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1 **Social modeling of food choices in real life conditions concerns specific food**
2 **categories.**

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7 **Abstract**

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3 8 The social context of eating has a profound effect on consumption choices. Social modeling, that
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5 9 involves using others' behavior as a guide for appropriate consumption, has been well documented
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8 10 for food intake, but less is known about social modeling of food choices. Moreover, social modeling
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10 11 has mainly been studied in laboratory settings. We conducted an observational study in a self-service
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12 12 canteen to examine whether the food choices of an individual were influenced by the choice of the
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14 13 person ahead in the queue. We recorded food choices of 546 individuals (333 men and 211 women)
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16 14 and those of the person in front of them in the queue along a linear buffet. Starters were sub-
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18 15 categorized into salads, mixed starters (e.g. avocado shrimp mayonnaise), and cold meat starters, and
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20 16 desserts were sub-categorized into fruits, dairy products and pastries. There was a significantly higher
21
22 17 probability of taking a starter in general (OR=1.65, IC=1.06-2.57, p=0.03), a salad (OR= 1.78, CI= 1.08-
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24 18 2.93, p= 0.02), a mixed starter (OR= 2.98, CI= 1.42-6.05, p<0.01), but not a cold meat, if the person
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26 19 ahead in the queue also took one compared to when the person ahead did not take one. No significant
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28 20 modelling was found for desserts which may be because almost all participants took a dessert. These
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30 21 results highlight that social modeling influences food choices, and that this phenomenon can be
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32 22 observed in a real life setting. These data also suggest that some food categories, such as starters,
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34 23 could be more susceptible to social modeling than are others. Finally, we observed modeling both
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36 24 between familiar and unfamiliar participants, which suggests that social norms could be used to
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38 25 promote healthier eating in a range of settings including friendship groups.
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46 26 Key words: social modeling, food choice
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28 Introduction

29 Eating is a complex social event, and the social context during a meal can have multiple influences on
30 food intake. For instance, it has been demonstrated that the quantity of food consumed increases
31 when eating with familiar others compared to eating alone, which is known as the social facilitation of
32 eating (de Castro & Brewer, 1992). However, not only the mere presence of others, but also their
33 consumption can have an impact on intake. Indeed, it has been shown that individuals adjust the
34 amount of food eaten to the quantities consumed by their commensals (Vartanian et al., 2015). This
35 phenomenon is called social modeling and involves using others' eating behavior as a norm, for
36 instance as an indicator of the appropriate amount of food to consume in a given situation. Social
37 modeling appears to be very robust because it has been observed in both men and women (Cruwys et
38 al., 2015) (with some evidence of a stronger effect for women (Herman & Polivy, 2010)), when eating
39 with both familiar and unfamiliar partners (Cruwys et al., 2015; Kaisari & Higgs, 2015; Salvy et al., 2007;
40 Vartanian et al., 2015), and independently of weight status (Rosenthal & Marx, 1979) and state of
41 hunger (Goldman et al., 1991). Additional studies have demonstrated that social modeling can occur
42 even in the absence of others, when participants are provided information regarding the quantity of
43 food consumed by previous eaters ("remote confederate" studies) (Robinson, Benwell, et al., 2013;
44 Vartanian et al., 2013). In such studies, a norm of consumption is established via descriptive norms,
45 which can be indirectly conveyed, e.g. via the presence of empty packaging, or conveyed via messages
46 that report the consumption patterns of a majority of individuals (social-norm based messages).

47 While social modeling of food intake is well established, less is known about social modeling of food
48 choices. Two reviews (Cruwys et al., 2015; Robinson, Thomas, et al., 2013) examined the literature on
49 the impact of social modeling on food intake and choices, and both concluded that the available data
50 is insufficient to draw conclusions about the robustness of the effect on food choices. Indeed, among
51 69 studies reviewed by Cruwys, Bevelander and Hermans (2015) on social modeling, only 11 examined
52 modeling of food choices, among which 8 succeeded in observing the phenomenon. However, 3

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53 studies did not find significant modeling effect (Hendy & Raudenbush, 2000; Pliner & Mann, 2004). For
54 instance, Pliner and Mann (2004) reported social modeling of food intake but not of food choices.
55 These authors suggested that food choices may be less influenced by others' behavior than intake
56 because individuals feel surer about their food likes and dislikes than the appropriate amount of food
57 to consume in a given situation.

58 Pliner and Mann (2004) were also interested in the impact of food healthfulness on modeling, and they
59 observed social modeling of intake for "unhealthy" (high energy density) cookies but not for "healthy"
60 (low energy density) ones. To date, little is known about the strength of social modeling effects on
61 "healthy" food items because the majority of studies have been done using high energy density food
62 items and only a small number of studies have focused on modeling of low energy density food items.
63 In a study by Hermans *et al.* (2009), social modeling of quantities of low energy density food
64 (vegetables) was observed, but investigations of the social modeling of food choices of low *versus* high
65 energy density food has been limited. Robinson and Higgs (2013) found that participants were less
66 likely to choose low energy density food items when eating with a participant making "unhealthy"
67 choices, than when eating alone or in the presence of a participant making "healthy" choices (Robinson
68 & Higgs, 2013). Thus, social modeling of food choices was observed, but this influence was only present
69 in the "unhealthy" condition. In another study conducted by Burger and colleagues, participants were
70 led to believe that previous participants took either a "healthy" or an "unhealthy" snack through the
71 provision of a descriptive norm (empty packaging) before having to make their own choice.
72 Participants were more likely to choose the snack they believed others had chosen, both in the
73 "unhealthy" and "healthy" norm conditions (Burger et al., 2010).

