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Daily distracted consumption patterns and their relationship with BMI

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ABSTRACT

The rapidly increasing prevalence of overweight and obesity has heightened the need for a better understanding of obesity-related eating patterns and dietary behaviours. Recent work suggests that distracted eating is causally related to increased immediate and later food, pushing the need for a better understanding of the prevalence of distracted consumption and how this relates to body weight. To extract insights in the relationship between demographics, daily consumption settings, and BMI, we performed secondary data analyses on data from 1011 individuals representative of the Dutch population (adults, 507F, BMI 17–50 kg/m^2). The most commonly reported distractions were talking to others (32.7%) and watching television (21.7%). Only 18.4% of respondents reported no distractions during meals. To examine how different distractions related to BMI, we performed OLS regression which showed, among other things, that watching tv while eating lunch ($\eta^2 = 0.37$) and working during dinner were associated with a higher BMI ($\eta^2 = 1.63$). To examine the robustness of these findings, machine learning techniques were used. A random forest analysis (RMSE = 4.09) showed that next to age and education level, distraction during lunch and snack was amongst the largest predictors of BMI. Multiple linear regression with lasso penalty (RMSE = 4.13) showed that specifically watching tv while eating lunch or snacks was associated with a higher BMI. In conclusion, our analyses confirmed the assumption that people are regularly distracted during their daily meals, with distinct distractors relating to BMI. These findings provide a starting point for evidence-based recommendations on which consumption *settings* are associated with healthier eating patterns and body weight.

1. Introduction

The current COVID-19 pandemic has exposed the vulnerability of the ever-increasing number of people with nutrition-related health problems such as obesity, hypertension, and type 2 diabetes (de Almeida-Pititto et al., 2020; Yang et al., 2021). In many countries worldwide, governments and scientists, therefore, aim to closely monitor the food and beverage intake of inhabitants to gain insight into the main issues involved around eating and drinking and to outline steps that can be taken to tackle the issues raised (Feunekes et al., 2020). When addressing the health implications of unhealthy eating, however, it is not only important to focus on what and how much people eat and drink, but also to take into account the context in which these foods and drinks are consumed.

Due to recent technological and societal developments, such as digitization and the 24/7 economy, people these days can engage in eating or drinking at any place or time while engaging in a wide array of competing activities such as interactions with electronic devices (e.g., televisions, computers, tablets, and smartphones) and active or passive commuting. Performing competing tasks during food and beverage consumption can lead to cognitive load (Carrier et al., 2015), which may interfere with the extent to which people focus on sensory stimulation from the food products they are consuming or satiation signals such as gastric signals (Morris et al., 2020; Van der Wal & Van Dillen, 2013).

Several controlled experiments have demonstrated that distracted eating could lead to reduced taste perception (Liang et al., 2018; Van der Wal & Van Dillen, 2013) and may increase immediate and later food intake (Robinson et al., 2013; Cui et al., 2021; Higgs & Woodward, 2009; Oldham-Cooper et al., 2010). A recent neuroimaging experiment revealed that when participants tasted milkshake under concurrent cognitive load (i.e. distraction), they showed lower connectivity between the brain areas involved in primary taste processing (insula) and higher order (taste) processing (orbitofrontal cortex), than when they tasted milkshake under low mental load (Duif et al., 2020). Interestingly, the connectivity strength between these areas predicted later food intake in an ad libitum buffet. These results suggest that distraction during food intake may alter the neural processing of taste, which may later lead to overconsumption.

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Even though the effect of distracted consumption on overconsumption has been quite consistently described in lab studies, the effects of regular distracted consumption in daily life are largely unknown. Regular distracted consumption may lead to frequent overconsumption, which in turn may lead to weight gain. For example, children and adults who frequently watch television during dinner have a higher body weight, as has been found in cross-sectional studies (Liang et al., 2009; Tumin & Anderson, 2017). Furthermore, it is not yet known if all distractions during consumption have the same effects. For example, competing activities that induce a higher cognitive load may have a larger effect on overconsumption than activities that are less mentally engaging.

In short, distracting consumption settings may have long-term health implications, through their effects on overconsumption and, in turn, body weight, pushing the need for a better understanding of what distracted consumption settings look like in people's daily lives. This study aims at filling these research gaps by examining the prevalence of distracted eating and the association between distracted consumption settings and body weight. We hypothesize that more regular distracted consumption is associated with a higher body mass index (BMI). To examine this, we used secondary data collected by the Netherlands Nutrition Centre. This data set contains information about distracted consumption, body height and weight, demographic variables and other eating habits. As this data was obtained via an online survey, consumption was not directly measured, and so body mass index (BMI) was used as the outcome variable. However, overweight and obesity are multifactorial problems related to a complex interplay of demographic characteristics, such as gender, age, education and income, and health behaviors such as diet, physical activity and sleeping patterns (Division of Nutrition, 2021; Grundy, 1998). All these possible factors may be confounded with the effect of distracted eating on BMI. Including all available information in an ordinary least squares regression model would lead to too high degrees of freedom for the available data points. Therefore, in addition to ordinary least squares regression to directly test our hypotheses, we make use of the machine learning techniques of random forest and multiple regression with LASSO penalty. These methods can take all available variables into account and report on how important the distracted consumption variables are for the model to predict BMI. This approach allows us to both directly test our hypotheses and assess the relative importance of distracted consumption for the prediction of BMI in comparison to all the other available variables.

