Eliciting meal preferences from households: a recipe to improve estimate accuracy.

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Abstract

This paper examines the congruence between meal preferences reported by couples. We aim to elicit the most effective way to retrieve preference estimates from households about difference attributes which make up their evening meals. In this paper, we make use of an empirical dataset, collected in Northern Ireland. This paper investigates the strength of similarity between members of couples, with findings suggesting that meal preference estimates retrieved from couples, even when relating to the shared behavioural experience of joint meal consumption, have a varying level of convergence. The findings of this study hold several implications for policy making and survey researchers. We found that while individuals cannot perfectly provide a representative response for their partner, this accuracy can be improved when the questioned are framed as trade-off based choices of evening meals.

Keywords: congruence; meal preferences; latent class models

1 Introduction

It is commonly believed that we are on the verge of an obesity crisis (see for example, Gortmaker et al., 2011; Sassi, 2010; Swinburn et al., 2011; Wang et al., 2011). Whilst in 1980, only 1 in 10 people were considered over-weight, now 1 in 2 are over-weight (Sassi, 2010). For many countries, the burden of tackling the different health effects of obesity is

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costing between 2% and 6% of their health care budget. This epidemic is further exacerbated by the finding that children who have at least one obese parent are 2 to 4 times more likely to be obese themselves. Whilst this is partly due to genetics (Karra et al, 2013), but also children generally share their parents' unhealthy diets and sedentary lifestyles; an influence which has played an important role in the spread of obesity (Hannon et al., 2003).

This has led to a surge of interest in why people choose to eat what they do. Much time and resources have been invested into the development of both dietary recommendations and food guides specifically tailored for several different audiences (Asp, 1999). These have been utilised by many health-related organizations and governmental agencies (see, for example Porter et al., 1998 and Senauer et al., 1991). However, even though significant efforts have been made to communicate guidance on food choices to the general public, much research is finding that consumers are having problems utilising this information (Nestle et al., 1998; Porter et al., 1998; Willett, 1994, 1998). One possibility is that there could be error in the survey methods that researchers are using to understand meal preferences and choices. Traditional approaches to collecting information about peoples preferences, have often relied on data collected from a single, sometimes randomly selected, family member. Individual reports on meal choices however, may not be reflective of the meals consumed in the household, as this would often be an activity that many members of the same household would partake in together (Cheng et al., 2007).

Therefore, in this paper, we make use of an empirical dataset, collected in Northern Ireland, that specifically contains households with both a male and female household 'head', which we will refer to as *dyadic* households. First, we consider the preferences from both spouses for different types of meal options, to establish if only asking one member alone can provide an accurate representation of meal choices within their household. Secondly, we compare the preferences elicited when asking the household members direct questions about their preferred calorie intake, to an alternative method where we embed the calorie content of their meal within a '*meal basket*'. This then provides us with the ability to determine if the way a respondent is asked, be it direct or embedded, will influence the analysts ability to retrieve accurate estimates about meal preferences. Finally, we make use of a scale-adjusted latent class model to test the degree of similarity in taste and variance in preferences between male and female household members. This approach enables us to examine sources of couple agreement/divergence with a focus on whether they relate to differences in taste, preference stability (scale parameter) or both. Offering the household members different meal choices, we analyse the cases in which individuals were asked *"Which of the meal options would you prefer most?"* and estimate the proportion of household members having similar (or the same) preferences.

The remainder of this paper is organised as follows. Section 2 presents an overview of the empirical data used in this study, including details of the stated choice component of the survey. This is followed by Section 3, which gives an overview of different response strategies, including an outline of the latent class model used to examine these. Results are shown in Section 4, while conclusions are presented in Section 5.

2 Empirical data

Data were collected from a random sample of Northern Ireland households during early 2011. The survey was conducted as a face-to-face Computer Aided Personal Interview (CAPI) by MRNI Research. A total of 290 households, which contained two 'household heads' were included in the present analysis. The aim of the survey was to elicit intra-household trade-offs between meal options. Questions were asked to obtain information on weekly food habits, preferences and in addition relationship status and attitudes between household members. The structure of the interviews was such that each *household head* was asked to complete individually (identical) questionnaires and then also complete together a *joint* questionnaire.

