be able to estimate portion size, and to remember all that information. As a result, these methods are prone to underreporting. It is common for people to report an unrealistically low energy intake: i.e. an energy intake that is too low to sustain their body at a low level of physical activity [6-9]. Current technological advances enable the development of tools that can facilitate the collection of reliable food intake data.

Currently there are some devices available that can be used to increase the reliability of food intake monitoring. The Mandometer®, for example, could be used to measure the size of meals. It is a weighing scale that is placed underneath the plate during a meal [10]. Furthermore, a number of wearable devices have been developed that can automatically detect eating (e.g.[11-14]). These are mostly ear- and neck-worn devices. They use sensors (e.g.a microphone or strain sensor) to collect signals that contain information on whether or not a person is eating. Pattern-recognition algorithms are used to extract this information.

Especially the devices that can detect eating events have the potential to reduce the issue of underreporting. Such a device can take away the need for people to be conscious about their eating. Moreover, this information can be used to prompt people to report what they are eating at the moment they are eating it. It can thereby also take away the need for people to remember what they ate. There, however, is not yet a device for the automatic detection of eating that is practical for everyday use, despite the progress made in this area. They, for example, require people to accurately position a sensor on the body with tape, or require people to wear items like glasses or a hat to carry the functional parts [13,15,16].

SPLENDID eating detection sensor

With the development of the SPLENDID eating detection sensor we aimed to take the next step in the development of a device for the automatic detection of eating events. It was decided to go with an ear-worn device as this was expected to be acceptable for the end-users. In the future it could be incorporated into the devices people are already using, such as earphones used for listening to music.

During the development of this ear-worn device different options were considered for signal collection:

- An air microphone placed at the beginning of the ear canal that measures sounds produced by chewing [17-19].
- A bone conduction microphone on the cheekbone just in front of the ear that measures the vibrations in the bone produced by chewing [20,21].
- A photoplethysmogram (PPG) sensor placed on the ear that measures the blood volume in the tissue of the ear which is affected by chewing activity [18,19,22]. This technique has never before been used for this application

Moreover, another device, i.e. the 'datalogger', was added to the eating detection sensor to make it wearable. It houses a datalogger, a battery and an accelerometer. It is connected to the eating detection sensor with a cable and is worn in the trouser pocket or on a belt. Furthermore, the eating detection sensor, together with the datalogger, was integrated in a larger system for added functionality (**Figure 1**).

This system includes, amongst others, a smartphone application and a webtool. The smartphone application can prompt the user to report detected eating events. A webtool can provide an overview of the recorded eating events. Furthermore, goals regarding a healthy eating pattern can be entered in this webtool. The smartphone application can then help the end-user to achieve these goals by providing real-time feedback when the eating detection sensor is worn. This system is used under the supervision of a health professional.

Current paper

The ability of the eating detection sensor to detect eating events has been described before [17-19,22]. The current paper describes how potential users were involved in the development of the SPLENDID eating detection sensor and provides qualitative results on how the potential users perceived and experienced this device. We consider two types of potential users: health professionals and end-users. Health professionals, in this paper, are people that deal with weight management professionally and could potentially facilitate the use of the eating detection sensor. The considered end-users are young adults, although the eating detection sensor may be used by a wider population in the future.

The sensor was evaluated at different stages of its development:

- Study 1, Concept SPLENDID eating detection sensor: At the start health professionals (n=12) were interviewed and a focus group was held with potential end-users (n=5) to find out about their thoughts on the concept.
- Study 2, Preliminary prototypes eating detection sensor: The first prototypes of the eating detection sensor were tested in a laboratory setting. The participants reported their experiences with the sensors.
- Study 3, First wearable version eating detection sensor: The next version of the eating detection sensor was tested in a semi-controlled study where young, overweight adults used the sensor on two days and reported their experiences.
- Study 4, Integrated version of the eating detection sensor: Finally, the eating detection sensor was tested in a 4-week feasibility study where young, overweight adults used the eating detection sensor in combination with other devices (see Figure 1) and reported their experiences.

The paper is structured accordingly.

Figure 1 The SPLENDID eating detection sensor integrated in the full SPLENDID system. This system combines the eating detection sensor with a datalogger/accelerometer, the Mandometer®, a smartphone application and a web tool. Together these components function as a 'wearable personal coach': i.e. a system that actively monitors eating behaviour and physical activity, and provides personalized feedback [23,24]. This system was developed within SPLENDID, and EU-funded ICT project.

Methods study 1: Concept SPLENDID eating detection sensor

At the start of the development potential users were asked about their thoughts on concept of the eating detection sensor: Health professionals were interviewed, and a focus group was held with potential end-users.

Interviews with health professionals

Twelve health professionals who had experience with weight management in their work (e.g.dietician or personal trainer) were interviewed face-to-face. First the concept was explained to them and subsequently they were asked about their views on different aspects of the concept. All interviews were recorded and later transcribed and systematically analyzed.

Focus group with potential end-users

A focus group was held with five young women (age: 22±2 yrs., BMI: 22.5±1.9 kg/m^2) interested in weight management. First the concept was explained to them and subsequently they were asked open-ended questions to facilitate discussion. The focus group was recorded and later transcribed and systematically analyzed.

Results study 1: Concept SPLENDID eating detection sensor

Interviews with health professionals

A device like the eating detection sensor was new to all health professionals (n=12), but some did already have some experience with an app (n=5) or accelerometer (n=4). In general the health professionals were enthusiastic about the eating detection sensor. Some were a bit sceptical at first (n=4), but after talking and thinking about it a bit more also they thought the sensor could be very useful in gaining insights into the users eating pattern. The users, however, need to forget that they are wearing the eating detection sensor

"The first thing I thought was: this is a bit excessive (...). But when thinking about myself when I am for example cooking, I unconsciously eat some food. People forget to write that down, so this could be very useful"

"An important thing is that end-users should 'forget' that they are wearing it. Then you will get a good overview of their eating patterns"

Furthermore, they stressed that the eating detection sensor should be reliable and accurate, should not cost them too much time, and should come with a clear protocol on how to work with it.

Focus group with potential end-users

The participants were already familiar with all kinds of smartphone applications to record food intake. They were enthusiastic about what the eating detection sensor has to add. One of the participants mentioned that it will help her when she 'secretly' eats something and this will give good insight in her eating pattern. The participants, however also had some concerns regarding the eating detection sensor. It should be made sure that it is comfortable to wear for a long time, and it should not be too noticeable.

Methods study 2: Preliminary prototypes eating detection sensor

When the preliminary prototypes for the eating detection sensor were developed these were tested in a laboratory setting [17]. Pictures of these prototypes are shown in **Figure 2**. One prototype uses an in-ear air microphone (a), another one a bone conduction microphone (b) and the last one a photoplethysmogram (PPG) sensor (c). With these prototypes it was yet not possible to move around freely.

Figure 2 Preliminary prototypes of the eating detection sensor: a) in-ear air microphone, b) bone conduction microphone, c) photoplethysmogram (PPG) sensor

Twenty-three healthy, young adults (m/w=13/10, age: 23±3 yrs., BMI: 22.6±3 kg/m^2) tested the prototypes. They visited the university for a test session of ca. 1.5 hour. During this session all three prototypes were worn simultaneously by the participants while they consumed a variety of foods and did some other activities such as talking. Afterwards the participants received a questionnaire on their experiences with the sensors.

This study was approved by the Medical Ethical Committee of Wageningen University (NL 48839.081.14).

Results study 2: Preliminary prototypes eating detection sensor

For wearer comfort the in-ear air microphone received an average grade of 6.7 (range: 2-9) on a scale of 1 to 10, the bone conduction microphone an average grade of 5.8 (range: 2-10), and the PPG sensor an average grade of 6.7 (range: 4-9). The grade for wearer comfort did not differ significantly between the prototypes (ANOVA, P=.13).

The participants indicated they would be able to wear the in-ear air microphone on average for 5.7 (range: 0-24) hours, the bone conduction microphone on average for 5.6 (range: 0.5-24), and the PPG sensor on average for 5.4 (range: 4-9) hours. This did not differ significantly between the prototypes (ANOVA, P=.99).

The most frequently mentioned remarks regarding the in-ear air microphone were that the sensor was comfortable to wear (n=18), but that it lowered their hearing (n=10) and that they would get tired of the sensor after wearing it for longer period of time (n=15). Regarding the bone conduction microphone they most frequently mentioned that it remained unnoticed while wearing (n=10), that the sensor could be annoying during exercise (n=9), and that the sensor put pressure on their head and neck (n=5). Often mentioned remarks for the PPG were that they did not notice that they were wearing the sensor (n=11), that the sensor lowered their hearing (n=6) and that the cable of the sensor was pulling and annoying (n=4).

Regarding the prototypes in general, the most frequently mentioned barrier for wearing them in real-life is that they are very noticeable and oddly shaped (n=8). In turn, the most common mentioned wishes were that they would need to be as invisible as possible (n=13) and that they need to be comfortable (n=10).

Methods study 3: First wearable version eating detection sensor

A year later the first wearable version of the eating detection sensor was tested in a semi-controlled study [18,19,22]. It is a commercial earhook in which both the in-ear air microphone and PPG sensor were incorporated (**Figure 3**). Also a magnet was included to ensure that the PPG sensor was positioned properly. Furthermore, the datalogger was added to the eating detection sensor to make it wearable (see 'Introduction' and **Figure 3**). The combination of the in-ear air microphone, the PPG sensor and the accelerometer incorporated in the datalogger enables more accurate detection of eating events [19].

Figure 3 First wearable version of the eating detection sensor (Left: only the eating detection sensor, Right: the eating detection sensor and the datalogger)

Twenty-two overweight, young adults (m/w=3/19, age: 23±2 yrs., BMI: 28.0±2.3 kg/m^2) tested the wearable eating detection sensor. They participated in two testing days. They arrived just before lunch (i.e. 11.00 h) and left after they had dinner (i.e. ±18.00 h). At these testing days they performed common, daily-life activities (incl. snacking) while wearing the eating detection sensor. Furthermore, the participants filled out some questionnaires on user comfort.

This study was approved by the Medical Ethical Committee of Wageningen University (NL52100.081.15).

Results study 3: First wearable version eating detection sensor

The participants graded the wearer comfort of the chewing sensor on average with a 3.8 (range: 2-7) on a scale of 1 to 10. Furthermore, participants indicated that on average they would be able/willing to wear the chewing sensor for 3.9 hours (range: 2-7 hours). Some participants, however, mentioned that they would be able to wear it for a longer time if there would be breaks in between.

There was large variation in the answers of the participants regarding how the chewing sensor affected eating, moving and talking. Most participants, agreed with the statement that the chewing sensor was bothering them: 19 out of the 20 participants scored higher than 5 on a 9-point Likert scale (1= Totally disagree, 5= Neutral, 9=Totally agree)).

The most frequently mentioned remarks regarding the wearer comfort of the eating detection sensor were: “the chewing sensor was painful to the ear” (n=16), “the cable was annoying/hindering” (n=14), “the sensor reduced hearing" (n=8) and “internal noises were heard better” (n=5). Three participants mentioned to have experienced no or only little discomfort.

Methods study 4: Integrated version of the eating detection sensor

Finally, the eating detection sensor was tested in a 4-week feasibility study by young, overweight adults. The eating detection sensor had now been integrated in a larger system (**Figure 1 & 4**). Furthermore, to increase wearer comfort the size of the datalogger and plug had been reduced (**Figure 5**). The eating detection sensor was virtually unchanged, and because of the known issues with wearer comfort the participants only had to wear it for 2 hours a day.

Figure 4 Integrated version of the SPLENDID eating detection sensor with its datalogger

Figure 5 Old version and new, smaller version of datalogger (left) and plug (right)

Twenty overweight, young adults (m/w=4/16, age: 25±2 yrs., BMI: 28.8±2.8 kg/m^2) motivated to adopt healthier behavior participated in the four-week feasibility study. During the first week the participants used the system to assess their baseline eating behavior. Based on the observed behavior personal goals were set for the following three weeks regarding number of snacks. During these three weeks the participants received personalized feedback through the smartphone application to help them achieve these goals. Afterwards they reported their experiences.

This study was approved by the Medical Ethical Committee of Wageningen University (NL56853.081.16).

Results study 4: Integrated version of the eating detection sensor

Nineteen out of the twenty participants experienced discomfort from the eating detection sensor; they started experiencing discomfort after on average 1 hour and 20 minutes. The participants graded the wearer comfort of the eating detection sensor on average with a 3.7 (range: 1-7) on a scale of 1 to 10. Moreover, they scored the statement "The sensor bothered me" on average with a 5.5 (range: 4-7) on a scale from 1 ('totally disagree') to 7 ('totally agree').

The participants reported to have used the eating detection sensor, on average, on 19 out of the intended 28 days, of which they used it for at least 2 hours on 17 days. During the first week compliance was highest; in this week they, on average, used the eating detection sensor on 6 days. The most frequently mentioned reasons for wearing the sensor less than 2 hours were discomfort (n=14) and technical issues (e.g.broken sensor) (n=8) (**Table 1**). Furthermore, if they used the sensor they used it on average for 1.9 hours (range: 1-4 hours) on average.

Table 1 Reasons mentioned for wearing the eating detection sensor less than 2 hours, and their frequency

Reason	Frequency
Discomfort	14
Technical issues (e.g.broken sensor)	8
Reduced hearing	6
Impractical (e.g.with sports)	6
Inappropriate (e.g.at work)	3
Noticeable	1
Forgotten	1
Not enough time	1

Regarding reactions from the social environment the participants gave mixed results. They scored the statement "People in my environment noticed the sensor" on average with a 3.4 (range: 1-7), and the statement "I did not like it when people noticed the sensor" on average with a 3.4 (range: 1-7) on a scale from 1 ('totally disagree') to 7 ('totally agree').

The most frequently mentioned additional comments were that the cable is not practical (n=7), that the sensor got noticed (n=7) and that the sensor reduced their hearing (n=5) (**Table 2**). Furthermore, some participants indicated that they did not see the added value of the sensor, since they believe they do not need the sensor to remind them to enter the foods consumed and the detections are not always accurate.

Table 2 Additional remarks regarding the eating detection sensor and their frequency

Additional remarks	Frequency
Cable is not practical	7
The eating detection sensor got noticed	7
The eating detection sensor reduced hearing	5
The eating detection sensor was uncomfortable	4
Experienced technical issues with the eating detection sensor	4
Had to explain what the eating detection sensor is	3
Inappropriate to use in certain situations	3
Added value of eating detection sensor unclear	3
Received no reactions from environment	2
Received positive reactions from environment	2
Experienced no problems	2
Looks like listening to music	2
Not practical	1

Discussion

Principal Results

The current paper describes how potential users were involved in the development of the SPLENDID eating detection sensor and provides qualitative results on how the potential users perceived and experienced this device. Across the different stages of development, the potential users were enthusiastic about the concept. They especially liked that it provides objective information on your eating pattern. They, however, stress that it needs to be comfortable to wear and discreet. The current version of the eating detection sensor did not yet meet these requirements.

In order for the eating detection sensor to meet the user requirements further improvements need to be made. Especially the wearer comfort of the eating detection sensor requires attention. After wearing the sensor for a while (i.e. on average after 80 minutes) the potential users started to experience discomfort. As a result they graded the wearer comfort of the eating detection sensor with a 3.7 on a scale of 1 to 10 in the final study. Moreover, the experienced discomfort was the main reason for the participants to wear the eating detection sensor less than two hours.

One option would be to offer different shapes and sizes of the eating detection sensor, so the users can find a sensor with a good fit. This would also improve the ability of the device to detect eating events. The current eating detection sensor fit some people better than others, which is reflected in the wide range in grades for wearer comfort (i.e. 1-7 for the last version, on a scale from 1 to 10). Another option would be to reduce the size of the eating detection sensor and to make it more like a hearing aid. These are made to be worn throughout the day, unlike earphones. It needs to be investigated what is technically feasible.

By resolving the issues with wearer comfort the visibility of the eating detection sensor is likely to be reduced as well. Furthermore, the visibility of the current version of the eating detection sensor was already acceptable for some of the participants. It was mentioned that, even though people in the environment notice the eating detection sensor, they do not recognize it as such as it looks like a device for listening to music. This is a major advantage of the ear-worn devices over some of the other devices that are being developed for the detection of eating events (e.g.neck-worn devices, or a device mounted onto eyeglasses)[14,25-27].

It would be interesting to repeat the feasibility study once the eating detection sensor has been improved on wearer comfort and visibility. The SPLENDID eating detection sensor is a device with great potential, as shown by its technical performance [17-19,22]. It could help provide a more complete picture of food intake, which is a major issue with the current methods for monitoring food intake [1-4,6-9].

Limitations

In the feasibility study, due to the issues with wearer comfort, the participants were asked to wear the eating detection for at least 2 hours, while it is intended to be used throughout the day. This will have affected the user experience. As was mentioned by the health professionals, people need to forget that they are wearing the eating detection sensor. Because the participants only used the eating detection sensor for on average 1.9 hours a day and started to experience some discomfort after a while, they might not have been able to forget that they are wearing the eating detection sensor.

If the participants of the feasibility study would have been less conscious about the fact that they are wearing the eating detection sensor they probably would also have been less conscious about their eating, and then the added value of the eating detection sensor would have been more evident. For some of the participants (i.e. 15%) the added value of the eating detection sensor was now unclear. They did not feel that they needed such a sensor to remind them to report the foods consumed.

Comparison with Prior Work

To our knowledge this is the first paper to describe how an ear-worn device for the detection of eating events is received by potential users and to describe their experiences with such a device in real-life. It shows that ear-worn devices for the detection of eating events need to meet high standards in order to be acceptable for everyday use.

When tested in a laboratory setting the eating detection sensor received a sufficient grade for wearer comfort, while it received an insufficient grade when it was tested in real-life. Moreover, the participants did not experience discomfort as soon as they started wearing the eating detection sensor; only after 80 minutes they experienced discomfort from the eating detection sensor. It is important to keep this in mind when interpreting results from laboratory studies.

Conclusions

The SPLENDID eating detection sensor is a promising new device that can facilitate the collection of reliable food intake data, as shown by its technical potential, which has been described before. Furthermore, potential users are enthusiastic about it. They especially like that it provides objective information on your eating pattern. However, in order to be successful, the wearer comfort and discreetness of the device need to be improved. Therefore, further development should mainly focus on the design of the hardware.

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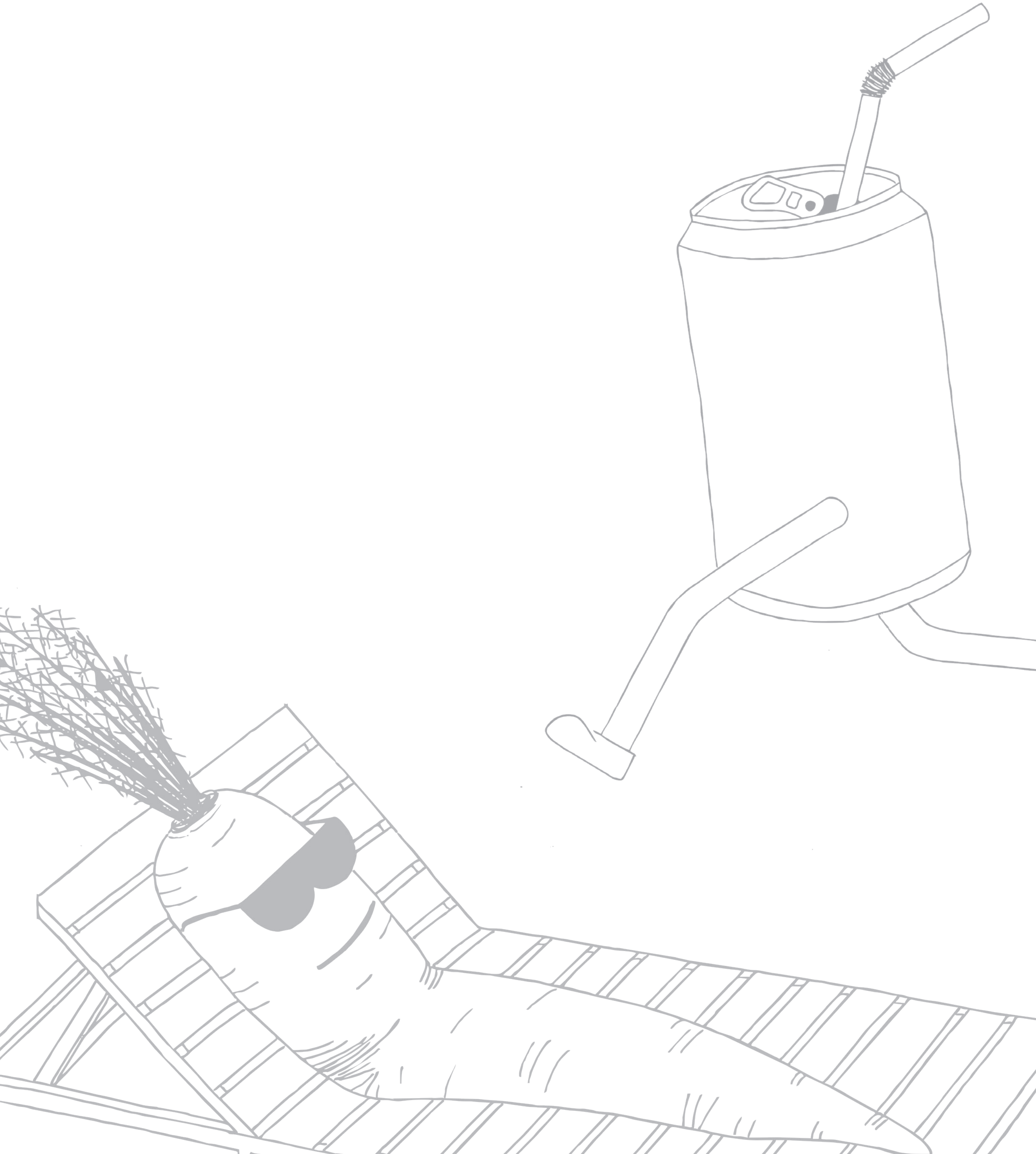

Chapter 4

The availability of slow and fast calories in the Dutch diet: The current situation and opportunities for interventions

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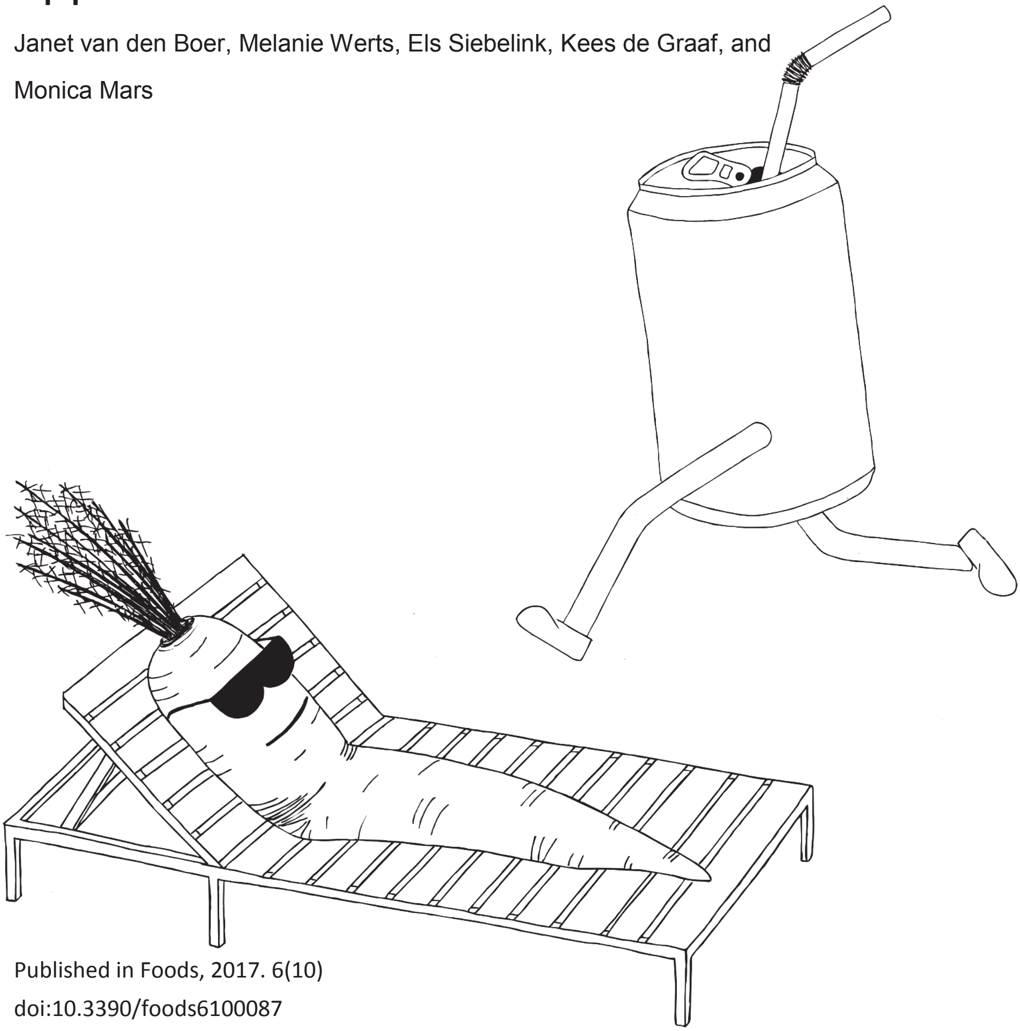

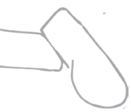

Published in Foods, 2017. 6(10)
doi:10.3390/foods6100087

Abstract

Choosing foods that require more time to consume and have a low energy density might constitute an effective strategy to control energy intake, because of their satiating capacity. The current study assessed the eating rate of Dutch food, and investigated the associations between eating rate and other food properties. We also explored the opportunities for a diet with a low energy intake rate (kJ/min). Laboratory data on the eating rate of 240 foods—representing the whole Dutch diet—was obtained. The results show a wide variation in both eating rate (from 2 g/min for rice waffle to 641 g/min for apple juice) and energy intake rate (from 0 kJ/min (0 kcal/min) for water to 1766 kJ/min (422 kcal/min) for chocolate milk). Eating rate was lower when foods were more solid. Moreover, eating rate was positively associated with water content and inversely with energy density. Energy intake rate differed substantially between and within food groups, demonstrating that the available foods provide opportunities for selecting alternatives with a lower energy intake rate. These findings offer guidance when selecting foods to reduce energy intake.

Introduction

Choosing foods that require more time to consume (i.e. foods with a low eating rate) might constitute an effective strategy to control energy intake [1-3]. Experimental studies have consistently shown that food (g) and energy (kJ) intake can be altered by manipulating eating rate (e.g. [4,3]). Moreover, literature indicates that a high eating rate is associated with a higher body mass index (BMI) [5,6]. It is hypothesized that when calories pass quickly through the oral cavity they do not bring about an adequate satiety response, resulting in an increased food and energy intake and eventually a higher BMI [7-10].

How quickly calories pass through the oral cavity also depends on the energy density of foods, which is another well-established predictor of energy intake [11,12]. Multiplying the eating rate with the energy density of foods is therefore expected to result in an even a stronger predictor of energy intake: "energy intake rate" (kJ/min). A recent experiment by McCrickerd*,* et al. [13] investigated the combined and separate effect of manipulating the eating rate and energy density of foods on energy intake using a 2 × 2 design. Their results show that the combined manipulation (i.e. rice porridge with a low eating rate and low energy density) is more effective at reducing energy intake than the individual manipulations alone (i.e. rice porridge with either a low eating rate, or a low energy density). These results demonstrate the added value of energy intake rate.

There is, however, limited information available on the eating rate—and therefore energy intake rate—of commonly consumed foods. Most studies that report the eating rate of foods involved manipulated or model foods [e.g. 14,15,16]. To our knowledge there are a few studies that have measured the eating rate of commonly consumed foods [17,18,2,3]. Viskaal-van Dongen et al. [3] measured the eating rate of 45 foods commonly consumed in the Netherlands. Forde et al. [17] measured the eating rate of 35 solid, savory meal components. Ferriday et al. [18] measured the eating rate of 20 different commercially available pre-packaged meals. Finally, Forde et al. [2] measured the food-specific eating rate of 47 commonly consumed Singaporean foods. These datasets, although substantial, do not represent a whole diet, nor did they consider the energy intake rate of the foods. Therefore the first aim of the current study was to assess the eating rate and energy intake rate of the foods commonly consumed in The Netherlands.

The second aim was to map the characteristics of slow and fast foods by investigating the associations between food-specific eating rate and other food properties (i.e. texture, food composition, and taste) in the obtained dataset. Moreover, this will provide more insight in the characteristics of slow and fast calories. Based on the literature solids were expected to have a lower eating rate when the texture is harder and drier, and liquids were expected to have a lower eating rate when viscosity is increased [15,16,19]. With regards to food composition, water content was expected to be positively associated with eating rate, while energy density and fiber content were expected to be negatively associated with eating rate [3,2]. Regarding taste eating, rate was expected to be inversely associated with taste intensity [2,20].

The third aim was to explore the opportunities for choosing foods with a low energy intake rate within the limits of the current Dutch diet. To this aim we tried to identify groups of food that differed in energy intake rate, within food groups, hereby investigating the possibility to vary in energy intake rate within the Dutch diet. Previous studies have indicated that the available foods will provide variation in both eating rate and energy density [3,2,18,1]. This suggests that it might be possible to design a diet low in energy intake rate given the available variation in energy intake rate.

Summarizing, the current paper will provide new insights regarding the eating rate and energy intake rate of commonly consumed foods. It will show (1) the variation in eating rate and energy intake rate across the Dutch diet, (2) the characteristics of slow and fast foods, and (3) the variation in energy intake rate present within food groups. This information could serve as a starting point when designing an intervention to reduce energy intake through the selection of foods with a low energy intake rate.

Materials and methods

A database was built with the eating rate of foods representing the whole Dutch diet (Appendix A, Table A1). First laboratory measurements were performed to obtain the eating rate of 192 foods. This dataset was then expanded with existing data on the eating rate 48 foods. Finally, information on texture, food composition and taste were added.

Building the eating rate database

Laboratory measurements

The eating rate of 192 foods was assessed in a laboratory setting. Every food was eaten by at least four participants while the time spent eating and amount eaten was recorded. Furthermore, three reference foods—eaten twice by all participants—were included to correct the eating rate data for the personal eating rate of the participants.

Foods

The foods were selected to reflect the Dutch diet with the help of a research dietician. To arrive at this selection the following aspects were considered: contribution to energy intake of Dutch population [21], representation of the different food groups, variation in texture, taste and macronutrient composition, and representation of different eating occasions (e.g. breakfast, snack). First a list was created with the foods reported in the Dutch national food consumption survey 2007–2010, sorted on their contribution to energy intake. The foods that contributed most to energy intake were included. It was then checked whether the obtained list covered the different food groups, the available variation in texture, taste and macronutrient composition, and different eating occasions.

The amount offered to the participants differed between foods, but in general they were smaller than commonly consumed servings. Together with a dietician it was decided on appropriate amounts, using standard portion sizes [22] as a starting point; the portions had to allow for multiple bites or sips, but not constrain further consumption. Finally, the participants were offered 12–65 g of solid foods, 75 g of semi-solid foods and 125 g of liquid foods. Furthermore, the foods were offered with cutlery where appropriate (e.g. yoghurt was offered with a spoon).

Reference foods

Three foods were selected to serve as a reference food and were offered twice to all participants. These were used to correct the eating rate data for the personal eating rate of the participants (see 2.1.1.5). The reference foods were apple (cultivar Elstar; 50 g), whole-wheat bread (AH Zaanse snijder volkoren heel, Albert Heijn BV.; 35 g (1 slice)) and semi-skimmed yoghurt (AH Milde yoghurt halfvol, Albert Heijn BV.; 75 g). These were selected because they cover different textures and are commonly consumed.

Participants

In total 89 healthy, normal weight, young adults (BMI 18.5–25 kg/m^2, 18–30 years old) were recruited through posters, social media and e-mail; the e-mails were sent to a list of people interested in participating in studies at the Division of Human Nutrition (Wageningen University).

People who indicated to be interested in participation were invited to attend an information meeting. Here they received further information, and if they decided to participate they were asked to provide oral and written consent. Subsequently they were asked to have their height and weight measured and to fill out some questionnaires (including food allergies and intolerances, liking of foods under study, and problems with chewing or swallowing). People could not participate if they could not eat the reference foods because of allergies or intolerances (n = 3), did not like the reference foods (n = 1), or experienced problems with chewing or swallowing (n = 0).