2. Methods

2.1. Participants and design

The data used for this study were obtained via a survey by market research firm MWM2 and was commissioned by the Netherlands Nutrition Center. The Netherlands Nutrition Centre provides information to the Dutch population about healthy eating (habits) (Feunekes et al., 2020). They have commissioned this study to see whether the Dutch eat with attention for their food, and to examine ways that the population could be made to eat more consciously. The data was used to describe how Dutch people eat, e.g. what distractions they have during meals, where they eat most of their meals, what the duration is of their meals etc. (Voedingscentrum, 2019). An external panel bureau was used to draw a sample that is representative of the population of the Netherlands on age, gender, region, education level and income level according to the Gouden Standaard (CBS, 2019). The sample has been drawn out of a panel that has an ISO-26362 certification (International Organization for Standardization, 2009), which is an international quality standard of access panels. The panel members were asked to participate by a link in an email message. They were not informed about the topic of the survey in the email. The Netherlands Nutrition Center requested a minimum sample size of $n = 1000$, to have a 3% margin of error with a 95% level of confidence. The dataset and analysis script can be viewed at https://osf.io/dwzts/. A cross-sectional design was used for this study. The data was collected over five days in October 2019. The exclusion criteria were age below 18 and inadequate knowledge of the Dutch language. Participants who did not inform gender, educational level, or household were also excluded from the analysis. The final analysis included 1011 participants who lived in the Netherlands at the moment of filling out the questionnaire. The sample included 507 men, 503 women, and one person who identified as non-binary. The sample's age was grouped into six levels: 18–24 years (8%), 25–34 years (16%), 35–44 years (14%), 45–54 years (18%), 55–64 years (17%) and 65 years or older (24%). Their average BMI was 25.7 kg/m^2 (SD = 4.23, range 17–50 kg/m^2). Further demographics on the sample's income and educational level can be found in Table A1 in Appendix A. Although our hypothesis is based on previous work, because data were collected for a different purpose, neither the hypothesis or the analysis was preregistered, and so this study can be considered exploratory.

2.2. Materials

The online questionnaire included items about demographic factors and eating habits. A total of 64 variables were recorded, such as the location and duration of the meal, and the type of distractions present while eating. In Appendix B, Table B1 gives an overview of each type of variable and an example of an item including the answer categories.

Height and weight were assessed to determine Body Mass Index (BMI). This question was made optional, 'I don't know/I don't want to say' was one of the answer options. This means that BMI was not available for 117 respondents. Complete cases analysis was used for all the analyses reported below.

2.3. Statistics

All data analyses were conducted in R (R Core Team, 2019).

2.3.1. Ordinary least squares regression

The effect of different distractions during different meal moments were assessed using ordinary least squares regression. In these regression models, covariates were added for gender, age, education level and income, since these have previously been described as the most robustly related to BMI (Kanerva, Kontto, Erkkola, Nevalainen, & Männistö, 2018).

2.3.2. Random forest

As a next step we aimed to assess how distracted consumption variables rank among all other available variables to predict BMI. The random forest algorithm was the first approach chosen to address this question for its ability to estimate the importance of each predictor variable in modelling the outcome variable. Random forest is an ensemble of decision trees, which are known for their simplicity and efficiency when dealing with domains with a large number of variables and/or cases. Rather than relying on individual decision trees, random forest builds multiple decision trees and merges their predictions to get a more accurate and stable prediction (Breiman, 2001).

The random forest algorithm has two parameters: the number of predictors that can be split at each node and the number of trees in the forest. The number of predictors at each node is limited to some percentage of the total. This ensures that the ensemble model does not rely too heavily on any individual feature and makes fair use of all potentially predictive predictors. Unfortunately, random forests are not intrinsically interpretable since their prediction results from averaging several hundreds of decision trees. Therefore, the reported variable importance was used to assess which variables are important in the data set to predict BMI. The ranger function from the ranger package (Wright & Ziegler, 2017) was chosen to fit the random forest model, as this function is a faster implementation of random forests. The predicted BMI values by the ranger function are based on out-of-bag samples, which prevents too optimistic estimates of MSE.

The data set was split into a training set and a test set. The training set was used to estimate the model parameters, and the test set to estimate the predicted BMI values using the estimates from the training set. The training sample consisted of 670 observations (75% of the data) and the test set of 224 observations (25% of the data).

The random forest model was fitted to the training data using all the predictors as the explanatory variables and the BMI as the outcome variable. To avoid overfitting, a grid search was used in the training set to find the optimal parameters for the random forest, which was used to make predictions about the test set. The importance was set to "permutation", in which the importance of a variable is measured by the Mean Decrease Accuracy (MDA) of the forest when the values of the variable are randomly permuted in the out-of-bag samples. The permutation accuracy importance measure for the random forest covers the impact of each predictor variable individually as well as in multivariate interactions with other predictor variables.

2.3.3. Multiple linear regression model using LASSO penalty

Although the random forest analysis provides a ranking of the importance of the variables, it does not give information on the direction of effects. To examine this, a multiple linear regression using the LASSO penalty was used as a complementary approach to investigate the association of the predictor variables and BMI. This method provided a less complex model, with more interpretable results. To determine which variables to include in the final multiple linear regression model, the LASSO method was fit to the data using the glmnet() function from package glmnet (Friedman et al., 2010) in R. LASSO stands for Least Absolute Shrinkage and Selection Operator and is a type of linear regression that uses shrinkage. A LASSO method performs regularization by adding a penalty term, known as lambda, as a constraint in the formula. The penalization will result in the shrinkage of some coefficients towards zero, leading to their exclusion from the model. A higher lambda will lead to more coefficients being shrunken to zero. The most appropriate value for lambda was selected by cross-validation. Cross-validation was performed on the training set to address the predictive accuracy using the test set. To answer the research questions, a LASSO model was fitted on the complete data set as well. To this end, the optimal lambda was first determined using cross-validation within the complete data set. Next, this optimal lambda was used to fit a LASSO model on the complete data set.