74 One feature of these studies is that they were conducted in a laboratory setting, which leaves open
75 the question of whether the modeling of food choices occurs in real-life situations. To date, one study
76 investigated modeling of choices in real life conditions, but this study was focused on modeling of
77 vegetarian versus non-vegetarian dishes (Christie & Chen 2018). Further research is needed to better

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78 characterize the effect of social modeling of food choices in real-life conditions, especially for meals
79 composed of a broad range of food items including low and high energy density food items. In addition,
80 there are other factors which could impact modeling effects in real life settings that are often not
81 present in laboratory studies. For instance the majority of studies conducted in the laboratory included
82 subjects paired with strangers, whereas in real life situations people are likely to eat with familiar
83 others. To date, only a few studies have examined modelling among familiar participants, but the
84 results suggest that modeling may occur both with familiar and unfamiliar individuals (Cruwys et al.,
85 2015; Kaisari & Higgs, 2015; Salvy et al., 2007; Vartanian et al., 2015). Further investigations are needed
86 to confirm these preliminary results and examine whether familiarity moderates modeling observed
87 in real life settings.

88 The aim of the present study was to determine whether modelling of food choices can be observed in
89 a real-life setting (a university self-service restaurant), examine whether modelling exists across a
90 range of food categories (defined using consumer perception of the nutritional quality of the items)
91 and whether familiarity with the person that serves as a model moderates any effects.

92

93 **Methods**

94

95 **Restaurant Venue**

96 The study took place at the employee restaurant of a university campus (Paris, France). The restaurant
97 serves almost 500 clients per day for lunch service. Ethical approval for the study was obtained from
98 the ethics committee of Paris-Saclay University (registration number CER-Paris-Saclay-2019-016). Data
99 collection took place on two Thursdays (one of the busiest days of the week) during spring, from 12pm
100 to 2pm. Clients were able to choose a main dish plus two additional items for their meal, meaning they
101 could choose one starter and one dessert, or two starters or two desserts. The price of the meal
102 remained the same, no matter which items were chosen. Food choices varied from day to day but

103 were always structured in the same way. Starters included a variety of raw vegetables, mixed salads
104 (such as pasta or potato salads with cheese), meat or fish, and cold meats. The desserts included a
105 variety of items including dairy products (different types of yoghurts, dairy desserts and cheeses), but
106 also fresh fruits, fruit salads, fruit compotes and different type of pastries. Finally, the main dish offered
107 usually included a choice between fish or meat and one or two types of sides (starches and vegetables).

108 We decided to focus our analysis on the choices of starters and desserts only, because these courses
109 offered a higher diversity and choice than the main dishes at the restaurant.

110 We sub-categorized starters into salads, mixed starters, and cold meats, and desserts into fruit, dairy
111 products and pastries (more details about food items included in subcategories are available in
112 supplementary file 1). These food categories were decided upon according to their perceived
113 healthiness by consumers. This perceived healthiness was assessed via an online questionnaire
114 completed by 118 individual (mean age of 42 years old). Participants were asked to rate each item
115 from 0 (unhealthy) to 8 (healthy). Detailed results are available in supplementary file 2.

117 **Data collection procedure**

118 Upon arrival at the restaurant, clients had to follow a linear queue along the buffet to choose their
119 lunch items. This linear configuration of the buffet was a crucial criterion for the choice of venue for
120 the study because it ensures that each client had to follow the same person all along the buffet. The
121 clients first had to choose a starter, then a dessert, and last the main dish. Two experimenters were
122 positioned at the cash register, behind the cashier, from where they had a clear view of the meal trays,
123 but were not seen by the clients in the queue so as not to influence their choices. The choices of each
124 client were recorded by the two experimenters. A third experimenter distributed individual
125 questionnaires to each client after the cash register. The aim of these questionnaires was to collect
126 demographic and contextual information from the clients. Finally, a fourth experimenter collected
127 individual questionnaires at the exit of the restaurant. An identification number was associated with

128 each client so that their food choice could be paired to the individual questionnaire, as well as to
129 identify who was following who. We did not record data on the clients who did not follow anyone in
130 the line (which typically happened at the very beginning and the very end of the lunch service).

131

132 **Questionnaires**

133 Two questionnaires were used during data collection. First, a food choice questionnaire was completed
134 by the experimenters for each client upon their check out at the cash register. This questionnaire
135 contained all food item options that were on sale the day of each data collection session. Second, the
136 individual questionnaire was distributed to the clients for self-assessment after they paid for the meal.
137 The individual questionnaire included questions about age, gender and Body Mass Index (BMI) of the
138 participant, and contextual information: whether **or not they knew** the person ahead in the queue,
139 whether they ate with that person, whether they were following a specific diet involving food
140 exclusions, and what were their usual food choices at the canteen (whether they usually take a starter,
141 a dessert, or both), and finally whether they thought that others' choices influenced their own choices.

142

143 **Study population**

144 The food choices of 797 clients were collected over two days of data collection separated by one and
145 a half months. We excluded 110 individuals who reported following a specific diet involving food
146 exclusions e.g. vegetarian. We also excluded observations of 141 individuals who did not return the
147 individual questionnaires, or returned incomplete questionnaires. The final sample comprised 546
148 individuals.

149

150 **Statistical analysis**

151 The choice of each food item, sub-category and category was coded as a binary variable (chosen as 1,
152 not chosen as 0). Binary logistic regressions were used to analyze whether the probability of choosing
153 an item from a specific food category or subcategory was associated with the choice of the person
154 ahead in the queue for this same food category or subcategory.

155 The models were adjusted for the age, sex, and BMI of individuals. The models were also adjusted for
156 contextual factors such as declared usual food choices at the self-service restaurant. We controlled for
157 habitual choices because this is a powerful predictor of eating behavior (Riet et al., 2011). Finally the
158 models were adjusted for the familiarity (whether individuals stated that they knew the person ahead
159 of them in the queue). This allowed us to investigate modeling, independently of the relation of
160 individuals with the previous person and to investigate if the familiarity could impact individuals'
161 choices, independently of the choices of the person ahead in the queue.

162 Finally, the possible moderating effect of the familiarity between subjects on modeling has been tested
163 in other models, through the investigation of interactions between the familiarity and the choice of
164 the person ahead.