Afterwards eligible participants were contacted and three test sessions were scheduled with each of the participants; additionally some participants (n = 32) were later asked to attend an extra test session, to fill in gaps that resulted from missing or unusable measurements. The final group of participants (n = 89) consisted of 69 females and 20 males, which were 21.2 ± 1.9 years old and had a BMI of 21.4 ± 1.9 kg/m^2.

This study was approved by the medical ethical committee of Wageningen University (NL47315.081.13), and was conducted according to the guidelines laid down in the declaration of Helsinki.

Procedure

Test sessions were scheduled in November–December 2016 during lunchtime for every participant at a fixed time with approximately one week between test sessions. Participants were not assigned to a session during which foods were offered that they were not familiar with or disliked (i.e. a score below 3 on a five-point Likert scale; 1, Dislike – 3, Neutral – 5, Really like). Furthermore, participants were asked not to eat or drink anything other than water in the two hours before a test session. A test session took approximately 30 min.

During a test session participants (generally five) were seated in sensory booths with a computer screen in front of them. They first received some questions regarding their satiety level. They were asked when they last had something to eat or to drink (other than water), and to indicate on a ten-point Likert scale their level of hunger (1, Not hungry at all – 10, Very hungry), level of fullness (1, Not full at all – 10, Very full), and their desire to eat (1, Very weak – 10, Very strong) [23].

Subsequently the participants were offered five foods. During their first and third session these included all three reference foods. The other foods were randomly assigned to a session. It, however, was made sure that the foods assigned to a single session offered variation in texture and taste. Furthermore, the order in which the foods were offered was randomized over participants.

Participants were instructed (both orally and in writing) to consume the foods like they normally would but without stops between bites or sips. Once they swallowed a bite or sip, they immediately had to take the next one. It was also allowed to take the next bite or sip before they had cleared their mouths. Furthermore, participants had to click on a button on the computer screen in front of them when taking the first bite or sip of a product. They could stop once they had finished the offered portion, or when two minutes had elapsed. When two minutes had elapsed (in 34% of the times a food was offered), a screen would appear with the instructions to stop after finishing the last bite or sip. In both cases, the participants had to again click on a button once they had swallowed the last bite or sip. The time between clicking the buttons was recorded, which represents the time spent eating. Afterwards participants were asked to indicate how much they liked the product on a nine-point Likert scale (1, Not tasty at all – 9, Very tasty) and to neutralize their pallet with water and a cracker. One minute later they could request the next product.

After completing this procedure for all five products the participant were again asked to rate their level of hunger, level of fullness, and their desire eat on a ten-point Likert scale [23]. Finally, the participants were asked to report any comments (e.g. if they failed to follow instructions); Adherence to the instructions was not directly monitored. Furthermore, the amount eaten was measured by weighing the foods prior to and after consumption.

Calculating food-specific eating rate and energy intake rate

The observed eating rate (g/min) was determined by dividing the amount eaten (g) by the time spent eating (min). This number was then calibrated to correct for the personal eating rate of the participant; the observed eating rate was divided by a calibration factor based on how fast the participant ate the reference foods relative to the rest of the participants.

$$\text{Calibration factor} = \frac{\left(\frac{\text{mean ER bread (participant)}}{\text{mean ER bread (group)}}\right)+\left(\frac{\text{mean ER apple (participant)}}{\text{mean ER apple (group)}}\right)+\left(\frac{\text{mean ER yoghurt (participant)}}{\text{mean ER yoghurt (group)}}\right)}{3}$$

The eating rate of the tested foods was then determined by averaging the calibrated eating rates. Finally, energy intake rate (kJ/min) was obtained by multiplying eating rate (g/min) with the energy density (kJ/g) of the corresponding product.

Additional eating rate data

Data on the eating rate of 48 foods was derived from two other studies performed at Wageningen University to maximize the final dataset. In both studies normal-weight, young adults were instructed to eat as they normally would, but without stops between bites or sips. In one of the studies participants consumed one food per test session, and regardless of the food they had to finish 50 g [3]. The data from this study was calibrated, like in the current study, to correct for the personal eating rate of the participants. Calibration was based on how fast the participants ate two reference foods: i.e. semi-skimmed yoghurt and whole-wheat bread. In the other study participants consumed 6 products per test session (unpublished results). They received 50 g portions for semi-solids and solids, and 125 g portions for liquids. The data from this study did not need calibration as all products were consumed by all participants (n = 25).

Data on other food properties

Texture

All foods were assigned to a texture category using the definitions used by Stieger and van de Velde [19]:

- Liquids: Foods that flow and do not require chewing before swallowing (e.g. milk, beverages, yoghurt drinks);
- Semi-solids: Foods that are predominantly processed by squeezing them between tongue and palate, without the use of the molars (e.g. pudding, custard);

- Soft solids: Foods that require (initial) chewing between the molars, but do not have crispy sensations (e.g. cheese, processed meat);
- Hard solids: Crispy foods that require chewing between the molars and generally produce an acoustic sound emission during oral processing (e.g. crackers, raw vegetables, apples).

One researcher assigned the texture categories to all foods, and in case of doubt the categorization was discussed with a second researcher.

Food composition

Information on food composition (i.e. energy-, protein-, fat-, carbohydrate-, monosaccharide-, disaccharide-, polysaccharide-, fiber-, water- and sodium-content) was derived from the Dutch Food Composition Database. This database contains food composition data of foods commonly consumed in the Netherlands (Dutch Food Composition Database version 5.0, Dutch National Institute for Public Health and the Environment, Bilthoven, The Netherlands). In this database it is assumed that fiber contributes to the energy content of foods: i.e. 8 kJ/g.

Taste

The taste intensities were retrieved from a study that used a trained sensory panel to score over 400 foods on sweet, sour, bitter, umami, salt and fat taste intensity using visual analogue scales [24-26]. Scores ranged from 0–100, with a higher score indicating a more intense taste.

Food groups

The foods were categorized into EPIC-Soft food groups (i.e. food groups developed for the European Prospective Investigation into Cancer and Nutrition (EPIC) study) to help describe the foods under study [27].

Recommended foods

The Netherlands Nutrition Centre uses the “Wheel of Five” to communicate the Dutch food-based recommendations to the public [28,29]. This Wheel of Five shows the type of foods needed to ensure the intake of the required nutrients. An online tool was used to see whether individual foods were part of the Wheel of Five (i.e. recommended foods), or not (i.e. not-recommend foods) [30].

Categorization of foods according to energy intake rate within food groups

The obtained dataset was manually inspected to identify groups of foods that distinguish themselves, based on their energy intake rate, from the other foods within the food group. First the foods were sorted on energy intake rate. The resulting list was then inspected to see whether certain foods tended to have higher or lower energy intake rate compared to the other foods within food group. These foods could be grouped based on any shared feature related to eating rate and/or energy density like, preparation/conservation method and food composition. For example, energy intake rate might differ between raw, boiled and fried foods; these preparation methods have the potential to affect both eating rate and energy density.

Statistical analyses

SAS version 9.4 (SAS Institute Inc., Cary, NC, USA) was used for the statistical analyses. Means and standard deviations are given, unless stated otherwise. p values of <0.05 were considered statistically significant.

To validate the calibration factor analyses of variance was used to check whether the eating rate of the participants divided by the group mean was the same between the reference foods. With paired samples *t*-tests it was investigated whether there was a differences in eating rate the first and second time the participants were offered the reference foods, and whether the satiety scores were different before and after the test sessions. Pearson correlation analysis was performed to see if eating rate was correlated with liking.

Secondly, the associations between eating rate and energy intake rate and food properties were investigated both in the whole dataset and in the dataset after excluding liquids. Quartiles were created for both eating rate and energy intake rate. Linear regression analyses were performed to investigate whether there was a linear trend between the eating rate and energy intake rate quartiles, and food properties (i.e. eating rate, energy intake rate, food composition and taste intensities). Chi-square tests were performed to see whether food properties (i.e. texture, food groups and recommended foods) were distributed differently over the eating rate and energy intake rate quartiles. Furthermore, Pearson correlation analysis was used to assess the correlation between eating rate and energy intake rate and food properties: i.e. food composition and taste intensities. These correlation analyses were repeated after excluding the eating rate data from previous studies. Non-parametric tests were performed to investigate whether eating rate and energy intake rate differed between the texture groups. The Kruskal-Wallis test was used to see if the median was significantly different between texture groups, and the Jonckheere-Terpstra test was used to see whether there was a linear trend. Moreover, with the use of independent samples *t*-test it was investigated whether eating rate and energy intake rate differed between recommended and not-recommended foods.

Results

Descriptives

The final dataset consisted of 240 foods; 192 from the current study, 37 from the study by [3], and 11 from the unpublished study (Figure 1 and Table A1 (Appendix A)). The dataset covers a wide variety of foods (Appendix A, Tables A2 and A3). The eating rate of the included foods ranged from 2 g/min (i.e. rice waffle) to 641 g/min (i.e. apple juice), and their energy intake rate ranged from 0 kJ/min (0 kcal/min) (i.e. water) to 1766 kJ/min (422 kcal/min) (i.e. full fat, chocolate-flavored milk).

Figure 1a displays the eating rate quartiles of the foods in the dataset. The food groups “Cereals and cereal products”, “Sugar and confectionary” and “Cakes” were predominantly present in the first eating rate quartile, while “Non-alcoholic beverages”, “Dairy products”, and “Soups, bouillon” were predominantly present in the fourth eating rate quartile (Appendix A, Table A2).

Figure 1b displays the energy intake rate quartiles. The food groups “Vegetables” and “Soups, bouillon” were predominantly present in the first quartile, while “Dairy products”, “Cakes” and “Snacks” were predominantly present in the higher quartiles (Appendix A, Table A2). Furthermore, within the “Non-alcoholic beverages” there was a clear divide; all non- and very low-caloric beverages were present in the first energy intake rate quartile, while the rest of the beverages were predominantly present in the fourth energy intake rate quartile.

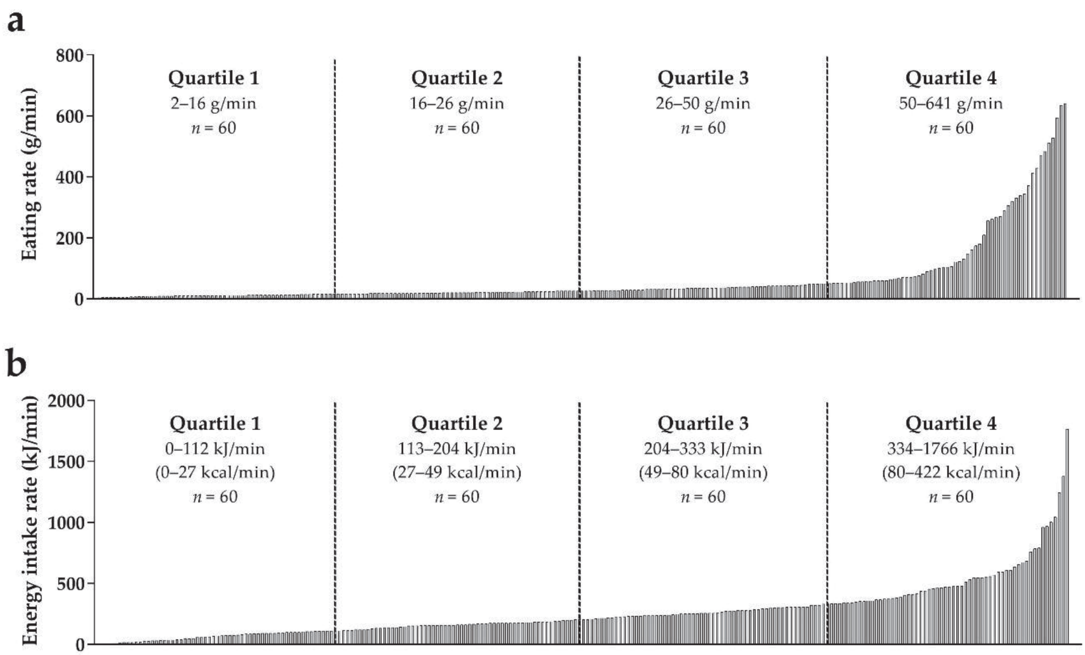

Figure 1. Food-specific eating rate (a) and food-specific energy intake rate (b) of the foods in the dataset.

Data checks

The eating rate of the reference foods did not differ significantly between the first and second time it was offered (paired samples *t*-tests: for apple $p = 0.07$, for bread $p = 0.62$ and for yoghurt $p = 0.15$). The mean eating rate for apple was 36 ± 11 g/min at session 1 and 38 ± 11 g/min at session 3, for bread 10 ± 4.2 g/min at session 1 and 10 ± 4.3 g/min at session 3, and for yoghurt 98 ± 32 g/min at session 1 and 103 ± 30 g/min at session 3. The coefficient of variation (i.e. standard deviation/mean × 100) at first consumption was 31% for apple, 42% for bread, and 33% for yoghurt. Furthermore, the eating rate of the participants divided by the group average was the same within the three reference foods ($F(2, 176) = 0.06$, $p = 0.95$).

The liking scores were not correlated with the eating rate of apple, but the liking scores were associated with the eating rate of bread and yoghurt (apple $r = 0.13$, $p = 0.09$; bread $r = 0.27$, $p \leq 0.001$; yoghurt $r = 0.27$, $p \leq 0.0001$). For bread the average eating rate was 9 g/min when it was not liked (i.e. liking score ≤4) and 11 g/min when it was liked (i.e. liking score ≥5). For yoghurt it was 84 g/min when it was not liked and 103 g/min when it was liked.

The participants were less hungry, felt more full and their desire to eat was less at the end of the test sessions compared to the start of the test sessions (paired samples *t*-test: for all three satiety scores $p < 0.0001$). The average scores at the end of the test sessions were 3.8 for level of hunger, 6.4 level of fullness, and 4.5 for desire to eat (on 10-point Likert scales, anchored from “not at all” to “very”).

Eating rate and other food properties

Food composition

Several associations between eating rate and food composition were found (Table 1). Eating rate was negatively correlated with energy density ($r = -0.45$, $p < 0.0001$), macronutrient content (protein content $r = -0.31$, $p < 0.0001$; fat content $r = -0.29$, $p < 0.0001$; carbohydrate content $r = -0.33$, $p < 0.0001$). The same was true for fiber content ($r = -0.33$, $p < 0.0001$) and sodium content ($r = -0.31$, $p < 0.0001$). Water content was positively correlated with eating rate ($r = 0.46$, $p < 0.0001$). Mono- and disaccharide content was not correlated with eating rate.

After excluding liquids from the dataset some differences were found in the associations between eating rate and food properties (Table 1). The association between water content and eating rate became stronger (before $r = 0.46$, $p < 0.0001$; after $r = 0.61$, $p < 0.0001$). Similarly, the correlation between eating rate and energy density became more pronounced (before $r = -0.45$, $p < 0.0001$; after $r = -0.57$, $p < 0.0001$).

Excluding the data from previous did not change the results.

Taste intensity

Some associations between eating rate and taste intensity were found (Table 1). Sweet and bitter taste intensity were not correlated with eating rate. Salt, fat and umami taste intensity were negatively correlated with eating rate (salt $r = -0.27$, $p < 0.001$; fat $r = -0.21$, $p < 0.01$; umami $r = -0.17$, $p = 0.01$), while sour taste intensity was positively correlated with eating rate ($r = 0.34$, $p < 0.0001$).

After excluding liquids from the dataset, the correlations between eating rate and sour taste intensity became stronger (before $r = 0.34$, $p < 0.0001$; after $r = 0.48$, $p < 0.0001$), while the correlations between eating rate and umami taste intensity (before $r = -0.17$, $p = 0.01$; after $r = -0.00$, $p > 0.99$) and fat taste intensity (before $r = -0.21$, $p < 0.01$; after $r = -0.01$, $p = 0.84$) disappeared. Finally, excluding the data from previous studies did not change the results.

Texture

The texture groups (i.e. liquids, semi-solids, soft solids and hard solid) were not equally distributed over the eating rate quartiles (Chi-square: $p < 0.0001$) (Table 2a). The hard solids were mainly present in the lower quartiles, while the semi-solids and liquids were mainly present in the upper quartiles. Moreover, the mean eating rate was 306 ± 177 g/min for liquids, 63 ± 40 g/min for semi-solids, 30 ± 16 g/min for soft solids and 19 ± 15 for hard solids. The median eating rate decreased as the food texture became more solid and harder (Kruskal-Wallis test: $H(3) = 111.85$, $p < 0.0001$); Jonckheere-Terpstra test: $J = 7954$, $z = -10.98$, $p < 0.0001$).

Dutch recommendations

The eating rate of the recommended foods (64 ± 97 g/min) was not significantly different from that of the not recommended foods (65 ± 119 g/min) (independent samples *t*-test: $t(238) = 0.09$, $p = 0.93$). After excluding liquids from the dataset the eating rate of the recommended foods (35 ± 23 g/min) remained not significantly different from that of the not recommended foods (28 ± 25 g/min) (independent samples *t*-test: $t(208) = -1.85$, $p = 0.07$).

Energy intake rate and other food properties

Food composition

Energy intake rate was positively associated with fat content ($r = 0.16$, $p = 0.01$) (Table 1). Fiber content was negatively correlated with energy intake rate ($r = -0.20$, $p < 0.01$). After excluding liquids from the dataset an association between energy intake rate and energy density became apparent (before $r = 0.08$, $p = 0.19$; after $r = 0.43$, $p < 0.0001$). Similarly, an association between water content and energy intake rate became apparent (before $r = -0.03$, $p = 0.63$; after $r = -0.33$, $p < 0.0001$).

Taste intensity

Table 1 shows that energy intake rate was positively associated with fat, sweet and sour taste intensity (fat taste intensity $r = 0.28$, $p < 0.0001$; sweet taste intensity $r = 0.35$, $p < 0.0001$; sour taste intensity $r = 0.15$, $p = 0.03$). After excluding liquids the association with sour taste intensity disappeared and a positive association with salt taste intensity became apparent (sour taste intensity $r = -0.10$, $p = 0.18$; salt taste intensity $r = 0.19$, $p < 0.01$).

Texture

The texture groups were not equally distributed over the energy intake rate quartiles (Chi square, $p < 0.0001$) (Table 2b). Liquids were predominantly present in the first and fourth quartile. Energy intake rate, however, was not significantly different between the texture groups (Kruskal-Wallis test: $H(3) = 6.21$, $p = 0.10$).

Dutch recommendations

The energy intake rate of the recommended foods (147 ± 137 kJ/min (35 ± 33 kcal/min)) was significantly lower than that of the not recommended foods (312 ± 250 kJ/min (75 ± 60 kcal/min)) (independent samples *t*-test: $t(228.04) = 6.61$, $p < 0.0001$). After excluding liquids from the dataset the energy intake rate of the recommended foods (133 ± 97 kJ/min (32 ± 23 kcal/min)) remained significantly lower than that of the not recommended foods (269 ± 145 kJ/min (64 ± 35 kcal/min)) (independent samples *t*-test: $t(180.63) = 7.98$, $p < 0.0001$).

Table 1. Pearson correlations between food-specific eating rate and energy intake rate, and food properties; with and without considering liquids.

	Eating Rate (g/min)				Energy Intake Rate (kJ/min)			
	Including Liquids [1]		Excluding Liquids [2]		Including Liquids [1]		Excluding Liquids [2]	
	r	*p*	*r*	*p*	*r*	*p*	*r*	*p*
Food Composition								
Energy (kJ/100 g)	−0.45	<0.0001	−0.57	<0.0001	0.08	0.19	0.43	<0.0001
Protein (g/100 g)	−0.31	<0.0001	−0.27	<0.0001	−0.002	0.97	0.19	<0.01
Fat (g/100 g)	−0.29	<0.0001	−0.31	<0.0001	0.16	0.01	0.47	<0.0001
Carbohydrate (g/100 g)	−0.33	<0.0001	−0.48	<0.0001	−0.02	0.75	0.12	0.07
Mono- and disaccharides (g/100 g)	−0.05	0.47	0.01	0.89	0.001	0.98	0.02	0.78
Polysaccharides (g/100 g)	−0.34	<0.0001	−0.47	<0.0001	−0.13	<0.05	−0.02	0.82
Fiber (g/100 g)	−0.33	<0.0001	−0.33	<0.0001	−0.20	<0.01	−0.16	0.02
Water (g/100 g)	0.46	<0.0001	0.61	<0.0001	−0.03	0.63	−0.33	<0.0001
Sodium (mg/100 g)	−0.31	<0.0001	−0.30	<0.0001	−0.07	0.25	0.11	0.10
Taste Intensities								
Sweet	0.11	0.09	−0.02	0.83	0.35	<0.0001	0.41	<0.0001
Sour	0.34	<0.0001	0.48	<0.0001	0.15	0.03	−0.10	0.18
Bitter	0.08	0.21	−0.01	0.92	−0.06	0.38	−0.08	0.26
Umami	−0.17	0.01	−0.00	>0.99	−0.12	0.08	0.05	0.47
Salt	−0.27	<0.001	−0.19	<0.01	−0.06	0.39	0.19	<0.01
Fat	−0.21	<0.01	−0.01	0.84	0.28	<0.0001	0.61	<0.0001

[1] *n* = 240 for correlations with food composition variables, and *n* = 224 for correlations with taste intensities
[2] *n* = 210 for correlations with food composition variables, and *n* = 194 for correlations with taste intensities.

Table 2a. Frequency (*n* (%)) of texture groups and recommended foods in the eating rate quartiles (*n* = 240).

	Eating Rate (g/min)				
	Quartile 1 2–16 g/min (*n* = 60)	**Quartile 2** 16–26 g/min (*n* = 60)	**Quartile 3** 26–50 g/min (*n* = 60)	**Quartile 4** 50–641 g/min (*n* = 60)	***p*** [1]
Food Texture					<0.0001
Liquids	0 (0.0)	0 (0.0)	1 (1.7)	29 (48.3)	
Semi-solids	3 (5.0)	3 (5.0)	6 (10.0)	15 (25.0)	
Soft solids	18 (30.0)	37 (61.7)	40 (66.7)	12 (20.0)	
Hard solids	39 (65.0)	20 (33.3)	13 (21.7)	4 (6.7)	
Dutch Dietary Guidelines					>0.05
Recommended	14 (23.3)	14 (23.3)	26 (43.3)	20 (33.3)	
Not recommended	46 (76.7)	46 (76.7)	34 (56.7)	40 (66.7)	

[1] ***p*-value Chi-square test.**

Table 2b. Frequency (*n* (%)) of texture groups and recommended foods in the energy intake rate quartiles (*n* = 240).

	Energy Intake Rate (kJ/min) [1]				
	Quartile 1 0–112 kJ/min (*n* = 60)	**Quartile 2** 113–204 kJ/min (*n* = 60)	**Quartile 3** 204–333 kJ/min (*n* = 60)	**Quartile 4** 334–1766 kJ/min (*n* = 60)	***p*** [2]
Food Texture					0.0001
Liquids	10 (16.7)	2 (3.3)	0 (0.0)	18 (30.0)	
Semi-solids	5 (8.3)	8 (13.3)	7 (11.7)	7 (11.7)	
Soft solids	24 (40.0)	29 (48.3)	34 (56.7)	20 (33.3)	
Hard solids	21 (35.0)	21 (35.0)	19 (31.7)	15 (25.0)	
Dutch Dietary Guidelines					<0.0001
Recommended	35 (58.3)	21 (35.0)	12 (20.0)	6 (10.0)	
Not recommended	25 (41.7)	39 (65.0)	48 (80.0)	54 (90.0)	

[1] **Energy intake rate quartiles (kcal/min); Quartile 1= 0–27 kcal/min, Quartile 2 = 27–49 kcal/min, Quartile 3 = 49–80 kcal/min, Quartile 4 = 80–422 kcal/min**

[2] ***p*-value Chi-square test.**

Energy intake rate of foods within food groups

Table 3 shows the categorization of foods, according to their energy intake rate (kJ/min), within the food groups (see Table A4 in Appendix A for the same table with energy intake rate expressed in kcal/min). For several food groups this categorization was based on differences in both eating rate and energy density. For example, in the "Potatoes" food group, mashed potatoes had a relatively high energy intake rate as the result of a high eating rate (52 g/min), while for fried potatoes and French fries this was the result of a high energy density (1107 kJ/100 g (265 kcal/100 g)). Similarly, in the "Dairy products" food group, both cheese and plain yoghurt and fromage frais had a relatively low energy intake rate. For the cheeses this was the result of a low eating rate (19 g/min), and for the plain yoghurt and fromage frais this was the result of a low energy density (215 kJ/100 g (51 kcal/min)).

For other food groups categorization was predominantly based on differences in eating rate (e.g. "Cereals and cereal products" and "Sugar and confectionery"), and for other food groups categorization was predominantly based on differences in energy density (e.g. "Non-alcoholic beverages").

Table 3. Energy intake rate (kJ/min) of foods relative to the other foods within the food group 1.

Food Group	Energy Intake Rate (kJ/min) Relative to Food Group		
	Low	Medium	High
		Potatoes (n = 6)	
Description	Boiled potatoes [2] (n = 2)		Mashed and (deep-)fried potatoes (n = 4)
Energy intake rate	76 (64–87) kJ/min		248 (183–308) kJ/min
Eating rate	23 (18–28) g/min		32 (22–52) g/min
Energy density	332 (311–352) kJ/100 g		917 (349–1300) kJ/100 g
		Vegetables (n = 24)	
Description	Raw vegetables [2] (n = 5)	Boiled [2] and pickled vegetables (n = 17)	Vegetables with added energy (n = 2)
Energy intake rate	28 (10–73) kJ/min	46 (10–119) kJ/min	131 (108–153) kJ/min
Eating rate	36 (12–76) g/min	37 (13–89) g/min	48 (44–51) g/min
Energy density	81 (52–139) kJ/100 g	121 (70–291) kJ/100 g	275 (247–303) kJ/100 g
		Legumes (n = 2)	
Description	Tinned brown beans [2] (n = 1)		Tinned beans in tomato sauce (n = 1)
Energy intake rate	129 kJ/min		176 kJ/min
Eating rate	28 g/min		45 g/min
Energy density	460 kJ/100 g		393 kJ/100 g
		Fruits, nuts and olives (n = 20)	
Description	Fruit (excluding soft fruit) [2] (n = 8)	Olives, conserved fruit and soft fruit [2] (n = 7)	Nuts [3], apple sauce (n = 5)
Energy intake rate	111 (60–176) kJ/min	164 (99–278) kJ/min	349 (206–479) kJ/min
Eating rate	46 (26–73) g/min	52 (12–97) g/min	39 (8–147) g/min
Energy density	243 (193–331) kJ/100 g	487 (123–1382) kJ/100 g	2053 (325–2586) kJ/100 g
		Dairy products (n = 26)	
Description	Plain yoghurt and fromage frais [3], cheese [2] (n = 8)	Deserts other than plain yoghurt or fromage frais (n = 8)	Dairy drinks [3] (n = 10)
Energy intake rate	225 (146–319) kJ/min	412 (231–546) kJ/min	749 (200–1766) kJ/min
Eating rate	58 (12–132) g/min	80 (33–122) g/min	322 (71–527) g/min
Energy density	776 (156–1529) kJ/100 g	643 (300–1453) kJ/100 g	232 (122–375) kJ/100 g

		Cereals and cereal products (n = 56)	
Description	Hard and dry products [3], plain bread slices [3] (n = 23)		Other (e.g. bread with topping, buns, pasta, rice) [3] (n = 33)
Energy intake rate	137 (37–258) kJ/min		241 (106–549) kJ/min
Eating rate	9 (2–13) g/min		24 (10–54) g/min
Energy density	1639 (990–2261) kJ/100 g		1069 (555–1481) kJ/100 g
		Meat and meat products (n = 18)	
Description	Fresh meat (excluding minced meat) [3] (n = 2)		Minced meat [3] and processed meat (n = 16)
Energy intake rate	176 (117–234) kJ/min		300 (71–654) kJ/min
Eating rate	27 (18–35) g/min		29 (13–58) g/min
Energy density	664 (661–667) kJ/100 g		1039 (520–1804) kJ/100 g
		Fish and shellfish (n = 6)	
Description		Fish and fish products [2] (n = 6)	
Energy intake rate		234 (123–372) kJ/min	
Eating rate		31 (24–48) g/min	
Energy density		761 (414–918) kJ/100 g	
		Eggs and egg products (n = 1)	
Description		Boiled egg [2] (n = 1)	
Energy intake rate		173 kJ/min	
Eating rate		32 g/min	
Energy density		535 kJ/100 g	
		Sugar and confectionery (n = 19)	
Description	Hard confectionary (non-chocolate), ice cream (n = 5)	Soft confectionary (non-chocolate) (n = 6)	Chocolate, candy bars, fruit drink (n = 8)
Energy intake rate	100 (63–156) kJ/min	210 (140–278) kJ/min	369 (185–610) kJ/min
Eating rate	9 (4–16) g/min	14 (9–19) g/min	47 (8–268) g/min
Energy density	1357 (856–1676) kJ/100 g	1513 (1358–1796) kJ/100 g	1898 (227–2342) kJ/100 g

		Cakes (n = 26)	
Description	Dry cakes, biscuits (n = 15)		Cakes, pies, pastries, puddings (non-milk-based) (n = 11)
Energy intake rate	317 (166–685) kJ/min		436 (239–636) kJ/min
Eating rate	17 (9–35) g/min		33 (18–58) g/min
Energy density	1861 (1314–2205) kJ/100 g		1409 (826–1868) kJ/100 g
		Non-alcoholic beverages (n = 15)	
Description	Non- and very low caloric beverages [3] (n = 5)		Caloric beverages (n = 10)
Energy intake rate	1 (0–3) kJ/min		673 (92–1379) kJ/min
Eating rate	334 (56–635) g/min		365 (59–641) g/min
Energy density	1 (0–5) kJ/100 g		173 (68–232) kJ/100 g
		Alcoholic beverages (n = 1)	
Description		Pilsner beer (n = 1)	
Energy intake rate		198 kJ/min	
Eating rate		106 g/min	
Energy density		187 kJ/100 g	
		Condiments and sauces (n = 7)	
Description	Tomato sauces (n = 3)		Mayonnaises and similar (n = 4)
Energy intake rate	93 (78–111) kJ/min		262 (207–321) kJ/min
Eating rate	28 (17–44) g/min		20 (11–31) g/min
Energy density	375 (253–546) kJ/100 g		1493 (975–2733) kJ/100 g
		Soups, bouillon (n = 7)	
Description	Soup from cube or package (n = 3)		Soup with more (semi-) solid components (n = 4)
Energy intake rate	50 (38–74) kJ/min		137 (104–199) kJ/min
Eating rate	89 (41–174) g/min		66 (59–70) g/min
Energy density	86 (22–140) kJ/100 g		214 (148–337) kJ/100 g

	Snacks (n = 6)	
Description	Spring roll fried (n = 1)	Other warm savoury snacks (n = 5)
Energy intake rate	204 kJ/min	494 (401–761) kJ/min
Eating rate	27 g/min	36 (27–51) g/min
Energy density	757 kJ/100 g	1366 (1139–1596) kJ/100 g

[1] Table A4 in Appendix A shows the same table with energy intake rate expressed in kcal/min and energy density in kcal/100g
[2] Recommended foods
[3] Both recommended and not recommended food.

Discussion

The aim of the current study was to assess the eating rate and energy intake rate of the foods commonly consumed in the Netherlands, to map the characteristics of slow and fast foods, and to explore the opportunities for a diet with a low energy intake rate. Food-specific eating rate was obtained for 240 foods. Eating rate ranged from 2–641 g/min, and energy intake rate ranged from 0–1766 kJ/min (0–422 kcal/min). After excluding liquids these ranges were considerably smaller (i.e. 2–147 g/min and 10–761 kJ/min (2–182 kcal/min)), as the liquids were consumed more quickly than the semi-solids and solids. Besides texture also food composition was associated eating rate. Eating rate was inversely associated with energy density and fiber content, and positively associated with water content. No clear association was found between eating rate and taste intensity. Moreover, within the food groups we were able to identify groups of food that distinguished themselves from the other foods in the food group based on their energy intake rate. Hereby demonstrating that natural variation in energy intake rate is present in the Dutch diet.

This is the first study to report the eating rate and energy intake rate of a large number of foods that represent a whole diet (i.e. the Dutch diet). In line with previous studies a large variation in eating rate was found, with the liquids and semi-solids being responsible for most variation [3,2]. Eating rate was lower when the texture was more solid and harder. To illustrate, water had a high eating rate (i.e. 339 g/min), while wholemeal crispbread had a low eating rate (i.e. 5 g/min). Previous studies have already shown that food texture directly affects eating rate [13,14]. As Hutchings and Lillford [31] show in their model the time to process a food depends on the degree of structure and lubrication. Foods that require more chewing and lubrication will take more time to process and therefore will have a lower eating rate. This is supported by the finding that water content was positively associated with eating rate.