3. Results

3.1. Frequency of distracted consumption

As a first step, we examined the prevalence of the different distractions during the different meal moments. Fig. 1 depicts the activities that respondents reported usually engaging in during meals. As little as 14.5% (during snack time) and at most 23.5% of respondents (during breakfast) reported eating with no distraction at all. Of all the activities, the most commonly reported distraction was talking to others, ranging from 23.6% during breakfast to 58.5% during dinner, followed up by watching television, which ranged from 11% during lunch to 34.9% during snacks.

3.2. Relationship between different distractors and BMI

3.2.1. Ordinary least squares regression

To examine the relationship of the different types of activities during meals and BMI we estimated a model per meal moment with BMI as dependent variable and regressors for type of activity during the meal and regressors for age, education and gender as control variables, as these demographic variables have been most robustly associated with BMI (Kanerva et al., 2018) For breakfast, we found effects of age ($b = 0.58$, $SE = 0.11$, $p < 0.001$), gender ($b = -0.74$, $SE = 0.28$, $p = 0.007$) and education level ($b = -0.50$, $SE = 0.11$, $p < 0.001$), but we did not find any of the activities to be associated with BMI. Income was not associated with BMI. We found that next to age ($b = 0.57$, $SE = 0.09$, $p < 0.001$), gender ($b = -0.77$, $SE = 0.27$, $p = 0.006$) and education level ($b = -0.51$, $SE = 0.11$, $p < 0.001$), watching television during lunch was associated with a higher BMI ($b = 1.55$, $SE = 0.51$, $p = 0.002$) and not eating lunch was associated with a lower BMI ($b = -3.9$, $SE = 1.67$, $p = 0.019$). Income was not associated with BMI. Fig. 2 depicts the observations for the different distractors during lunch.

For dinner, in addition to effects of age ($b = 0.61$, $SE = 0.09$, $p < 0.001$), gender ($b = -0.70$, $SE = 0.28$, $p = 0.0113$), and education level ($b = -0.49$, $SE = 0.11$, $p < 0.001$), we found that working during dinner was associated with a higher BMI ($b = 6.90$, $SE = 2.88$, $p = 0.017$). Income was not associated with BMI. There were no significant associations of distractors during snacks and BMI (effect of age: $b = 0.60$, $SE = 0.09$, $p < 0.001$; gender: $b = -0.72$, $SE = 0.28$, $p = 0.010$; education level: $b = -0.47$, $SE = 0.11$, $p < 0.001$, no effect of income).

In OLS regression only a limited number of regressors can be included before power becomes too low to detect effects. Consequently,

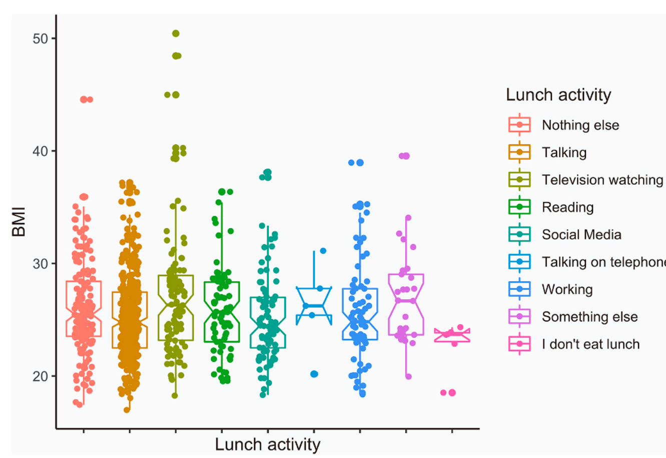

Fig. 2. Boxplot with scatterplot overlay to visualize the observations per distractor activity during lunch. The notches depict medians. Jitter has been added to prevent overplotting.

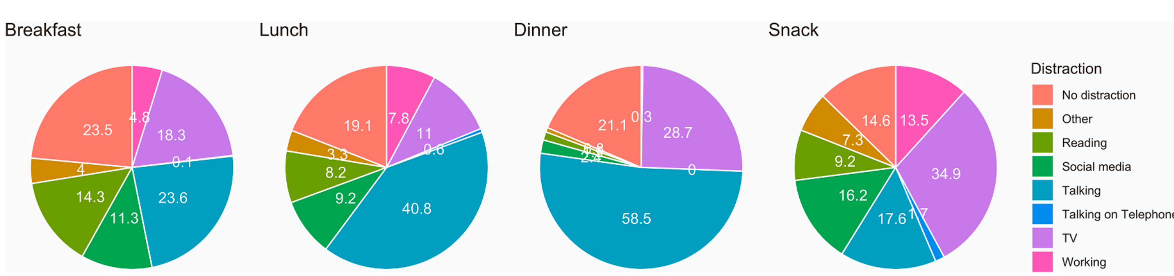

Fig. 1. Percentage of respondents who reported to engage in the different activities.

in the regression models above we could not control for all relevant confounds that could have (partly) explained the effects of specific distractor-meal combinations on BMI. Therefore, in the next sections, we will perform two different machine learning techniques in which all the available data in the dataset will be used to predict BMI.

3.2.2. Random forest

The results of the first 15 most important predictors in the random forest model are displayed in Fig. 3. The Root Mean Square Error (RMSE) of the model was 4.09. The mean decrease in accuracy for the random forest analysis was used to identify predictor variables having the largest influence on the BMI. An overview of the importance of all predictors in the random forest model can be found in Appendix C (Table C1 & Figure C1).