In the stated choice component of the survey, respondents were presented with the choice between three different meal options, described in terms of calories, cooking time, food type and cost. Taste was not included as a direct variable in the choice tasks as it was deemed subject to *interpretation* by the respondent. Instead, "food type" was used as a proxy for taste. Table 1 shows the three levels used for the different attributes, where the specific combinations presented in a given choice scenario were obtained from a D-efficient experimental design with Bayesian priors (Ferrini and Scarpa, 2007).

To allow respondents to better relate to the attribute levels for calories, cooking time and food type, they were provided with illustrative reference cards that showed what type of meal could be expected for given attribute combinations. In each choice task, respondents were asked to choose both their most preferred option and their least preferred option for a typical evening meal, which would be cooked at home and shared with their partner. Respondents were also asked which of the meal options they thought would be most preferred and least preferred by their partner.

Each member of the household was asked 8 choice tasks individually. An example choice scenario is shown in Figure 1. There were 3 different block designs which were used for the survey. These were randomised across households. Respondents were told that each option represented a typical evening meal that they would share with their partner at home. In the choice tasks a "no choice" option was not explicitly included, however if the respondents could not decide, then this was recorded as a "don't know" by the interviewer.

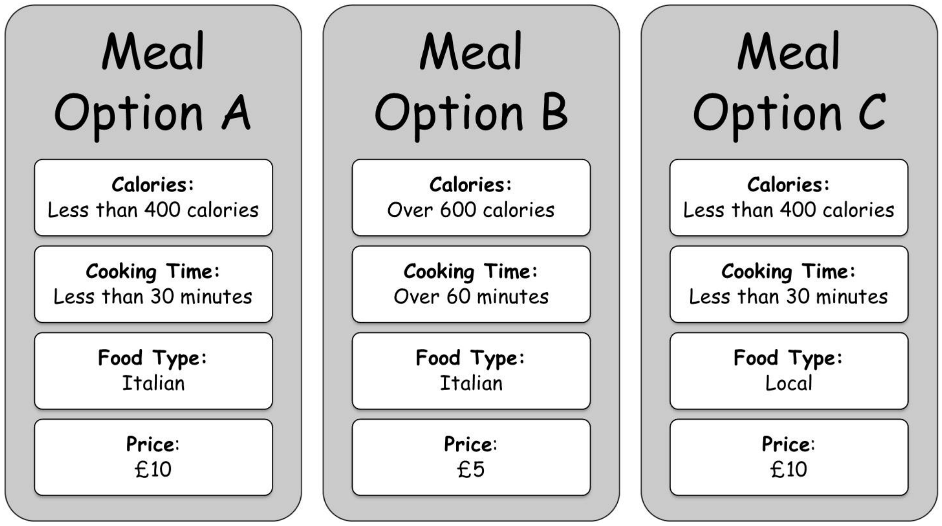

Fig. 1: Example choice task

In Section 3.1 we will compare the responses of each member of the household to the choice tasks, whereas in the following section, we examine the responses to other food related questions.

2.1 Attribute preferences

Both members of the household were asked to indicate, out of the attributes, Calorie Content, Time Spent to Prepare and Cook, Food Type and Cost, which was the most and least

Tab. 1: Attribute levels

Attribute	Levels
Calories *(per portion)*	Less than 400 calories
	Between 400 and 600 calories
	Over 600 calories
Cooking Time	Less than 30 minutes
	Between 31 and 60 minutes
	Over 60 minutes
Food Type *(proxy for taste)*	Asian
	Italian
	Local
Cost	£5
	£10
	£15

Tab. 2: Which of these four features is most important to you?

		Male					
		Calorie Content	Time Spent to Prepare/ Cook	Food Type	Cost	Don't Know	Total
Female	Calorie Content	25	18	18	3	15	79
	Time Spent to Prepare/Cook	6	29	16	22	24	97
	Food Type	3	7	27	9	18	64
	Cost	-	-	-	2	1	3
	Don't Know	4	10	6	6	21	47
	Total	38	64	67	42	79	290

important to themselves.

As you can see from Table 2, only 3 females consider Cost to be the most important attribute when considering an evening meal choice, compared with 42 males. Considering the Calorie Content of their evening meals, in only 25 couples both the male and female stated that this was the most important attribute to them, just 8.62% of our sample. Calculating a Stuart-Maxwell coefficient of concordance for the two household members (Stuart, 1955; Maxwell, 1970), we can reject the null hypothesis that the male and female choices are independent at the .01 significance level. This indicates that the two household members disagree significantly in at least one category of the four meal features.