Regarding food composition, water content was the best predictor of eating rate, which is in line with previous research [3,2]. On the other hand, energy density, and protein, fat, carbohydrate and fiber content were inversely associated with eating rate. The correlations between eating rate and energy density, water content, and carbohydrate content became stronger after excluding liquids, indicating that the association between eating rate and food composition is different in liquids compared to non-liquids. Energy density, fiber and water content all are associated with the texture of a food, which could explain the association with eating rate [19]. For fat, however, the relation with eating rate might be more complex. On the one hand it contributes to the energy density of foods, which is negatively associated with eating rate. On the other hand fat can act as a lubricator, which would have an inverse effect [19,31]. Further research is needed to better understand the relation between fat content and the eating rate of commonly consumed foods.

For the relation between taste intensity and eating rate we expected to find a negative association. Some studies have shown that taste intensity is inversely associated with eating rate, but this is not consistently found [2,14,20]. In the current study salt taste intensity was inversely correlated with eating rate, also after excluding liquids. The same was true for sodium content. This can partly be explained by the presence of foods from the "Cereals and cereal products" food group (e.g. salty biscuits) in the lower eating rate quartiles. Furthermore, sour taste intensity was positively correlated with eating rate, also after excluding liquids. This correlation can be explained by the presence of foods from the "Dairy products" and "Fruits, nuts and seeds" food group in the higher eating rate quartiles (after excluding liquids). No associations were found between eating rate and sweet and bitter taste intensity. This could be due to the omnipresence of sweet and the lack of bitter foods in our diet [32]. Across eating rate quartiles sweet taste intensity and mono- and disaccharide content remained relatively high, while bitter taste intensity remained very low.

The current study was designed to measure food-specific eating rate; other factors influencing eating rate were standardized as much as possible. Eating rate was measured in a laboratory setting and participants were not allowed to take breaks in between bites or sips. Moreover, a calibration factor was used to correct the data for the personal eating rate of the participants, as the participants did not consume all foods. This calibration factor assumes that eating rate is a personal characteristic [33,34]. The fact that the eating rate of the participants compared to the group mean was similar within products confirms this assumption and validates the use of the calibration factor. The absolute numbers, however, will still depend on the population, but the relative differences in eating rate between foods are expected to be similar. Moreover, participants were not offered foods if they indicated beforehand that they did not like it. There, however, was a significant positive correlation between the liking scores and eating rate for bread and yoghurt. Perhaps this is because these products usually are not consumed plain. Nonetheless this is not expected to have altered our findings, considering the small absolute differences in eating rate when the product is liked and when it is not liked.

Furthermore, it was chosen not to offer equal portions for all foods, like previous studies with a similar design have offered 50 g portions [3,2,17]. This was not feasible considering the wide range of foods included in this study. It, for example, would mean that participants had to eat a complete roll of peppermint (i.e. approximately 50 g). On the other hand, offering portions smaller than 50g would not be informative for other foods (e.g. liquids). Therefore it was decided to offer portions that allowed for multiple bites/sips, but did not constrain further consumption. This is reflected in the satiety scores;

although the participants felt fuller at the end of the test sessions they indicated they could still eat more. Furthermore, data was added from previous studies that used slightly different methods (e.g. regarding the portions offered), but this did not affect the results. Excluding data from these previous studies did not change the results.

The results of the current study provide valuable information on the eating rate and energy intake rate of commonly consumed foods. They improve our understanding of the determinants of eating rate and energy intake rate, although the number of repetitions per food is limited. Furthermore, the dataset is not complete but the foods included were carefully selected to represent the range of foods present in the Dutch diet. The eating rate of foods, however, might be different when not consumed in isolation. Nonetheless, when a meal component is replaced by an alternative with a lower eating rate this is expected to result in a lower overall eating rate, as illustrated by Bolhuis et al. [1]. They, for example, showed that a hamburger was eaten more slowly when the soft bread was replaced by hard bread, which has a lower eating rate. Moreover, this example shows that lowering the eating rate—and therefore the energy intake rate—of a diet does not necessarily require big adaptations.

The current study shows that it is possible to choose alternatives with a lower energy intake rate across the diet. This is also expected to be true for other western countries because of the similarities between western diets [27,35]. Alternatives with a lower energy density can be chosen from either another food group or from the same food group. Differences in energy intake rate within a food group were, in general, either the result of a difference in eating rate or a difference in energy density; this reflects the negative association between eating rate and energy density. Furthermore, the results show that adhering to the current dietary guidelines will lower energy intake rate in most individuals [29,30,36]. Most individuals do not consume enough fruit and vegetables, while these have a low energy intake rate [37]. Moreover, the energy intake rate of not-recommended foods was twice as high compared to the recommended foods. This suggests that there is room for improvement regarding the energy intake rate of the diet for people that are already adhering to the guidelines, but especially for people that are not. When not just considering the commonly consumed foods even bigger differences could be obtained; for example with foods designed to lower eating rate, and therefore energy intake rate [38]. Selecting foods with a low energy intake rate will make it easier for people to control their energy intake because of the satiating capacity of these foods [1,11,13].

Conclusions

The foods present in the Dutch diet vary greatly in eating rate and energy intake rate. Foods with a low eating rate are mainly characterized by a solid texture, high energy density and low water content. Foods with a low energy intake rate are by definition characterized by a low eating rate and low energy density. Furthermore, we have demonstrated that it is possible to choose alternatives with a lower energy intake rate, either from the same or another food group. This study, therefore, demonstrates that commonly consumed foods provide opportunities for reducing energy intake rate, and may serve as a starting point when designing an intervention to reduce energy intake by selecting foods with a low energy intake rate (kJ/min). Such an intervention, targeting both the eating rate and energy density of foods, is expected to be more effective compared to an intervention that only targets the eating rate or the energy density of foods.

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Chapter 5

How much slow and fast calories are we consuming? Food consumption in terms of energy intake rate

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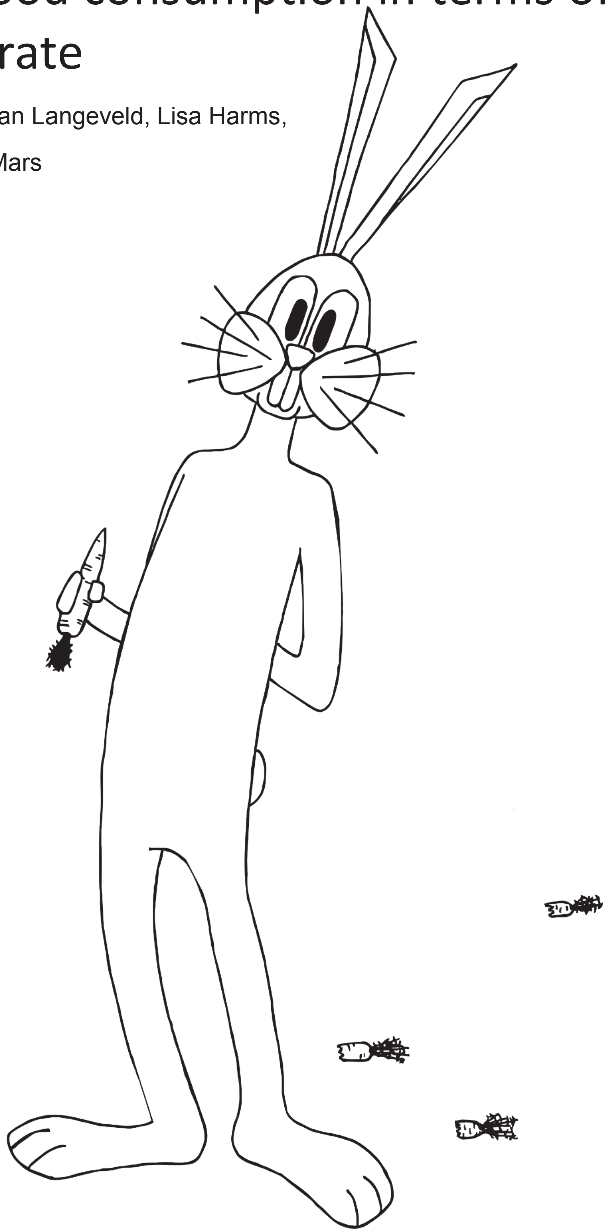

In preparation

Abstract

The consumption of foods with a low eating rate and energy density—and thus low energy intake rate (EIR, kJ/min)—could help people to control their energy intake and eventually body weight However, in order to apply this strategy one needs to know to what extent the population already eats these low EIR foods. Hence, this study investigated the consumption pattern of Dutch adults in terms of EIR, and explored its association with energy intake and BMI. Dietary recall data of 1280 18-50 year old adults (m/w=671/609) from the 2007-2010 Dutch Food Consumption Survey was combined with an EIR-database. All uniquely reported foods were categorized into quartiles of EIR and their contribution (%) to energy intake was analyzed. Furthermore, it was investigated whether dietary EIR (i.e. weighted average of EIR) was associated with daily energy intake and BMI, by means of multiple linear regression analyses. The contribution of the EIR-quartiles to energy intake was 20.3±12.0%, 26.7±14.2%, 26.4±13.5%, and 26.6±13.2%; for the lowest, second, third and highest quartile, respectively. A positive linear trend was found between tertiles of dietary-EIR (i.e. low, medium, high) and energy intake ($p<0.001$). No such association was found between tertiles of dietary-EIR and BMI ($p=0.11$). To conclude, dietary energy intake rate was positively associated with energy intake, although not with BMI. Furthermore, this study shows that Dutch adults have ample possibilities to shift their diets towards foods with a lower EIR, which is a promising strategy for lowering daily energy intake.

Introduction

The consumption of foods with a low eating rate and a low energy density may help people to control their energy intake, and eventually their body weight. These foods have a higher satiating capacity, which makes it easier to moderate energy intake [1,2]. Laboratory studies have consistently shown that intake is reduced when foods have a lower eating rate or when they have a lower energy density [3-7]. Eating rate has been shown to affect energy intake through the weight of food consumed [8,7,9-11], and energy density has been shown to directly affect energy intake as it has a limited to no effect on the weight of food consumed [7,4,2].

Moreover, a recent experiment from McCrickerd, et al. showed that even greater reductions in energy intake can be achieved through lowering both the eating rate and energy density of a food, compared to lowering only its eating rate or energy density [7]. Energy intake rate (kJ/min or kcal/min) is therefore a food property of special interest, as it reflects both the eating rate and the energy density of a food [12]. The potential of energy intake rate for controlling long-term energy intake, however, has not yet been explored. Nonetheless, research on the individual effects of eating rate and energy density on long-term energy intake and weight status shows that it is worthwhile investigating.

Evidence indicates that the eating rate of foods could affect long-term energy intake and possibly weight status. Experimental studies have shown that 24h energy intake can be reduced by lowering the eating rate of a single meal [10,13,14]. Bolhuis et al. [10], for example, showed that by replacing a hamburger's soft bun with a hard bun—which has a lower eating rate—ad libitum intake was reduced and this was not compensated for in a subsequent meal. Furthermore, dietary intervention studies have shown that participants tend to gain more weight when calories are consumed through beverages [15,16], which are known to have a high eating rate [9]. Moreover, the consumption of more 'liquid calories' has been found to be associated with a higher BMI [17,16].

Similarly, literature suggests that the energy density of foods affects long-term energy intake and weight status. Experimental studies have shown that energy intake can be reduced by lowering energy density (e.g. by increasing the water content of foods), and that people only partly compensate for this reduced energy intake during the remainder of the day [5,18,19]. Dietary intervention studies indicate that the consumption of foods with a lower energy density can reduce long-term energy intake and body weight [20-22]. Moreover, observational studies have confirmed that a higher dietary energy density is associated with a higher BMI [23,24].

To date, research on energy intake rate—so eating rate and energy density combined—has been limited as it is a new concept. It has yet to be investigated what people are currently consuming in terms of energy intake rate, and whether this is associated with energy intake and weight status. From a recent study we performed we do know that the foods available in the Dutch diet allow for substantial variation in energy intake rate [12]. However, more research is needed to see whether it would be interesting to promote the consumption of foods with a lower energy intake rate to reduce energy intake. Hence, this study investigated the consumption patterns—in terms of energy intake rate (EIR)—within the Dutch population, and explored its association with energy intake and weight status.

Materials and methods

Design

Food consumption data of Dutch adults was coupled with data on the energy intake rate of foods [12,25]. The resulting dataset was used to investigate the consumption patterns—in terms of energy intake rate—and its association with energy intake and weight status.

Food consumption data

Food consumption data was derived from the 2007-2010 Dutch National Food Consumption Survey (DNFCS) [25]. Participants were 7-69 years old, and were selected to represent the Dutch population in terms of age, sex, education level, region, and level of urbanization. Food consumption was assessed by means of two 24-hour dietary recalls per participant with 2-6 weeks in between. The dates and times were unannounced to the participants. During the 24-hour recalls the participants were also asked to report their weight and height.

The total study population consisted of 3819 participants. For the current study we included participants of 18 to 50 years old (n=1526). Participants who were on an energy restricted diet (n=103), pregnant or breastfeeding (n= 4), missing information on weight status (n=1), or missing food intake data (n=1) were excluded. Additionally, participants with an unrealistic energy intake, taking into account day-to-day variations, were excluded [26,27].

Participants were excluded if daily energy intake divided by the estimated basal metabolic rate was lower than 0.91 (i.e. underreporters) or greater than 2.63 (i.e. overreporters) [26,27]. In total 121 underreporters were identified and 16 overreporters. The BMI of both the underreporters (28.7±5.7 kg/m^2) and overreporters (21.3±2.0 kg/m^2) were different from that of the other participants (24.5±4.6 kg/m^2) ($F(2)=49.60$, $P<0.0001$; post-hoc, in all cases $P<0.05$). More information on the characteristics of the under- and overreporters can be found in **Table B1** in **Appendix B**.

The final study population consisted of 1280 participants (m/w=671/609, age=31.7±9.6 yrs., BMI=24.5±4.6 kg/m^2).

Foods included in the analyses

The food consumption dataset included 1572 unique foods. These included deconstructed foods; Foods were deconstructed whenever possible to obtain detailed information on the nutrient composition of the foods consumed. For example, if a participant consumed fried potatoes its ingredients (i.e. boiled potatoes and preparation fat) would be reported separately, if the preparation fat was known. If not, it would have been reported as 'fried potatoes, average'. The current study, however, focuses on the energy intake rate of the foods consumed and not nutrient intake. Therefore fats and oils (n=48) were not included in the analyses. Instead, unprepared foods (e.g. boiled potatoes) in the dataset were replaced by their prepared counterparts (e.g. 'fried potatoes, average'), under the assumption that this would account for all excluded fats and oils.

Also toppings (i.e. condiments, sauces and bread toppings; n=217) were excluded. These are consumed in combination with other foods. The data do not report the combinations consumed, only that they were consumed at the same occasion. Furthermore, it is not yet known how toppings affect the energy intake rate of the foods they are added to. As a result it is not possible to include them in the main analyses. Instead, energy from toppings was included as a confounder in the analyses. They contributed 17% to the total energy intake.

Finally, 1307 foods were included in the main analyses.

Energy intake rate data

Laboratory data

This dataset contains data on the eating rate (g/min) and energy intake rate (kJ/min) of 240 commonly consumed foods [28]. Eating rate was assessed by having multiple participants eat the foods (without stops in between bites or sips) while measuring the time spent eating and the amount eaten. Energy intake rate was obtained by multiplying the eating rate (g/min) of the foods with their energy density (kJ/g). Energy density data was derived from the Dutch Food Composition Database (NEVO version 2016/5.0, RIVM, Bilthoven). The resulting dataset has demonstrated that energy intake rate differs substantially between and within food groups. A more detailed description of the dataset is provided by Van den Boer et al. [12].

This food database provided the energy intake rate for 204 out of the 1307 foods included in the main analyses; Together these foods were responsible for 53% of the energy intake from the foods included in the main analyses.

Extrapolating energy intake rate-data

The energy intake rate of the remainder of the foods was estimated. They were assigned the average eating rate of a group of foods that are expected to have a similar eating rate: i.e. foods within the same EPIC SOFT food group [29] that are expected to have a similar eating rate, based on the available laboratory data. Potato waffels, for example, were assigned the average eating rate of non-mashed potatoes for which laboratory data was available. Table B2 in Appendix B describes the groups used to estimate eating rate.

Finally, the eating rate estimations were multiplied with the energy density of the individual foods to obtain their estimated energy intake rate.

Dietary-energy intake rate

Dietary-energy intake rate is a weighted average of the energy intake rate of the foods consumed by a participant. It was obtained by: 1) multiplying the energy intake rate of the individual foods consumed with the amount (g) consumed from these foods, 2) adding up the results, and 3) dividing the result by the total amount of food consumed (g).

Additional participant information

For the 2007-2010 Dutch National Food Consumption Survey (DNFCS) additional information on the participants was collected through a questionnaire [25]. This questionnaire consisted of some general questions and questions regarding the lifestyle of the participants; It included questions on the sex and date of birth. Furthermore, the 'Short questionnaire to assess health-enhancing physical activity' (SQUASH) was incorporated to assess the number of days a week with at least 30 minutes of moderate-to-vigorous activity [30].

Statistical analyses

SAS version 9.4 (SAS Institute Inc., Cary, NC, USA) was used for the statistical analyses. Means and standard deviations are given, unless stated otherwise. *P*-values of <0.05 were considered statistically significant.

All uniquely reported foods were divided into quartiles based on their EIR. This was done both with and without including beverages. The contribution of these quartiles to energy intake (%) was analyzed for the total population and subgroups of the population (i.e., based on sex, age, energy intake and weight status). To categorize participants according to their energy intake they were divided into tertiles of energy intake. By means of GLM analyses it was investigated whether there was an effect of the participant characteristics on the proportion of energy derived from the quartiles. If statistically significant post hoc analyses (i.e. Bonferroni) were performed. Furthermore, with chi-square tests it was investigated whether beverage consumption differed between weight status-categories.

Linear regression analyses (with and without including beverages) were performed to investigate the association between dietary-EIR and energy intake, and dietary-EIR and BMI. For both associations first a crude model was tested with two dummy variables based on tertiles of dietary-EIR: i.e. one dummy variable for comparing participants with a high dietary-EIR to participants with a medium dietary-EIR, and one for comparing participants with a low dietary-EIR to participants with a medium dietary-EIR. Subsequently, the proportion of energy derived from toppings was added to the models, followed by sex and age. Then, to the model explaining energy intake also BMI and physical activity were added. To the model explaining BMI also physical activity and energy intake were added. Furthermore, it was investigated whether there was a linear trend between dietary-EIR and energy intake, and dietary-EIR and BMI by replacing the dummy variables with the categorical variable for dietary-EIR tertile in the different models.

Finally, chi-square tests, analyses of variance and linear regression analyses were performed to test whether participant characteristics (i.e. sex, age, BMI, physical activity, energy intake and proportion of energy derived from toppings) differed between the dietary EIR-tertiles.

Results

Energy intake rate of consumed foods

In total 1307 unique foods were included in the analyses. Their energy intake rate ranged from 0 kJ/min (0 kcal/min) for water to 2235 kJ/min (529 kcal/min) for a breakfast drink. 246 out of the 1307 foods were beverages, after excluding them energy intake rate ranged from 10 kJ/min (2 kcal/min) for iceberg lettuce to 1078 kJ/min (257 kcal/min) for tiramisu. **Table 1** describes the distribution of the food groups across the EIR-quartiles, before and after excluding beverages.

The beverages were responsible for most variation in energy intake rate. The lowest EIR-quartile contained 46 beverages, and the highest EIR-quartile 161 beverages. Together the beverages contributed 1844±1246 kJ/day (441±298 kcal/day) to energy intake, which is 17±9% of total energy intake (i.e. 10376±2781 kJ/day (2480±665 kcal/day)).

Contribution of energy intake rate-quartiles to daily energy intake

The participants on average derived 20.3±12.0% of their energy intake from quartile 1, 26.7±14.2% from quartile 2, 26.4±13.5% from quartile 3, and 26.6±13.2% from quartile 4 (**Table 2**). Regarding food weight they derived 53.7±18.7% from quartile 1, 13.4±11.7% from quartile 2, 8.3±5.9% from quartile 3, and 24.6±16.2% from quartile 4. The relative contribution of the EIR-quartiles to energy intake differed between some of the participant-categories (**Table 2**).

The proportion of energy derived from the lowest EIR-quartile differed between age-categories, though no differences between individual age-categories were found ($F(2)=4.35$, $P=0.01$; post hoc in all cases $P>0.05$). The proportion of energy derived from the highest EIR-quartile was significantly higher in 18-30 year old participants (i.e. 28.0±13.0%) compared to 31-40 year old participants (i.e. 24.8±13.1%) and 41-50 year old participants (i.e. 25.0±13.4%) ($F(2)=8.86$, $P=0.0001$; post hoc in both cases $P<0.05$). The observed differences between the age categories disappeared after excluding beverages.

Table 1 Distribution of food groups across the energy intake rate-quartiles, both before and after excluding beverages

Food groups [a]	Energy intake rate-quartiles incl. beverages				Energy intake rate-quartiles excl. beverages			
	Quartile 1	**Quartile 2**	**Quartile 3**	**Quartile 4**	**Quartile 1**	**Quartile 2**	**Quartile 3**	**Quartile 4**
	0-132 kJ/min (*n*=327)	132-235 kJ/min (*n*=326)	236-354 kJ/min (*n*=327)	354-2235 kJ/min (*n*=327)	10-127 kJ/min (*n*=265)	127-213 kJ/min (*n*=265)	213-309 kJ/min (*n*=266)	310-1078 kJ/min (*n*=265)
Potatoes	3	13	5	2	3	10	6	4
Vegetables	168	14	4	4	167	14	5	4
Legumes	1	5	0	0	0	5	1	0
Fruits, nuts and olives	26	25	25	11	26	24	19	18
Dairy products	2	25	42	68	2	16	35	45
Cereals and cereal products	48	68	27	1	42	57	42	3
Meat and meat products	13	82	68	27	9	75	62	44
Fish and shellfish	8	24	20	4	4	23	21	8
Eggs and egg products	1	3	1	2	1	3	1	2
Sugar and confectionery	14	26	26	18	11	24	14	19
Cakes	0	13	65	61	0	8	38	93
Non-alcoholic beverages	27	7	9	89	0	0	0	0
Alcoholic beverages	0	4	5	21	0	0	0	0
Soups, bouillon	16	6	2	0	0	0	0	0
Miscellaneous	0	11	28	19	0	6	22	25

[a] EPIC-Soft food group

Interestingly, participants with a relatively high energy intake derived a smaller proportion of their energy intake from the lowest EIR-quartile (i.e. 17.7±11.3%), compared to participants with a medium of high energy intake (i.e. 20.8±12.0% and 22.3±12.4%, respectively) ($F(2)=13.59$, $P<0.0001$; post-hoc, in both cases $P<0.05$). The proportion of energy derived from the highest EIR-quartile also differed between the energy intake-tertiles; However, no significant differences between the individual tertiles of energy intake were found, though the observed differences were in the expected direction ($F(2)=4.79$, $P<0.01$; post hoc in all cases $P>0.05$).

Regarding the EIR-quartiles without beverages, participants with a relatively low energy intake derived a larger proportion of their energy intake from the lowest EIR-quartile (i.e. 24.5±14.2%) compared to participants with a relatively high energy intake (i.e. 20.7±13.9) ($F(2)=7.80$, $P<0.001$; post hoc low-high $P<0.05$). Conversely, the participants with a relatively low energy intake derived a smaller proportion of their energy intake from the highest EIR-quartile (i.e. 23.5±16.0%) compared to participants with a relatively high energy intake (i.e. 28.8±17.0) ($F(2)=7.80$, $P<0.001$; post hoc low-high $P<0.05$).

The proportion of energy consumed from the lowest EIR-quartile differed significantly between the weight status-categories, but no significant differences were found between the individual weight status categories ($F(2)=3.19$, $P=0.04$; post hoc in all cases $P>0.05$). Similar results were found after excluding beverages. The proportion of energy consumed from the third EIR-quartile also differed between the weight status-categories, but not between the individual weight status-categories ($F(2)=3.44$, $P=0.03$; post hoc in all cases $P>0.05$). Regarding the EIR-quartiles without beverages the contribution of the third EIR-quartile did not differ between weight status-categories.

Furthermore, is interesting to mention that the consumption frequency of beverages from quartile 1 (i.e. non- and very low caloric beverages) increased with weight status ($\chi^2(2)=37.06$, $P<0.0001$). For the lean participants 56% of the reported foods in the lowest EIR-quartile were beverages, while this was 59% for the overweight participants and 60% for the obese participants. Moreover, the consumption frequency of beverages in the highest EIR-quartile (i.e. caloric beverages) decreased with weight status ($\chi^2(2)=8.86$, $P=0.01$). For the lean participants 73% of the reported foods in the highest EIR-quartile were beverages, while this was 71% for the overweight participants and 70% for the obese participants.

Table 2 Contribution of energy intake rate-quartiles to energy intake rate (Mean%±SD): For the total population and subgroups of the population, and both including and excluding beverages [a]

	n	Contribution to daily energy intake (Mean%±SD)							
		Energy intake rate-quartiles, incl. beverages				Energy intake rate-quartiles, excl. beverages			
		Quartile 1	**Quartile 2**	**Quartile 3**	**Quartile 4**	**Quartile 1**	**Quartile 2**	**Quartile 3**	**Quartile 4**
Total	1280	20.3±12.0	26.7±14.2	26.4±13.5	26.6±13.2	23.0±14.1	24.0±14.5	26.7±14.6	26.4±16.9
Sex									
Men	671	20.0±12.1	27.0±15.2	26.8±13.4	26.2±13.1	23.3±14.6	22.7±14.6^{A}	27.0±14.8	27.0±17.3
Women	609	20.6±12.0	26.4±13.1	26.0±13.6	27.0±13.3	22.6±13.6	25.4±14.2^{B}	26.3±14.3	25.7±16.4
		0.45^{b}	*0.46*	*0.25*	*0.26*	*0.39*	***<0.01***	*0.40*	*0.14*
Age									
18-30 yrs.	698	19.3±12.0	26.7±14.2	26.0±13.5	28.0±13.0^{A}	22.4±14.4	24.5±14.6	26.8±14.7	26.3±16.9
31-40 yrs.	291	21.7±12.1	26.4±14.6	27.2±13.6	24.8±13.1^{B}	23.8±13.9	23.5±15.0	25.8±13.0	26.9±17.0
41-50 yrs.	291	21.3±11.8	26.9±14.0	26.7±13.4	25.0±13.4^{B}	23.6±13.7	23.3±13.7	27.1±15.7	26.0±16.9
		0.01	*0.88*	*0.36*	***0.0001***	*0.31*	*0.40*	*0.55*	*0.79*
Energy intake									
Low	426	22.3±12.4^{A}	26.4±13.8	26.1±14.1	25.1±13.3	24.5±14.2^{A}	25.1±14.9	26.9±14.6	23.5±16.0^{A}
Medium	427	20.8±12.0^{A}	25.9±14.3	26.5±13.2	26.7±13.8	23.7±14.0^{AB}	23.8±14.5	25.6±14.5	26.9±17.3^{AB}
High	427	17.7±11.3^{B}	27.7±14.6	26.6±13.2	27.9±12.3	20.7±13.9^{B}	23.1±13.9	27.4±14.5	28.8±17.0^{B}
		<0.0001	*0.12*	*0.82*	***<0.01***	***<0.001***	*0.14*	*0.19*	***<0.0001***
Weight status									
Lean	787	21.0±12.5	26.2±14.0	25.7±13.5	27.1±13.7	23.8±14.5	24.1±14.6	26.2±14.5	25.9±16.8
Overweight	354	19.3±11.2	27.9±14.4	27.3±13.5	25.4±12.6	22.0±13.6	24.1±14.4	27.4±15.1	26.6±17.1
Obese	139	18.7±11.1	26.5±14.6	28.3±13.5	26.5±11.6	20.6±13.5	23.4±14.3	27.7±13.6	28.3±16.5
		0.04	*0.11*	***0.03***	*0.12*	***0.02***	*0.87*	*0.32*	*0.22*

[a] Values in a column with different superscript upper-case letters are significantly different ($P < 0.05$), Bonferroni; [b] *P*-value effect within quartile, GLM

Association between energy intake rate and energy intake

In line with the above mentioned results linear regression analyses showed a positive linear trend between tertiles of dietary-EIR and energy intake, both before and after adjusting for confounders (in both cases *P*<0.0001) (**Table 3**). Average energy intake was 9.1±2.3 MJ/day in participants with a low dietary-EIR, 10.8±2.8 MJ/day in participants with a medium dietary-EIR and 11.2±2.7 MJ/day in participants with a high dietary-EIR (**Table B3**, **Appendix B**).

Participants with a low dietary-EIR had a 1.65 MJ (95% CI :2.01, 1.30) lower energy intake compared to participants with a medium dietary-EIR in the crude model. In the same model participants with a high dietary EIR had a 0.55 MJ (95% CI :0.21, 1.30) higher energy intake compared to participants with a medium dietary-EIR. Adding contribution of toppings to energy intake to the crude model did not change the results. Moreover, the contribution of toppings to energy intake did not differ between the dietary EIR-tertiles (F(2)=1.17, *P*=0.18) (**Table B3**, **Appendix B**).

After also adding sex, age, BMI and physical activity to the model participants with a low dietary-EIR had a 1.16 MJ (95% CI :1.47, 0.84) lower energy intake compared to participants with a medium dietary-EIR. Participants with a high dietary EIR had a 0.39 MJ (95% CI :0.08, 0.70) higher energy intake compared to participants with a medium dietary-EIR.

Similar results were found after excluding beverages.

Table 3 Association between energy intake (MJ) (i.e. dependent variable) and dietary-energy intake rate (i.e. independent variable) according to multiple linear regression analysis and linear trend analyses (n=1280), both including and excluding beverages [a]

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
	Partial regression coefficient	95 % CI or *P*	Partial regression coefficient	95 % CI or *P*	Partial regression coefficient	95 % CI or *P*	Partial regression coefficient	95 % CI or *P*	Partial regression coefficient	95 % CI or *P*
Beverages included										
Dietary EIR-tertiles										
Low	-1.65	(-2.01, -1.30)	-1.66	(-2.02, -1.31)	-1.17	(-1.48, -0.85)	-1.16	(-1.48, -0.85)	-1.16	(-1.47, -0.84)
Medium	0.00	(reference)	0.00	(reference)	0.00	(reference)	0.00	(reference)	0.00	(reference)
High	0.55	(0.21, 0.90)	0.59	(0.25, 0.93)	0.36	(0.06, 0.67)	0.38	(0.07, 0.68)	0.39	(0.08, 0.70)
Linear trend		<0.0001		<0.0001		<0.0001		<0.0001		<0.0001
Beverages excluded										
Dietary EIR-tertiles										
Low	-0.53	(-0.84, -0.22)	-0.62	(-0.95, -0.31)	-0.49	(-0.76, -0.21)	-0.48	(-0.75, -0.20)	-0.49	(-0.77, -0.22)
Medium	0.00	(reference)	0.00	(reference)	0.00	(reference)	0.00	(reference)	0.00	(reference)
High	0.40	(0.10, 0.70)	0.44	(0.15, 0.74)	0.44	(0.17, 0.70)	0.43	(0.17, 0.70)	0.42	(0.16, 0.69)
Linear trend		<0.0001		<0.0001		<0.0001		<0.0001		<0.0001

[a] Model 1 = Crude model
Model 2 = Crude model with en% toppings
Model 3 = Crude model with en% toppings, sex, age
Model 4 = Crude model with en% toppings, sex, age and BMI
Model 5 = Crude model with en% toppings, sex, age, BMI and physical activity (i.e. days per week with at least 30 minutes of strenuous activity)

Association between energy intake rate and BMI

Linear regression analyses showed a negative linear trend between dietary-EIR and BMI before adjusting for confounders (*P*<0.0001) (**Table 4**). This trend was no longer significant after adjusting for confounders (*P*=0.11). BMI was 25.1±4.8 kg/m^2 in participants with a low dietary-EIR, 24.7±4.5 kg/m^2 in participants with a medium dietary-EIR and 23.8±4.2 kg/m^2 in participants with a high dietary-EIR (**Table B3**, **Appendix B**).