The results of the random forest analysis indicate that activity during lunch and activity during snacks were among the 25 predictors that contributed the most to the model. However, the random forest analysis does not give us any information about the direction of effects. From the OLS regression results, and earlier work, for example, we would expect age and education to have opposing effects on BMI. Moreover, based on the current analysis, we cannot tell which activities during lunch or snacks contribute to BMI. To get additional information about this, we performed a multiple linear regression with LASSO.

3.2.3. Multiple linear regression with LASSO

After selecting the most appropriate value for lambda using cross-validation, there were 33 variables left in the model. The Root Mean Square Error (RMSE) of the model was 4.13. The results of the variable selection show which predictors are related to BMI. Table 1 shows which predictors were included in the final model and their associated values based on a linear model with a lasso penalty.

These results show that, next to the expected effects of gender, age, education, and income several factors that have to do with consumption settings were associated with BMI. For example, eating dinner at a different location, working during dinner, and watching television during snacks or lunch were associated with a higher BMI (but note that the prevalence of working during dinner in this sample was very low, 0.34% or 3 respondents). Reversely, having lunch with friends or at the table were associated with a lower BMI.

Figure C2. in Appendix C shows the order with which lambda the variables enter the model. This shows that time taken for breakfast and 'other' dinner location were the first to enter the model. Watching television during lunch and during snacks were amongst the first 10 variables to enter the model.

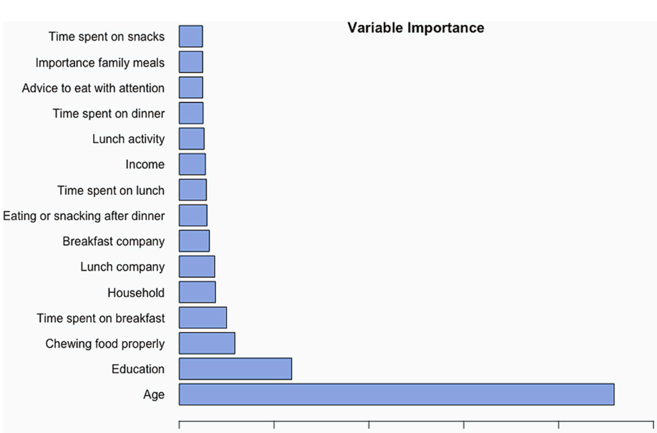

Fig. 3. Predictor variable importance based on the mean decrease in accuracy of the random forest model.

Table 1
Predicted parameters from the multiple linear regression with lasso penalty.

Indicator	Standardized Coefficient
Intercept	25.699230
Age	0.936669
Dinner activity Working	0.451035
'I take big bites'	0.277114
'I eat until I am full'	0.214551
Lunch activity Watching television	0.199341
Snack activity Watching television	0.168416
'I have started to take more time for dinner over the last 5 years'	0.132910
	0.101100
Gender	0.089212
Male	
'I eat or snack after dinner'	0.075623
Breakfast company	0.067028
With colleagues	
Age child	0.061460
Over 18	
Time spent on breakfast	0.047372
Time spent on lunch	0.046160
Lunch company	0.000000
'I don't eat lunch'	
Lunch activity	−0.000001
'I don't eat lunch'	
Lunch time change	−0.000010
'I don't eat lunch'	
Breakfast location	−0.000960
'I don't eat breakfast'	
Region	−0.001297
Zeeland, Noord-Brabant or Limburg	
Breakfast company	−0.004632
'I don't eat breakfast'	
Age child	−0.008708
No children	
Lunch company	−0.010465
Other	
Dinner company	−0.019417
Other	
Number of days homecooked meals	−0.025252
Income	−0.033943
€84.700 or more	
Lunch company	−0.064671
Friends	
Income	−0.071804
I don't know/don't want to say	
Lunch location	−0.083046
I don't eat lunch	
'I take the time to properly chew my food'	−0.104622
Lunch location	−0.111177
At the table	
Household composition	−0.179672
I live with my parents	
Education	−0.428837

4. General discussion

Distracted consumption has been consistently linked to increased immediate and delayed intake in controlled lab studies (Robinson et al., 2013; Cui et al., 2021). In this study, we aimed to examine the prevalence of distracted consumption in daily life and the relationship of different distractors with BMI. We found that in our sample representative of the Dutch population, distracted consumption was highly prevalent, with on average only 18.4% of respondents who reported no distractions during meals. The most commonly reported distractions were talking to others (32.7%) and watching television (21.7%). Previous studies examining the prevalence of distractions during meals have mostly focused on a single distractor (e.g., television watching; Roos et al., 2014; or smartphone use; Yong et al., 2021) and on young adults or children (Roos et al., 2014; Yong et al., 2021), which makes it difficult to compare the prevalence found in this study to previous findings. Future work could look into this further.

The OLS regression results per meal event showed that watching television during lunch and working during dinner were associated with a higher BMI when controlling for age, gender, and education level. Other distractors and other meal moments were not significantly associated with BMI. The random forest and LASSO regression results converged with the regular regression results, and indicated that television watching during lunch and snacking, in particular, were consistently associated with a higher BMI. The random forest and LASSO regression indicated that watching television during lunch was similarly as or slightly less important for the prediction of BMI than taking big bites or chewing food properly, but more important than items assessing other dietary habits such as the number of days respondents ate home-cooked meals or ate take-out.