Considering now Table 3, we can see that the total numbers of males and females considering Calorie Content and Time Spent to Prepare/Cook to be least important to them are now very similar, although at the household level there is still a high level of heterogeneity. Once again calculating a Stuart-Maxwell coefficient of concordance for the two household members, we can reject the null hypothesis that the male and female choices within couples are independent at the .01 significance level.

Additionally, each member of the household was asked to indicate which level of calories (per portion), out of the three categories; less than 400, between 400 and 600, and over 600, was the most and least preferable to them. The results for this question are shown in Tables 4 and 5.

We can see in Tables 4 and 5 a high rate of respondents answering Don't Know, when asked to rank their most and least preferred level of Calories they would like their evening meal to contain. This is especially prominent when asked to rate their least preferred level. Taking into consideration the previous finding of a low level of couples selecting Calorie Content to be the most important attribute about their evening meal, these results could indicate that the respondents do not necessary understand the Calorie Content aspect of their meals - this finding is supported in other studies, where they have found that consumers have problems utilising guidance on healthy food choices (Nestle et al., 1998; Porter et al., 1998; Willett, 1994, 1998).

Tab. 3: Which of these four features is least important to you?

		Male					
		Calorie Content	Time Spent to Prepare/ Cook	Food Type	Cost	Don't Know	Total
Female	Calorie Content	20	16	10	7	6	59
	Time Spent to Prepare/Cook	11	26	14	6	15	72
	Food Type	2	7	9	5	3	26
	Cost	9	8	3	19	-	39
	Don't Know	10	18	19	10	37	94
	Total	52	75	55	47	61	290

Tab. 4: Thinking about your preferences for the number of calories a typical evening meal should contain, which of the three levels would you most prefer your evening meal to contain?

		Male				
		Less than 400	400 - 600	Over 600	Don't Know	Total
Female	Less than 400	31	25	-	35	91
	400 - 600	5	57	3	76	141
	Over 600	-	2	-	-	2
	Don't Know	6	12	-	38	56
	Total	42	96	3	149	290

Tab. 5: Thinking about your preferences for the number of calories a typical evening meal should contain, which of the three levels would you least prefer your evening meal to contain?

		Male				
		Less than 400	400 - 600	Over 600	Don't Know	Total
Female	Less than 400	4	1	4	2	11
	400 - 600	1	2	5	5	13
	Over 600	8	2	72	78	160
	Don't Know	2	1	23	80	106
	Total	15	6	104	165	290

3 Preferences' analysis

We found in Section 2.1 that there are significant differences in the attributes that each member of a couple consider important to their choice of evening meal. To further understand the dynamics between the houshold members with respect to their meal choices, we asked each member of the couple to consider what they thought their partner preferred most and least.

In our food survey, we find a high rate of respondents who believe that their partners preferences are aligned to their own. This is in contrast to the finding of Beck et al. (2012), who report an anchoring rate of 59%, which dropped to 52% when they considered real choice convergence. When asked which of the meal options they thought their partner would prefer most, 83.6% claimed that their partners response would be identical to their own most preferred option. Similarly, when asked which of the meal options they thought their partner would prefer least, in 84.6% of the choices respondents thought their partner would choose the same option. Indeed, when comparing these results to the proportion of times where both household members individually chose the same option, we found convergence in 67.6% of the responses for most preferred meal option, with this figure dropping to 63.1% for their least preferred meal option.

There could be many possible reasons for such a high rate of anchoring on ones own preferences. The first possibility relates to the inconvenience of not eating the same meal. For many people the dis-utility associated with the added complexity of having to cook more than one 'meal type' is compounded and can far outweigh the dis-utility of *compromising* and eating a 'meal type' that would not be otherwise chosen by the *chef*. The result of this could be that many household members responsible for the cooking are perceived by their partners to like/dislike the same meal types. Conversely it could be, as is suggested by Kenny and Acitelli (2001), that information held about a partner is often replaced with projections of one's own preferences and attitudes, due to uncertainty about how to provide answers on behalf of this partner. Another potential reason, could be the repeated nature of eating a meal together, leading to respondents finding it difficult to establish an 'average' for their partners preferences. Finally, a last hypothesis that we will explore below, could be that the household members genuinely have similar preferences.