In the crude model participants with a low dietary-EIR had a 0.35 kg/m^2 (95% CI :-0.27, 0.96) higher BMI compared to participants with a medium dietary-EIR. In the same model participants with a high dietary EIR had a 0.92 kg/m^2 (95% CI :1.52, 0.33) lower BMI compared to participants with a medium dietary-EIR. Adding contribution of toppings to energy intake to the crude model did not change the results. After also adding sex, age, physical activity and energy intake to the model participants with a low dietary-EIR had a 0.08 kg/m^2 (95% CI :-0.53, 0.70) higher BMI compared to participants with a medium dietary-EIR. Participants with a high dietary EIR had a 0.42 kg/m^2 (95% CI: -0.16, 1.01) lower BMI compared to participants with a medium dietary-EIR.

After excluding beverages, the direction of the association between dietary-EIR and BMI changed, though the association was not significant. In the fully adjusted model participants with a low dietary-EIR had a 0.26 kg/m^2 (95% CI :-0.34, 0.85) lower BMI compared to participants with a medium dietary-EIR. Participants with a high dietary EIR had a 0.11 kg/m^2 (95% CI: -0.47, 0.68) higher BMI compared to participants with a medium dietary-EIR.

Table 4 Association between BMI (kg/m^2) (i.e. dependent variable) and dietary-energy intake rate (i.e. independent variable) according to multiple linear regression analysis and linear trend analyses (n=1280), both including and excluding beverages [a]

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Partial regression coefficient	95 % CI or *P*	Partial regression coefficient	95 % CI or *P*	Partial regression coefficient	95 % CI or *P*	Partial regression coefficient	95 % CI or *P*	Partial regression coefficient	95 % CI or *P*
Beverages included										
Dietary EIR-tertiles										
Low	0.35	(-0.27, 0.96)	0.35	(-0.27, 0.96)	-0.08	(-0.68, 0.52)	-0.10	(-0.70, 0.50)	0.08	(-0.53, 0.70)
Medium	0.00	(reference)	0.00	(reference)	0.00	(reference)	0.00	(reference)	0.00	(reference)
High	-0.92	(-1.52, -0.33)	-0.93	(-1.52, -0.33)	-0.32	(-0.90, 0.26)	-0.36	(-0.95, 0.22)	-0.42	(-1.01, 0.16)
Linear trend		<0.0001		<0.0001		0.44		0.38		0.11
Beverages excluded										
Dietary EIR-tertiles										
Low	-0.39	(-1.01, 0.23)	-0.38	(-1.00, 0.24)	-0.32	(-0.95, 0.27)	-0.32	(-0.92, 0.27)	-0.26	(-0.85, 0.34)
Medium	0.00	(reference)	0.00	(reference)	0.00	(reference)	0.00	(reference)	0.00	(reference)
High	-0.04	(-0.65, 0.56)	-0.05	(-0.65, 0.56)	0.16	(-0.42, 0.73)	0.16	(-0.41, 0.74)	0.11	(-0.47, 0.68)
Linear trend		0.28		0.30		0.11		0.11		0.30

[a] Model 1 = Crude model
Model 2 = Crude model with en% toppings
Model 3 = Crude model with en% toppings, sex and age
Model 4 = Crude model with en% toppings, sex, age and physical activity (i.e. days per week with at least 30 minutes of strenuous activity)
Model 5 = Crude model with en% toppings, sex, age, physical activity (i.e. days per week with at least 30 minutes of strenuous activity) and energy intake

Discussion

The current study investigated the consumption patterns—in terms of energy intake rate—within Dutch adults using 24h dietary recall data. Foods with a high and low energy intake rate (i.e. foods from the two lower and two upper quartiles, respectively) contributed equally to energy intake. Foods with a high energy intake rate contributed approximately one third of the food weight consumed. Furthermore, the association between energy intake rate and energy intake and weight status was explored. A positive association was found between energy intake rate and energy intake. No association between energy intake rate and BMI was found.

This is the first study to investigate to what extent people are consuming foods with a low and high energy intake rate. The results show that the consumption patterns of Dutch adults provide opportunities for lowering energy intake rate, as a considerable proportion of energy intake (i.e. 53 %) was derived from foods with a high energy intake rate. In particular the consumption of caloric beverages provides opportunities for lowering energy intake rate. They were the most prevalent food in the highest energy intake rate-quartile (i.e. 161 out of the 327 foods) and contributed substantially to energy intake (i.e. 17%). These findings are in line with previous studies that have demonstrated that lowering the intake of caloric beverages can help control energy intake [15-17].

The current study is also the first to explore the association between dietary-EIR and energy intake and weight status. Based on previous research, we expected that people with a diet with a high energy intake rate would have a higher energy intake and as a result a higher BMI. In line with our hypothesis we found a positive association between energy intake rate and energy intake. No association between energy intake rate and BMI was found. These results, however, are only explorative.

Further research is needed to get a more detailed picture of what people are consuming in terms of energy intake rate and to determine the effect of energy intake rate on long-term energy intake and weight status. The current study merely provides a global picture of the current situation and some first indications on the relation between energy intake rate, long-term energy intake and weight status, though it represents the state-of-the-art. This area of research is still in its infancy and there are several hurdles to be overcome.

It was not possible to include toppings (i.e. condiments, sauces and bread toppings) in the main analyses. The eating rate of toppings, when eaten in isolation, is not very informative as they are normally eaten in combination with other foods. Moreover, food consumption data does not report the food combinations consumed, and it is not yet known how toppings affect the eating rate of the foods they are added to (i.e. carrier foods). There, however, are indications that by adding a topping the eating rate of the carrier food could increase as a topping can lower the need to lubricate the carrier food during oral processing [31,12,32]. The eating rate of plain bread (i.e. 10 g/min), for example, has been shown to increase by the addition of a topping (i.e. 23 g/min) [12]. Nonetheless, the carrier foods are expected to be the main determinant of the eating rate of the resulting 'composite foods' (i.e. carrier food with topping) [32]. This would mean that the eating rate of composite foods will be of the same order of magnitude as that of the carrier foods. Furthermore, the proportion of energy derived from toppings was included in the analyses as a confounder and this did not change the results. Finally, excluding toppings will not have affected the observed range in energy intake rate, as the foods with the lowest and highest energy intake rate are beverages; Beverages are not consumed in combination with toppings, and the addition of toppings to other foods is not expected to results in composite foods with an energy intake outside the observed range.

Furthermore, the current study merely provides a global picture of the consumption patterns. For the majority of the foods included in the main analyses energy intake rate had to be estimated; Laboratory data on eating rate was available only for 204 out of the 1307 foods included in the analyses. These foods, however, did account for 53% of the energy consumed from the foods included in the main analyses. Moreover, these foods represented a wide range of foods, which enabled us to make fairly good estimations of the eating rate—and therefore energy intake rate—of the other foods. In making these estimations, however, it was not possible to take into account in what form (e.g. pureed or not) the foods were consumed and whether they were consumed in combination with other foods. Both can affect eating rate [12,13,31,32]. The dataset used to estimate eating rate, however, represents foods as they are normally consumed [12]. Moreover, the eating rate of mixed dishes is expected to represent the eating rate of its components; If, for example, the soft bun of a hamburger is replaced by a hard bun, which has a lower eating rate, the overall eating rate of the hamburger is reduced [10]. In the end, the estimations and assumptions regarding the eating rate of foods are not expected to have affected our conclusions, as our conclusions do not focus on specific foods.

Additionally, there are some characteristics of 24h dietary recall data that need to be considered when interpreting the results. The data may be biased and therefore may not represent actual behaviour [33,23,34,35]. For example, overweight participants reported a higher consumption of non-caloric beverages and a lower consumption of caloric beverages compared to lean participants. This observed difference in beverage consumption, which had an impact on the results, could reflect actual behaviour, but it is also possible that this merely reflects how accurately the lean and overweight participants reported their behaviour [35]. Overweight people are more likely to underreport energy intake [34]. We also observed this in the current study; Identified underreporters had a higher BMI compared to the other participants. This may have affected the observed associations between energy intake rate, energy intake and BMI. Therefore the results do not preclude that energy intake rate is positively associated with BMI, although this is not what we found. Intervention studies are needed before we can draw conclusions on the effect of energy intake rate on long-term energy intake and BMI.

Although challenging, it is important that the potential of energy intake rate is further investigated. Foods with a lower energy intake rate would allow people to enjoy more food and to enjoy it for longer, for the same amount of calories. As mentioned above, lowering the consumption of caloric beverages can help people to reduce energy intake. Quantifying the food characteristic that is expected to be responsible for the low satiating capacity of caloric beverages—i.e. energy intake rate—allows us to identify more foods with a low satiating capacity. To do this, however, we need more accurate data on the energy intake rate, and therefore eating rate, of foods as they are consumed in real-life.

Conclusion

The current study shows that both foods with a low and high energy intake rate are well represented in the consumption patterns of Dutch adults. Foods with a high and low energy intake rate contributed equally to energy intake. Furthermore, foods with a high energy intake rate contributed considerably to the food weight consumed. These results show that the consumption patterns of Dutch adults allow room for lowering energy intake rate. This is expected to increase the satiating capacity of the diet and thereby make people feel full on fewer calories. Furthermore, explorative analyses showed a positive association between energy intake rate and energy intake, though no association between energy intake rate and with BMI was found.

The results of the current study confirm that lowering the energy intake rate of the diet is an interesting avenue to explore further. It shows that Dutch adults have ample possibilities to shift their diets towards foods with a lower EIR, which is a promising strategy for lowering daily energy intake. Future research is needed to identify effective strategies for lowering the energy intake rate of the diet, and to investigate whether they are successful in lowering long-term energy intake and eventually body weight.

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Chapter 6

Modeling of eating style and its effect on intake

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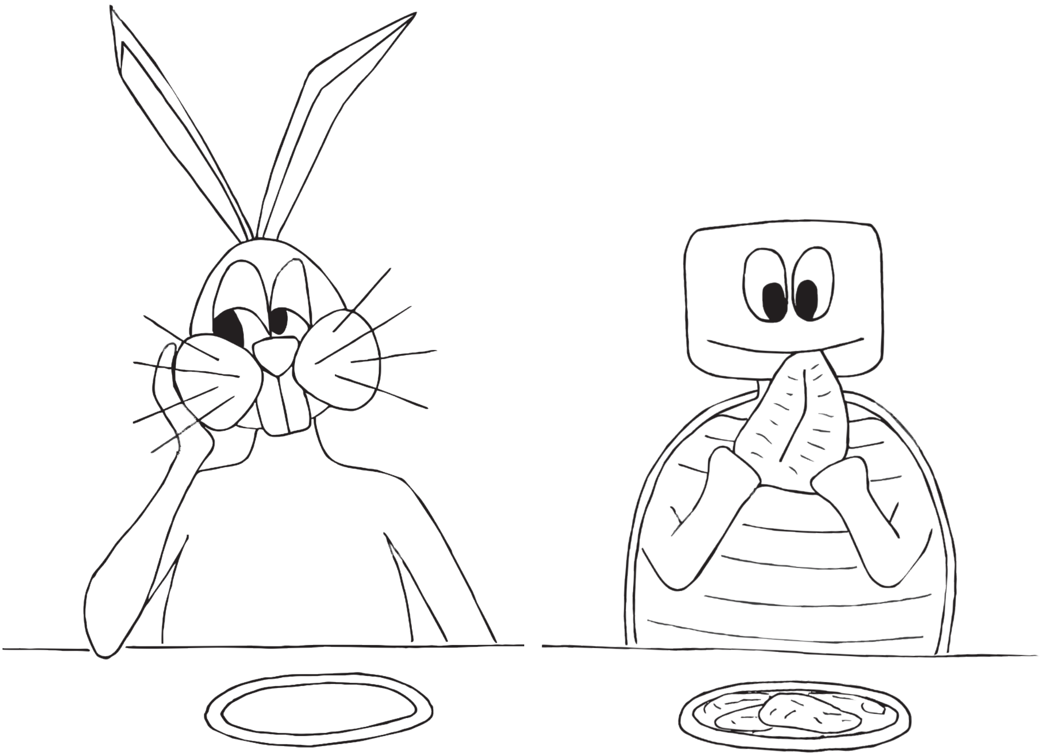

Published in: Appetite, 2015. 86(0): p.25-30
doi: http://dx.doi.org/10.1016/j.appet.2014.08.032.

Abstract

Observational research has indicated that modeling of eating style might occur when eating in the presence of an eating companion. This experiment investigated the effect of bite frequency of a same-sex eating companion on bite frequency, meal size and meal duration. A total of 30 normal weight young adults (m/f = 8/22, age: 21.2 ± 1.9 years, BMI: 21.2 ± 1.6 kg/m2) had three ad libitum meals together with a same-sex confederate (i.e. instructed eating companion). Confederates were instructed to eat at a slow (3 bites/min), medium (5 bites/min) or fast (7 bites/min) bite frequency in randomized order. Eating style was assessed through video registration and weighing left-overs. It was found that the participants' bite frequency was similar during all three conditions, i.e. slow: 3.9 ± 1.3, medium: 4.0 ± 1.1, fast: 4.0 ± 1.3 bites/ min ($p = 0.75$), as was average bite size (11 ± 2.6 g). Time eaten of the participants was shorter in the medium (14.9 ± 3.6 min) and fast condition (14.4 ± 3.7 min) compared to the slow condition (16.8 ± 4.8 min) (post hoc in both cases $p < 0.01$), and intake was lower in the medium (634 ± 183 g) and fast condition (624 ± 190 g) compared to the slow condition (701 ± 220 g) (post hoc in both cases $p < 0.05$). This experimental study suggests that bite frequency is not affected by the confederate. However, the meal duration of the confederates showed a significant effect on the meal duration and meal size of the participants. It seems that intake was influenced as a result of copying meal termination.

Introduction

Many factors affect the amount of food that people ingest. These factors can be roughly divided into three categories: 1) the food, palatability and physical structure of the food [e.g. 1]; 2) the individual, i.e. psychological and physiological factors [2]; and 3) the environment, e.g. the surroundings or the presence of others during eating (e.g. [3]). Modeling of intake is an example of the latter category; it can be defined as the process during which food intake is affected by the intake of an eating companion [4].

It has been shown repeatedly that people adjust their intake to that of others; i.e. people eat more when their eating companion eats more and they eat less when their eating companion eats less [e.g. 5,4,6]. A clear example is the study by Goldman et al. [5]. In this study, confederates were instructed to eat six bite-sized foods or to eat 16 bite sized foods. Participants who were eating together with the confederates were affected by the eating behavior of the confederates; they consumed on average 10 in the six foods condition and 14 in the 16 foods condition. A study conducted by Hermans et al. [6] showed similar findings; when confederates were instructed to eat four chocolate candies the participants ate on average two chocolate candies, and when the confederates were instructed to eat 25 chocolate candies the participants ate on average 10 chocolate candies.

Although it has been repeatedly shown that modeling of food intake exists, little is known about the mechanism underlying it. An important process might be mimicry of motor movement, in other words copying the act of the hand bringing food to the mouth [7]. It has been shown that people unconsciously mimic motor behaviors of the people they interact with [8-10]. For example, Chartrand and Bargh [11] found that participants were more likely to rub their face or shake their foot if the other person present was doing so. This illustrates the presence of a 'perception–behavior link'. Simply perceiving a behavior increases the likelihood of executing it, as perceiving a behavior activates neurons involved in the execution of that behavior [12,10,13,11]. This could also explain the occurrence of modeling of intake in the above described studies [5,6], as in both studies it concerns intake of bite sized foods, which involves clearly visible motor movement with each bite. As Hermans et al. [14] already mentioned, mimicry of the act of taking a bite, and therefore modeling intake, might be explained by this perception–behavior link.

However, when it comes to a meal instead of bite sized foods, the interplay between eating companions can be more complex. Hermans et al. [14] analyzed the timing and interplay of 70 female couples who had a meal together. The analyses showed that participants were most likely to take a bite when their eating companion had also taken a bite, that is within 5 seconds, suggesting that the participants copied the bites taken by their eating companion. However, as this analysis was based on observational data, it could not be ruled out that other factors may have played a role in this interplay between eating companions, such as the conversation.

The current experiment has been designed to test whether people copy the act of taking a bite and whether it affects their meal intake. Participants had three meals in the company of a same-sex confederate, who was instructed to take bites at a different frequency (i.e. slow, medium or fast) every meal. This experimental design enabled investigation of the cause–effect relation between bites taken by eating companions. Furthermore, the meals were homogeneous of structure, which allowed for variation in bite size and as result for distinguishing between effects on bites taken and intake. We expected to demonstrate mimicry of the act of taking a bite, with the participants adjusting their bite frequency to that of the confederates.

Material and methods

Participants and confederates

Participants and confederates were recruited among students of Wageningen University. In order to participate people had to be native Dutch, 18–25 years old, healthy, non-dieting, non-vegetarian, and they needed to have a normal BMI (18.5–25 kg/m2), a normal appetite and no allergy or intolerance for the food under study.

Subjects were invited for an intake interview after coupling them with another subject of the same sex. During the intake interviews one person of each couple was informed on what to expect as a participant. The other person was instructed to be a confederate (i.e.instructed eating companion). Furthermore, height was measured using a stadiometer (Seca 213, Seca GmbH& Co., Hamburg, Germany) and weight with a digital scale (Seca 877, Seca GmbH & Co.).

Written informed consent was obtained from both participants and confederates. Additionally, the confederates received information on their task and signed a confidentiality statement. During the recruitment and the experimental phase a cover story was used for the participants. Participants were told that the study aimed to investigate the effects of having dinner on mood. After finalizing the experiment the participants were debriefed. Furthermore, after completing the experiment confederates and participants received a gift certificate. In total 30 participants and 30 gender matched confederates participated in the experiment. There were no drop-outs. The descriptive characteristics of both participants and confederates are shown in Table 1. Four out of the 30 couples were already acquainted prior to the experiment; two as friends and two as acquaintances.

Table 1 Descriptive characteristics (mean±SD) of the confederates (n=30) and participants (n=30).

	Males		**Females**	
	Confederates (n=8)	**Participants** (n=8)	**Confederates** (n=22)	**Participants** (n=22)
Age (yr)	22.2±1.8	21.2±1.8	22.0±1.6	21.2±2.0
Height (m)	1.73±0.08	1.74±0.06	1.74±0.09	1.73±0.08
Weight (kg)	64.7±6.7	64.4±7.0	65.3±8.9	67.9±9.8
BMI (kg/m^2)	21.6±2.2	21.6±1.6	22.8±2.7	21.1±1.6

Study design

The experiment had a randomized cross-over design with three experimental conditions. In the period of October to December 2012 the participants came to the university three times to have a warm meal with the same confederate. These sessions were scheduled either at lunchtime or at dinnertime, which was a fixed time per couple. Furthermore, they were preferably scheduled on the same week day, but with at least 1 week in between.

During the sessions the confederates were instructed to eat at one of the three predefined bite frequencies; 3, 5 or 7 bites/min in the slow, medium and fast condition, respectively. These frequencies were based on pilot measurements, in which 5 bites/min was the average bite frequency. The order of the experimental conditions was randomized within subjects. Furthermore, the subjects were secretly filmed and their leftovers were covertly weighed in order to assess their eating style.

Setting and experimental procedure

At the entry of the dining room two isolated places were created for the participants and the confederates to fill in questionnaires in private. Further along the room the dining table and two chairs were positioned. The chairs were positioned opposite to each other. Across the dining table a hidden camera was placed between the ceiling and wall to record both the participants' and the confederates' eating style. The room was decorated with table cloths and soft music (21, Adele, XL Recordings, 2011, London, England) was played throughout the sessions to create a pleasant atmosphere.

Participants and confederates came to the research site after at least 1 hour of fasting. They then filled in a short questionnaire, including questions on satiety feelings and mood (see 'Questionnaires'). After both the participant and confederate had finished the questionnaire the researcher invited them to the dining table for their meal.

Here they were served a large portion of readymade hotchpotch with kale and bacon (968 ± 21 g, per 100 g: 548 kJ, 2.9 g protein, 10.2 g carbohydrate, 8.2 g fat, 2.7 g fiber, Bonfait B.V., Denekamp, The Netherlands). This hotchpotch is a traditional Dutch food, which has a homogeneous structure. The meal was heated for 8.5–10 minutes using a microwave just before the start of the meals. Participants and confederates were then instructed to eat until they were pleasantly satisfied. The couples were free to talk while they were eating.

As stated before, the participants and confederates had fixed places at the dining table opposite to each other. The confederates were instructed to take bites at a certain frequency, according to the experimental condition. This frequency was signaled by a laptop which was placed diagonally behind the participant, so that the confederates could look at the participant and the laptop screen simultaneously. When a black screen appeared on the laptop the confederates had to take a bite as quickly as possible. Note that the confederates were free in choosing the size of their bites and were instructed to stop eating when pleasantly satisfied. The participants were only instructed to eat until pleasantly satisfied.

After both the participant and the confederate had finished their meal they filled in a second questionnaire. They also received a glass of water, as they did not get anything to drink during the meal. After the third session participants received an additional questionnaire in which we asked what they thought was the study aim. None of the participants were aware of the actual aim.

Food intake

Intake was calculated by subtracting the weight of the plate after consumption from the weight of the plate before consumption. This was measured to the nearest 1 g on a digital scale (Kern EMB 2200-0, Kern & Sohn, Balingen, Germany).

Measurements of eating style

Measures of eating style for both participants and confederates were obtained by analyzing film recordings. A predefined protocol was used for the analyses and all recordings were analyzed by the same person. A random sample of10% of the recordings was analyzed in duplicate. The duplicate analyses showed only slight differences; i.e. bites reported to have been taken 1 second earlier or later. Other outcomes showed no differences between duplicates.

The components of eating style that were extracted from the recordings were:

- Stopping with eating, i.e. performing at least two of the following actions: pushing away the plate, placing the cutlery on the plate and adopting a more distant posture towards the food.
- Total number of bites, i.e. the total number of bites a person took during a session. This includes bites that were taken after he/ she has stopped eating, according to the definition

above. The total number of bites was only incorporated in the calculation of average bite size, so not in the calculation of bite frequency.

- Total time eaten (min), i.e. the total time a person spent eating, including the time during which the eating companion may already have stopped eating.
- Time eaten together (min), i.e. the total time eaten of the person within the couple that finished first.
- Bite frequency (bites/min), i.e. the number of bites during the time eaten together divided by the time eaten together. However, when a person was occupied with activities unrelated to eating or communicating with their eating companion (e.g. playing with a mobile phone or putting on extra clothes) for more than 10 seconds this time was not incorporated in the bite frequency calculations. This means; bite frequency = number of bites/(time eaten – time spent on other activities). This only applied to three meals.
- Bite frequency first and second half (bites/min), i.e. the number of bites during the first and second half of the time eaten together divided by half of the time eaten together, respectively. However, like with bite frequency, when a person was occupied with activities unrelated to eating or communicating with their eating companion for more than 10 seconds this time was not incorporated.
- Average bite size (g), i.e. total intake (g) divided by the total number of bites.
- Eating rate (g/min), i.e. average bite size (g) multiplied by the bite frequency during the time eaten together (bites/min).

Questionnaires

Satiety state was rated before and after the meals. This was measured by rating their feelings of hunger, fullness, desire to eat and prospective consumption on a 10-point Likert scale anchored from “not at all” to “extremely present” [15]. Liking of the test food was measured after consumption of the meals with a nine-point Likert scale anchored from ‘not tasty at all’ to ‘very tasty’. Moreover, participants were also asked to rate the fattiness, saltiness, and temperature of the meal on a nine-point Likert scale. Additionally, after their first meal participants and confederates were asked whether they already knew their eating companion prior to the experiment. They were provided with four possible answers: ‘Yes, he/she is family’, ‘Yes, he/she is a friend’, ‘Yes, he/she is an acquaintance’ or ‘No’.

Statistical analysis

SPSS (IBM SPSS Statistics, Version 20, IBM Corporation, Armonk, NY, USA) was used for the statistical analyses. Means and standard deviations are given, unless stated otherwise. P-values of <0.05 were considered statistically significant. Furthermore, normality was judged by visual inspection using QQplots; all data were normally distributed. The primary analysis consisted of one-way analyses of variance to check whether there were within person differences in eating style between experimental conditions among the participants and the confederates. If statistically significant between conditions, post hoc analyses were performed by means of LSD. In the same way it was tested whether levels of satiety before and after the meal differed between conditions.

Furthermore, with independent samples t-tests, differences between eating style components of males and females were investigated. A paired samples t-test was used to compare the participant's bite frequency between the first and second half of the meal, and to compare the time eaten of participants and confederates. Additionally, it was tested through Pearson correlation analyses whether eating style components of the participants were related to characteristics of the participants, to other eating style components of the participants, and to eating style components of the confederates.

Results

The eating style of the participants and confederates are shown in Table 2 and Figure 1.

Manipulation check

The bite frequency of the confederates in the slow, medium and fast condition was 2.8 ± 0.3, 4.5 ± 0.6 and 5.7 ± 0.9 bites/min, respectively ($F(2) = 298.347$, $p < 0.001$; post hoc, all p-values <0.001) (Figure 1a). During all conditions bite frequency was slightly higher in the first half of the meal compared to the second half of the meal (paired t-test $t(89) = 3.945$, $p < 0.001$). Average bite size was largest in the slow condition and smallest in the fast condition (Table 2). Eating rate was higher in the medium and fast condition, compared to the slow condition (Table 2). The total time eaten by the confederate was significantly shorter in the medium (13.8 ± 4.1 min) and fast condition (13.3 ± 3.7 min), compared to the slow condition (17.0 ± 4.9 min) ($F(2) = 16.392$, $p < 0.001$; post hoc slow-medium and slow-fast $p < 0.001$, medium-fast $p = 0.51$) (Figure 1b). Total food intake of the confederates was similar during all three eating occasions ($F(2) = 0.055$, $p = 0.95$) (Figure 1c). On average this was 709 ± 171 g.

Eating style participants

As can be seen from Figure 1a, the participants ate with a similar bite frequency during all three conditions; i.e. 3.9 ± 1.3, 4.0 ± 1.1 and 4.0 ± 1.3 bites/min in the slow, medium and fast condition, respectively ($F(2) = 0.294$; $p = 0.75$). During the first half of the meal, participants ate faster compared to the second half of the meal for all conditions (first half: 4.1, second half: 3.8 bites/min; paired t-test $t(89) = 3.534$, $p = 0.001$). No statistically significant differences were observed between conditions for bite frequency during the first half of the meal, bite frequency during the second half of the meal, average bite size and eating rate (Table 2). The participants' total time eaten was significantly longer during the slow condition (16.8 ± 4.8 min) compared to the medium (14.9 ± 3.6 min) and fast condition (14.4 ± 3.7 min) ($F(2) = 6.911$, p =< 0.01; post hoc slow-medium and slow-fast $p < 0.01$, medium-fast $p = 0.472$) (Figure 1b). Total intake was significantly higher in the slow condition compared to the other two conditions, i.e. slow: 701 ± 220, medium: 634 ± 183 and fast: 624 ± 190 g ($F(2) = 3.477$, $p = 0.038$; post hoc slow-medium and slow-fast $p < 0.05$, medium-fast $p = 0.720$) (Figure 1c).

Satiety levels were equal between conditions, both before the test session ($F(2) = 0.876$, $p = 0.422$) as well as after the test session ($F(2) = 0.024$, $p = 0.976$). Additionally, repeated measures ANOVA showed no order effect of the sessions on bite frequency ($F(2) = 1.101$, $p = 0.34$), nor on total intake ($F(2) = 2$, $p = 0.84$).

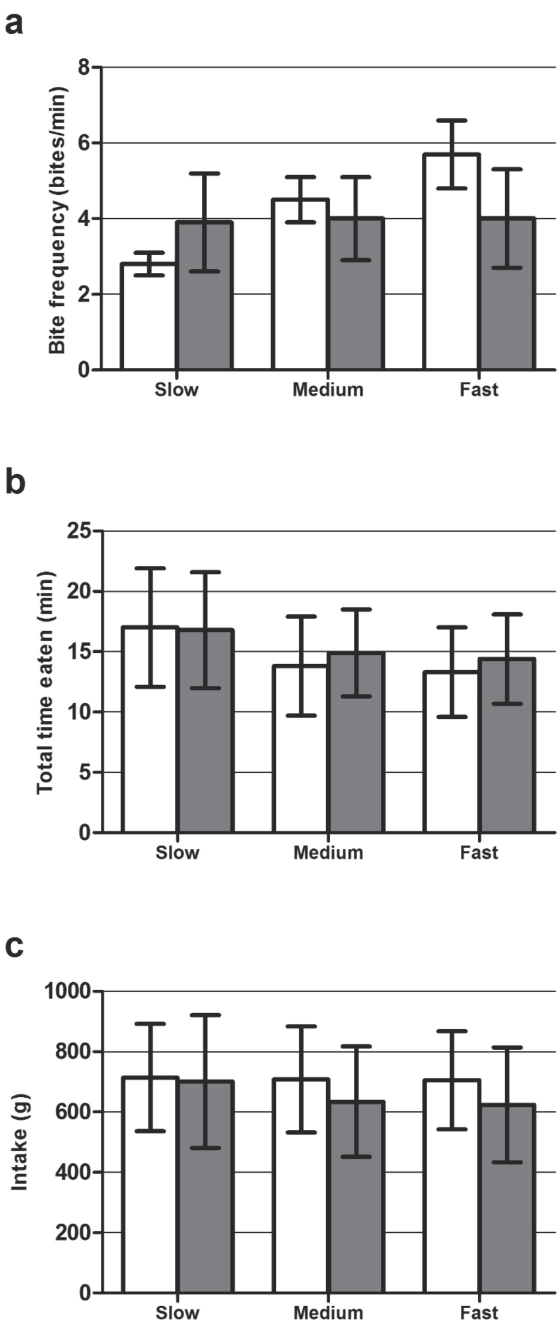

Figure 1 Bite frequency (a), total time eaten (b) and intake (c) of confederates (i.e. □, n=30) and participants (i.e. ■, n=30) (mean ±SD), according to experimental condition. In the slow, medium and fast condition the confederates (i.e. instructed eating companions of the participants) were instructed to eat at a bite frequency of 3, 5 or 7 bites/min, respectively.

Chapter 6

Table 2 Eating style of confederates (n=30) and participants (n=30), according to experimental condition. In the slow, medium and fast condition the confederates (i.e. instructed eating companions of the participants) were instructed to eat at a bite frequency

		Condition			One-way ANOVA *p*-value
		Slow	Medium	Fast	
Bite frequency 1st half (bites/min)					
	Confederates	2.9±0.3 [a]	4.6±0.5 [b]	5.9±0.8 [c]	<0.001
	Participants	4.1±1.3	4.1±1.2	4.2±1.2	0.93
Bite frequency 2nd half (bites/min)					
	Confederates	2.8±0.3 [a]	4.3±0.9 [b]	5.5±1.0 [c]	<0.001
	Participants	3.7±1.3	3.8±1.1	3.8±1.5	0.93
Average bite size (g/bite)					
	Confederates	15±4 [a]	12±3 [b]	10±3 [c]	<0.001
	Participants	11±2	11±3	11±3	0.88
Eating rate (g/min)					
	Confederates	43±10 [a]	53±14 [b]	55±13 [b]	<0.001
	Participants	42±12	44±12	45±15	0.36

[1] Values in a row with different superscript letters are significantly different (p<0.05), LSD

Eating style within couples

In the slow condition, the confederates' and participants' time eaten was similar (paired t-test; t(29) =−0.473, p = 0.64). However, during the medium and fast condition, the time eaten of the confederates was shorter than that of the participants (paired t-test; t(29) = 2.377, p = 0.02 and t(29) = 3.069, p =< 0.01, respectively).

Overall correlations were calculated between participants and confederates for the different eating style components, i.e. bite frequency, bite size, eating rate, total time eaten and total intake. All eating style components were significantly correlated between participants and confederates, except bite frequency (Table 3). Additionally, partial correlations between eating style of the participants and confederates were calculated, taking into account the couple they belonged to. Statistically significant correlations were found for eating rate, time eaten and intake, but not for bite frequency and bite size (Table 3). Furthermore, participants' intake was significantly correlated to total time eaten (r = .49, p

≤ 0.001). Total time eaten of the participants, in turn, showed to be highly related to the total time eaten of the confederates (r = .83, and p < 0.001).

Table 3 Pearson correlations between the eating style components of the participants (n=30) and the confederates (n=30).