Our result that that watching television during meals was associated with a higher BMI aligns with previous findings that television watching during consumption leads to higher consumption both during the same and subsequent occasions (Robinson et al., 2013). Furthermore, in African American women a relationship between watching television while eating and the consumption of energy-dense snacks has been observed (Roy et al., 2019). Other studies have shown that regular television watching during meals is associated with a higher BMI (Boulos et al., 2012; Liebman et al., 2003; Roos et al., 2014), although one large study found no effect of increased television watching during meals on BMI increase over time (Cleland et al., 2018). In one large-scale study, individuals with overweight and obesity were more likely to eat while doing other activities than individuals with normal weight (Liebman et al., 2003; the type of activity was not recorded). Furthermore, an interdisciplinary review observed a direct relationship between the number of hours of television watched per week and body weight (Boulos et al., 2012). Thus, regular television watching during consumption, especially during lunch and snacking, may increase consumption, and thus contribute to weight gain, which in turn can lead to overweight and obesity. Note though, that television watching also increases sedentary time, which has been found to be independently related to weight gain (Boulos et al., 2012). In our current dataset, no information about total television watching, media use or physical activity was available. Future studies could examine these variables further to distinguish between the effect of television watching on body weight caused by increased sedentary time and by overconsumption related to distracted eating.

In the OLS regression and the regression with LASSO penalty, working during dinner was positively associated with BMI as well. However, the random forest analysis indicated the model actually would improve if this predictor was left out. Therefore, our results are inconsistent when it comes to working during dinner.

The results from this study cannot inform about why a particular distraction, like television watching, would more likely lead to a higher BMI than another distraction during consumption. Our analyses about the different distractors were exploratory in the sense that we did not formulate hypotheses about which would be more influential than others. That is, the study does not speak to the underlying mechanisms. Distraction during eating and drinking can induce cognitive load (Carrier et al., 2015; Robinson et al., 2013). This cognitive load may reduce people's attentional resources for the sensory perceptions of consumption, satiation signals, and/or memory formation (Morris et al., 2020; Oldham-Cooper et al., 2010; Van der Wal & Van Dillen, 2013). This reduced sensory perception and memory of consumption may lead people to consume more (Duif et al., 2020; Higgs & Woodward, 2009; Van der Wal & Van Dillen, 2013). Future studies could use distractors varying in cognitive load during consumption and examine the effects on sensory perception, satiation, food memory, and current and subsequent consumption amount, to elucidate the mechanisms through with different distractors may lead to overconsumption.

Although there were consistencies between the results of the different analytical approaches, there were also differences. Gender for example, was identified as a relatively important factor to predict BMI in the OLS and LASSO regression, but not the random forest analysis. A possible explanation for this could be multicollinearity. Although the predictive accuracy for both LASSO regression and random forest analysis is robust against multicollinearity (McNeish, 2015; Strobl et al., 2008), the variable importance of the random forest and the selection of variables for the LASSO regression could be affected. After testing our dataset for multicollinearity, we indeed found that some of the variables correlated highly (e.g. gender and income, age and education; see analysis script). There is therefore a chance, that in a different dataset, a slightly different set of predictors would be identified as important by the LASSO regression and random forest analysis. However, in this study we were mostly interested in the consistency between the OLS regression results testing our hypothesis regarding distracted eating, and machine learning approaches. Because each statistical method has its specific strengths and weaknesses, we sought convergence across models to provide more robust insights. While collinearity may cause slightly different outcomes between the models, it is unlikely that predictors consistently identified across models would be affected by it. Even though these machine learning approaches have their weaknesses, they have been found to be a superior choice to OLS methods in almost all cases, because of their strenuous focus on model checking (Hindman, 2015).

A strength of the current study is the use of a large sample that is representative of the Dutch population and the number of control variables that were taken into account using the machine learning analyses. Making use of the machine learning analyses in addition to the regular regression analysis to directly test our hypothesis, has allowed us to assess the relative importance of distracted consumption for the prediction of BMI in comparison to all the other available information. Furthermore, to our knowledge, this is one of the first studies that assesses the prevalence and effect on BMI of a wide range of different activities performed consumption. A weakness is the missing BMI for a substantial number of respondents, which may have induced a sampling bias, as it is possible that participants with higher body weights were more likely not to report their weight. Furthermore, this study has made use of self-report data. Previous studies have shown that people are often not able to accurately report on their dietary intake patterns (Subar et al., 2015). Moreover, there were some distractors that only very few respondents reported to engage in during consumption, which limits the interpretability of their relationship with BMI. Future research should address these limitations.

In conclusion, distracted consumption is highly prevalent, with the vast majority of respondents engaging in other activities for all meal moments. This distraction, in turn, is associated with body weight, as television watching during lunch, in particular, was consistently related to a higher BMI in the regular regression analyses and both machine learning analyses. These findings suggest distracted consumption as a potential target for public health nutrition communication. They could help to develop evidence-based messages that encourage consumers to minimize distractions during consumption as part of healthy eating pattern.

Ethical statement "daily distracted consumption patterns and their relationship with BMI"

The data used in this study was secondary data from an online survey conducted in an existing panel by commercial research bureau MWM2 on request by the Netherlands Nutrition Center. All procedures performed were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Conflict on interest

None of the authors declare a conflict on interest.