3.1 Similar preferences

We now explore the degree of similarity between the preferences of male and female household members in the stated choice component of the survey. We make use of the cases in which individuals were asked *"Which of the meal options you would prefer most?"* and estimate the proportion of household members having similar (or the same) preferences. In order to do so, we make use of a latent class model specification, which has been adjusted to also account for scale differences.

The latent class model (LCM), whilst considered by some as a less flexible mixed logit model[1], has a major advantage in that it does not require the analyst to make prior assumptions about the distributions of parameters across individuals (Greene and Hensher, 2003). The basic principle of the LCM is that an individuals' behaviour will depend not only on the observable attributes but also on some latent heterogeneity which varies across unobserved attributes. The development of the LCM is detailed in Greene and Hensher (2003), including comparison with the mixed logit model. We reproduce below the LCM specification.

Latent class model specification

An individual n, is probabilistically assigned[2] to a specific latent class c, based on his or her preferences and/or characteristics. The share of the population in class c is given by the membership probability π_c, defined by the following multinomial logit process:

$$\pi_c = \frac{exp\left(\mathrm{CTE}_c\right)}{\sum_{c=1}^{C} exp\left(\mathrm{CTE}_c\right)} \tag{1}$$

[1] The latent class model assumes discrete mixing distributions, whereas the more commonly known random parameter model assumes continuous mixing distributions for the parameters.

[2] Membership probability can be based only on a constant (Scarpa and Thiene, 2005) or be informed by socio-economic covariates (Boxall and Adamowicz, 2002). In this paper, we follow the former approach.

where CTE_c is a class-specific constant, which can be estimated in the LCM along with the parameter coefficients, β, for each class[3]. Thus, the probability that individual n will choose alternative i over alternative j, in a choice task is given by:

$$P_{ni} = \sum_{c=1}^{C} \pi_c \left(\frac{exp\,(\beta_c x_{ni})}{\sum_j (\beta_c x_{nj})} \right) \tag{2}$$

The assumption in the LCM is that individuals in the same class will all have similar preferences, but individuals in different classes will have differing preferences (Swait and Adamowicz, 2001). LCMs have been widely used to identify preference segments among users (see, for example Boxall and Adamowicz, 2002, Greene and Hensher, 2003, Hess and Rose, 2007, Hess et al., 2009, Provencher et al., 2002, Scarpa and Thiene, 2005 and Scarpa et al., 2008).

To best establish if the household members genuinely have similar preferences, we compare three different MNL specifications, with a LCM:

Model 1: **Same preferences and same scale**. In this model we assume that males and females have identical preferences and subsequently only estimate one set of coefficients, β, to represent both members of the household.

Model 2: **Same preferences, but different scale**. In this second model we again assume that males and females have identical preferences, but we consider the possibility that they have different levels of scale heterogeneity[4] (also referred to as heteroskedasicity). Thus, we estimate one set of coefficients, β and an additional scale coefficient for females, μ_f.

Model 3: **Different preferences**. Thirdly, we assume that males and females have different preferences and subsequently, we estimate separate coefficients for them. For males we estimate β^m and for females β^f.

Model 4: **Heteroskedasic latent class model (HLCM)**. In this final model we use the specifications of the previous three models as our different latent classes and estimate the corresponding class probabilities, π_c. Hence, accounting for both taste and scale heterogeneity.

If we now consider only the deterministic component of utility that an individual n obtains from choosing alternative i. Equation 3 shows the specification for our first model

[3] In estimation, for identification purposes only C 1 set of coefficients can be independently identified.