Eating style component	r	*p*-value
Participant vs. confederate		
Bite frequency	0.02	0.84
Bite size	0.22	0.04[a]
Eating rate	0.49	<0.001[a]
Time eaten	0.83	<0.001[a]
Intake	0.42	<0.001[a]
Participant vs. confederate, adjusted for couple[b]		
Bite frequency	0.02	0.84
Bite size	0.20	0.07
Eating rate	0.48	<0.001[a]
Time eaten	0.83	<0.001[a]
Intake	0.42	<0.001[a]

[a] Significantly different (*p*<0.05)
[b] Adjusted by partial correlation

Effect of gender and additional factors on eating style

Subgroup analyses showed that male participants tended to have a higher bite frequency compared to females (males = 4.4 ± 1.0, females = 3.8 ± 1.2 bites/min; t(88) =−1.899, p = 0.06). Males had a significant higher intake (males = 776 ± 214 g, females = 609 ± 175 g; t(86) =−3.693, p < 0.001) and eating rate (males = 54 ± 11, females = 40 ± 11 g; t(86) =−5.504, p < 0.001) compared to females. Furthermore, in females no significant relation was found between the total intake of the participants and the confederates (r = .22, p = 0.09). In males a significant correlation was found between the total intake participants and confederates (r = .57, p =< 0.01).

Explorative correlation analyses were performed to check whether bite frequency, meal duration and intake were correlated to BMI, age, liking of the test food, opinion on the temperature of the test food and familiarity with the eating companion. Only a positive correlation between bite frequency and BMI (r = .30, p =< 0.01), and between bite frequency and liking of the test food (r = .31, p < 0.01) was observed in the participants.

Discussion

The aim of this experiment was to test whether people copy the act of taking a bite. If this was the case the participants would adjust their bite frequency to that of the confederates (i.e. 3, 5 or 7 bites/min). However, we did not observe this adjustment; the bite frequency of the participants remained constant over conditions (i.e. on average 4.0 ± 1.2 bites/min) and was not influenced by the bite frequency of the confederates, despite the successful manipulation. Interestingly, the size of the meal was affected by the different experimental conditions. The participants' intake was significantly higher in the slow bite frequency condition, compared to the medium and fast bite frequency condition; 701 ± 229, 634 ± 183 and 624 ± 190 g, respectively.

At first glance these findings seem not to be in line with the observational findings of Hermans et al. [14]. In that study it was observed that within a meal participants were most likely to take a bite after their eating companion took a bite, i.e. within 5 seconds. In our experiment we investigated the most straightforward mechanism explaining their findings; i.e. mimicry of the act of taking a bite. We could, however, not confirm that one's bite frequency is affected by the bite frequency of the person he/she eats with. An alternative explanation for the findings of Hermans et al. [14] could be that the dynamics between eating companions played a role in their data. The interplay and dynamics between the different actions of eating companions, such as speaking, listening, chewing and taking a bite might have caused this apparent copying of bites. For practical reasons certain moments during a meal might be just more suitable for taking a bite; when the eating companions are having a conversation during which eating, speaking and listening are alternated.

Looking more closely at the results of our experiment it seems that participants, instead of mimicking the act of taking a bite, copied meal termination. The confederates stopped eating earlier when they were instructed to eat with a medium or fast bite frequency, compared to when they were instructed to eat with a slow bite frequency. It seems that once the confederate stopped eating and was waiting for the participant to finish, the participant became more self-conscious, was put in an uncomfortable position and was stimulated to stop eating as well. Previous studies have already shown that people drastically inhibit their food intake in the presence of a noneating other (i.e. an observer) [16,4,17].

The shortened meal duration of the participants in the medium and fast condition, combined with their constant eating rate (i.e. bite frequency multiplied by bite size) over conditions, resulted in a lower intake in participants in the medium and fast condition. Nevertheless, participants' satiety after the meal was equal for all conditions. This indicates that the participants were not aware of their altered intake. On the other hand the confederates maintained a constant intake over conditions, despite the imposed bite frequencies. This could not be due to the offered amount of hotchpotch; in all conditions the intake was lower than the amount that was offered (i.e. on average 968 (SD = 21) g).

The current findings also offer an alternative explanation for the phenomenon of 'modeling of intake' described in the aforementioned studies [5,6]. It might very well be that instead of copying the motor movement of taking a bite, the termination of a meal or the absence of eating is copied. The time spent eating by an eating companion increases with his/ her intake. Therefore a higher intake will result in a delayed meal termination. Assuming that the meal termination of an eating companion constitutes a cue to stop eating, this will result in a longer meal duration and therefore a higher intake in the other person as well. This mechanism also works the other way round; a lower intake of the eating companion results in earlier meal termination by the eating companion, suppressing further intake of the other person. This mechanism is supported by previous studies that have already shown that meal duration plays a role in social effects on eating [18-20]. Furthermore, it fits the normative framework of Herman and Polivy [21] in which they argue that people use the intake of others to determine an upper limit of appropriate intake; i.e. how much they can eat themselves without eating 'excessively'. Maybe the participants in the current study tried to avoid eating excessively by copying meal termination. However, to our knowledge none of the studies on modeling of intake have reported the actual time spent eating by or the moment of meal termination of the participants and confederates, nor have they controlled for it (e.g. [16,5,6,22,23]). It may very well be that also in these studies the absence of eating acted as a cue and not the act of eating.

Nonetheless, it should be noted that in the current experiment we investigated a meal which had a distinct ending, characterized by actions like putting down the cutlery and pushing away the plate of food, which might be visual cues that were mimicked. The majority of the modeling studies concern snack consumption (e.g. [16,5,6,22]), during which the end of an eating episode is less definite. Here initiation and termination of eating are repeatedly present. Furthermore, it is questionable if one can speak of 'a time spent eating' in such studies. As is common when snacking, in these studies the main focus is on activities other than eating (e.g. solving a puzzle or having a break).

Additionally, in our study the findings on which the suggested cause–effect relations are based were only evident between the slow, and the medium and fast condition. It might be that the differences between the confederates' bite frequency in the medium and fast condition were not distinctive enough to produce statistically significant different outcomes, as the confederates did not manage to fully comply with the imposed faster bite frequencies of 5 and 7 bites/min. Another possible explanation is that both the medium and fast conditions elicit a similar effect, as they both can be considered conditions with a high bite frequency; in both conditions the confederates' bite frequency was higher than the mean bite frequency of the participants. Nevertheless, this does not affect the main conclusions of the study. The bite frequency of the participants was very consistent over conditions and a bigger difference in the bite frequency of the confederates is not expected to change that.

In conclusion, in the current experiment the bite frequency of young adults was not influenced by manipulating the bite frequency of eating companions. However, the experiment showed that food intake can be altered indirectly by affecting the meal duration of the eating companion. This experiment therefore suggests that the moment of meal termination of eating companions is a relevant predictor of food intake and possibly also of modeling of intake.

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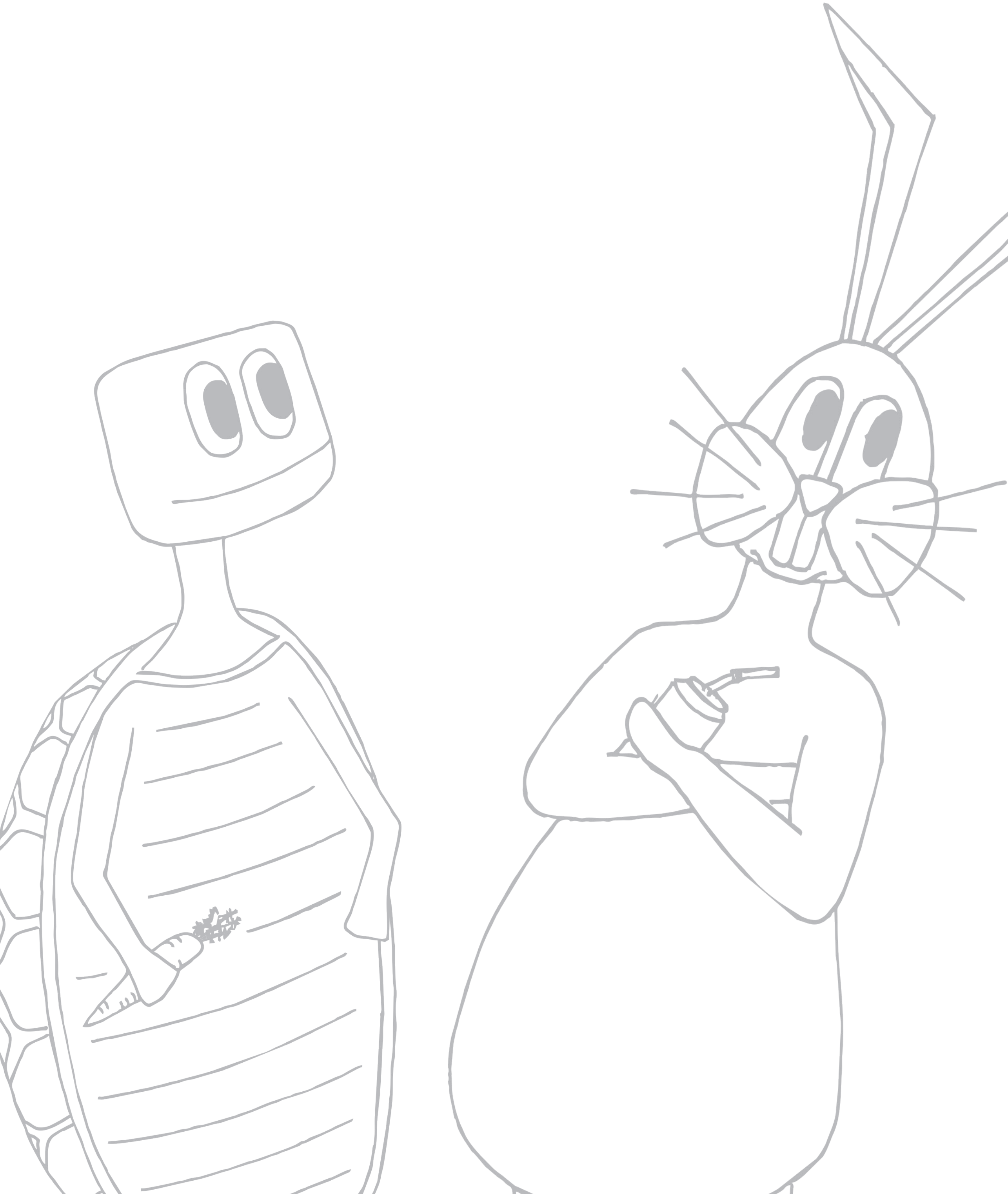
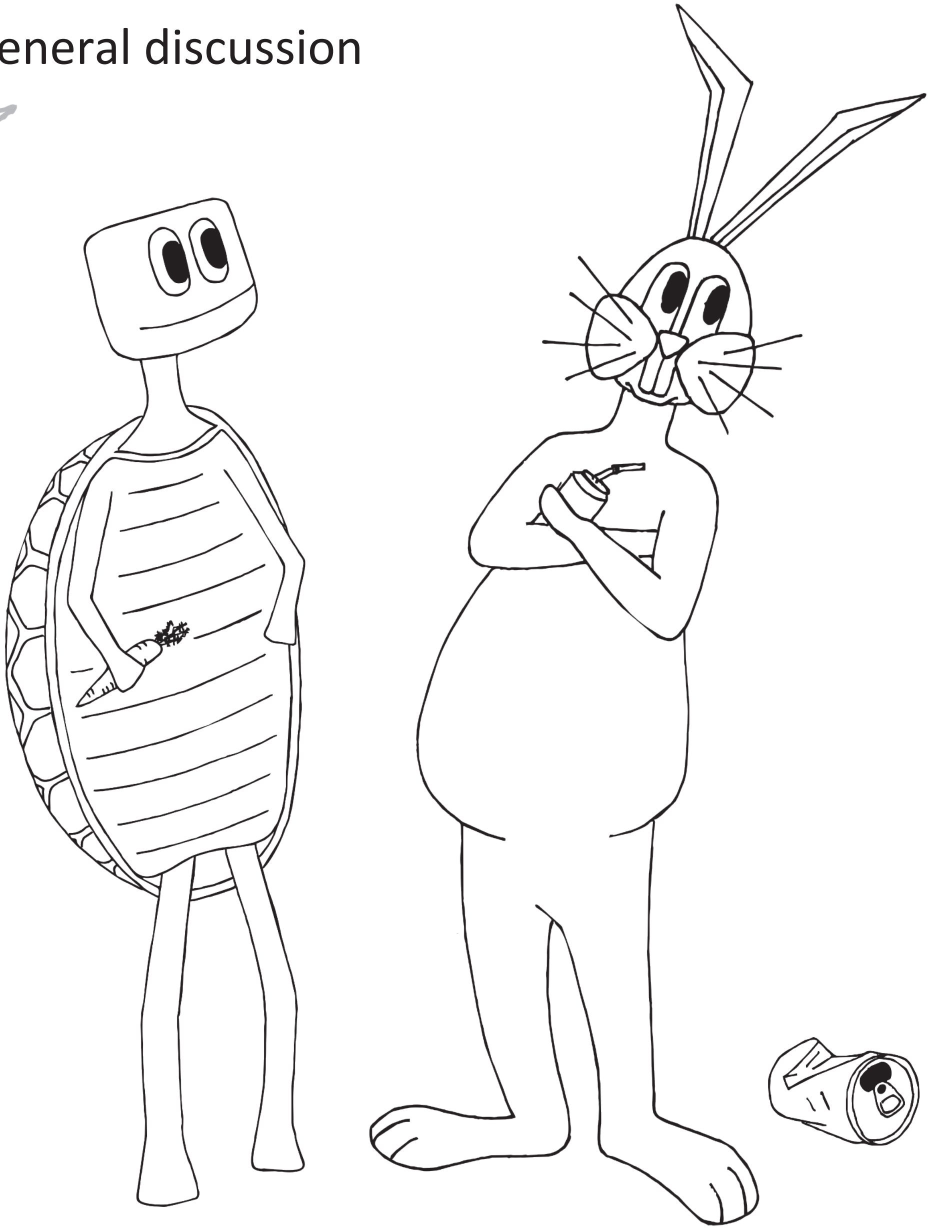


Chapter 7

General discussion



The obesity epidemic demonstrates that people are having difficulties with limiting energy intake to match energy expenditure. Lowering eating rate is expected to facilitate the control of energy intake and body weight by increasing satiety. Randomized controlled trials are needed to confirm whether there is a causal relation between eating rate, long-term energy intake and weight status. In order to perform these randomized controlled trials we first need to identify effective approaches for lowering long-term eating rate that would be successful at lowering long-term energy intake and BMI.

Hence, this thesis explored the opportunities for lowering long-term eating rate, and their potential to reduce long-term energy intake and body weight. Different levels at which eating rate can be targeted were considered: the person (Chapter 2 and 3), the food (Chapter 4 and 5), and the eating environment (Chapter 6). A variety of methods, ranging from laboratory studies to epidemiological studies, were used. In the current chapter the main findings are discussed, and directions for future research and implications for weight management are provided.

Main findings

Below the main findings are discussed according to the levels at which eaing rate can be targeted: i.e. the person, the food and the direct eating environment. Table 1 provides an overview of the main findings of this thesis.

Person

It was repeatedly found that eating rate is a stable characteristic of individuals, which is in line with previous research [1-4]. People that consumed one food relatively fast also consumed other foods relatively fast (Chapter 2 and 4). Additionally, when people were offered the same food on multiple occasions their eating rate was similar (Chapter 4 and 6); 81% of the variance in eating rate was explained for by the participant when eating hotchpot on three similar occasions ($F(29)=8.37$, $P<.0001$, *partial* $\eta^2=.81$) (Chapter 6).

Moreover, results from Chapter 2 indicate that people are aware of their own personal eating rate to some extent. Participants gave similar answers when they were asked to describe their eating rate (i.e. very slow, slow, average, fast or very fast) twice, with approximately 1 year between the questions (κ-value=0.64). This self-reported eating rate, however, only showed fair agreement with actual eating rate and therefore is not a good measure for the eating rate of individuals. Nevertheless, self-reported eating rate was found to be valid measure for eating rate on a group-level, as it was positively associated with actual eating rate.

Table 1 Overview of main findings

Level	Finding	Chapter
Person	Eating rate is a stable characteristic of individuals	2, 4, 6
	Self-reported eating rate reflects actual eating rate on group-level	2
	Self-reported eating rate was positively associated with energy intake	2
	A high self-reported eating rate is associated with a higher BMI	2
	Technological solutions may provide opportunities for monitoring and retraining eating behavior	3
	Individuals are open to the idea of using technologies for monitoring and retraining eating behavior	3
Food	The foods consumed in the Netherlands offer variety in eating rate, both between and within food groups	4
	The eating rate of commonly consumed foods is associated with food texture, energy density and water content	4
	Energy intake rate (kcal/min), i.e. eating rate multiplied with energy density, is a newly identified food characteristic that is expected to predict energy intake	4, 5
	The foods consumed in the Netherlands offer variety in energy intake rate, both between and within food groups	4
	Current consumption patterns provide opportunities for lowering energy intake rate	5
	Dietary energy intake rate was associated with energy intake	5
	No association between dietary energy intake rate and BMI was found	5
Eating environment	A person's bite frequency is not affected by the bite frequency of an eating companion	6
	The moment of meal termination was affected by the moment an eating companion terminates his meal	6

In Chapter 2 we investigated whether self-reported eating rate is associated with energy intake and BMI in a Dutch cohort study (i.e. NQplus [5]). Self-reported eating rate was positively associated with energy intake, but only after excluding suspected underreporters of energy intake. A stronger association between self-reported eating rate and energy intake may be found with measures of energy intake that are less prone to underreporting, as underreporting is more prevalent in overweight people [6,7]. Regarding BMI, also a positive association with self-reported eating rate was found. People with a self-reported high or very high eating rate had a 0.90 kg/m^2 (95%CI: 0.48, 1.32) higher BMI compared to people with a self-reported average eating rate. These findings, however, are based on cross-sectional data and therefore cannot confirm whether there is a causal relation between eating rate, energy intake and BMI. Nevertheless, the results are in the expected direction and are in line with previous studies [8,9].

The positive association between self-reported eating rate, energy intake and BMI shows that—potentially—energy intake and BMI can be reduced by lowering a person's eating rate. It, however, is not clear whether it is possible to retrain peoples' eating habits and sustainably lower their personal eating rate. Eating is a highly automatic behavior [10] and, as described above, eating rate is a stable characteristic of individuals [1-4]. Furthermore, intervention studies indicate that eating rate is not easily changed [11,12]. For example, Spiegel et al. [11] provided obese women with advice on lowering eating rate (i.e. putting utensils down between bites and cutting food into small partions) as part of a larger weight controll program. These women did manage to lower their eating rate, but this change was not maintained over time. Furthermore, Ford et al. [12] attempted to lower the eating rate of children in a 1 year-intervention with the help of the Mandometer©: i.e. a scale that is placed uderneath the plate during a meal that provides feedback on eating rate. Eating rate was reduced at the end of the intervention, though not significantly. Moreover, their results suggest that 'retraining' is needed to maintain behavioural change after the intervention.

New technological solutions could increase the chances of success as they may provide opportunities for monitoring and retraining eating rate. To our knowledge, there are currently two devices that can monitor and provide feedback on a person's eating rate: the Mandometer©, which is described above, and the 10SFork (i.e. an electronic fork that vibrates if there is not enough time between bites) [12-15]. These devices, however, can only be used during main meals. Currently several wearable devices that can detect eating events are under development [16-19]. Such devices are equiped with sensors that provide information on eating behavior (e.g. eating rate). These devices may therefore enable real-time feedback on eating rate. An example of such a device is the eating detection sensor described in Chapter 3 [20-23]. It is an ear-worn device that detects eating event using signals collected by an in-ear microphone, an optical sensor (i.e. PPG sensor) and an accelerometer. With more advanced algorithms this device may provide information on bite and chewing frequency. Furthermore, results from Chapter 3 show that people would be open to using such a device if it would be comfortable to wear and discreet.

Finally, instead of retraining a persons eating behavior, it would also be an option to limit a person's ability to eat fast. This may be achieved with at device like the SmartByte™ [24-26]. This device is worn in the upper palate while eating and restricts the oral volume. As a result bite size and eating rate are reduced. Interventions studies have shown that more frequent use of the SmartByte™ is associated with more weight loss [24,25]. However, adherence is an issue with this device [25]. Another option would be to reduce bite size through changing the mode of consumption [27-30]. For example, Bolhuis et al. [27] showed that eating rate was higher in participants that chose to eat a pasta lunch (i.e. elbow macaroni) with a spoon compared to those that chose to eat the pasta lunch with a fork. And others have shown that eating rate and intake is reduced if a liquid food (e.g. soup or liquid yogurt) is eaten with a spoon instead of consumed as a beverage [29,28].

Food

The foods consumed in the Netherlands were found to offer a wide variation in eating rate (Chapter 4). Eating rate ranged from 2 g/min for rice waffle to 641 g/min for apple juice. Moreover, variety in eating rate was found both between and within food groups. Food texture explained most variation in eating rate, with liquids foods being consumed more quickly than more solid and harder foods. After excluding liquids, the range in eating rate was reduced considerably (i.e. 2-147 g/min). Moreover, water content (g/100g) was found to be positively associated with eating rate, and energy density (kcalc/100g) was found to be negatively associated with eating rate. These findings are in line with previous research [31-33].

Furthermore, in Chapter 4 we introduced a new food property: energy intake rate (kcal/min). It represents the rate at which energy is consumed. It adds an extra dimension to eating rate; it is obtained by multiplying the eating rate of a food with the energy density of the food. Energy intake rate is expected to be a stronger predictor of energy intake than eating rate or energy density as such. Result from a recent experiment showed that greater reductions in energy intake can be achieved by lowering both the eating rate and the energy density of a food, compared to lowering only its eating rate or energy density [34]. The results of Chapter 4 show that the foods consumed in the Netherlands also offer a wide variation in energy intake rate: ranging from 0 kcal/min for water to 422 kcal/min for chocolate milk.

In Chapter 5 it was investigated whether the consumption patterns of Dutch adults provide opportunities for lowering the energy intake rate of the diet. It was found that foods with a relatively high and low energy intake rate (i.e. foods below and above the median, respectively) contributed equally to energy intake. Foods with a relatively high energy intake rate contributed about one third of the food weight consumed. These results show that Dutch adults have ample possibilities to shift their diet more towards foods with a low energy intake rate. For example, by limiting the consumption of caloric beverages. Furthermore, the energy intake rate of the diet was found to be positively associated with energy intake, although not with BMI. The study, however, was cross-sectional and therefore does not provide information on causal relations.

The results of Chapter 4 and 5, although they represent the state-of-the-art, merely provide a global picture of the current situation and a first indication on the association between the energy intake rate of the diet and long-term energy intake and BMI. Several assumptions had to be made in the analyses. For example, it was assumed that all reported foods were consumed in isolation and that eating rate is not affected by the addition of toppings. These assumptions, however, are not expected to have affected our conclusions as the conclusions are not very specific. Further research is needed to obtain more details on what people are consuming in terms of eating rate and energy intake rate, and to determine whether a higher eating rate and energy intake rate results in a higher long-term energy intake and BMI. Summarizing, the results show that the foods available in the Netherlands do offer a wide variety in eating rate and energy intake rate, and that the consumption patterns of Dutch adults provide opportunities for a shift towards towards food with a low energy intake rate.

Interventions that aim to lower the eating rate of the diet (g/min) should primarily focus on food texture. In Chapter 4 food texture was found to be the main predictor of eating rate, which is line with previous research [31,34,32,33,35-39]. A first step would be to limit the consumption of caloric beverages. Regarding the remainder of the foods one could choose slower options from the readily available foods and food industry may develop slower alternatives [40]. Furthermore, to decide on what slower options are not only the food itself should be considered, but also how it is prepared [36,34,41]. The eating rate of vegetables, for example, can be increased by boiling them; the eating rate of raw carrots was 12 g/min, while the eating rate of boiled carrots was 89 g/min (Chapter 4).

When designing an intervention that aims to reduce eating rate through food choice also the palatability of the foods needs to be considered, as this is a major predictor of intake. Palatability is affected by a food's texture [42,43]. Their relation, however, is complex and depends on a number of factors, such as expectations and personal preference [42]. Enhancing the texture of foods may result in less palatable foods [44,36,39], although this is not necessarily the case [34]. Furthermore, findings from Chapter 4 suggest that foods may need to have a certain eating rate to be acceptable. Although the eating rate of vegetables is increased by processing them (e.g. boiling or stir-frying) the eating rate of processed vegetables was similar to that of unprocessed vegetables in our dataset (i.e. 39 g/min and 34 g/min, respectively). However, note that this dataset includes foods as they are commonly prepared in the Netherlands. It seems that 'slow vegetables' (e.g. cabbage and leek) are more frequently processed prior to consumption compared to 'faster vegetables'. As a result they have an eating rate similar to that of the vegetables commonly consumed raw (e.g. cucumber).

Furthermore, it is not yet known to what extent providing slower alternatives will reduce the eating rate of the whole diet. It, for example, is possible that in real-life people compensate for the slow eating rate by adding toppings, which is expected to increase their eating rate. Standard portion sizes for toppings (obtained from dietetics guidelines used for estimating food intake) suggest that relatively more topping goes onto drier, harder—and therefore slower—bread products; for example, 15g jam on a slice of bread (i.e. 35g) and 10g jam on a piece of rusk (i.e. 10g) [45]. This needs to be investigated and needs to be taken into consideration when designing interventions that aim to reduce eating rate through food choice.

Moreover, it would be interesting to investigate the potential of interventions that target the energy intake rate of the diet (kcal/min). When designing an intervention that targets the energy intake rate of the diet it may be best to target eating rate and energy density separately for reasons of simplicity. Energy intake rate, as such, is probably more appropriate for research purposes as a predictor of the satiating capacity of foods, but might be too complex to apply in practice; the inverse association between eating rate and energy density adds to this complexity (Chapter 4). An intervention could focus on avoiding foods with a high eating rate (with the exception of non- and very low-caloric beverages) and foods with a high energy density. Moreover, also following the current Dutch dietary recommendations would reduce the energy density of the diet (Chapter 4). Although energy density is already included in the recommendations, eating rate is not included yet [46].

Eating environment

Lastly, it was investigated whether eating rate could be affected by making changes to the direct environment of a person eating (excl. the food). The results of Chapter 6 show that a person's bite frequency, and therefore eating rate, is not affected by the bite frequency of an eating companion. The bite frequency and eating rate of participants remained unchanged, despite the successful manipulation of the bite frequency of their eating companions. The eating companions, however, adjusted their meal duration to compensate for the different bite frequencies (e.g. stopped sooner when bite frequency was high). This affected the moment of meal termination in the participants; if the eating companion stopped sooner the participant would stop sooner as well, which is in line with previous research [47-49]. Moreover, by affecting meal duration also meal size was affected, since eating rate (g/min) was unchanged. The reported satiety levels, however, were unaffected.

How these effects on meal termination and meal size translate to real-life situations is unclear. Perhaps the observed differences would be less pronounced when eating with familiar people [47-49]. Furthermore, the underlying mechanism is unclear. It may be that people stop sooner because they feel uncomfortable when someone is waiting for them to finish, but it may also be that they simply are more aware of their behavior once their eating companion is finished eating [47-49].

The results from Chapter 6 do not provide indications for strategies to lower eating rate the direct eating environment. Research in this field is limited, there however is research that suggests that eating rate can be increased by playing music, and more so by playing fast tempo music compared to slow tempo music [50,51].

Conclusions

The research described in this thesis confirms that eating rate positively associated with energy intake and weight status. Furthermore, it provides new insights into the opportunities for lowering long-term eating rate.

The results show that lowering a person's eating rate may result in a lower long-term energy intake and BMI. Eating rate was found to be positively associated with energy intake and BMI in a Dutch population and thereby confirms the generalizability of the associations previously found in Asian populations. Moreover, this thesis has demonstrated that current technological developments may provide opportunities for monitoring and retraining eating behavior. Furthermore, the results demonstrate that Dutch adults have ample possibilities to shift their diets towards foods with a lower eating rate, and that it could be a promising strategy for lowering long-term energy intake. The food available to them offer a wide variation in eating rate (i.e. 2-641 g/min), and their consumption patterns show that a substantial proportion of their energy intake is derived from beverages (which have a high eating rate). Finally, we found no evidence that eating rate can be lowered through changes in the direct eating environment.

The results of this thesis provide input for the development of randomized controlled trials. These are needed to confirm whether there is a causal relation between eating rate, long-term energy intake and weight status. First it should be investigated whether long-term energy intake and body weight can be reduced by lowering eating rate through the person and the food, as these approaches have already shown great promise.

It is important that the potential of eating rate is further investigated. Lowering eating rate is expected to make people feel full on fewer calories and thereby make controlling energy intake easier and more enjoyable.

Suggestions for future research

At all three levels (i.e. the person, the food and the eating environment) more research is needed to identify ways to successfully lower long-term eating rate and to see whether they are successful at reducing long-term energy intake and body weight. This is described below.

Person

A substantial amount of research has investigated the association between a person's eating rate, energy intake and weight status [8,9,52-56]. Their results, together with the results of this thesis, suggest that having a higher personal eating rate will result in a higher energy intake and BMI. At this point randomized controlled trials are needed to confirm this relation. These should also investigate whether changes in a person's eating rate are maintained after the intervention has stopped, as research suggest that a person's eating rate is not easily changed [11,12]. Furthermore, it would be worthwhile to first investigate the potential of new technological solutions for the delivery of the interventions. They could increase the chances of success by providing opportunities for monitoring and retraining eating rate. The results of Spiegel et al. [11] suggest that simply providing advice on lowering eating rate is not sufficient to lower long-term eating rate.

Subsequently, if these randomized controlled trials have shown to be successful in lowering energy intake and body weight, it would be interesting to investigate when and how a person's eating rate is developed. Their results might reveal opportunities for preventing the development of a fast personal eating rate.

Food

To date, several studies have investigated the eating rate of foods [57,39,3,35,58,31,32]. With the findings of these studies and this thesis pretty good predictions can be made on which product will be faster when it concerns products with distinct textures (e.g. bread versus yoghurt, and non-toasted versus toasted bread). Moreover, the results from Chapter 4 provide a rough indication on how the foods in our diet compare in terms of eating rate. However, more research is needed to quantify the eating rate of the foods consumed. At this moment, for example, it is not possible to estimate the eating rate of a dish based on its components. All we can say is that when one of the components is replaced by a slower alternative this is expected to decrease the eating rate of the dish [36].

It, however, might not be necessary to fully understand the eating rate of the consumed foods to design an intervention. Instead one could lower the eating rate of the diet with relatively simple changes like excluding caloric-beverages and replacing pureed foods with their non-pureed version. It, however, needs to be investigated to what extent such changes are acceptable and how they affect the eating rate of the overall diet.

Furthermore, it would be interesting to see if we can identify groups of people that, compared to the rest of the population, derive a relatively large proportion of their energy intake from foods that can be consumed quickly. These groups could benefit most from an intervention that reduces eating rate through food choice. Moreover, if such groups are identified, it would be interesting to investigate whether the consumption of more 'fast foods' reflects food preference and to investigate when and how these preferences are developed. Their results might reveal opportunities for preventing the development of a preference for foods that can be consumed quickly.

Eating environment

It might be possible to lower eating rate through changes in the direct eating environment. Research on this topic, however, is very limited [50,51]. There are no concrete indications on how eating rate can be lowered through the eating environment. It might be best to first investigate whether long-term energy intake and body weight can be reduced by lowering eating rate with the above mentioned approaches, before venturing into a new area of research to discover new ways for lowering eating rate.

Implications for weight management

Lowering eating rate could facilitate the control of energy intake in weight management. Extensive research has shown that lowering eating rate will make it easier for people to limit enery intake by increasing satiety [39,59-63,56,36,64,65]; the result of the current thesis are in line with these findings.

Based on previous research and the current thesis there are a number of things that can be done that are expected to lower eating rate and thereby facilitate the control of energy intake. These either target the person or the food.

Person

By explaining the benefits of eating slowly and providing advice on how to eat slowly, people may be able to reduce their personal eating rate [11]. Advice on reducing eating rate could include: put down utensils in between bites, take small bites, and choose cutlery that does not allow you to eat fast. These techniques have shown to be effective, at least on short-term [27-30,11]. Moreover, the Netherlands Nutrition Centre endorses the benefit of limiting one's ability to eat fast through the choice of cutlery [66].