165 R Studio version 1.1.463 (RStudio Team, 2016) was used for data analysis.

167 Results

169 Descriptive analysis

170 Population characteristics

171 Of the 546 individuals observed, 333 (61%) were men and 211 (39%) were women (2 individuals did
172 not give their sex). The mean age was 40.2 +/- 13.1 years old and the estimated mean BMI was 23.5
173 +/- 3.5 kg/m². The sample was composed of university employees including PhD students (21%),
174 permanent research staff (44%) and administrative and support employees (27%) (8% of the sample
175 did not state their profession).

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177 Food choices

178 We observed that 39% of the population chose at least one starter, 93% chose at least one dessert,
179 and 35% chose both starter(s) and dessert(s). This compares with 54% of the sample who stated that
180 they usually take a starter, 90% a dessert, and 44% both (Table 1). Only 2% (14 individuals) of the
181 sample took more than one starter while 30% (169 individuals) took more than one dessert.

	Starter(s)	Dessert(s)	Starter(s) + Dessert(s)
Observed Choices	212 (39%)	510 (93%)	188 (35%)
Declared usual choices	290 (54%)	478 (90%)	236 (44%)

182 **Table 1:** Numbers and percentages of observed choices compared to declared usual choices.

183

184 Among starters, salads were the most frequently chosen category, representing 57% of starter choices,
185 with mixed starters accounting for 28% of choices and cold meats accounting for 16% of choices.
186 Among desserts, fruit were the most chosen category with 43% of choices, then came pastries with
187 32% of choices and last dairy products with 25% of choices.

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189 Relationship with the person ahead in the queue

190 65% of the sample reported they knew the person ahead in the queue, and 62% declared that they ate
191 at the same table. Among the 65% of individuals who declared knowing the person ahead in the queue,
192 93% also declared that they ate with this same person. Due to the high association between two
193 variables, we only used the knowledge of the person ahead in the queue as a covariate in the model.

194

195 Awareness

196 The vast majority of the population (91%) reported that in making their own choice, they were not
197 influenced by the previous person's choice, while only 5% reported that they were influenced. Due to

198 the unequal distribution of this variable, we decided not to use it as a covariate in order to adjust our
199 models.

200

201 **Social modelling of food choices**

202 Starters

203 There was a significantly higher probability of taking a starter if the person ahead in the queue also
204 took one compared to when the person ahead in the queue did not take one (OR= 1.65, CI= 1.06-2.57,
205 p= 0.03). Regarding subcategories of starters, individuals had a significantly higher probability of taking
206 a salad (OR= 1.78 CI= 1.08-2.93, p= 0.02), or a mixed starter (OR= 2.98, CI= 1.42-6.05, p<0.01) if the
207 person ahead in the queue also took one, which was not the case for cold meats (OR= 1.89, CI= 0.42-
208 6.19, p= 0.34).

209

210 Desserts

211 The probability of taking a dessert was not significantly related to whether the person ahead in the
212 queue did or did not take one (OR= 1.28, CI= 0.26-4.64, p= 0.73). Regarding desserts subcategories,
213 none of the choices was significantly influenced by the choices of the person ahead in the queue for
214 those subcategories (fruit: OR= 0.97, CI= 0.69-1.38, p=0.88; dairy products: OR=1.26, CI= 0.84-1.87,
215 p=0.27; pastries: OR= 1.42, CI=0.97-2.07, p= 0.07).

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217 Other variables explaining food choices

218 Declared usual choices was the most significant variable explaining individuals' choices for starters and
219 all starters' subcategories, and for desserts in general as well as for fruits and pastries. Complete
220 statistical results of each model are available in supplementary files 3 for starters and 4 for desserts.

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222 Familiarity and modeling

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223 We found no significant interaction between the familiarity and the choice of the person ahead in the

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224 queue in any of the categories and subcategories (Table 3).

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Food categories	Familiarity*Choice of the person ahead (p-value)
Starters	0.49
Salads	0.96
Mixed starters	0.59
Cold Meats	0.99
Desserts	0.50
Fruits	0.75
Dairy Products	0.08
Pastries	0.64

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225 **Table 3:** Moderating effect of familiarity on modeling. Interactions are tested using binary logistic

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226 regressions.

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228 **Discussion**

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230 We observed that choice of starters, but not desserts, was influenced by the choice of the person

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231 ahead in a queue in a restaurant setting. We also found that whether or not participants knew the

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232 person ahead in the queue had no influence on whether or not modelling was observed. These results

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233 are significant because they demonstrate social modeling of food choices in a real-life restaurant

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234 setting, which has only been observed in one previous study of food choices of vegetarian versus non-

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235 vegetarian main dishes (Christie & Chen, 2018). Taken together, these findings suggest that modeling

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236 of food choices is a robust phenomenon that exists outside of the laboratory.

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238 We observed a modeling effect for starters and two of the starter subcategories (salads and mixed

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239 starters), but not for desserts and none of the dessert subcategories. One reason why modeling was

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240 observed for starters but not desserts may be that 93% of participants reported that they usually take
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2 241 a dessert whereas only 54% reported usually taking a starter. In situations where people have clear
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4 242 eating routines and/or strong pre-established preferences, social modelling is less likely to be observed
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7 243 (Cruwys et al., 2015). Pliner and Mann (2004) observed social modeling for intake of
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9 244 palatable/unhealthful cookies but not for unpalatable/healthful cookies. In addition, these authors did
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11 245 not observe any influences of informational social norms on choice of cookies (participants chose the
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13 246 palatable over the unpalatable cookies regardless of social information). These authors suggested that
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16 247 one reason for these findings might have been because the participants were sure of their preference
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18 248 for cookies and so did not look to others to guide their choices. In the present study it is possible that
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21 249 choice of dessert was less susceptible to social influence than was choice of starter because the
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23 250 participants were sure of their preference for these items. An additional explanation why choices of
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26 251 starters were modeled, but not choices of dessert, may be the fact that the starter was the first item
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28 252 to be chosen and this may have made the starter more visible on the tray of the person ahead in the
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31 253 queue as it was the only item added on it. In addition, because the starter was the first item to be
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33 254 chosen, choice of starter was not restricted by already having chosen other items. The choice of the
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35 255 dessert (which was the second item to be chosen) may have been in part influenced by the choice of
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38 256 the starter for the sake of having a balanced complete meal and makes it more susceptible to external
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40 257 influences.