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Appendix A

Table A1
Demographic characteristics sample

Variable	Percentage/Mean (SD)
Gender	
Male	49.8%
Female	50.1%
Other	0.0%
Age	
18-24 y	8.6%
25-34 y	16.9%
35-44 y	14.9%
45-54 y	18.1%
55-64 y	17.9%
65 y and older	23.5%
Education level	
LBO/MAVO/VMBO	23.9%
MBO	31.1%
HAVO/VWO	14.3%
HBO	22.4%
University	8.3%
Income	
Less than €13.700	5.7%
€13.700 - € 28.600	14.4%
€28.600 – €35.500	16.8%
€35.500 - €42.400	17.3%
€42.400 - €71.000	20.3%
€71.000 - €84.700	3.6%
€84.700 or more	4.5%
I don't know/I don't want to say	17.2%
BMI	25.7 (4.23)

Appendix B

Overview of the variables in the dataset.

Table B1

Overview of the variables Variable and type	Example of an item with answer categories and score range	Coded as
Gender *Factor*	What is your gender? *Male (1), Female (2), Other(3).*	*gender*
Age *Factor*	*What is your age? Below 18 (1), 8–24 (2), 24–35 (3), 35–44 (4), 45–54 (5), 55–64(6), 65+(7).*	*age*
Education *Factor*	What is your highest completed education? *None or elementary school (1), LBO/MAVO/VMBO (2), MBO (3), HAVO/VWO (4), HBO (5), University (6).*	*education*
Household *Factor*	What is the composition of your household? *I live alone (1), I live with my parents/caretakers (2), I live together with my partner (3), I live together with my partner and child(ren) (4), I live together with my child(ren) (5), I live together with other persons (other than my partner or child(ren) (6).*	*household*
Age of child *Factor*	In what age category is your (oldest) in house living child? *Less than one year (1), 1–4 years (2), 5–8 years (3), 9–12 years (4), 13–17 years (5), 18+ years (6), No child (7).*	*age_child*
Location of meal *Factor*	Where do you eat breakfast/lunch/dinner/snacks? *At the table (1), On the couch (2), At a desk (3), On my way (4), Walking/ Outside (5), Other (6), I don't eat this meal (7).*	*breakfast_location lunch_location dinner_location snacks_location*
Other people during meal *Factor*	With whom do you eat breakfast/lunch/dinner/snacks? *Alone (1), With partner/family members (2), With friends (3), With colleagues (4), Other (5), I don't eat this meal (6).*	*breakfast_who lunch_who dinner_who snacks_who*
Activity during meal *Factor*	What do you do during breakfast/lunch/dinner/snacks? *Nothing else (1), Talk with other people (2), Watch television (3), Read something (4), Social media (5), Call (4), Work (5), Other (6), I don't eat this meal (7).*	*breakfast_activity lunch_actitivty dinner_actitivity snacks_actitivity*
	What is the average amount of minutes you spent on breakfast/lunch/dinner/snacks? *From 0 till 90*	*breakfast_time*

(*continued on next page*)

Table B1 (*continued*)

Overview of the variables Variable and type	Example of an item with answer categories and score range	Coded as
Amount of time spent during meal *Numeric*		*lunch_time* *dinner_time* *snacks_time*
Change in the amount of time *Factor*	Did you in the last five years start to take less or more time for breakfast/lunch/dinner/snacks? *Less time (1), Same amount of time (2), More time (3), I don't know (4), I don't eat this meal (5).*	*breakfast_changetime* lunch_changetime dinner_changetime snacks_changetime
Amount of different meals *Numeric*	On average, how many times do you eat the following meals per week? *Home-cooked meals, Ready-made meals, Take-out or delivery, Bought on the way, Dining out. Range from 0 till 7.*	*days_homecooked* *days_readymeals* *days_delivered* *days_ontheway* *days_diningout*
Satisfaction attention during the meal *Factor*	How satisfied are you with your attention paid during breakfast/dinner? *Very satisfied (1), Satisfied (2), Neutral (3), Dissatisfied (4), Very dissatisfied (5), I don't eat this meal (6)*	*satisf_attention_b* *satisf_attention_d*
Satisfaction location during meal *Factor*	How satisfied are you with your location during breakfast/dinner? *Very satisfied (1), Satisfied (2), Neutral (3), Dissatisfied (4), Very dissatisfied (5), I don't eat this meal (6)*	*satisf_location_b* *satisf_location_d*
Satisfaction time taken for meal *Factor*	How satisfied are you with the time taken for breakfast/dinner? *Very satisfied (1), Satisfied (2), Neutral (3), Dissatisfied (4), Very dissatisfied (5), I don't eat this meal (6)*	*satisf_time_b* *satisf_time_d*
Statements about behaviour *Factor*	To what degree do you agree with the following statement? *Statements:* *1. I eat with a lot of attention for the food* *2. I get distracted while eating* *3. Smartphones are allowed during meals* *4. I take big bites.* *5. I eat slowly.* *6. I take the time to chew my food properly.* *7. I scoop a large portion on my plate.* *8. I eat so fast I can barely taste my food.* *9. I stop eating when I feel full, even if I like the food I am eating* *10. After the meal I feel like I have eaten too much* *11. I eat or snack after dinner, in front of the computer or tv* *Never/almost never (1), Sometimes (2), Often (3), Always/Most of the time (4).*	*degree_attention* *degree_distraction* *degree_smartphone* *degree_bites* *degree_slowly* *degree_bites* *degree_chew* *degree_scoop* *degree_fast* *degree_stop* *degree_full* *degree_snack*
Importance of eating behaviour *Factor*	To what degree do you find the following statement important? *Examples of statements:* *1. Eating a warm meal at the table.* *2. Eating without distraction.* *3. Eating while seated, not while walking.* *4. Eating with the family* *Very important (1), Important (2), Neutral (3), Not important (4), Not important at all (5).*	*degree_warm_meal* *degree_relaxed* *degree_nodistraction* *degree_seated* *degree_eat_family*
Attitude towards advice Factor	What is your attitude towards different types of advice from the Voedingscentrum? Examples of advice: 1. Wait until your mouth is completely empty before taking another bite 2. Eat with attention. 4. Make it attractive to eat at the table 5. Take the time for a meal. 6. Really taste what you eat. 7. Put down your cutlery sometimes. Very positive (1), Positive (2), Neutral (3), Negative (4), Very negative (5).	*advice_another_bite* *advice_attention* *advice_attractive* *advice_time* *advice_taste* *advice_cutlery*
Region Factor	What region of the Netherlands are you from? Amsterdam (1), Rotterdam (2), Den Haag (3), Noord-Holland, Zuid-Holland or Utrecht (exclusion previously mentioned) (4), Groningen, Friesland or Drenthe (5), Overijssel, Gelderland or Flevoland (6), Zeeland, Noord-Brabant or Limburg (7).	*region*
Income Factor	What is the bruto year income of your household? Less than €13.700 (1), €13.700 - €28.600 (2), €28.600 - €35.500 (3), €35.500 - €42.400 (4), €42.400 - €71.000 (5), €71.000 - €84.700 (6), More than €84.700 (7), I don't know/want to answer (7).	*income*
Length in cm Numeric	What is your length in centimeters? Range from 152 cm to 206 cm.	*length*
Weight in km Numeric	What is your weight in kilograms? Range from 43 kg to 158 kg.	*weight*
BMI Numeric	Value of the calculated BMI using length and weight	*BMI*
BMI category Factor	Assigned category based on BMI: Underweight (1), Healthy weight (2), Overweight (3), Severe overweight (4).	*BMI_cat*