Another option would be to use electronic devices that provide feedback on a person's eating rate. To our knowledge, there is one commercially available device that provides feedback on eating rate: an electronic fork that vibrates if there is not enough time between bites (10SFork, SlowControl). It has shown to be effective in reducing eating rate on a single occasion, but its effect on food intake and the effect on long-term usage needs to be investigated [14,13,15]. In the future more electronic devices for monitoring and retraining eating rate might become available.

Food

Furthermore, eating slowly can be made easier by choosing foods that require more chewing. These tend to be the more solid and harder foods (this thesis and [31,34,32,33,35-39]). A first step would be to limit the consumption of caloric beverages from the diet, as they can be consumed very fast. This is endorsed by the Netherlands Nutrition Centre; they report that it is better to eat fruits and vegetables, than to consume them as a beverage [66]. Additionaly one could prepare foods in such a way that they require more chewing. For example, by not pureeing or finely chopping foods.

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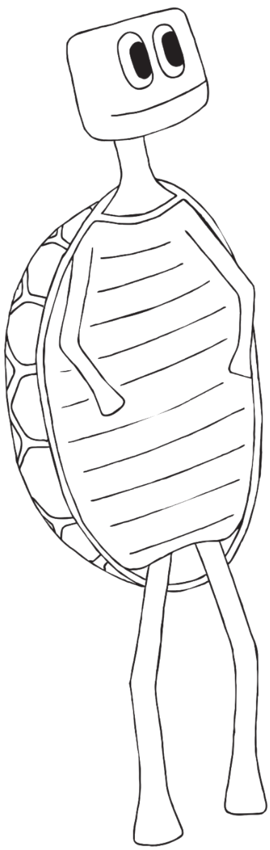

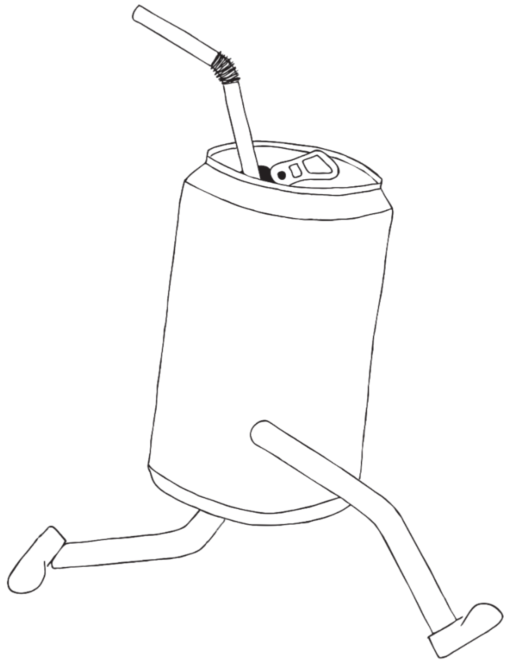

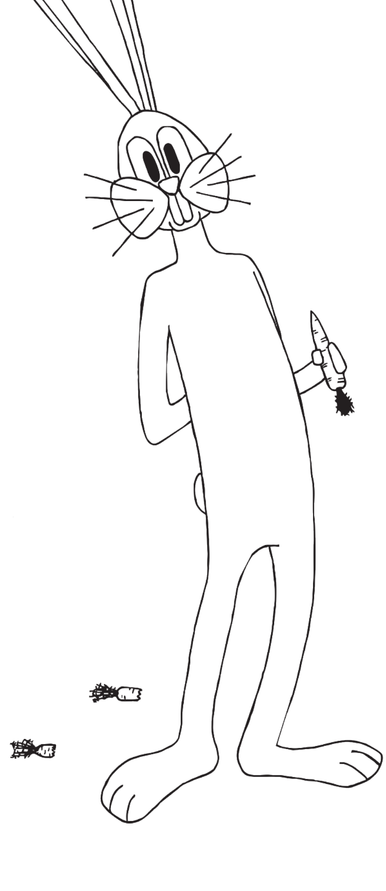

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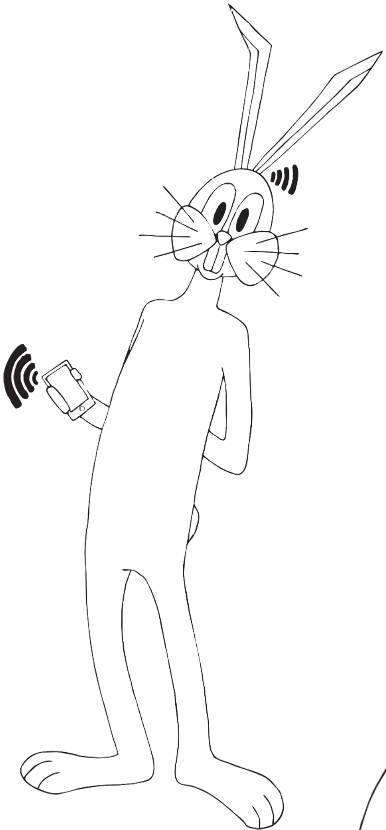
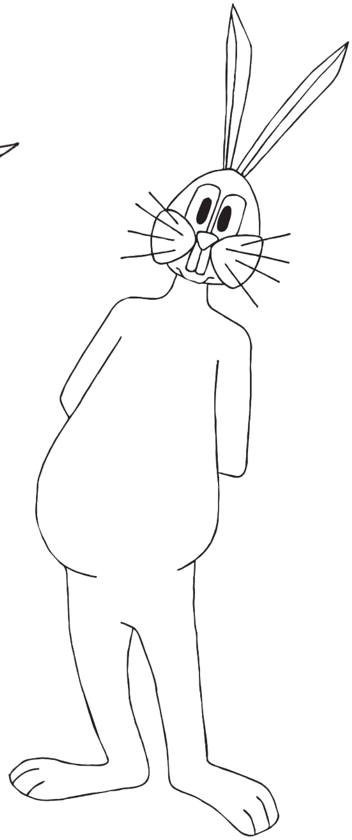
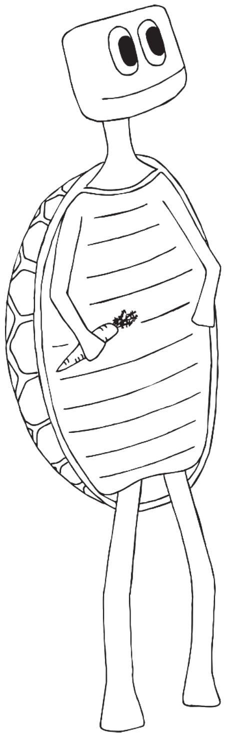
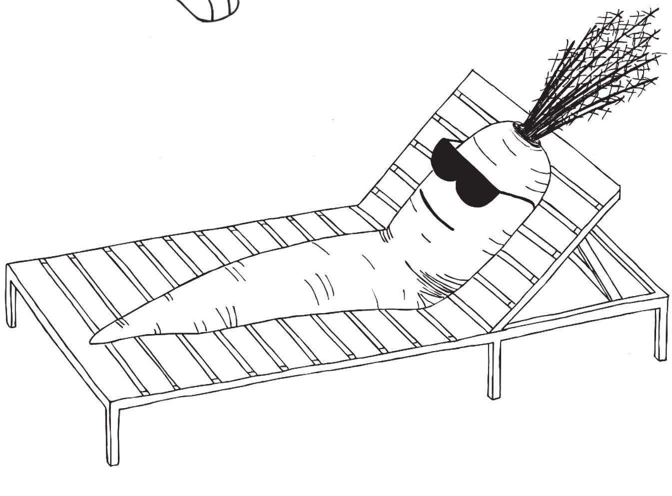








The obesity epidemic demonstrates that people are having difficulties with limiting energy intake to match energy expenditure. Therefore strategies to make controlling energy intake easier and more enjoyable need to be identified. Research suggests that lowering eating rate, i.e. the amount of food consumed per unit of time (g/min), could be an effective strategy. Lowering eating rate is expected to facilitate the control of long-term energy intake and body weight by increasing satiety.

Eating rate can be targeted by means of different approaches. It, however, is still unclear what would be an effective approach for lowering long-term eating rate, and whether it would be successful at lowering long-term energy intake and body weight. Hence, the current thesis investigated several opportunities for lowering eating rate and explored their potential to lower energy intake and body weight. Different approaches were considered:

1. Targeting the person: i.e. to change habitual eating rate (Chapter 2 and 3)
2. Targeting the food: i.e. to select foods that take more time to consume (Chapter 4 and 5)
3. Targeting the eating environment: i.e. to make changes to the direct eating environment of a person (Chapter 6)

In **Chapter 2** it was investigated whether eating rate is a stable personal characteristic that is associated with energy intake and BMI using data from the NQplus-cohort. The results confirm that eating rate is highly dependent on the individual and is relatively constant within an individual. Moreover, the analyses show that being a fast eater is associated with a higher long-term energy intake and BMI in the Dutch population.

In **Chapter 3** the acceptability of the 'eating detection sensor' (i.e. a new electronic device that can potentially be used to retrain a person's eating rate) was investigated by means of 4 evaluation studies. The results show that people are open to the idea of using such devices for monitoring and retraining eating behavior. These devices, however, need to be comfortable to wear and discreet.

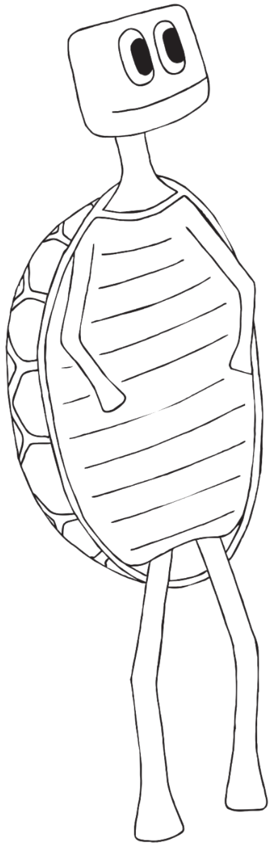
In **Chapter 4** the eating rate of the most commonly consumed foods (i.e. how fast they can be consumed, g/min) was investigated. Moreover, it was investigated what the energy intake rate (i.e. the eating rate of a food multiplied by the energy density of a food, kcal/min) of these foods is. Energy intake rate is expected to be a stronger predictor of energy intake than eating rate or energy density as such. The eating rate of 240 foods—representing the whole Dutch diet—was measured in a laboratory setting. The results showed a wide variation in eating rate (range: 2-641 g/min) and energy intake rate (range: 0-422 kcal/min), both within and between food groups. This demonstrates that the foods consumed provide opportunities for selecting alternatives with a lower eating rate and energy intake rate.

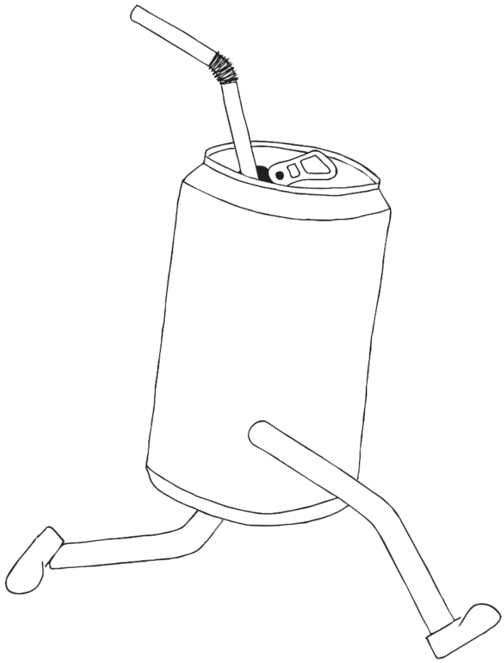
In **Chapter 5** it was investigated to what extent Dutch adults are consuming foods with a low and high energy intake rate (kcal/min), and whether this is associated with their energy intake and BMI. The dataset described in Chapter 4 was merged with 24h-recall data from the Dutch National Food Consumption Survey to enable these analyses. The results show that the consumption pattern of Dutch adults provide opportunities for lowering energy intake rate. The energy intake rate of the diet was found to be positively associated with long-term energy intake, but not with BMI.

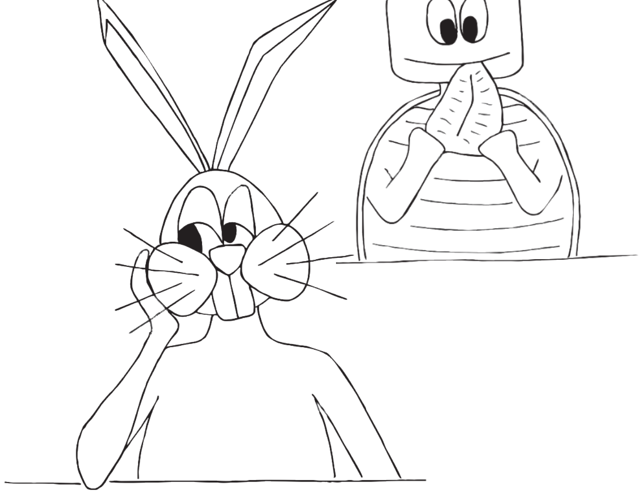
Finally, **Chapter 6** describes an experiment that tested whether a person's bite frequency (i.e. number of bites per minute), and therefore eating rate, is affected by the bite frequency of an eating companion, and whether this has an effect on food intake. It was found that a person's bite frequency is unaffected by the bite frequency of an eating companion.

Summarizing, the research described in this thesis provides new insights into the opportunities for lowering long-term eating rate, and thereby long-term energy intake and body weight. The results show that lowering a person's eating rate may result in a lower long-term energy intake and BMI, and that technological solutions could be used to lower a person's eating rate. Furthermore, the results demonstrate that Dutch adults have ample possibilities to shift their diets towards foods with a lower eating rate, and that it could be a promising strategy for lowering long-term energy intake. We found no evidence that eating rate can be lowered through changes in the direct eating environment.

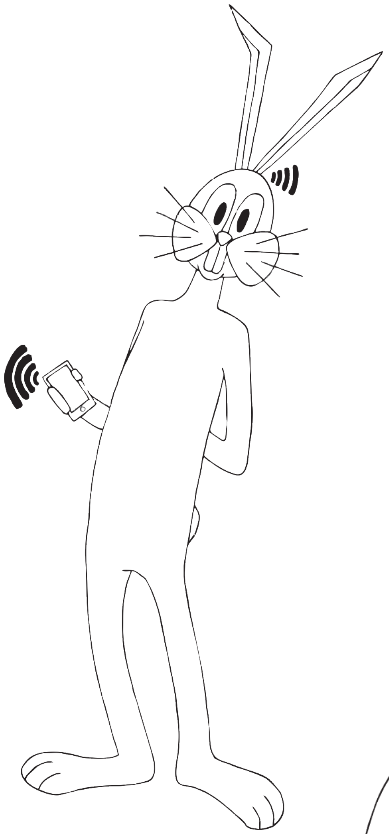
To conclude, the results of this thesis provide input for the development of randomized controlled trials. These are needed to confirm whether there is a causal relation between eating rate, long-term energy intake and weight status. It is important that the potential of eating rate is further investigated, as lowering eating rate is expected to make people feel full on fewer calories and thereby make controlling energy intake easier and more enjoyable.

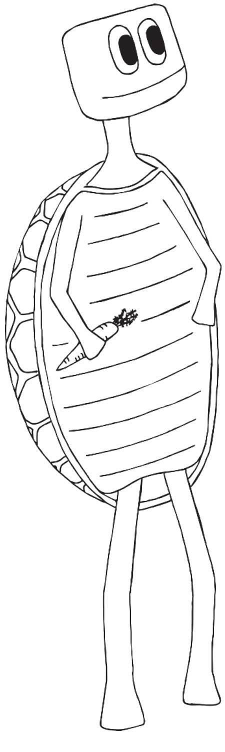






Samenvatting





De obesitas epidemie laat zien dat mensen moeite hebben met het beperken van hun energie-inname en deze zo te matchen met hun energieverbruik. Het is daarom nodig om strategieën te ontwikkelen die het makkelijker en plezieriger maken om energie-inname te controleren. Onderzoek heeft laten zien dat het verlagen van eetsnelheid (de hoeveelheid voedsel gegeten per tijdseenheid (g/min)) een effectieve strategie zou kunnen zijn. Door eetsnelheid te verlagen zullen gevoelens van verzadiging toenemen. Dit zou het gemakkelijker kunnen maken om energie-inname, en daarmee lichaamsgewicht, te controleren.

Er bestaan meerdere mogelijkheden voor het verlagen van eetsnelheid. Het is alleen nog onduidelijk of deze effectief zijn in het verlagen van eetsnelheid op de lange termijn, en of deze daarmee succesvol zijn in het verlagen van energie-inname en lichaamsgewicht. In dit proefschrift hebben we daarom verschillende strategieën voor het verlagen van eetsnelheid en hun potentie voor het verlagen van energie-inname en lichaamsgewicht onderzocht. De onderzochte strategieën zijn:

1. De persoon veranderen: iemands persoonlijke eetsnelheid verlagen (Hoofdstuk 2 en 3)
2. Het voedsel veranderen: producten kiezen die meer tijd kosten om te consumeren (Hoofdstuk 4 en 5)
3. De omgeving veranderen: de directe omgeving van iemand die aan het eten is veranderen (Hoofdstuk 6)

In **Hoofdstuk 2** hebben we onderzocht of eetsnelheid een stabiel persoonskenmerk is en of het geassocieerd is met energie-inname op de lange termijn en BMI. De resultaten bevestigen dat eetsnelheid in grote mate afhankelijk is van het individu en relatief constant is binnen een individu. Bovendien laten de analyses zien dat het hebben van een hoge eetsnelheid samenhangt met een hogere energie-inname en een hogere BMI in de Nederlandse populatie.

Hoofdstuk 3 beschrijft 4 evaluatie studies waarin we de aanvaardbaarheid van de ‘eetdetectie sensor’ (een nieuw elektronisch apparaatje dat mogelijk gebruikt kan worden bij het aanleren van een lagere eetsnelheid) hebben onderzocht. De resultaten laten zien dat mensen het wel zouden zien zitten om een dergelijk apparaatje te gebruiken voor het monitoren en trainen van hun eetgedrag. Het is hierbij wel van belang dat het apparaatje comfortabel en discreet is.

In **Hoofdstuk 4** hebben we de eetsnelheid van de meest gegeten producten (i.e. hoe snel ze gegeten kunnen worden, g/min) onderzocht. Ook hebben we gekeken naar de ‘energie-inname snelheid’ van deze producten (de eetsnelheid van de producten vermenigvuldigd met de energiedichtheid van de producten, kcal/min). Van energie-inname snelheid wordt verwacht dat het een betere voorspeller van energie-inname is dan eetsnelheid en energiedichtheid op zichzelf. We hebben de eetsnelheid van 240 producten, die geselecteerd zijn om het Nederlandse dieet te vertegenwoordigen, gemeten in een laboratorium setting. De resultaten laten veel variatie in eetsnelheid (range: 2-641 g/min) en energie-inname snelheid (range: 0-422 kcal/min) zien, zowel tussen als binnen productgroepen. Dit laat zien dat de aanwezige producten mogelijkheden bieden voor het kiezen van alternatieven met een lagere eetsnelheid en energie-inname snelheid.

In **Hoofdstuk 5** hebben we onderzocht in hoeverre Nederlandse volwassenen producten met een lage en hoge energie-inname snelheid (kcal/min) consumeren, en of dit geassocieerd is met energie-inname en BMI. Hiervoor hebben we de dataset beschreven in hoofdstuk 4 gecombineerd met 24-uurs voedingsnavraag data van de Nederlandse Voedselconsumptiepeiling. De resultaten laten zien dat het consumptiepatroon van Nederlandse volwassenen mogelijkheden biedt voor het verlagen van energie-inname snelheid. Verder was energie-inname snelheid positief geassocieerd met energie-inname, maar niet met BMI.

Tenslotte beschrijft **Hoofdstuk 6** een experiment waarbij we getest hebben of iemands hapfrequentie (aantal happen per minuut), en daardoor eetsnelheid, wordt beïnvloed door de hapfrequentie van een tafelgenoot en of dit van invloed is op hoeveel iemand eet. Dit bleek niet het geval te zijn. Hapfrequentie werd niet beïnvloed door de hapfrequentie van een tafelgenoot.

Samenvattend biedt dit proefschrift nieuwe inzichten in de mogelijkheden voor het verlagen van eetsnelheid op de lange termijn en daarmee het verlagen van energie-inname en lichaamsgewicht. De resultaten laten zien het verlagen van iemands persoonlijke eetsnelheid zou kunnen resulteren in een lagere energie-inname en BMI, en dat hierbij gebruik zou kunnen worden gemaakt van technologische oplossingen. Bovendien laten de resultaten zien dat het dieet van Nederlandse volwassenen ruimte biedt om langzamere alternatieven te kiezen en dat dit een veelbelovende strategie is voor het verlagen van energie-inname. We hebben geen bewijs gevonden dat eetsnelheid verlaagd kan worden d.m.v. veranderingen in de directe eetomgeving.

Concluderend bieden de resultaten van dit proefschrift input voor de ontwikkeling van 'randomized controlled trials'. Dergelijke studies zijn nodig om te bevestigen of er een oorzakelijk verband is tussen eetsnelheid, energie-inname op de lange termijn en gewichtsstatus. Het is belangrijk dat de potentie van eetsnelheid verder wordt onderzocht, omdat het verlagen van eetsnelheid het controleren van energie-inname makkelijker en plezieriger zou kunnen maken.

Acknowledgements

Of course all of this would not have been possible without a supportive environment. A lot of people contributed to my thesis: colleagues, participants, friends and family. I am very grateful for their contribution and would like to thank all of them. There, however, are a number of persons that made a special contribution to my thesis. I would like to thank them in particular:

First of all, I would like to thank my co-promotor Monica Mars. It has been a real pleasure working with her. She introduced me to the wonderful world of science with her down-to-earth mentality and pragmatic mindset. I have learned a lot from her; she has been a great mentor. I would also like to thank my promotor Kees de Graaf for his support, enthusiasm and input.

Additionally, I would like to thank some of my direct colleagues: my paranymphs, Korrie Pol and Moniek van Zutphen, and Astrid van Langeveld. They supported me both personally and in my work. They were the place to go to for a nice chat or some good advice. Moreover, they gave me the right push when I needed it. Together with my other colleagues they created a wonderful working environment.

Then there are a number of people that contributed more directly to my research. I would like to thank research dieticians Els Siebelink and Renske Hubers-Geers for their expertise, their practical insights and the pleasant collaboration. I would also like to thank Annemiek van der Lee, Melanie Werts, Lisa Harms and Jentina Kranendonk for their contribution. They were involved in my research as MSc-students. I am very proud to have them as co-authors of my papers.

Furthermore, I would like to thank my SPLENDID-colleagues for the pleasant and fruitful collaboration, in particular: Irini Lekka, Lingchuan Zhou, Vassilis Papapanagiotou, Christos Diou, Anastasios Delopoulos, Per Södersten, Ioannis Ioakeimidis, and Billy Langlet. They have shown me that you can achieve great things through collaboration and by bringing together different fields of expertise.

Finally, special thanks go to the 'home front': my parents and Jort (my partner). They have always been very supportive. They have created a loving environment and have actively helped me on several occasions. I am truly blessed to have them in my live.

About the author

Curriculum vitae

Janet van den Boer was born in Koningslust (Nl) on February 23rd 1990. After completing secondary school (Atheneum, 'Bouwens van der Boijecollege' in Panningen) in 2008 she went on to study 'Nutrition and Health' at Wageningen University. During the bachelor's and master's programme she specialized in behaviour and health promotion. During the bachelor's programme she completed a minor 'Consumer behaviour' and a thesis on dietary variety scores. During the master's programme she completed a thesis on modelling of eating style and evaluated a diabetes prevention programme during her internship. In 2011 she received her bachelor's degree and in 2013 she received her master's degree.

In 2013 she started as a researcher at the Division of Human Nutrition of Wageningen University to work on SPLENDID, i.e. an EU-funded ICT-project. In this project she collaborated with multiple technical partners of different nationalities to develop a system of devices that can act as a wearable personal coach. Her role mainly concerned the mapping of user requirements and the evaluation of the devices. Results of this project are described in chapter 3 of this thesis.

In 2015 she was appointed as a PhD candidate at the chair group Sensory Science and Eating Behaviour of the Division of Human Nutrition (Wageningen University). Her research focussed on opportunities for reducing eating rate, and thereby reducing energy intake and body weight, as described in this thesis. Furthermore, she performed several side activities. She visited and provided a presentation at several conferences and scientific meetings, she followed several courses and was involved in a number of teaching activities. She supervised bachelor and master students with their thesis, was involved in several courses and provided lectures at the University of Groningen.

List of publications

Publications in peer reviewed journals

van den Boer, J. and M. Mars (2015). "Modeling of eating style and its effect on intake." Appetite 86(0): 25-30.

Papapanagiotou, V., C. Diou, Z. Lingchuan, **J. van den Boer**, M. Mars and A. Delopoulos (2015). Fractal Nature of Chewing Sounds. New Trends in Image Analysis and Processing -- ICIAP 2015 Workshops, Springer International Publishing. 9281: 401-408.

Moulos, I., C. Maramis, I. Ioakimidis, **J. van den Boer**, J. Nolstam, M. Mars, C. Bergh and N. Maglaveras (2015). Objective and Subjective Meal Registration via a Smartphone Application. New Trends in Image Analysis and Processing -- ICIAP 2015 Workshops, Springer International Publishing. 9281: 409-416.

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van den Boer, J., M. Werts, E. Siebelink, C. de Graaf and M. Mars (2017). "The Availability of Slow and Fast Calories in the Dutch Diet: The Current Situation and Opportunities for Interventions." Foods 6(10): 87.

van den Boer, J., J. Kranendonk, A. van de Wiel, E. Feskens, A. Geelen and M. Mars (2017). "Self-reported eating rate is associated with weight status in a Dutch population: a validation study and a cross-sectional study." International Journal of Behavioral Nutrition and Physical Activity 14(1): 121.

Papers in preperation for submission

van den Boer, J., A. van der Lee, L. Zhou, V. Papapanagiotou, C. Diou, A. Delopoulos and M. Mars. “The user-informed development of the SPLENDID eating detection sensor”

van den Boer, J., A. van Langeveld, L. Harms, C. de Graaf and M. Mars. “How much slow and fast calories are we consuming? Food consumption in terms of energy intake rate”

Published datasets

Papapanagiotou, V., C. Diou, L. Zhou, **J. van den Boer**, M. Mars and A. Delopoulos (2017). The SPLENDID chewing detection challenge. 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Jeju Island, South Korea, 2017, pp. 817-820. (doi: 10.1109/EMBC.2017.8036949, URL: http://ieeexplore.ieee.org/document/8036949/)

Oral presentations and poster presentations

Occasion	Title	Type	Year
Food Oral Processing, Wageningen	*Modeling of eating style and its effect on intake*	Oral	2014
Dutch Nutritional Science Days, Deurne	*Individuals who report to be fast eaters have higher body weight and BMI: Validation and results of questioning eating rate in NQplus*	Oral	2014
WeVo, Utrecht	*SPLENDID: Personalised Guide for Eating and Activity Behaviour for the Prevention of Obesity and Eating Disorders*	Oral	2014
British Feeding and Drinking Group, Wageningen	*Preventing Obesity and Eating Disorders through Behavioural Modifications: the SPLENDID Vision*	Poster	2015
Dutch Nutritional Science Days, Heeze	*Acceptance of SPLENDID system by consumers and health professionals*	Oral	2015
British Feeding and Drinking Group, London	*Acceptance of SPLENDID system by consumers and health professionals*	Oral	2016
Dutch Epidemiology Conference, Wageningen	*Self-reported eating rate is associated with weight status in a Dutch population: Validation and results of questioning eating rate in an observational study*	Poster	2016
SPLENDID workshop, Thessaloniki (Gr)	*SPLENDID for young adults: Testing SPLENDID in real-life*	Oral	2016
University of Groningen, Groningen	*Determinants of eating behaviour: Improve health and wellbeing by better eating behaviour*	Lecture	2016, 2017
Mobile Health symposium, Amsterdam	*SPLENDID: Een draagbare personal coach*	Oral	2017
Dutch Nutritional Science Days, Heeze	*The availability of slow and fast calories in the Dutch diet: The current situation and opportunities for interventions*	Oral	2017

Overview of completed training activities

Discipline specific courses and activities

Courses and activities	Organizer and location	Year
WeVo, autumn meeting	WeVo, Wageningen (NL)	2013
Course ‘Sensory Perception and Food Preference’	VLAG, Wageningen (NL)	2013
Food Oral Processing-conference*	FOP, Wageningen (NL)	2014
WeVo spring meeting	WeVo, Nijmegen (NL)	2014
Dutch Nutritional Science Days*	NAV, Deurne (NL)	2014
WeVo autumn meeting*	WeVo, Utrecht (NL)	2014
WeVo spring meeting	WeVo, Den Haag (NL)	2015
British Feeding and Drinking Group-meeting*	BFDG, Wageningen (NL)	2015
Dutch Association for the Study of Obesity-meeting	NASO, Utrecht (NL)	2015
Course ‘ICT Assisted Methods for Measuring Dietary Behaviour in Complex Foodscapes’	Aalborg University, Kopenhagen (DK)	2015
Dutch Nutritional Science Days*	NAV, Heeze (NL)	2015
Symposium ‘Nutritional Sciences: The Future is Ours’	WUR, Wageningen (NL)	2015
Masterclass ‘Public Health Practice in Research’	VLAG, Wageningen (NL)	2015
Symposium ‘Smart solutions for a healthy food lifestyle’	i3B/WUR, Wageningen (NL)	2015
British Feeding and Drinking Group-meeting*	BFDG, London (UK)	2016
Dutch Epidemiology Conference*	WEON, Wageningen (NL)	2016
Symposium ‘State of Nutrition Communication’	NZO/WUR, Wageningen (NL)	2017
Symposium ‘The (im)possibiliy of changing eating behaviour through technology’	Take it slow, Nijmegen (NL)	2017
Symposium ‘Mobile Health’*	ACHC, Amsterdam (NL)	2017
Dutch Association for the Study of Obesity-meeting	NASO, Utrecht (NL)	2017
WeVo spring meeting	WeVo, Utrecht (NL)	2017
Dutch Nutritional Science Days*	NAV, Heeze (NL)	2017