[4] Scale heterogeneity refers to heterogeneity in the variance associated with the random component of utility, ε (c.f. Swait and Louviere, 1993). Additionally, Swait and Adamowicz (2001) define the scale parameter as the *ability* to choose, which they specify as a function of choice task complexity and respondent effort.

and also class 1 in the HLCM model, where x_{ni} is a vector of attributes describing alternative i as faced by individual n, and β is a vector of estimated parameters:

$$V_{ni}^{C_1} = \beta x_{ni} \tag{3}$$

If we expand Equation 3 to account for females and males having different levels of scale heterogeneity, we have Equation 4 below, which represents the specification for both model 2 and class 2:

$$V_{ni}^{C_2} = \left(\delta^m \mu_m + (1 - \delta^m)\, \mu_f\right) \beta x_{ni} \tag{4}$$

where, μ_f is scale coefficient for females, with the equivalent scale coefficient for males (μ_m) being fixed to 1 and δ^m is an indicator equal to 1 if the respondent is male and 0 otherwise. Given that our interest is in how the scale parameter for females differs from the male scale parameter[5], we specify $\mu_f = 1 + \eta_f$, subject to the constraint[6] $\eta_f \geq -1$.

Additionally, we have Equation 5 below, which represents our final specification for model 3 and class 3, in which we assume that males and females have different preferences:

$$V_{ni}^{C_3} = \delta^m \beta^m x_{ni} + (1 - \delta^m)\, \beta^f x_{ni} \tag{5}$$

where, β^f represents the estimated coefficients for females and β^m represents the estimated coefficients for males.

Finally, we have Equation 6 representing our heteroskedastic latent class model (HLCM), which is a combination of Equation 3, Equation 4 and Equation 5, weighted by their associated class probabilities π_c, where $c = \{C1, C2, C3\}$:

$$V_{ni} = \pi_{C_1} V_{ni}^{C_1} + \pi_{C_2} V_{ni}^{C_2} + \pi_{C_3} V_{ni}^{C_3} \tag{6}$$

The models were estimated with Pythonbiogeme (c.f. Bierlaire, 2003, 2008) using the CFSQP algorithm (Lawrence et al., 1997). In order to deal with the problem of local maxima in discrete mixture of parameters (LC models), between 50-100 random starting values were used[7].

[5] We specify males as our baseline group, for which the scale parameter is fixed to one to avoid specification problems.

[6] Note that by enforcing the constraint $\eta_\mathrm{f} \geq -1$ the scale factor is subsequently constrained to $\mu_f \geq 0$. This is possible as the algorithm used in the maximization, namely the CFSQP algorithm (Lawrence et al., 1997) is able to manage these types of constraints.

[7] This was coded in 'PERL' and used in combination with Pythonbiogeme run under Ubuntu 10.04 LTS - the Lucid Lynx. For a more in-depth discussion, see Boeri (2011)

4 Results

Table 6 shows the results for models $1-3$ and the HLCM. Comparing first models 1 and 2, we see minimal differences between the two models in both the parameter coefficients β and the log-likelihood $\mathcal{L}\left(\hat{\beta}\right)$. This is due to the small and non-significant effect of the scale coefficient for females, η_f, suggesting that there is no difference between members' *ability* to choose.

Looking now at the results for model 3, where we have estimated separate coefficients for males β^m and females β^f, we start to notice some gender related preference differences, such as a higher preference for low calorie meals for female respondents. However these differences are still relatively small. Again, we do not see a significant improvement in log-likelihood with model 3 only improving on model 1 by 5.2 units and model 2 by 5.17 units, which at the cost of 7 parameters compared with model 1 and 6 parameters compared with model 2 is only significant at the 83% and 89% level respectively.

However, when we consider model 4, we see a highly significant improvement over the three previous models. This improvement is largely due to model 4 taking into account the panel nature of the data. There are some small changes in sign and significance across all coefficients. Most noticeable is the change in the scale parameter η_f, which has increased to 11 and is significant. This high scale could imply that the females in that class (i.e. the ones that have the same preferences as their male counterparts, but a different level of scale) have more stable and defined preferences. Additionally, as we see in Table 7 the proportion of people in this class (just 10.44%) is very small, whereas the scale difference calculated in model 2 included the whole sample, most of which (64.31%) have similar (the same) preferences and scale.

Finally, we also notice that in models $1-3$, the coefficients for low time and Italian are not significant. High calories was combined with the base medium calories in all models, as it was not found to be significantly different from medium in any of the models. Although, β_{Cost} for class 1 in the HLCM is positive, it is very small and not significant.