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43 258 For the choice of starters, we observed social modeling of choice of the salads and mixed starters but
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45 259 not for the cold meats. There are at least two potential reasons for this finding: 1) the cold meat
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48 260 starters were not chosen very often and so it may be that there were insufficient observations for
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51 261 modelling to be evident but it is also possible that 2) the participants were also more sure of their
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53 262 preference for the cold meats than they were of their preference for the salads/mixed starters and so
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55 263 while choice of the latter was susceptible to social influence the former was not.

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265 Regardless of the specific explanation for this pattern of results, we did observe modelling of lower
266 energy “healthier” items (salads). This is significant because to date, the majority of studies on social
267 modeling have examined modelling of high energy foods and the effect of social context on the choice
268 of low versus high energy food items during a meal remains poorly studied. Robinson and Higgs (2013)
269 reported findings that differ somewhat from the present results. They found that participants choosing
270 from a buffet in the presence of an ‘unhealthy’ eating partner were significantly less likely to choose
271 and consume a low-energy-dense food item than when choosing alone or in the presence of a ‘healthy’
272 eater, suggesting that the presence of an ‘unhealthy’ eating partner may undermine intentions to
273 consume low-energy-dense foods (Robinson & Higgs, 2013). This study was conducted in a laboratory
274 setting and the fact that the participants knew they were taking part in an experiment may have
275 affected their responses. As argued by Robinson and Higgs (2013), it may have been that in the
276 ‘choosing-alone’ condition and the ‘healthy’ confederate condition, there was a social norm operating
277 to encourage the choice of at least some healthier items (perhaps because they thought their food
278 intake was being monitored), but this this norm may have been undermined in the ‘unhealthy’
279 confederate condition, leading participants to abandon the ‘healthy’ choice. The present results are
280 encouraging in suggesting that modeling could have a positive impact on healthier food choices in a
281 real life setting.

282
283 Social modelling of starter choice was unaffected by whether or not the participant reported knowing
284 the model. In other words, we observed modelling of food choices both under conditions of familiarity
285 with the model and when the model was not known to the participants. This is an important finding
286 because the majority of studies to date on modelling have involved testing of strangers. Reviews by
287 Cruwys and colleagues (2015), and Vartanian and colleagues (2015) found modeling in studies of
288 children eating with familiar models such as parents or teachers but to date only a few studies have
289 reported social modeling in pre-existing friendship groups of adults (Howland et al., 2012; Kaisari &

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290 Higgs, 2015; Salvy et al. 2007). Taken together, these data support the suggestion that that modelling
291 within friendship networks may underlie the social transmission of food choices (Pachucki et al., 2011).
292 **Ninety-six percent** of our population reported that they were not influenced by others' choices in
293 making their own choices. Other research has found that people generally report being unaware of
294 social influence when it comes to food choices, although it may be that people are aware of social
295 influence under some circumstances, **but** are motivated to deny it (e.g. Spanos et al., 2014; Vartanian
296 et al., 2008, Robinson & Field, 2015). One explanation for a lack of awareness is that social influence
297 on eating could be operating on an automatic level. Indeed it has been argued that **an** automatic
298 mimicry process may underlie modelling at least in part (Bevelander et al., 2013; Hermans et al., 2012;
299 Higgs & Thomas, 2016; Huh et al., 2014). In their review, Cruwys and colleagues (2015) concluded that
300 the evidence suggests that while modeling can be automatic, it is also accessible to conscious control.
301 For example modeling has also been observed in studies using descriptive social norm-based
302 messages, which is unlikely to be explained by automatic mimicry process (Cruwys et al., 2015). More
303 research is needed to better understand mechanisms underlying social modeling.

304 This study has some limitations. Our study was observational and did not involve manipulation of food
305 choices, and so we cannot draw conclusions about causal effects in relation to modelling. Moreover,
306 the potential role of confounding factors cannot be ruled out, **such as the order of choice of the**
307 **different items for example as discussed above**. However, observational studies yield complementary
308 data and lend external validity to evidence obtained from laboratory studies conducted under
309 controlled conditions. Another point is that we recorded food choices, but we did not measure the
310 quantity of food actually consumed. Future work could examine whether modelled foods are more or
311 less likely to be wasted than are non-modelled foods.

312 This research has implications for interventions on healthy eating behavior. For example, it may be
313 possible to encourage choice of healthier menu items using social influence. Studies have already
314 succeeded in increasing the purchase of vegetables/salads in restaurants (Mollen et al., 2013, Thomas

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315 et al., 2017) through the use of descriptive social norm messages and there is some evidence that
316 social-norm-based messages may be more effective than health-based messages (Collins et al., 2019;
317 Robinson et al., 2014), especially when using descriptive norms (information about what others are
318 eating) rather than injunctive norms (information about others approve of) (Mollen et al., 2013;
319 Robinson et al., 2014; Stok et al., 2014). Future studies could examine whether social-norm-based
320 message can also be applied to a wider range of healthier items and in a wider range of field settings.

321 In conclusion, we observed modelling of food choices in a real life setting but our data suggest that
322 choices in some food categories, such as starters, may be more susceptible to social modeling than
323 others, such as desserts, possibly because choice of dessert is habitual. Finally, we found that modeling
324 occurs both between familiar and unfamiliar participants, which suggests that social norms could be
325 used to promote healthier eating in a range of settings including friendship groups.

326

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330 restaurant. The authors thank David Blumethal for his helpful assistance with the data analysis.