*oral presentation or poster presentation

General courses and activities

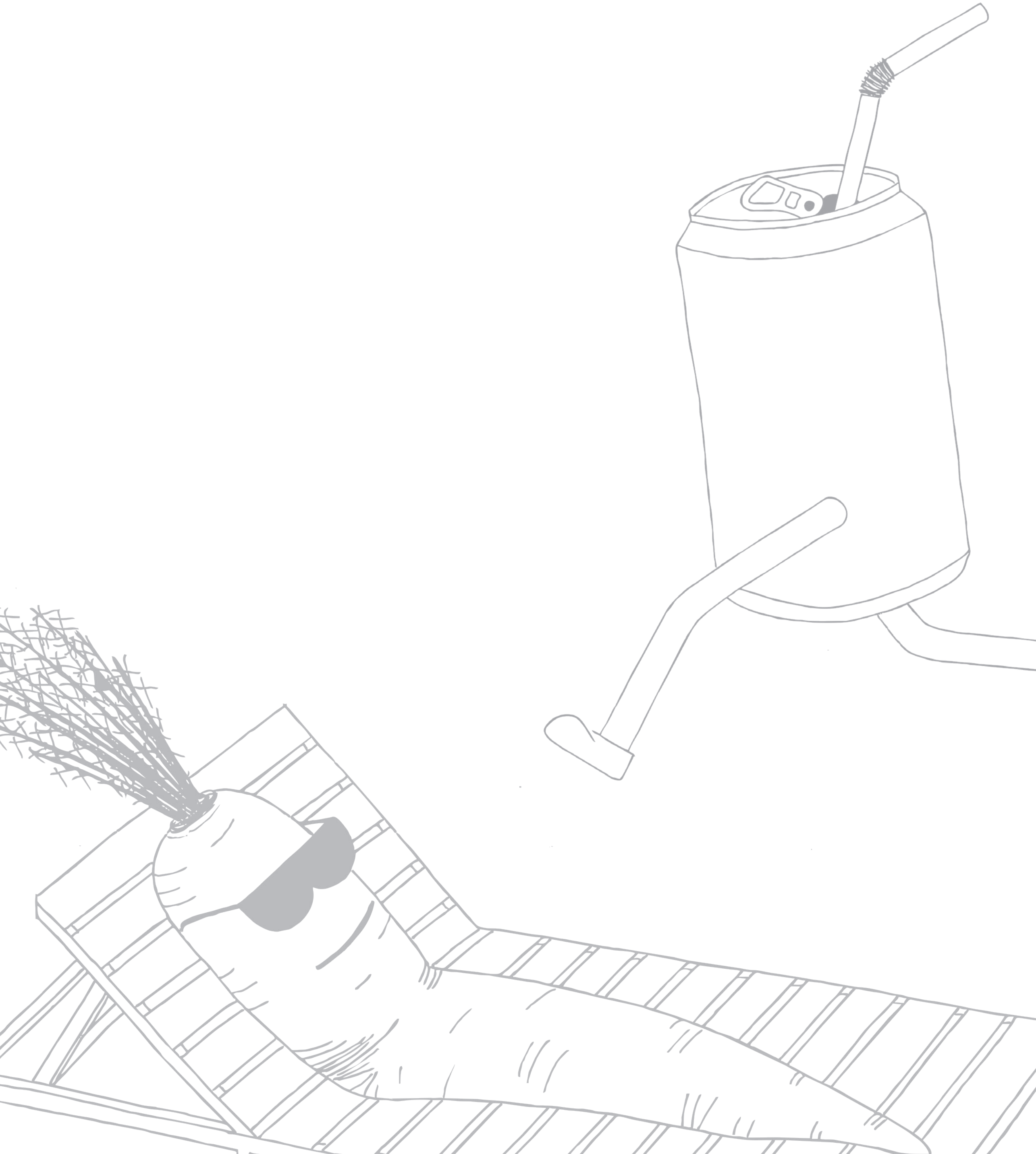
Courses and activities	Organizer and location	Year
Good Clinical Practice Training	ZGV/Rijnstate, Arnhem (NL)	2014
Ethics masterclass	NAV/VLAG, Wageningen (NL)	2016
Course ‘Reviewing a Scientific Paper’	WGS, Wageningen (NL)	2016
Course ‘Scientific Publishing’	WGS, Wageningen (NL)	2016
Stress Less-training	AFSG, Wageningen (NL)	2016
Brain Training	WGS, Wageningen (NL)	2016
Course ‘Scientific Writing’	WGS, Wageningen (NL)	2016
Symposium ‘Publish for Impact’	WGS, Wageningen (NL)	2017
Course ‘Mixed Models’	VLAG	2017
Symposium ‘Interdisciplinary Research’	Edema-Steernberg fdn., Wageningen (NL)	2017
Symposium ‘Gender Bias in Academic Publishing’	Elsevier, online	2017
Symposium ‘Handling Press and Public Debates’	HNE/FBR, Wageningen (NL)	2017
Course ‘Career Orientation’	WGS, Wageningen (NL)	2017
Course ‘Career Assessment’	WGS, Wageningen (NL)	2017
Course ‘Orientation on Teaching’	ESD/WUR, Wageningen (NL)	2017

*oral presentation or poster presentation

Optional courses and activities

Courses and activities	Organizer and location	Year
SPLENDID project meetings* (5x) and EU reviews* (3x)	SPLENDID/EU, Europe	‘13-‘16
Meetings Sensory Science and Eating Behaviour Group*	SSEB, Wageningen (NL)	‘13-‘16
Staff seminar ‘Technological Advances’*	HNE, Wageningen (NL)	2014
Writing project proposal	VLAG, Wageningen (NL)	2015
Staff seminar ‘Nutritional Guidelines’	HNE, Wageningen (NL)	2016
Staff seminar ‘Education’	HNE, Wageningen (NL)	2016
Lecture ‘A Global one Health’	HNE, Wageningen (NL)	2016
Application ‘European Nutrition Leadership Programme’	ENLP, Wageningen (NL)	2016
Provide lecture at University of Groningen*	RUG, Groningen (NL)	‘16, ‘17
Meetings ‘Working in Industry’	VLAG, Wageningen (NL)	2017

*oral presentation or poster presentation



Appendix A

Supplementary tables

Chapter 4: The availability of slow and fast calories in the Dutch diet: The current situation and opportunities for interventions

Table A1 A detailed description of the foods included in the dataset (n = 240) (header repeats at top of each page)

Food	Food Group	Texture	Source eating rate data	Portion size (g)	*n*	Energy intake rate		Eating rate (g/min)	Energy density	
						kJ/min	kcal/min		kJ/100g	kcal/100g
Mineral water (Spa)	Non-alcoholic beverages	Liquid	Current study	125	5	0 ± 0	0 ± 0	210 ± 53	0	0
Water	Non-alcoholic beverages	Liquid	Current study	125	5	0 ± 0	0 ± 0	339 ± 219	0	0
Tea	Non-alcoholic beverages	Liquid	Previous study	50	2	0 ± 0	0 ± 0	428 ± 165	0	0
Cola light soft drink	Non-alcoholic beverages	Liquid	Previous study	50	4	0 ± 0	0 ± 0	635 ± 508	0	0
Coffee	Non-alcoholic beverages	Liquid	Current study	125	5	3 ± 1	1 ± 0	56 ± 14	5	1
Bean sprouts boiled	Vegetables	Hard-solid	Current study	50	5	10 ± 3	2 ± 1	13 ± 4	75	18
Lettuce iceberg raw	Vegetables	Hard-solid	Previous study	50	3	10 ± 6	2 ± 1	17 ± 9	62	15
Chicory boiled	Vegetables	Soft-solid	Current study	50	5	15 ± 7	4 ± 2	21 ± 10	70	17
Carrot raw	Vegetables	Hard-solid	Previous study	50	2	17 ± 10	4 ± 2	12 ± 7	139	33
Cucumber with skin raw	Vegetables	Hard-solid	Previous study	50	4	18 ± 9	4 ± 2	34 ± 17	54	13
Leek boiled	Vegetables	Soft-solid	Current study	50	4	21 ± 10	5 ± 2	23 ± 11	91	22
Cucumber without skin raw	Vegetables	Hard-solid	Current study	50	5	22 ± 7	5 ± 2	43 ± 13	52	12
Silver-skin onion sweet pickled	Vegetables	Hard-solid	Current study	25	5	25 ± 5	6 ± 1	17 ± 3	142	34
Cabbage oxheart boiled	Vegetables	Soft-solid	Current study	50	5	27 ± 10	7 ± 2	31 ± 11	88	21
Beans French boiled	Vegetables	Soft-solid	Current study	50	5	31 ± 13	7 ± 3	29 ± 12	105	25
Courgettes boiled	Vegetables	Soft-solid	Current study	50	5	31 ± 8	7 ± 2	39 ± 10	79	19
Mushroom boiled	Vegetables	Soft-solid	Current study	50	4	33 ± 8	8 ± 2	36 ± 9	90	21
Spinach frozen boiled	Vegetables	Semi-solid	Current study	50	5	37 ± 30	9 ± 7	35 ± 28	104	25
Rice waffle	Cereals and cereal products	Hard-solid	Previous study	50	2	37 ± 38	9 ± 9	2 ± 2	1587	374
Stock from cube	Soups, bouillon	Liquid	Current study	75	4	38 ± 13	9 ± 3	174 ± 59	22	5
Soup vegetable based dried packet	Soups, bouillon	Liquid	Current study	75	5	39 ± 11	9 ± 3	41 ± 12	95	23
Celeriac boiled	Vegetables	Soft-solid	Current study	50	5	40 ± 20	9 ± 5	23 ± 11	175	42
Broccoli boiled	Vegetables	Soft-solid	Current study	50	5	47 ± 21	11 ± 5	42 ± 19	112	27
Sweet pepper red boiled	Vegetables	Soft-solid	Current study	50	5	48 ± 16	11 ± 4	42 ± 14	113	27
Gherkins sweet pickled	Vegetables	Hard-solid	Current study	50	5	49 ± 14	12 ± 3	43 ± 13	113	27
Cauliflower boiled	Vegetables	Soft-solid	Current study	50	5	58 ± 23	14 ± 6	61 ± 24	95	23
Pear with skin	Fruits, nuts and olives	Soft-solid	Current study	50	5	60 ± 15	14 ± 4	26 ± 7	231	55

Food	Food Group	Texture	Source eating rate data	Portion size (g)	*n*	Energy intake rate		Eating rate (g/min)	Energy density	
						kJ/min	kcal/min		kJ/100g	kcal/100g
Peppermint	Sugar and confectionery	Hard-solid	Current study	20	5	63 ± 44	15 ± 11	4 ± 3	1676	394
Potatoes without skins boiled	Potatoes and other tubers	Soft-solid	Previous study	50	2	64 ± 24	15 ± 6	18 ± 7	352	83
Boiled sweets	Sugar and confectionery	Hard-solid	Current study	17	5	65 ± 62	16 ± 15	4 ± 4	1615	380
Ham lean boiled	Meat and meat products	Soft-solid	Previous study	50	22	71 ± 32	17 ± 8	13 ± 6	564	135
Tomato raw	Vegetables	Hard-solid	Previous study	50	3	73 ± 19	17 ± 5	76 ± 20	96	23
Soup portion	Soups, bouillon	Liquid	Current study	75	5	74 ± 13	18 ± 3	53 ± 9	140	33
Crispbread wholemeal	Cereals and cereal products	Hard-solid	Current study	13	5	75 ± 15	18 ± 4	5 ± 1	1529	363
Brussels sprouts boiled	Vegetables	Soft-solid	Current study	50	5	76 ± 14	18 ± 3	40 ± 7	189	45
Ketchup tomato	Condiments and sauces	Semi-solid	Current study	25	4	78 ± 72	19 ± 17	24 ± 22	327	77
Bread brown wheat	Cereals and cereal products	Soft-solid	Previous study	50	25	83 ± 25	20 ± 6	8 ± 3	1000	236
Crispbakes Dutch wholemeal	Cereals and cereal products	Hard-solid	Current study	13	5	87 ± 22	21 ± 5	5 ± 1	1664	394
Potatoes boiled with skin	Potatoes and other tubers	Soft-solid	Current study	50	5	87 ± 30	21 ± 7	28 ± 10	311	74
Apple without skin	Fruits, nuts and olives	Hard-solid	Previous study	50	25	89 ± 25	21 ± 6	36 ± 10	247	58
Breadsticks	Cereals and cereal products	Hard-solid	Current study	13	5	89 ± 17	21 ± 4	5 ± 1	1694	401
Ketchup curry	Condiments and sauces	Semi-solid	Current study	25	4	91 ± 40	22 ± 9	17 ± 7	546	129
Sandwich meat chicken	Meat and meat products	Soft-solid	Current study	30	5	92 ± 25	22 ± 6	18 ± 5	520	124
Coffee cappuccino instant	Non-alcoholic beverages	Liquid	Current study	125	4	92 ± 34	22 ± 8	59 ± 22	156	37
Mandarins	Fruits, nuts and olives	Soft-solid	Current study	50	5	93 ± 44	22 ± 10	48 ± 23	193	45
Pear without skin	Fruits, nuts and olives	Soft-solid	Current study	50	5	94 ± 36	22 ± 9	40 ± 16	232	55
Apple with skin	Fruits, nuts and olives	Hard-solid	Current study	50	174	96 ± 22	23 ± 5	38 ± 9	254	60
Popcorn popped sweet	Sugar and confectionery	Hard-solid	Current study	13	6	99 ± 35	24 ± 8	6 ± 2	1649	389
Bread wholemeal	Cereals and cereal products	Soft-solid	Current study	35	174	99 ± 27	24 ± 6	10 ± 3	990	234
Strawberries	Fruits, nuts and olives	Soft-solid	Current study	50	5	99 ± 55	24 ± 13	81 ± 45	123	29
Cocktail snacks Nibbits	Cereals and cereal products	Hard-solid	Current study	12	5	100 ± 31	24 ± 7	5 ± 2	2021	482
Soup thickened with vegetables	Soups, bouillon	Semi-solid	Previous study	50	4	104 ± 30	25 ± 7	70 ± 21	148	35
Low fat margarine on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	40	5	106 ± 51	25 ± 12	10 ± 5	1047	249

Food	Food Group	Texture	Source eating rate data	Portion size (g)	*n*	Energy intake rate		Eating rate (g/min)	Energy density	
						kJ/min	kcal/min		kJ/100g	kcal/100g
Bread multigrain with seeds	Cereals and cereal products	Soft-solid	Current study	35	5	107 ± 23	25 ± 6	10 ± 2	1099	261
Cabbage red with apple pieces frozen boiled	Vegetables	Soft-solid	Current study	50	5	108 ± 46	26 ± 11	44 ± 19	247	59
Tomato juice	Non-alcoholic beverages	Liquid	Current study	125	5	109 ± 35	26 ± 8	160 ± 51	68	16
Japanese rice cracker mix	Cereals and cereal products	Hard-solid	Current study	25	5	111 ± 20	26 ± 5	7 ± 1	1645	387
Prawn crackers natural	Cereals and cereal products	Hard-solid	Current study	12	5	111 ± 42	26 ± 10	5 ± 2	2158	516
Sauce tomato readymade	Condiments and sauces	Semi-solid	Current study	25	5	111 ± 36	26 ± 9	44 ± 14	253	61
Toast	Cereals and cereal products	Hard-solid	Current study	17	5	112 ± 32	27 ± 8	7 ± 2	1522	359
Peas fresh boiled	Vegetables	Soft-solid	Previous study	50	4	113 ± 71	27 ± 17	39 ± 24	291	69
Soup clear with meat vegetables and noodles	Soups, bouillon	Semi-solid	Current study	75	5	114 ± 55	27 ± 13	66 ± 32	173	41
Pork fillet	Meat and meat products	Soft-solid	Current study	50	5	117 ± 54	28 ± 13	18 ± 8	661	157
Ice cream dairy cream based	Sugar and confectionery	Semi-solid	Previous study	50	4	117 ± 58	28 ± 14	14 ± 7	856	205
Carrot boiled	Vegetables	Soft-solid	Previous study	50	3	119 ± 86	28 ± 21	89 ± 65	133	32
Orange	Fruits, nuts and olives	Soft-solid	Current study	50	5	120 ± 50	29 ± 12	56 ± 23	215	51
Olives ripe in brine	Fruits, nuts and olives	Hard-solid	Current study	25	5	121 ± 36	29 ± 8	18 ± 5	663	162
Cod prepared in microwave oven	Fish and shellfish	Soft-solid	Current study	50	4	123 ± 34	30 ± 8	30 ± 8	414	98
Beans brown tinned	Legumes	Soft-solid	Current study	50	5	129 ± 29	31 ± 7	28 ± 6	460	109
Soup vegetable readymade	Soups, bouillon	Semi-solid	Previous study	50	4	132 ± 57	32 ± 14	67 ± 29	196	47
Bread white water based	Cereals and cereal products	Soft-solid	Current study	35	5	133 ± 25	32 ± 6	13 ± 2	1046	247
Ham shoulder medium fat boiled	Meat and meat products	Soft-solid	Current study	40	5	139 ± 34	33 ± 8	25 ± 6	556	133
Ham shoulder medium fat boiled on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	60	5	140 ± 46	33 ± 11	16 ± 5	861	205
Biscuit salted average	Cereals and cereal products	Hard-solid	Current study	25	5	140 ± 9	33 ± 2	7 ± 0	1975	472
Winegum/fruitgum	Sugar and confectionery	Soft-solid	Current study	20	5	140 ± 33	33 ± 8	10 ± 2	1358	320
Rice brown boiled	Cereals and cereal products	Soft-solid	Previous study	50	3	142 ± 75	34 ± 18	26 ± 14	555	131
Yoghurt low fat	Dairy products	Semi-solid	Current study	75	5	146 ± 25	35 ± 6	94 ± 16	156	37

Food	Food Group	Texture	Source eating rate data	Portion size (g)	*n*	Energy intake rate		Eating rate (g/min)	Energy density	
						kJ/min	kcal/min		kJ/100g	kcal/100g
Spinach creamed frozen boiled	Vegetables	Semi-solid	Current study	50	5	153 ± 34	37 ± 8	51 ± 11	303	73
Roll white hard	Cereals and cereal products	Hard-solid	Current study	35	4	153 ± 42	37 ± 10	13 ± 4	1173	277
Pineapple in syrup	Fruits, nuts and olives	Hard-solid	Current study	40	5	155 ± 36	37 ± 9	53 ± 12	291	69
Roll brown hard	Cereals and cereal products	Hard-solid	Current study	35	5	155 ± 16	37 ± 4	13 ± 1	1177	278
Ice cream stracciatella	Sugar and confectionery	Semi-solid	Current study	50	5	156 ± 34	37 ± 8	16 ± 3	991	237
Grapes with skin	Fruits, nuts and olives	Hard-solid	Current study	50	5	156 ± 42	37 ± 10	47 ± 13	331	78
Muesli with fruit	Cereals and cereal products	Hard-solid	Current study	25	5	156 ± 44	37 ± 10	10 ± 3	1505	357
Crisps potato light unflavored	Cereals and cereal products	Hard-solid	Current study	25	5	156 ± 54	37 ± 13	8 ± 3	2051	490
Fromage frais low fat	Dairy products	Semi-solid	Current study	75	4	157 ± 87	38 ± 21	63 ± 35	248	58
Cheese Mozzarella on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	55	5	158 ± 70	38 ± 17	15 ± 7	1026	244
Peaches in syrup	Fruits, nuts and olives	Soft-solid	Current study	50	5	158 ± 100	38 ± 24	60 ± 38	263	62
Toffees	Sugar and confectionery	Soft-solid	Previous study	50	3	158 ± 58	38 ± 14	9 ± 3	1796	428
Roll white soft	Cereals and cereal products	Soft-solid	Current study	25	5	163 ± 59	39 ± 14	15 ± 5	1108	262
Liquorice Dutch type salted	Sugar and confectionery	Soft-solid	Current study	20	5	163 ± 51	39 ± 12	11 ± 4	1418	334
Raisins dried	Fruits, nuts and olives	Soft-solid	Current study	30	6	163 ± 38	39 ± 9	12 ± 3	1382	326
Biscuit sweet	Cakes	Hard-solid	Current study	13	5	166 ± 51	40 ± 12	9 ± 3	1841	437
Sandwich meat chicken on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	60	5	168 ± 22	40 ± 5	20 ± 3	849	202
Bread pita white	Cereals and cereal products	Hard-solid	Current study	25	5	169 ± 34	40 ± 8	16 ± 3	1040	245
Banana	Fruits, nuts and olives	Soft-solid	Previous study	50	25	171 ± 55	41 ± 13	43 ± 14	401	95
Margarine 80% fat on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	40	5	171 ± 55	41 ± 13	14 ± 4	1237	295
Eggs chicken boiled	Eggs and egg products	Soft-solid	Previous study	50	24	173 ± 72	41 ± 17	32 ± 13	535	128
Roll brown soft	Cereals and cereal products	Soft-solid	Current study	30	5	175 ± 35	42 ± 8	16 ± 3	1087	258
Crackers cream	Cereals and cereal products	Hard-solid	Previous study	50	3	175 ± 19	42 ± 5	9 ± 1	1973	469
Pineapple	Fruits, nuts and olives	Hard-solid	Previous study	50	2	176 ± 112	42 ± 27	73 ± 46	242	57

Food	Food Group	Texture	Source eating rate data	Portion size (g)	*n*	Energy intake rate		Eating rate (g/min)	Energy density	
						kJ/min	kcal/min		kJ/100g	kcal/100g
Wrap/Tortilla	Cereals and cereal products	Soft-solid	Current study	40	5	176 ± 61	42 ± 15	13 ± 5	1349	320
Beans baked in tomato sauce tinned	Legumes	Soft-solid	Current study	50	4	176 ± 75	42 ± 18	45 ± 19	393	93
Herring salted	Fish and shellfish	Soft-solid	Current study	60	5	176 ± 80	42 ± 19	24 ± 11	720	172
Biscuit sponge fingers	Cakes	Hard-solid	Current study	12	5	177 ± 34	42 ± 8	10 ± 2	1702	402
Crisps tortilla unflavored	Cereals and cereal products	Hard-solid	Current study	25	5	178 ± 34	43 ± 8	9 ± 2	2039	487
Biscuit fruit	Cakes	Hard-solid	Current study	15	5	179 ± 18	43 ± 4	11 ± 1	1662	393
Cheese Gouda 48+	Dairy products	Soft-solid	Previous study	50	24	179 ± 67	43 ± 16	12 ± 4	1529	369
Potatoes mashed	Potatoes and other tubers	Soft-solid	Previous study	50	3	183 ± 152	44 ± 36	52 ± 44	349	83
Muesli crunchy	Cereals and cereal products	Hard-solid	Current study	25	5	185 ± 32	44 ± 8	10 ± 2	1841	438
Chocolate plain	Sugar and confectionery	Hard-solid	Current study	35	5	185 ± 78	44 ± 19	8 ± 4	2209	531
Cake sponge Dutch Eierkoek	Cakes	Soft-solid	Current study	15	5	185 ± 36	44 ± 9	14 ± 3	1314	310
Bread ciabatta no filling	Cereals and cereal products	Hard-solid	Current study	50	5	188 ± 19	45 ± 5	17 ± 2	1079	255
Biscuit brown/wholemeal	Cakes	Hard-solid	Current study	17	5	190 ± 25	45 ± 6	10 ± 1	1928	459
Potato crisps oven baked	Cereals and cereal products	Hard-solid	Current study	25	5	191 ± 96	46 ± 23	11 ± 6	1731	411
Beer pilsner	Alcoholic beverages	Liquid	Previous study	125	24	198 ± 128	47 ± 31	106 ± 69	187	45
Soup legume based readymade	Soups, bouillon	Semi-solid	Current study	75	5	199 ± 47	47 ± 11	59 ± 14	337	80
Hot chocolate	Dairy products	Liquid	Current study	125	5	200 ± 139	48 ± 33	71 ± 50	280	66
Pork schnitzel breaded	Meat and meat products	Hard-solid	Current study	50	4	204 ± 49	49 ± 12	26 ± 6	788	188
Beef steak tartare	Meat and meat products	Soft-solid	Current study	40	5	204 ± 52	49 ± 12	26 ± 7	782	186
Spring roll fried	Miscellaneous	Hard-solid	Current study	25	5	204 ± 52	49 ± 12	27 ± 7	757	181
Cashew nuts unsalted	Fruits, nuts and olives	Hard-solid	Current study	50	5	206 ± 81	49 ± 19	8 ± 3	2552	615
Sandwich spread original on wholemeal bread	Condiments and sauces	Soft-solid	Current study	55	5	207 ± 48	49 ± 12	21 ± 5	975	235
Sauce for chips 25% oil	Condiments and sauces	Semi-solid	Current study	25	5	213 ± 243	51 ± 58	17 ± 20	1226	296
Yoghurt half fat	Dairy products	Semi-solid	Current study	75	174	215 ± 55	51 ± 13	102 ± 26	212	50
Tortellini boiled	Cereals and cereal products	Soft-solid	Current study	50	5	216 ± 80	52 ± 19	33 ± 12	656	155

Food	Food Group	Texture	Source eating rate data	Portion size (g)	*n*	Energy intake rate		Eating rate (g/min)	Energy density	
						kJ/min	kcal/min		kJ/100g	kcal/100g
Cheese 30+ on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	60	5	217 ± 47	52 ± 11	20 ± 4	1094	261
White fish fillet in batter deep-fried	Fish and shellfish	Hard-solid	Current study	50	5	221 ± 88	53 ± 21	25 ± 10	883	211
Potato slices fried	Potatoes and other tubers	Soft-solid	Current study	50	5	223 ± 51	53 ± 12	28 ± 7	789	189
Cultured confetti fruit-flavored on wholemeal bread	Cereals and cereal products	Hard-solid	Current study	55	4	224 ± 110	54 ± 26	19 ± 9	1192	282
Biscuit fortified with currants (LigaEvergreen)	Cakes	Hard-solid	Current study	20	4	229 ± 93	55 ± 22	14 ± 6	1643	390
Yoghurt vanilla half fat	Dairy products	Semi-solid	Current study	75	5	231 ± 100	55 ± 24	70 ± 30	330	78
Bun wholemeal with muesli	Cereals and cereal products	Hard-solid	Current study	35	5	231 ± 32	55 ± 8	19 ± 3	1221	290
Cheese spread 48+ on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	55	5	234 ± 57	56 ± 14	23 ± 6	1032	246
Chicken fillet	Meat and meat products	Soft-solid	Previous study	50	4	234 ± 134	56 ± 32	35 ± 20	667	158
Biscuit spiced Speculaas	Cakes	Hard-solid	Previous study	50	25	235 ± 71	56 ± 17	12 ± 4	1993	475
Chocolate flakes plain on wholemeal bread	Cereals and cereal products	Hard-solid	Current study	55	4	236 ± 80	56 ± 19	19 ± 6	1245	296
Beef steak tartare spiced (filet americain) on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	55	5	238 ± 58	57 ± 14	24 ± 6	1009	240
Biscuit fortified (Liga Milkbreak)	Cakes	Hard-solid	Current study	20	5	238 ± 38	57 ± 9	13 ± 2	1863	444
Cake Dutch spiced (Ontbijtkoek)	Cakes	Soft-solid	Previous study	50	25	239 ± 77	57 ± 18	18 ± 6	1305	308
Candy bar Snickers	Sugar and confectionery	Hard-solid	Current study	37	5	239 ± 79	57 ± 19	12 ± 4	2029	484
Cheese 30+	Dairy products	Soft-solid	Current study	50	5	241 ± 213	58 ± 51	20 ± 18	1203	289
Salami sausage saveloy on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	60	5	245 ± 138	59 ± 33	21 ± 12	1189	284

Food	Food Group	Texture	Source eating rate data	Portion size (g)	*n*	Energy intake rate		Eating rate (g/min)	Energy density	
						kJ/min	kcal/min		kJ/100g	kcal/100g
Marsh mallows	Sugar and confectionery	Soft-solid	Current study	25	5	249 ± 109	60 ± 26	18 ± 8	1402	330
Peanuts coated	Fruits, nuts and olives	Hard-solid	Current study	25	5	251 ± 109	60 ± 26	11 ± 5	2251	540
Cheese Brie 60+ on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	60	5	252 ± 27	60 ± 7	21 ± 2	1185	283
Crisps potato	Cereals and cereal products	Hard-solid	Current study	25	4	252 ± 72	60 ± 17	11 ± 3	2261	542
Salmon prepared in microwave oven	Fish and shellfish	Soft-solid	Current study	40	5	254 ± 75	61 ± 18	28 ± 8	918	220
Minced beef/pork shallow fried	Meat and meat products	Soft-solid	Current study	50	5	254 ± 165	61 ± 39	19 ± 12	1322	317
Cake Dutch spiced (Ontbijtkoek) wholemeal	Cakes	Soft-solid	Current study	30	5	256 ± 77	61 ± 18	20 ± 6	1303	308
Tuna in oil tinned	Fish and shellfish	Soft-solid	Current study	50	5	256 ± 58	61 ± 14	30 ± 7	862	206
Cheese cream soft (Boursin) on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	50	5	257 ± 53	62 ± 13	21 ± 4	1202	287
Crisps potato light flavored	Cereals and cereal products	Hard-solid	Previous study	50	5	258 ± 138	62 ± 33	13 ± 7	2015	481
Biscuit Dutch (Krakeling)	Cakes	Hard-solid	Current study	17	5	263 ± 53	63 ± 13	13 ± 3	2075	496
Cheese Mozzarella	Dairy products	Soft-solid	Current study	35	5	264 ± 117	63 ± 28	24 ± 11	1089	262
Liquorice Dutch sweet	Sugar and confectionery	Soft-solid	Previous study	50	3	273 ± 92	65 ± 22	19 ± 6	1437	338
Chips oven frozen prepared	Potatoes and other tubers	Hard-solid	Previous study	50	3	276 ± 205	66 ± 49	22 ± 17	1231	293
Syrup apple on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	55	4	276 ± 92	66 ± 22	26 ± 9	1061	251
Hamburger prepared	Meat and meat products	Soft-solid	Current study	40	5	277 ± 75	66 ± 18	26 ± 7	1062	255
Liquorice allsorts	Sugar and confectionery	Soft-solid	Current study	20	5	278 ± 57	66 ± 14	17 ± 3	1665	394
Kiwi fruit green	Fruits, nuts and olives	Soft-solid	Current study	50	5	278 ± 80	67 ± 19	97 ± 28	286	68
Cheese Brie 60+	Dairy products	Soft-solid	Current study	50	6	279 ± 121	67 ± 29	18 ± 8	1529	369
Pasta wholemeal boiled	Cereals and cereal products	Soft-solid	Previous study	50	2	286 ± 26	68 ± 6	52 ± 5	555	131
Chocolate confetti plain on wholemeal bread	Cereals and cereal products	Hard-solid	Current study	55	6	287 ± 99	69 ± 24	23 ± 8	1251	297
Bun currant/raisin	Cereals and cereal products	Soft-solid	Current study	35	6	293 ± 65	70 ± 16	26 ± 6	1134	268

Food	Food Group	Texture	Source eating rate data	Portion size (g)	*n*	Energy intake rate		Eating rate (g/min)	Energy density	
						kJ/min	kcal/min		kJ/100g	kcal/100g
Sausage luncheon meat on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	60	5	294 ± 75	70 ± 18	27 ± 7	1102	263
Croissant	Cakes	Hard-solid	Current study	27	5	299 ± 89	71 ± 21	18 ± 5	1684	403
Jam on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	55	5	301 ± 58	72 ± 14	29 ± 6	1026	243
Peanut butter on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	55	5	303 ± 105	72 ± 25	20 ± 7	1481	355
Rice white boiled	Cereals and cereal products	Soft-solid	Previous study	50	4	304 ± 232	73 ± 55	49 ± 37	621	146
Mayonnaise	Condiments and sauces	Semi-solid	Current study	25	3	307 ± 171	73 ± 41	11 ± 6	2733	664
Spread chocolate hazelnut on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	55	5	307 ± 146	73 ± 35	22 ± 11	1376	328
Chicken nuggets prepared in oven	Meat and meat products	Hard-solid	Current study	40	5	307 ± 115	73 ± 27	28 ± 11	1083	259
Yoghurt low fat with fruit	Dairy products	Semi-solid	Current study	75	5	308 ± 73	74 ± 18	103 ± 24	300	71
Chips fried in liquid frying fat	Potatoes and other tubers	Hard-solid	Current study	50	5	308 ± 41	74 ± 10	24 ± 3	1300	311
Sausage luncheon meat	Meat and meat products	Soft-solid	Current study	40	5	309 ± 172	74 ± 41	24 ± 13	1280	309
Yoghurt full fat	Dairy products	Semi-solid	Current study	75	6	319 ± 112	76 ± 27	132 ± 46	242	58
Peanut sauce ready to eat	Condiments and sauces	Semi-solid	Current study	25	6	321 ± 95	77 ± 23	31 ± 9	1039	249
Liver pate sausage on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	55	5	322 ± 117	77 ± 28	29 ± 11	1097	262
Sausage pork (Braadworst)	Meat and meat products	Soft-solid	Current study	50	5	333 ± 151	80 ± 36	33 ± 15	1025	246
Mousse chocolate	Dairy products	Semi-solid	Current study	75	4	334 ± 130	80 ± 31	44 ± 17	763	182
Salami sausage saveloy	Meat and meat products	Soft-solid	Current study	50	6	334 ± 204	80 ± 49	22 ± 13	1541	372
Bread white with sugar (Suikerbrood)	Cereals and cereal products	Soft-solid	Current study	35	5	336 ± 66	80 ± 16	26 ± 5	1291	305
Buttermilk	Dairy products	Liquid	Previous study	125	25	336 ± 308	80 ± 74	262 ± 241	128	30
Energy drink (Red Bull)	Non-alcoholic beverages	Liquid	Current study	125	5	338 ± 195	81 ± 47	181 ± 104	187	44
Chocolate chip cookie	Cakes	Hard-solid	Current study	38	5	341 ± 39	81 ± 9	16 ± 2	2120	506
Meringue cake (Bokkenpootje)	Cakes	Hard-solid	Current study	25	5	342 ± 50	82 ± 12	18 ± 3	1903	454