5 Conclusions

The findings in this paper suggest that meal preference estimates retrieved from couples, even when relating to the shared behavioural experience of joint meal consumption, have a varying level of convergence. This paper has sought to disentangle the level of convergence for a range of indicators relating to meal preferences, both in terms of importance of single food attributes and trade-off based choices of evening meals. We made use of an empirical data

Tab. 6: Results: models 1 - 3 and HLCM

	Model 1: same		Model 2: scale		Model 3: different		Model 4: HLCM	
	est.	rob. t-rat.	est.	rob. t-rat.	est.	rob. t-rat.	est.	rob. t-rat.
β_{LowCal}	0.2280	6.79	0.2270	6.84	-	-	0.3170	6.39
β_{LowTime}	0.0043	0.11	0.0044	0.11	-	-	0.0434	1.90
β_{HighTime}	-0.2050	-4.72	-0.2030	-4.64	-	-	-0.0768	-2.45
β_{Asian}	-0.3570	-9.21	-0.3550	-8.86	-	-	-0.1800	-3.31
β_{Italian}	-0.0769	-1.81	-0.0763	-1.81	-	-	0.0492	1.40
β_{Cost}	-0.0490	-12.17	-0.0486	-11.07	-	-	0.0043	1.17
β_{DK}	-3.7700	-27.96	-3.7400	-20.61	-	-	-2.8700	-16.16
η_{f}	-	-	0.0153	0.23	-	-	11.0000	4.29
β^m_{LowCal}	-	-	-	-	0.1280	2.69	0.2880	1.13
β^m_{LowTime}	-	-	-	-	-0.0108	-0.19	0.4100	1.95
$\beta^m_{\text{HighTime}}$	-	-	-	-	-0.2180	-3.58	0.0976	0.41
β^m_{Asian}	-	-	-	-	-0.3440	-6.24	-1.0400	-3.22
β^m_{Italian}	-	-	-	-	-0.0825	-1.36	-1.2000	-2.83
β^m_{Cost}	-	-	-	-	-0.0519	-9.19	-0.3760	-10.37
β^m_{DK}	-	-	-	-	-3.8900	-19.95	-7.4700	-12.35
β^f_{LowCal}	-	-	-	-	0.3260	6.88	0.5780	1.70
β^f_{LowTime}	-	-	-	-	0.0197	0.34	0.6570	3.26
$\beta^f_{\text{HighTime}}$	-	-	-	-	-0.1920	-3.10	0.3580	1.91
β^f_{Asian}	-	-	-	-	-0.3720	-6.82	-0.9210	-3.30
β^f_{Italian}	-	-	-	-	-0.0727	-1.21	-1.2600	-3.29
β^f_{Cost}	-	-	-	-	-0.0459	-8.02	-0.3640	-7.88
β^f_{DK}	-	-	-	-	-3.6500	-19.55	-6.7600	-7.30
$\mathcal{L}\left(\hat{\beta}\right)$	-5,169.712		-5,169.683		-5,164.511		-4,749.827	

Tab. 7: HLCM class membership probabilities

	est.	rob. t-rat.
CTE_1	0.935	5.40
π_{C_1}	64.31%	-
CTE_2	-0.883	-2.99
π_{C_2}	10.44%	-
CTE_3	0	-
π_{C_3}	25.25%	-

set, collected to elicit intra-household trade-offs between meal options in Northern Ireland. The analysis was carried out both at the level of single features (preferred calorie level and meal attributes) alongside the preference for different meal options.

Interestingly, we found that when respondents were only asked at the level of single features (as shown in Section 2.1) we retrieved highly significantly different preferences. This is in stark contrast with the results from the stated choice component of the survey, where respondents were asked to consider a meal option containing multiple attributes. In this second analysis, we found that only 25% of males and females have different preferences. We also found evidence in our data of significant anchoring regarding the identification of the partners most and least preferred meal options. Indeed more than 80% of respondents claimed their partner had the same preference as their own, where in reality, preferences truly coincided in 68% of cases for the most preferred and 63% for least preferred meal options.

The findings of this study hold several implications for policy making and survey researchers. We found that while individuals cannot perfectly provide a representative response for their partner, this accuracy can be improved when the questioned are framed as trade-off based choices of evening meals.

However, an important warning that comes with our suggestions is that our results are based on a survey for meal preferences, specific to evening meal choices, where a large proportion of the sample showed similar preferences. Additionally, this is an area where we found a clear female dominance, namely females interact with the food much more than males. Hence similar analysis should be conducted in order to compare our findings and make conclusions in different contexts.

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