Appendix C

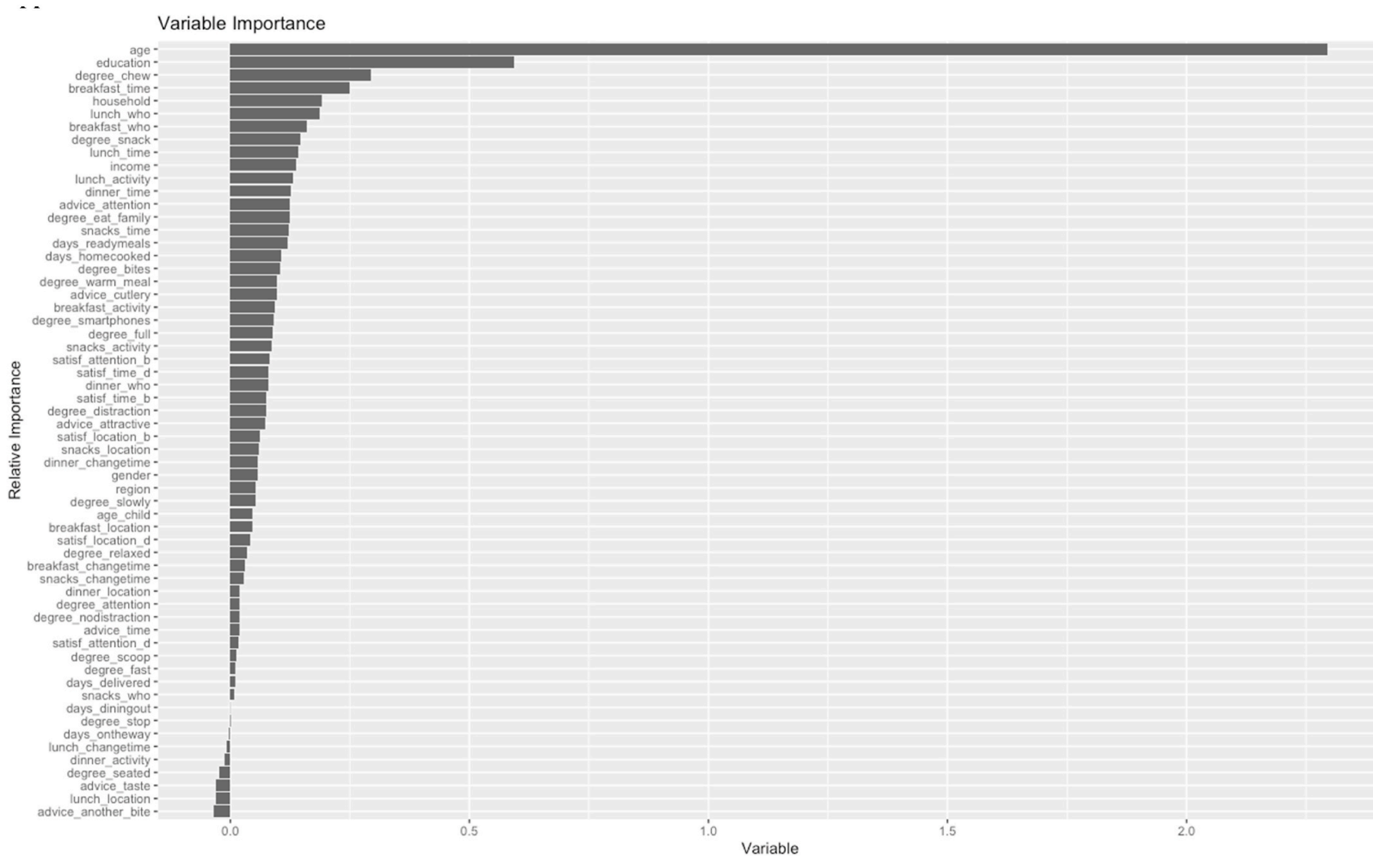

Fig. C1. Predictor variable importance based on the mean decrease in accuracy of the random forest model

Table C1
Random Forest Predictor variable importance.