331 **Author Contributions**

332 Armelle Garcia was responsible for the study design, data collection and analysis, and writing of the
333 manuscript. Nicolas Darcel, Suzanne Higgs and Olga Davidenko were responsible for the study design
334 and writing of the manuscript. Alya Hammami, Lucie Mazellier and Julien Lagneau participated to assist
335 with the data collection. All the authors approved the final manuscript.

336 The authors declare that they have no conflicts of interest.

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430 Annex 1: Detailed composition of food categories

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Starters		Desserts	
Salads	-Salads (grated carrots, beetroots, endives, cucumber and tomatoes etc) -Grapefruit	Fruit	-Fresh Fruit - Canned fruit - Canned fruit salad - Fruit compote
Mixed starters	-Potato salad with ham and nuts - Salad and goat cheese - Mackerel - Salmon - Mimosa eggs (mayo) - Salmon pasta salad - Potatoes salad with bacon - Corn and chicken salad - Tabbouleh	Dairy	-Plain yoghurt - Sweetened and flavored yoghurt - Full fat yoghurt - Dairy dessert - Cheese
Cold meat	Small plates with a variety of cold meat with butter	Pastries	-Traditional Basque cake - Fruit crumble - Custard pie - « Ile flottante » (whipped egg white with custard sauce and caramel) - Chocolate mousse - « Paris-Brest » (choux pastry filled with hazelnut flavored custard cream). - “Religieuse” (cream puffs with caramel) - Cherry pie - Lemon pie - Chocolate pie - Coconut pie - Apple pie - « Tarte tatin » (apple pie with caramel)

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436 Annex 2: Perceived healthiness of food items (rated from 0 (unhealthy) to 7 (healthy))

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Food categories	Mean perceived healthiness	Standard Deviation
Starters	4.60	1.97
Salads	6.58	0.75
Mixed starters	4.57	0.76
Cold Meats	2.64	0.61
Desserts	4.09	1.26
Fruits	5.22	1.56
Dairy Products	4.32	1.44
Pastries	2.73	0.46

438

439 An online questionnaire filled by 118 individuals with a mean age of 42 years old (which fit with our
 440 population). They were asked to rate from 0 (unhealthy) to 7 (healthy) each items that were
 441 proposed during our data collection.

442 Annex 3: Results of binary logistic regression for starter and starters' subcategories.

443

Variables	OR	CI 97,5%	p-value
Starter			
Choice of the person ahead	1.65	1.06-2.57	0.03
Age	0.97	0.96-0.99	< 0.01
Sex	1.35	0.85-2.13	0.21
BMI	1.22	0.49-2.12	0.70
Familiarity	0.97	0.60-1.56	0.91
Usual choices			
<i>Starter</i>	12.19	6.05-25.20	< 0.01
<i>Starter + Dessert</i>	18.75	11.32-32.22	< 0.01
Raw Vegetables			
Choice of the person ahead	1.78	1.08-2.93	0.02
Age	1.01	0.99-1.02	0.69
Sex	0.80	0.50-1.31	0.38
BMI	0.74	0.27-1.86	0.53
Familiarity	1.05	0.64-1.74	0.84
Usual choices			
<i>Starter</i>	10.75	4.48-26.11	< 0.01
<i>Starter + Dessert</i>	17.38	9.02-37.12	< 0.01
Mixed Starters			
Choice of the person ahead	2.98	1.42-6.05	< 0.01
Age	0.94	0.91-0.96	< 0.01
Sex	1.16	0.63-2.21	0.64
BMI	1.26	0.34-3.80	0.70
Familiarity	1.29	0.67-2.61	0.46
Usual choices			
<i>Starter</i>	5.09	1.84-14.00	< 0.01
<i>Starter + Dessert</i>	4.83	2.37-10.75	< 0.01
Cold Meats			
Choice of the person ahead	1.89	0.42-6.19	0.34
Age	1.00	0.97-1.03	0.84
Sex	2.43	1.05-6.37	0.05
BMI	1.64	0.36-5.34	0.47
Familiarity	0.57	0.27-1.21	0.14
Usual choices			
<i>Starter</i>	5.24	1.39-19.82	0.01
<i>Starter + Dessert</i>	4.69	1.87-14.29	< 0.01

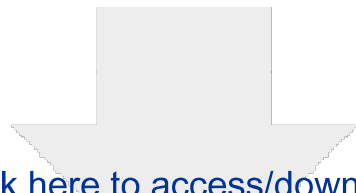
444 OR: Odd Ratios, CI: Confidence Intervals

445 Annex 4: Results of binary logistic regression for dessert and desserts' subcategories.

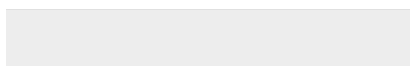
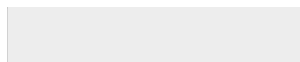
Variables	OR	CI 97,5%	p-value
Dessert			
Choice of the person ahead	1.28	0.26-4.64	0.73
Age	1.01	0.98-1.05	0.56
Sex	2.28	0.99-5.36	0.05
BMI	1.80	0.30-35.75	0.60
Familiarity	0.77	0.28-1.92	0.59
Usual choices			
<i>Dessert</i>	18.31	6.91-54.92	< 0.01
<i>Entrée + Dessert</i>	12.73	4.97-35.70	< 0.01
Fruits			
Choice of the person ahead	0.97	0.69-1.38	0.88
Age	1.01	0.99-1.02	0.41
Sex	0.71	0.50-1.03	0.07
BMI	1.27	0.57-2.20	0.56
Familiarity	0.89	0.60-1.30	0.54
Usual choices			
<i>Dessert</i>	2.18	1.17-4.18	0.02
<i>Entrée + Dessert</i>	2.65	1.41-5.11	< 0.01
Dairy Products			
Choice of the person ahead	1.26	0.84-1.87	0.27
Age	1.02	1.00-1.03	0.02
Sex	0.81	0.55-1.20	0.29
BMI	1.83	0.81-4.05	0.14
Familiarity	1.33	0.88-2.04	0.19
Usual choices			
<i>Dessert</i>	1.48	0.76-3.06	0.27
<i>Entrée + Dessert</i>	1.38	0.70-2.97	0.37
Pastries			
Choice of the person ahead	1.42	0.97-2.07	0.07
Age	0.98	0.97-0.99	< 0.01
Sex	2.34	1.58-3.50	< 0.01
BMI	0.57	0.21-1.37	0.23
Familiarity	1.39	0.92-2.10	0.12
Usual choices			
<i>Dessert</i>	4.60	2.14-11.13	< 0.01
<i>Entrée + Dessert</i>	3.29	1.52-7.96	< 0.01