Food	Food Group	Texture	Source eating rate data	Portion size (g)	*n*	Energy intake rate		Eating rate (g/min)	Energy density	
						kJ/min	kcal/min		kJ/100g	kcal/100g
Chocolates filled/Belgium chocolate	Sugar and confectionery	Soft-solid	Current study	50	5	348 ± 93	83 ± 22	16 ± 4	2136	512
Candy bar Twix	Sugar and confectionery	Hard-solid	Current study	20	5	354 ± 108	85 ± 26	17 ± 5	2071	495
Biscuit Dutch shortbread sprits	Cakes	Hard-solid	Current study	25	5	355 ± 53	85 ± 13	16 ± 2	2205	527
Sausage (Frikandel) deep-fried	Meat and meat products	Soft-solid	Current study	37	5	357 ± 166	85 ± 40	34 ± 16	1049	252
Waffle Luikse	Cakes	Soft-solid	Current study	30	5	358 ± 228	85 ± 54	19 ± 12	1868	446
Candy bar (Milky Way)	Sugar and confectionery	Hard-solid	Current study	30	5	368 ± 147	88 ± 35	20 ± 8	1883	448
Peanuts salted	Fruits, nuts and olives	Hard-solid	Previous study	50	4	370 ± 173	88 ± 41	14 ± 7	2586	624
Salmon smoked	Fish and shellfish	Soft-solid	Previous study	50	3	372 ± 249	89 ± 59	48 ± 32	771	185
Yoghurt drink with sweetener	Dairy products	Liquid	Previous study	50	4	375 ± 312	90 ± 75	307 ± 256	122	29
Eclair with whipped cream filling	Cakes	Soft-solid	Current study	40	5	378 ± 157	90 ± 38	32 ± 13	1186	286
Bacon rasher	Meat and meat products	Soft-solid	Current study	40	5	381 ± 102	91 ± 24	21 ± 6	1804	435
Chocolate bar milk with nuts	Sugar and confectionery	Hard-solid	Current study	25	5	386 ± 168	92 ± 40	16 ± 7	2342	562
Croissant with ham and cheese	Miscellaneous	Hard-solid	Current study	45	5	401 ± 125	96 ± 30	27 ± 9	1460	350
Croquette meat deep-fried in liquid fat	Miscellaneous	Hard-solid	Current study	40	5	410 ± 84	98 ± 20	36 ± 7	1139	273
Pudding airy	Dairy products	Semi-solid	Current study	75	6	413 ± 147	99 ± 35	43 ± 15	967	231
Sausage frankfurter tinned	Meat and meat products	Soft-solid	Current study	40	4	415 ± 112	99 ± 27	50 ± 13	837	201
Cashew nuts salted	Fruits, nuts and olives	Hard-solid	Previous study	50	2	438 ± 373	105 ± 89	17 ± 15	2552	615
Roll bapao	Miscellaneous	Soft-solid	Current study	60	5	440 ± 128	105 ± 30	38 ± 11	1152	273
Ice tea (non-sparkling)	Non-alcoholic beverages	Liquid	Current study	125	5	454 ± 105	109 ± 25	344 ± 79	132	31
Snack sausage roll with bread dough pastry	Miscellaneous	Hard-solid	Current study	40	5	459 ± 55	110 ± 13	29 ± 3	1596	382
Sausage smoked traditional cooked	Meat and meat products	Soft-solid	Current study	50	5	463 ± 135	111 ± 32	36 ± 10	1287	311
Chocolate milk	Sugar and confectionery	Hard-solid	Previous study	50	4	464 ± 184	111 ± 44	20 ± 8	2286	548
Custard vanilla full fat	Dairy products	Semi-solid	Previous study	50	4	472 ± 213	113 ± 51	121 ± 55	390	93

Food	Food Group	Texture	Source eating rate data	Portion size (g)	*n*	Energy intake rate		Eating rate (g/min)	Energy density	
						kJ/min	kcal/min		kJ/100g	kcal/100g
Cream slice Dutch (Tompouce)	Cakes	Hard-solid	Current study	45	5	472 ± 138	113 ± 33	39 ± 11	1208	288
Pancake prepared with margarine	Cakes	Soft-solid	Current study	65	5	478 ± 211	114 ± 50	58 ± 26	826	196
Apple sauce	Fruits, nuts and olives	Semi-solid	Previous study	50	3	479 ± 307	115 ± 73	147 ± 95	325	77
Cream whipped with added sugar	Dairy products	Semi-solid	Current study	25	5	479 ± 212	115 ± 51	33 ± 15	1453	351
Custard chocolate full fat	Dairy products	Semi-solid	Current study	75	4	512 ± 159	122 ± 38	122 ± 38	419	100
Apple pie Dutch with shortbread	Cakes	Soft-solid	Current study	50	5	531 ± 104	127 ± 25	50 ± 10	1064	253
Ice tea (sparkling)	Non-alcoholic beverages	Liquid	Current study	125	4	546 ± 295	130 ± 70	414 ± 223	132	31
Fromage frais half fat with fruit	Dairy products	Semi-solid	Current study	50	5	546 ± 185	131 ± 44	104 ± 35	523	124
Dairy spread plain/herbs on wholemeal bread	Cereals and cereal products	Soft-solid	Current study	55	5	549 ± 802	131 ± 192	54 ± 78	1022	244
Apple turnover with puff pastry	Cakes	Hard-solid	Current study	55	5	552 ± 146	132 ± 35	37 ± 10	1506	361
Milk semi-skimmed	Dairy products	Liquid	Previous study	125	25	555 ± 383	133 ± 92	289 ± 200	192	46
Cupcake iced	Cakes	Soft-solid	Current study	38	5	568 ± 93	136 ± 22	31 ± 5	1833	437
Almond paste filled tarts	Cakes	Soft-solid	Current study	20	5	593 ± 234	142 ± 56	35 ± 14	1697	404
Smoothie fruit	Non-alcoholic beverages	Liquid	Current study	125	5	594 ± 26	142 ± 6	257 ± 11	231	54
Cake wrapped in marzipan and chocolate	Cakes	Soft-solid	Current study	30	4	608 ± 239	145 ± 57	32 ± 13	1900	454
Fruit drink concentrate diluted	Sugar and confectionery	Liquid	Current study	125	5	610 ± 278	146 ± 66	268 ± 122	227	54
Cake without butter	Cakes	Soft-solid	Previous study	50	4	636 ± 303	152 ± 72	34 ± 16	1856	444
Minced meat ball with egg/crumbs	Meat and meat products	Soft-solid	Previous study	50	3	654 ± 109	156 ± 26	58 ± 10	1127	270
Breakfast drink (Goede Morgen original)	Dairy products	Liquid	Current study	125	5	673 ± 135	161 ± 32	271 ± 55	248	59

Food	Food Group	Texture	Source eating rate data	Portion size (g)	*n*	Energy intake rate		Eating rate (g/min)	Energy density	
						kJ/min	kcal/min		kJ/100g	kcal/100g
Waffle syrup	Cakes	Soft-solid	Previous study	50	3	685 ± 387	164 ± 93	35 ± 20	1936	461
Snack sausage roll puff pastry	Miscellaneous	Hard-solid	Current study	37	5	761 ± 275	182 ± 66	51 ± 19	1484	356
Milk skimmed	Dairy products	Liquid	Current study	125	5	786 ± 97	188 ± 23	527 ± 65	149	35
Yoghurt drink	Dairy products	Liquid	Current study	125	5	793 ± 296	190 ± 71	330 ± 123	240	57
Milk whole	Dairy products	Liquid	Current study	125	5	961 ± 567	230 ± 136	373 ± 220	258	62
Juice orange pasteurized	Non-alcoholic beverages	Liquid	Current study	125	5	971 ± 598	232 ± 143	511 ± 315	190	45
Juice orange freshly squeezed	Non-alcoholic beverages	Liquid	Current study	125	5	1004 ± 468	240 ± 112	483 ± 225	208	49
Milk chocolate-flavored semi-skimmed	Dairy products	Liquid	Current study	125	5	1044 ± 307	249 ± 73	319 ± 94	327	77
Juice apple	Non-alcoholic beverages	Liquid	Previous study	50	2	1243 ± 175	297 ± 42	641 ± 90	194	46
Breakfast drink (HeroFruitontbijt)	Non-alcoholic beverages	Liquid	Previous study	50	4	1379 ± 1095	330 ± 262	595 ± 472	232	55
Milk chocolate-flavored full fat	Dairy products	Liquid	Previous study	50	4	1766 ± 1388	422 ± 332	471 ± 370	375	89

Table A2. Frequency (*n* (%)) of food groups in the eating rate and energy intake rate quartiles (*n* = 240).

	Eating rate (g/min)					Energy intake rate (kJ/min)[1]				
	Quartile 1 2–16 g/min (n = 60)	**Quartile 2** 16–26 g/min (n = 60)	**Quartile 3** 26–50 g/min (n = 60)	**Quartile 4** 50–641 g/min (n = 60)	***p*** [2]	**Quartile 1** 0–112 kJ/min (n = 60)	**Quartile 2** 113–204 kJ/min (n = 60)	**Quartile 3** 204–333 kJ/min (n = 60)	**Quartile 4** 334–1766 kJ/min (n = 60)	***p*** [2]
Food groups					<0.0001					<0.0001
Potatoes	0 (0.0)	3 (5.0)	2 (3.3)	1 (1.7)		2 (3.3)	1 (1.7)	3 (5.0)	0 (0.0)	
Vegetables	2 (3.3)	5 (8.3)	13 (21.7)	4 (6.7)		21 (35.0)	3 (5.0)	0 (0.0)	0 (0.0)	
Legumes	0 (0.0)	0 (0.0)	2 (3.3)	0 (0)		0 (0)	2 (3.3)	0 (0)	0 (0)	
Fruits, nuts and olives	4 (6.7)	3 (5.0)	6 (10.0)	7 (11.7)		6 (10.0)	8 (13.3)	3 (5.0)	3 (5.0)	
Dairy products	1 (1.7)	3 (5.0)	3 (5.0)	19 (31.7)		0 (0.0)	4 (6.7)	7 (11.7)	15 (25.0)	
Cereals and cereal products	30 (50.0)	19 (31.7)	5 (8.3)	2 (3.3)		12 (20.0)	20 (33.3)	22 (36.7)	2 (3.3)	
Meat and meat products	1 (1.7)	8 (13.3)	8 (13.3)	1 (1.7)		2 (3.3)	4 (6.7)	6 (10.0)	6 (10.0)	
Fish and shellfish	0 (0.0)	2 (3.3)	4 (6.7)	0 (0.0)		0 (0.0)	2 (3.3)	3 (5.0)	1 (1.7)	
Eggs and egg products	0 (0.0)	0 (0.0)	1 (1.7)	0 (0.0)		0 (0.0)	1 (1.7)	0 (0.0)	0 (0.0)	
Sugar and confectionery	10 (16.7)	8 (13.3)	0 (0.0)	1 (1.7)		3 (5.0)	6 (10.0)	4 (6.7)	6 (10.0)	
Cakes	11 (18.3)	5 (8.3)	8 (13.3)	2 (3.3)		0 (0.0)	5 (8.3)	7 (11.7)	14 (23.3)	
Non-alcoholic beverages	0 (0.0)	0 (0.0)	0 (0.0)	15 (25.0)		7 (11.7)	0 (0.0)	0 (0.0)	8 (13.3)	
Alcoholic beverages	0 (0.0)	0 (0.0)	0 (0.0)	1 (1.7)		0 (0.0)	1 (1.7)	0 (0.0)	0 (0.0)	
Condiments and sauces	1 (1.7)	4 (6.7)	2 (3.3)	0 (0.0)		3 (5.0)	0 (0.0)	4 (6.7)	0 (0.0)	
Soups, bouillon	0 (0.0)	0 (0.0)	1 (1.7)	6 (10.0)		4 (6.7)	3 (5.0)	0 (0.0)	0 (0.0)	
Snacks	0 (0.0)	0 (0.0)	5 (8.3)	1 (1.7)		0 (0)	0 (0)	1 (1.67	5 (8.3)	

[1] Energy intake rate-quartiles (kcal/min); Q1=0-27 kcal/min, Q2=27-49 kcal/min, Q3=49-80 kcal/min, Q4=80-422 kcal/min; [2] *p*-value Chi-Square

Table A3 Characteristics (mean ± SD) of the foods in the eating- and energy intake-rate quartiles (n = 240): eating rate, energy intake rate, food composition and taste

	Eating rate (g/min)					Energy intake rate (kJ/min) [1]				
	Quartile 1 2–16 g/min (n = 60)	**Quartile 2** 16–26 g/min (n = 60)	**Quartile 3** 26–50 g/min (n = 60)	**Quartile 4** 50–641 g/min (n = 60)	***p*** [2]	**Quartile 1** 0–112 kJ/min (n = 60)	**Quartile 2** 113–204 kJ/min (n = 60)	**Quartile 3** 204–333 kJ/min (n = 60)	**Quartile 4** 334–1766 kJ/min (n = 60)	***p*** [2]
Eating rate (g/min)	11 ± 3	21 ± 3	36 ± 7	192 ± 170	<0.0001	58 ± 106	30 ± 25	29 ± 24	143 ± 173	<0.0001
Energy intake rate					<0.0001					<0.0001
kJ/min	162 ± 76	230 ± 108	254 ± 183	398 ± 375		62 ± 36	161 ± 25	262 ± 35	560 ± 278	
kcal/min	39 ± 18	55 ± 26	61 ± 44	95 ± 90		15 ± 9	38 ± 6	63 ± 8	134 ± 66	
Food composition										
Energy (kJ/100 g)	1586 ± 545	1144 ± 582	747 ± 5552	285 ± 282	<0.0001	500 ± 633	951 ± 619	1226 ± 539	1086 ± 764	<0.0001
Protein (g/100 g)	9 ± 5	10 ± 8	8 ± 8	3 ± 3	<0.0001	3 ± 5	8 ± 7	10 ± 8	7 ± 7	<0.01
Fat (g/100 g)	14 ± 16	12 ± 12	9 ± 9	2 ± 4	<0.0001	2 ± 5	7 ± 11	14 ± 13	14 ± 13	<0.0001
Carbohydrate (g/100 g)	54 ± 24	30 ± 25	17 ± 17	9 ± 8	<0.0001	21 ± 29	32 ± 27	30 ± 24	26 ± 22	0.34
Mono- and disaccharides (g/100 g)	17 ± 21	14 ± 19	8 ± 11	18 ± 94	0.93	7 ± 16	23 ± 95	12 ± 16	16 ± 16	0.54
Polysaccharides (g/100 g)	37 ± 22	15 ± 14	9 ± 11	3 ± 6	<0.0001	14 ± 24	21 ± 22	19 ± 15	10 ± 12	0.15
Fiber (g/100 g)	4 ± 3	3 ± 2	2 ± 2	1 ± 1	<0.0001	2 ± 2	3 ± 3	3 ± 2	1 ± 1	0.02
Water (g/100 g)	19 ± 23	44 ± 26	64 ± 24	85 ± 14	<0.0001	71 ± 35	49 ± 32	41 ± 24	51 ± 32	<0.001
Sodium (mg/100 g)	361 ± 275	356 ± 300	258 ± 301	87 ± 142	<0.0001	217 ± 302	278 ± 277	333 ± 234	234 ± 309	0.53
Taste intensity [3]										
Sweet	22 ± 19	24 ± 23	20 ± 20	23 ± 17	0.87	12 ± 12	18 ± 17	22 ± 20	36 ± 21	<0.0001
Sour	4 ± 6	8 ± 12	9 ± 12	20 ± 18	<0.0001	10 ± 14	9 ± 13	11 ± 16	11 ± 14	0.43
Bitter	2 ± 5	2 ± 3	2 ± 3	6 ± 13	0.01	5 ± 10	3 ± 10	2 ± 2	3 ± 3	0.09
Umami	5 ± 8	8 ± 9	11 ± 11	5 ± 9	0.37	8 ± 11	6 ± 9	9 ± 10	5 ± 9	0.41
Salt	18 ± 15	18 ± 13	18 ± 18	10 ± 15	<0.01	12 ± 15	17 ± 16	21 ± 14	14 ± 16	0.30
Fat	22 ± 18	34 ± 19	29 ± 20	20 ± 15	0.28	12 ± 10	21 ± 15	36 ± 17	37 ± 19	<0.0001

[1] Energy intake rate-quartiles (kcal/min); Quartile 1 = 0–27 kcal/min, Quartile 2 = 27–49 kcal/min, Quartile 3 = 49–80 kcal/min, Quartile 4 = 80–422 kcal/min;
[2] p-value linear trend; [3] n = 225.

Table A4 Energy intake rate (kcal/min) of foods relative to the other foods within the food group

Food group	Energy intake rate (kcal/min) relative to food group		
	Low	Medium	High
Potatoes (*n* = 6)			
Description	**Boiled potatoes [1] (*n* = 2)**		**Mashed and (deep-)fried potatoes (*n* = 4)**
Energy intake rate	18 (15–21) kcal/min		59 (44–74) kcal/min
Eating rate	23 (18–28) g/min		32 (22–52) g/min
Energy density	79 (74–83) kcal/100 g		219 (83–311) kcal/100 g
Vegetables (*n* = 24)			
Description	**Raw vegetables [1] (*n* = 5)**	**Boiled [1] and pickled vegetables (*n* = 17)**	**Vegetables with added energy (*n* = 2)**
Energy intake rate	7 (2–17) kcal/min	11 (2–28) kcal/min	31 (26–37) kcal/min
Eating rate	36 (12–76) g/min	37 (13–89) g/min	48 (44–51) g/min
Energy density	19 (12–33) kcal/100 g	29 (17–69) kcal/100 g	66 (59–73) kcal/100 g
Legumes (*n* = 2)			
Description	**Tinned brown beans [1] (*n* = 1)**		**Tinned beans in tomato sauce (*n* = 1)**
Energy intake rate	31 kcal/min		42 kcal/min
Eating rate	28 g/min		45 g/min
Energy density	109 kcal/100 g		93 kcal/100 g
Fruits, nuts and olives (*n* = 20)			
Description	**Fruit (excluding soft fruit) [1] (*n* = 8)**	**Olives, conserved fruit and soft fruit [1] (*n* = 7)**	**Nuts [2], apple sauce (*n* = 5)**
Energy intake rate	26 (14–42) kcal/min	39 (24–66) kcal/min	83 (49–114) kcal/min
Eating rate	46 (26–73) g/min	52 (12–97) g/min	39 (8–147) g/min
Energy density	57 (45–78) kcal/100 g	116 (29–326) kcal/100 g	494 (77–624) kcal/100 g
Dairy products (*n* = 26)			
Description	**Plain yoghurt and fromage frais [2], cheese [2] (*n* = 8)**	**Deserts other than plain yoghurt or fromage frais (*n* = 8)**	**Dairy drinks [2] (*n* = 10)**
Energy intake rate	54 (35–76) kcal/min	98 (55–130) kcal/min	179 (48–422) kcal/min
Eating rate	58 (12–132) g/min	80 (33–122) g/min	322 (71–527) g/min
Energy density	187 (37–369) kcal/100 g	154 (71–351) kcal/100 g	55 (29–89) kcal/100 g

Cereals and cereal products (*n* = 56)			
Description	**Hard and dry products, plain bread slices [2] (*n* = 23)**		**Other (e.g. bread with topping, buns, pasta, rice) [2] (*n* = 33)**
Energy intake rate	33 (9–62) kcal/min		58 (25–131) kcal/min
Eating rate	9 (2–13) g/min		24 (10–54) g/min
Energy density	389 (234–542) kcal/100 g		254 (131–355) kcal/100 g
Meat and meat products (*n* = 18)			
Description	**Fresh meat (excluding minced meat) [2] (*n* = 2)**		**Minced meat [2] and processed meat (*n* = 16)**
Energy intake rate	42 (28–56) kcal/min		72 (17–156) kcal/min
Eating rate	27 (18–35) g/min		29 (13–58) g/min
Energy density	158 (157–158) kcal/100 g		250 (124–435) kcal/100 g
Fish and shellfish (*n* = 6)			
Description		**Fish and fish products [1] (*n* = 6)**	
Energy intake rate		56 (29–89) kcal/min	
Eating rate		31 (24–48) g/min	
Energy density[1]		182 (98–220) kcal/100 g	
Eggs and egg products (*n* = 1)			
Description		**Boiled egg [1] (*n* = 1)**	
Energy intake rate		41 kcal/min	
Eating rate		32 g/min	
Energy density		128 kcal/100 g	
Sugar and confectionery (*n* = 19)			
Description	**Hard confectionary (non-chocolate), ice cream (*n* = 5)**	**Soft confectionary (non-chocolate) (*n* = 6)**	**Chocolate, candy bars, fruit drink (*n* = 8)**
Energy intake rate	24 (15–37) kcal/min	50 (33–66) kcal/min	88 (44–146) kcal/min
Eating rate	9 (4–16) g/min	14 (9–19) g/min	47 (8–268) g/min
Energy density	321 (205–394) kcal/100 g	357 (320–428) kcal/100 g	454 (54–562) kcal/100 g

Cakes (*n* = 26)			
Description	**Dry cakes, biscuits (*n* = 15)**		**Cakes, pies, pastries, puddings (non-milk based) (*n* = 11)**
Energy intake rate	76 (40–164) kcal/min		104 (57–152) kcal/min
Eating rate	17 (9–35) g/min		33 (18–58) g/min
Energy density	443 (310–527) kcal/100 g		336 (196–446) kcal/100 g
Non-alcoholic beverages (*n* = 15)			
Description	**Non– and very low caloric beverages [2] (*n* = 5)**		**Caloric beverages (*n* = 10)**
Energy intake rate	0 (0–1) kcal/min		161 (22–330) kcal/min
Eating rate	334 (56–635) g/min		365 (59–641) g/min
Energy density	0 (0–1) kcal/100 g		41 (16–55) kcal/100 g
Alcoholic beverages (*n* = 1)			
Description		**Pilsner beer (*n* = 1)**	
Energy intake rate		47 kcal/min	
Eating rate		106 g/min	
Energy density		45 kcal/100 g	
Condiments and sauces (*n* = 7)			
Description	**Tomato sauces (*n* = 3)**		**Mayonnaises and similar (*n* = 4)**
Energy intake rate	22 (19–27) kcal/min		63 (49–77) kcal/min
Eating rate	28 (17–44) g/min		20 (11–31) g/min
Energy density	89 (61–129) kcal/100 g		361 (235–664) kcal/100 g
Soups, bouillon (*n* = 7)			
Description	**Soup from cube or package (*n* = 3)**		**Soup with more (semi-) solid components (*n* = 4)**
Energy intake rate	12 (9–18) kcal/min		33 (25–48) kcal/min
Eating rate	89 (41–174) g/min		66 (59–70) g/min
Energy density	20 (5–33) kcal/100 g		51 (35–80) kcal/100 g

Snacks (*n* = 6)		
Description	**Spring roll fried (*n* = 1)**	**Other warm savory snacks (*n* = 5)**
Energy intake rate	49 kcal/min	118 (96–182) kcal/min
Eating rate	27 g/min	36 (27–51) g/min
Energy density	181 kcal/100 g	327 (273–382) kcal/100 g

[1] Recommended foods. [2] Both recommended and not recommended foods

Appendix B

Supplementary tables

Chapter 5: How much slow and fast calories are we consuming? Food consumption in terms of energy intake rate

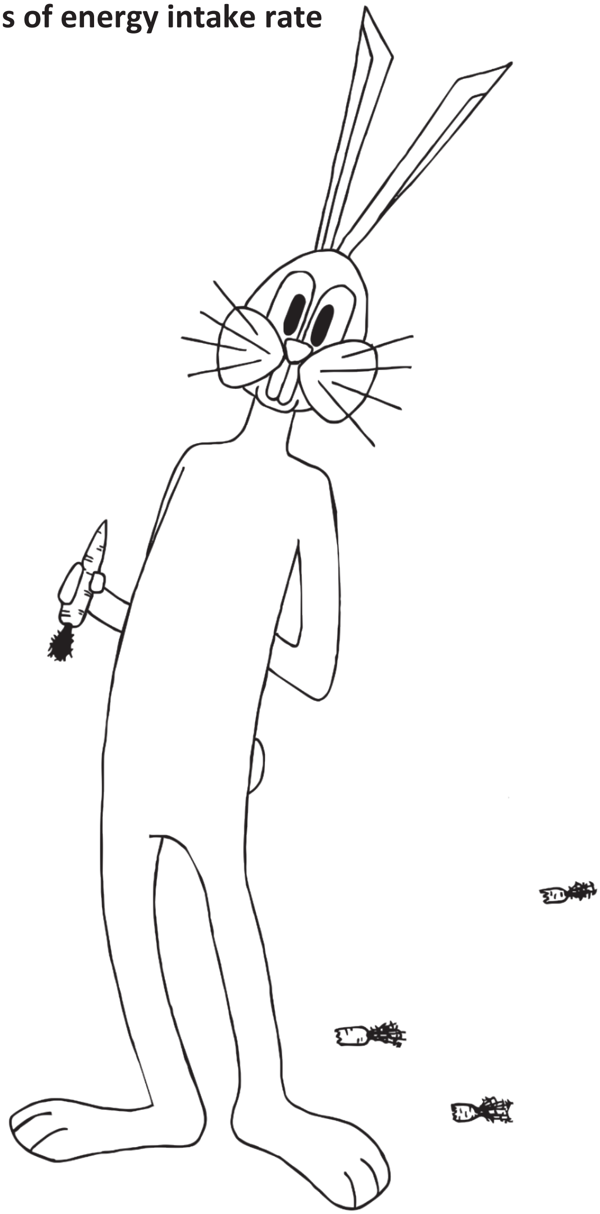


Table B1 Characteristics of identified underreporters (i.e., EI/BMR < 0.91), adequate reporters (i.e., 2.63 > EI/BMR ≥ 0.91), and overreporters (i.e., EI/BMR > 2.63) [a]

	Underreporters	Adequate reporters	Overreporters	*P*
	n(%)	**n(%)**	**n(%)**	
n	121(8.5%)	1280(90.3%)	16(1.1%)	
Sex				
Men	53(43.8%)	671(52.4%)	11(68.8%)	0.08 [b]
Women	68(56.2%)	609(47.6%)	5(31.3%)	
	Mean±SD	**Mean±SD**	**Mean±SD**	
Age (yrs)	32.6±9.7 [A]	31.7±9.6 [A]	25.6±6.6 [B]	0.02 [c]
BMI (kg/m^2)	28.7±5.7 [A]	24.5±4.6 [B]	21.3±2.0 [C]	<0.0001 [c]
Dietary EIR (kJ/min)	147±106 [A]	226±116 [B]	261±95 [B]	<0.0001 [c]

[a] Values in a row with different superscript upper-case letters are significantly different (*P* < 0.05), Bonferroni
[b] *P*-value Chi-square test
[c] *P*-value GLM

Table B2 Foods grouped according to their expected eating rate, and the available laboratory data for estimating the eating rate of the foods in these groups

Description	Food groups concerned [a]	Available laboratory data	
		n products	Mean eating rate (g/min)
Potatoes, not mashed	1. Potatoes and other tubers	4	24
Potatoes, mashed	1. Potatoes and other tubers	1	52
Vegetables, no preparation	2. Vegetables	7	34
Vegetables, with preparation	2. Vegetables	17	39
Legumes	3. Legumes	2	36
Fruit	4.1 Fruits 4.3 Mixed fruits	15	57
Nuts and olives	4.2 Nuts and seeds 4.4 Olives	3	11
Cheese	5.5 Cheese	4	19
Desserts, airy (e.g. chocolate mousse)	5. Dairy products	2	43
Desserts, non-airy	5. Dairy products	9	101
Dairy and soy drinks	5. Dairy products 17.1 Soya products	10	322
Cereal and cereal products, dry	6.3.2 Crisp bread, rusks 6.5 Salty biscuits, aperitif biscuits, crackers	17	8
Bread and bread products	6.3.1 Bread 17.3 Snacks	18	20
Pasta, rice, other grain	6.2 Pasta, rice, other grain	4	40
Meat and vegetarian alternatives	7. Meat and meat products 17.1 Soya products 17.3 Snacks	19	28
Fish and shellfish	8. Fish and shellfish	5	31
Eggs and egg products	9. Eggs and egg products	1	32
Confectionary, non-chocolate	11.3 Confectionary, non-chocolate	9	11
Confectionary, chocolate	11.2 Confectionary, chocolate	7	16
Ice cream, water ice	11.5 Ice cream, water ice	2	15
Syrup	11.4 Syrup	1	268
Cakes and biscuits, dry	12.2 Dry cakes, biscuits	14	16
Cakes and biscuits, non-dry	12.1 Cakes, pies, pastries, etc	11	32
Coffee, tea and herbal teas	13.3 Coffee, tea and herbal teas	3	181
Non-alcoholic drinks other than coffee and tea	13. Non-alcoholic beverages	11	402
Alcoholic beverages	14. Alcoholic beverages	1	106
Soups, bouillon	16. Soups, bouillon	7	76

[a] EPIC-Soft food groups

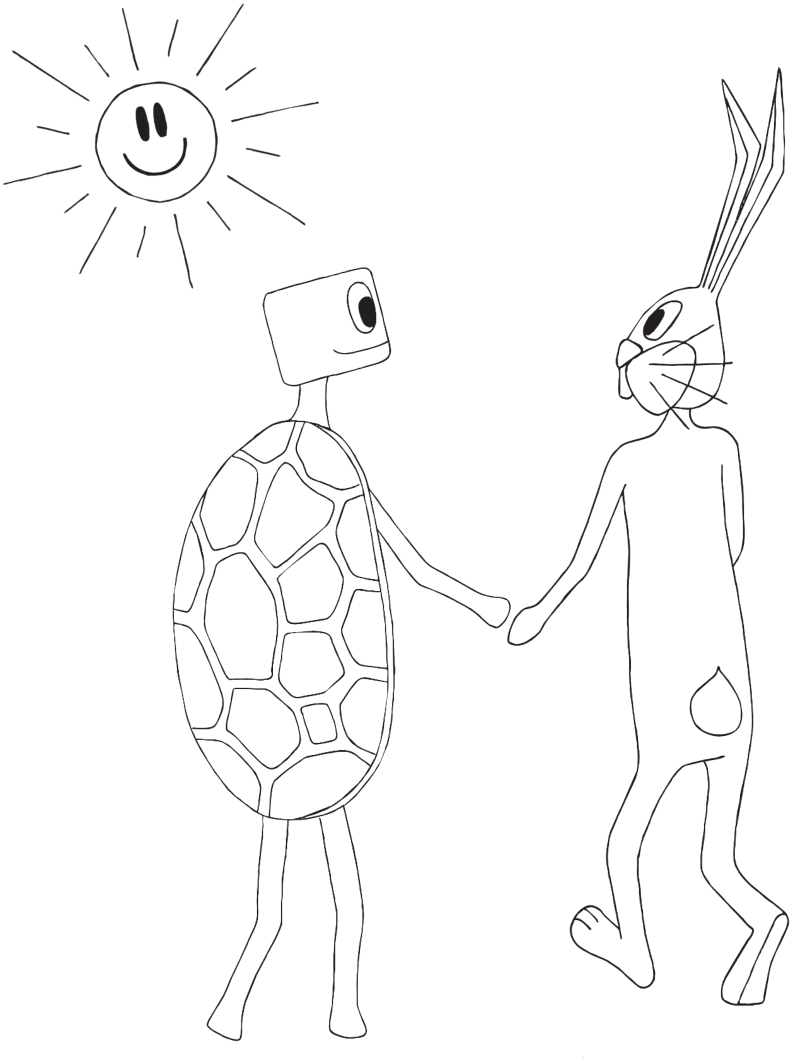
Table B3 Characteristics of participants with a low, medium and high dietary energy intake rate

Participant characteristics	Dietary EIR-tertiles				
	Low (*n* = 426)	Medium (*n* = 427)	High (*n* = 427)	***P***	***P* for trend**
	n (%)	**n (%)**	**n (%)**		
Sex				<0.0001[a]	
Men	159(37.3)	243(56.9)	269(63.0)		
Women	267(62.7)	184(43.1)	158(37.0)		
	mean±SD	**mean±SD**	**mean±SD**		
Age (yrs.)	35.1±9.4	32.2±9.4	27.8±8.7	<0.0001[b]	<0.0001
BMI (kg/m^2)	25.1±4.8	24.7±4.5	23.8±4.2	<0.0001[b]	<0.0001
Physical activity [c]	5.1±2.0	5.2±1.9	4.8±2.1	0.02[b]	0.048
Energy intake (MJ/day)	9.1±2.3	10.8±2.8	11.2±2.7	<0.0001[b]	<0.0001
Energy from toppings (%)	17.0±7.9	17.1±7.2	16.3±6.5	0.18[b]	<0.0001

[a] *p*-value Chi-square test

[b] *p*-value ANOVA

[c] Days per week with at least 30 minutes of strenuous activity



Towards easy and enjoyable weight management

Colophon

The research described in chapter 3 was financially supported by the European Community's ICT Programme under Grant Agreement No. 610746, 01/10/2013 - 30/09/2016.

Financial support from Wageningen University for printing this thesis is gratefully acknowledged.

Cover design and illustrations: Janet van den Boer

Lay-out: Janet van den Boer

Printing: Digiforce – proefschriftmaken.nl, Vianen