Variable	Importance
age	2.29363464
education	0.5934076
degree_chew	0.29386948
breakfast_time	0.24993782
household	0.19155367
lunch_who	0.18725859
breakfast_who	0.15898703
degree_snack	0.14635241
lunch_time	0.1429766
income	0.13822669
lunch_activity	0.13102336
dinner_time	0.12612204
advice_attention	0.12388328
degree_eat_family	0.12335355
snacks_time	0.12280088
days_readymeals	0.1197683
days_homecooked	0.10590296
degree_bites	0.10501427
degree_warm_meal	0.09843645
advice_cutlery	0.09735128
breakfast_activity	0.09284826
degree_smartphones	0.09030658
degree_full	0.08900465
snacks_activity	0.08628965
satisf_attention_b	0.08181264
satisf_time_d	0.0805025
dinner_who	0.07902392
satisf_time_b	0.07601364
degree_distraction	0.07418896
advice_attractive	0.07313996
satisf_location_b	0.06062929

(*continued on next page*)

Table C1 (*continued*)

Variable	Importance
snacks_location	0.05833694
dinner_changetime	0.05803668
gender	0.05726124
region	0.05196562
degree_slowly	0.05166992
age_child	0.04692579
breakfast_location	0.04621503
satisf_location_d	0.0408841
degree_relaxed	0.03513443
breakfast_changetime	0.03011759
snacks_changetime	0.0271839
dinner_location	0.02008078
degree_attention	0.01997154
degree_nodistraction	0.01950434
advice_time	0.01817901
satisf_attention_d	0.01740978
degree_scoop	0.01203457
degree_fast	0.01131794
days_delivered	0.00917627
snacks_who	0.00723426
days_diningout	−0.0006848
degree_stop	−0.0016981
days_ontheway	−0.0026949
lunch_changetime	−0.0064845
dinner_activity	−0.0123702
degree_seated	−0.0239054
advice_taste	−0.0290521
lunch_location	−0.0301503
advice_another_bite	−0.0351726

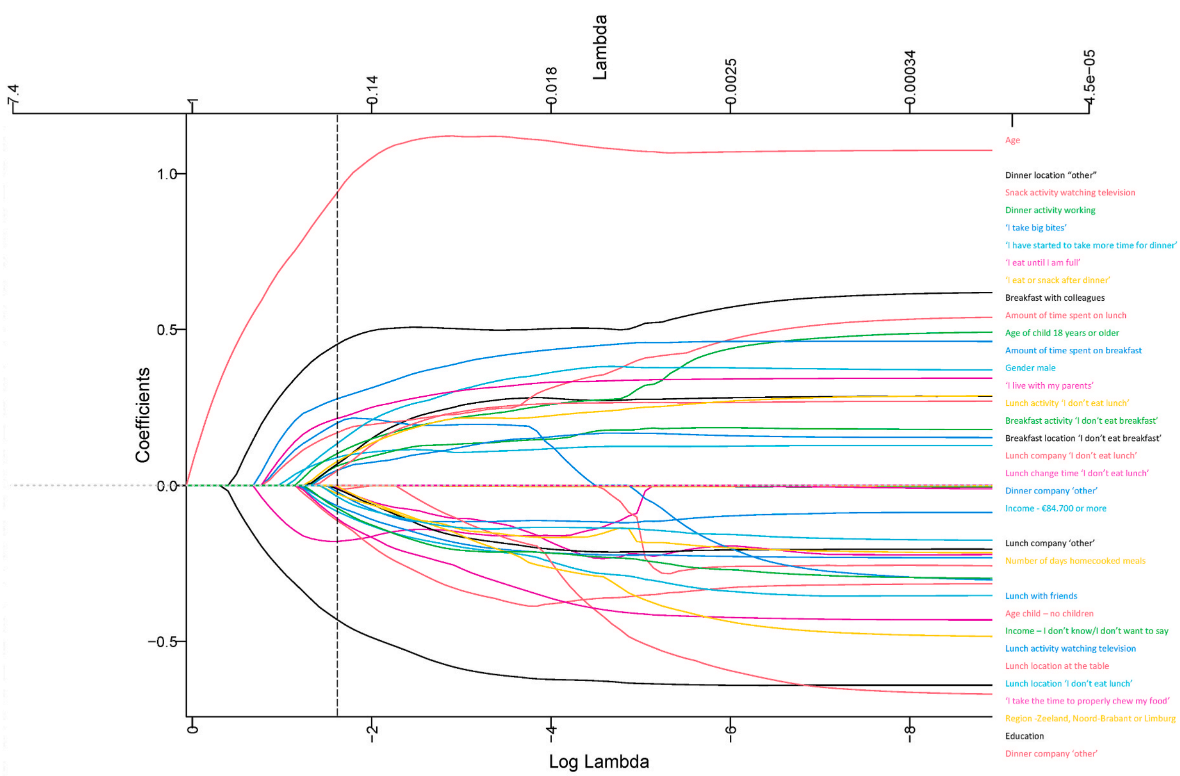

Fig. C2. Trace plots showing the Lasso regression coefficients β versus the penalty parameter λ. The penalty strength decreases from left to right, allowing larger magnitude and more nonzero elements in the regression coefficients. The parameter importance is reflected in the order of the coefficients tending to nonzero, so the leftmost nonzero parameter is the most important in this model. For visualization only coefficients that were left in the model are displayed. The dashed line depicts the lambda min (0.2).

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