446 OR: Odd Ratios, CI: Confidence Intervals

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Avis donné par les membres du Comité d’Ethique pour la Recherche (CER) de l’Université Paris-Saclay présents lors de la réunion du 18 avril 2019, au LIMSI (Orsay)

Référence de l’étude : 85

Titre de l’étude : Etude observationnelle des choix alimentaires au restaurant

Demandeur de l’étude : Olga Davidenko

Laboratoire de rattachement : AgroParisTech

Lieux de l’étude : Restaurant universitaire CROUS de Nanterre, CROUS Censier et CROUS Jussieu

Version d’évaluation : 2ème

Avis précédemment donné (si pas 1ère évaluation) : 2

Tenant compte des réponses et spécifications fournies par le demandeur, les membres présents lors de la réunion ont voté à la majorité l’avis suivant :

Avis 1. Favorable.

La référence associée à cet avis est la suivante : CER-Paris-Saclay-2019-016

1 **Social modeling of food choices in real life conditions concerns specific food**
2 **categories.**

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7 **Abstract**

8 The social context of eating has a profound effect on consumption choices. Social modeling, that
9 involves using others' behavior as a guide for appropriate consumption, has been well documented
10 for food intake, but less is known about social modeling of food choices. Moreover, social modeling
11 has mainly been studied in laboratory settings. We conducted an observational study in a self-service
12 canteen to examine whether the food choices of an individual were influenced by the choice of the
13 person ahead in the queue. We recorded food choices of 546 individuals (333 men and 211 women)
14 and those of the person in front of them in the queue along a linear buffet. Starters were sub-
15 categorized into salads, mixed starters (e.g. avocado shrimp mayonnaise), and cold meat starters, and
16 desserts were sub-categorized into fruits, dairy products and pastries. There was a significantly higher
17 probability of taking a starter in general (OR=1.65, IC=1.06-2.57, p=0.03), a salad (OR= 1.78, CI= 1.08-
18 2.93, p= 0.02), a mixed starter (OR= 2.98, CI= 1.42-6.05, p<0.01), but not a cold meat, if the person
19 ahead in the queue also took one compared to when the person ahead did not take one. No significant
20 modelling was found for desserts which may be because almost all participants took a dessert. These
21 results highlight that social modeling influences food choices, and that this phenomenon can be
22 observed in a real life setting. These data also suggest that some food categories, such as starters,
23 could be more susceptible to social modeling than are others. Finally, we observed modeling both
24 between familiar and unfamiliar participants, which suggests that social norms could be used to
25 promote healthier eating in a range of settings including friendship groups.

26 Key words: social modeling, food choice

27

28 Introduction

29 Eating is a complex social event, and the social context during a meal can have multiple influences on
30 food intake. For instance, it has been demonstrated that the quantity of food consumed increases
31 when eating with familiar others compared to eating alone, which is known as the social facilitation of
32 eating (de Castro & Brewer, 1992). However, not only the mere presence of others, but also their
33 consumption can have an impact on intake. Indeed, it has been shown that individuals adjust the
34 amount of food eaten to the quantities consumed by their commensals (Vartanian et al., 2015). This
35 phenomenon is called social modeling and involves using others' eating behavior as a norm, for
36 instance as an indicator of the appropriate amount of food to consume in a given situation. Social
37 modeling appears to be very robust because it has been observed in both men and women (Cruwys et
38 al., 2015) (with some evidence of a stronger effect for women (Herman & Polivy, 2010)), when eating
39 with both familiar and unfamiliar partners (Cruwys et al., 2015; Kaisari & Higgs, 2015; Salvy et al., 2007;
40 Vartanian et al., 2015), and independently of weight status (Rosenthal & Marx, 1979) and state of
41 hunger (Goldman et al., 1991). Additional studies have demonstrated that social modeling can occur
42 even in the absence of others, when participants are provided information regarding the quantity of
43 food consumed by previous eaters ("remote confederate" studies) (Robinson, Benwell, et al., 2013;
44 Vartanian et al., 2013). In such studies, a norm of consumption is established via descriptive norms,
45 which can be indirectly conveyed, e.g. via the presence of empty packaging, or conveyed via messages
46 that report the consumption patterns of a majority of individuals (social-norm based messages).

47 While social modeling of food intake is well established, less is known about social modeling of food
48 choices. Two reviews (Cruwys et al., 2015; Robinson, Thomas, et al., 2013) examined the literature on
49 the impact of social modeling on food intake and choices, and both concluded that the available data
50 is insufficient to draw conclusions about the robustness of the effect on food choices. Indeed, among
51 69 studies reviewed by Cruwys, Bevelander and Hermans (2015) on social modeling, only 11 examined
52 modeling of food choices, among which 8 succeeded in observing the phenomenon. However, 3

53 studies did not find significant modeling effect (Hendy & Raudenbush, 2000; Pliner & Mann, 2004). For
54 instance, Pliner and Mann (2004) reported social modeling of food intake but not of food choices.
55 These authors suggested that food choices may be less influenced by others' behavior than intake
56 because individuals feel surer about their food likes and dislikes than the appropriate amount of food
57 to consume in a given situation.

58 Pliner and Mann (2004) were also interested in the impact of food healthfulness on modeling, and they
59 observed social modeling of intake for "unhealthy" (high energy density) cookies but not for "healthy"
60 (low energy density) ones. To date, little is known about the strength of social modeling effects on
61 "healthy" food items because the majority of studies have been done using high energy density food
62 items and only a small number of studies have focused on modeling of low energy density food items.
63 In a study by Hermans *et al.* (2009), social modeling of quantities of low energy density food
64 (vegetables) was observed, but investigations of the social modeling of food choices of low *versus* high
65 energy density food has been limited. Robinson and Higgs (2013) found that participants were less
66 likely to choose low energy density food items when eating with a participant making "unhealthy"
67 choices, than when eating alone or in the presence of a participant making "healthy" choices (Robinson
68 & Higgs, 2013). Thus, social modeling of food choices was observed, but this influence was only present
69 in the "unhealthy" condition. In another study conducted by Burger and colleagues, participants were
70 led to believe that previous participants took either a "healthy" or an "unhealthy" snack through the
71 provision of a descriptive norm (empty packaging) before having to make their own choice.
72 Participants were more likely to choose the snack they believed others had chosen, both in the
73 "unhealthy" and "healthy" norm conditions (Burger *et al.*, 2010).

74 One feature of these studies is that they were conducted in a laboratory setting, which leaves open
75 the question of whether the modeling of food choices occurs in real-life situations. To date, one study
76 investigated modeling of choices in real life conditions, but this study was focused on modeling of
77 vegetarian versus non-vegetarian dishes (Christie & Chen 2018). Further research is needed to better

78 characterize the effect of social modeling of food choices in real-life conditions, especially for meals
79 composed of a broad range of food items including low and high energy density food items. In addition,
80 there are other factors which could impact modeling effects in real life settings that are often not
81 present in laboratory studies. For instance the majority of studies conducted in the laboratory included
82 subjects paired with strangers, whereas in real life situations people are likely to eat with familiar
83 others. To date, only a few studies have examined modelling among familiar participants, but the
84 results suggest that modeling may occur both with familiar and unfamiliar individuals (Cruwys et al.,
85 2015; Kaisari & Higgs, 2015; Salvy et al., 2007; Vartanian et al., 2015). Further investigations are needed
86 to confirm these preliminary results and examine whether familiarity moderates modeling observed
87 in real life settings.

88 The aim of the present study was to determine whether modelling of food choices can be observed in
89 a real-life setting (a university self-service restaurant), examine whether modelling exists across a
90 range of food categories (defined using consumer perception of the nutritional quality of the items)
91 and whether familiarity with the person that serves as a model moderates any effects.

92

93 **Methods**

94

95 **Restaurant Venue**

96 The study took place at the employee restaurant of a university campus (Paris, France). The restaurant
97 serves almost 500 clients per day for lunch service. Ethical approval for the study was obtained from
98 the ethics committee of Paris-Saclay University (registration number CER-Paris-Saclay-2019-016). Data
99 collection took place on two Thursdays (one of the busiest days of the week) during spring, from 12pm
100 to 2pm. Clients were able to choose a main dish plus two additional items for their meal, meaning they
101 could choose one starter and one dessert, or two starters or two desserts. The price of the meal
102 remained the same, no matter which items were chosen. Food choices varied from day to day but

103 were always structured in the same way. Starters included a variety of raw vegetables, mixed salads
104 (such as pasta or potato salads with cheese), meat or fish, and cold meats. The desserts included a
105 variety of items including dairy products (different types of yoghurts, dairy desserts and cheeses), but
106 also fresh fruits, fruit salads, fruit compotes and different type of pastries. Finally, the main dish offered
107 usually included a choice between fish or meat and one or two types of sides (starches and vegetables).
108 We decided to focus our analysis on the choices of starters and desserts only, because these courses
109 offered a higher diversity and choice than the main dishes at the restaurant.

110 We sub-categorized starters into salads, mixed starters, and cold meats, and desserts into fruit, dairy
111 products and pastries (more details about food items included in subcategories are available in
112 supplementary file 1). These food categories were decided upon according to their perceived
113 healthiness by consumers. This perceived healthiness was assessed via an online questionnaire
114 completed by 118 individual (mean age of 42 years old). Participants were asked to rate each item
115 from 0 (unhealthy) to 8 (healthy). Detailed results are available in supplementary file 2.

116

117 **Data collection procedure**

118 Upon arrival at the restaurant, clients had to follow a linear queue along the buffet to choose their
119 lunch items. This linear configuration of the buffet was a crucial criterion for the choice of venue for
120 the study because it ensures that each client had to follow the same person all along the buffet. The
121 clients first had to choose a starter, then a dessert, and last the main dish. Two experimenters were
122 positioned at the cash register, behind the cashier, from where they had a clear view of the meal trays,
123 but were not seen by the clients in the queue so as not to influence their choices. The choices of each
124 client were recorded by the two experimenters. A third experimenter distributed individual
125 questionnaires to each client after the cash register. The aim of these questionnaires was to collect
126 demographic and contextual information from the clients. Finally, a fourth experimenter collected
127 individual questionnaires at the exit of the restaurant. An identification number was associated with

128 each client so that their food choice could be paired to the individual questionnaire, as well as to
129 identify who was following who. We did not record data on the clients who did not follow anyone in
130 the line (which typically happened at the very beginning and the very end of the lunch service).

131

132 **Questionnaires**

133 Two questionnaires were used during data collection. First, a food choice questionnaire was completed
134 by the experimenters for each client upon their check out at the cash register. This questionnaire
135 contained all food item options that were on sale the day of each data collection session. Second, the
136 individual questionnaire was distributed to the clients for self-assessment after they paid for the meal.
137 The individual questionnaire included questions about age, gender and Body Mass Index (BMI) of the
138 participant, and contextual information: whether **or not they knew** the person ahead in the queue,
139 whether they ate with that person, whether they were following a specific diet involving food
140 exclusions, and what were their usual food choices at the canteen (whether they usually take a starter,
141 a dessert, or both), and finally whether they thought that others' choices influenced their own choices.

142

143 **Study population**

144 The food choices of 797 clients were collected over two days of data collection separated by one and
145 a half months. We excluded 110 individuals who reported following a specific diet involving food
146 exclusions e.g. vegetarian. We also excluded observations of 141 individuals who did not return the
147 individual questionnaires, or returned incomplete questionnaires. The final sample comprised 546
148 individuals.

149

150 **Statistical analysis**

151 The choice of each food item, sub-category and category was coded as a binary variable (chosen as 1,
152 not chosen as 0). Binary logistic regressions were used to analyze whether the probability of choosing
153 an item from a specific food category or subcategory was associated with the choice of the person
154 ahead in the queue for this same food category or subcategory.

155 The models were adjusted for the age, sex, and BMI of individuals. The models were also adjusted for
156 contextual factors such as declared usual food choices at the self-service restaurant. We controlled for
157 habitual choices because this is a powerful predictor of eating behavior (Riet et al., 2011). Finally the
158 models were adjusted for the familiarity (whether individuals stated that they knew the person ahead
159 of them in the queue). This allowed us to investigate modeling, independently of the relation of
160 individuals with the previous person and to investigate if the familiarity could impact individuals'
161 choices, independently of the choices of the person ahead in the queue.

162 Finally, the possible moderating effect of the familiarity between subjects on modeling has been tested
163 in other models, through the investigation of interactions between the familiarity and the choice of
164 the person ahead.

165 R Studio version 1.1.463 (RStudio Team, 2016) was used for data analysis.

166

167 **Results**

168

169 **Descriptive analysis**

170 Population characteristics

171 Of the 546 individuals observed, 333 (61%) were men and 211 (39%) were women (2 individuals did
172 not give their sex). The mean age was 40.2 +/- 13.1 years old and the estimated mean BMI was 23.5
173 +/- 3.5 kg/m². The sample was composed of university employees including PhD students (21%),
174 permanent research staff (44%) and administrative and support employees (27%) (8% of the sample
175 did not state their profession).

176

177 Food choices

178 We observed that 39% of the population chose at least one starter, 93% chose at least one dessert,
179 and 35% chose both starter(s) and dessert(s). This compares with 54% of the sample who stated that
180 they usually take a starter, 90% a dessert, and 44% both (Table 1). Only 2% (14 individuals) of the
181 sample took more than one starter while 30% (169 individuals) took more than one dessert.

	Starter(s)	Dessert(s)	Starter(s) + Dessert(s)
Observed Choices	212 (39%)	510 (93%)	188 (35%)
Declared usual choices	290 (54%)	478 (90%)	236 (44%)

182 **Table 1:** Numbers and percentages of observed choices compared to declared usual choices.

183

184 Among starters, salads were the most frequently chosen category, representing 57% of starter choices,
185 with mixed starters accounting for 28% of choices and cold meats accounting for 16% of choices.
186 Among desserts, fruit were the most chosen category with 43% of choices, then came pastries with
187 32% of choices and last dairy products with 25% of choices.

188

189 Relationship with the person ahead in the queue

190 65% of the sample reported they knew the person ahead in the queue, and 62% declared that they ate
191 at the same table. Among the 65% of individuals who declared knowing the person ahead in the queue,
192 93% also declared that they ate with this same person. Due to the high association between two
193 variables, we only used the knowledge of the person ahead in the queue as a covariate in the model.

194

195 Awareness

196 The vast majority of the population (91%) reported that in making their own choice, they were not
197 influenced by the previous person’s choice, while only 5% reported that they were influenced. Due to

198 the unequal distribution of this variable, we decided not to use it as a covariate in order to adjust our
199 models.

200

201 **Social modelling of food choices**

202 Starters

203 There was a significantly higher probability of taking a starter if the person ahead in the queue also
204 took one compared to when the person ahead in the queue did not take one (OR= 1.65, CI= 1.06-2.57,
205 $p= 0.03$). Regarding subcategories of starters, individuals had a significantly higher probability of taking
206 a salad (OR= 1.78 CI= 1.08-2.93, $p= 0.02$), or a mixed starter (OR= 2.98, CI= 1.42-6.05, $p<0.01$) if the
207 person ahead in the queue also took one, which was not the case for cold meats (OR= 1.89, CI= 0.42-
208 6.19, $p= 0.34$).

209

210 Desserts

211 The probability of taking a dessert was not significantly related to whether the person ahead in the
212 queue did or did not take one (OR= 1.28, CI= 0.26-4.64, $p= 0.73$). Regarding desserts subcategories,
213 none of the choices was significantly influenced by the choices of the person ahead in the queue for
214 those subcategories (fruit: OR= 0.97, CI= 0.69-1.38, $p=0.88$; dairy products: OR=1.26, CI= 0.84-1.87,
215 $p=0.27$; pastries: OR= 1.42, CI=0.97-2.07, $p= 0.07$).

216

217 Other variables explaining food choices

218 Declared usual choices was the most significant variable explaining individuals' choices for starters and
219 all starters' subcategories, and for desserts in general as well as for fruits and pastries. Complete
220 statistical results of each model are available in supplementary files 3 for starters and 4 for desserts.

221

222 Familiarity and modeling

223 We found no significant interaction between the familiarity and the choice of the person ahead in the
224 queue in any of the categories and subcategories (Table 3).

Food categories	Familiarity*Choice of the person ahead (p-value)
Starters	0.49
Salads	0.96
Mixed starters	0.59
Cold Meats	0.99
Desserts	0.50
Fruits	0.75
Dairy Products	0.08
Pastries	0.64

225 **Table 3:** Moderating effect of familiarity on modeling. Interactions are tested using binary logistic
226 regressions.

227

228 **Discussion**

229

230 We observed that choice of starters, but not desserts, was influenced by the choice of the person
231 ahead in a queue in a restaurant setting. We also found that whether or not participants knew the
232 person ahead in the queue had no influence on whether or not modelling was observed. These results
233 are significant because they demonstrate social modeling of food choices in a real-life restaurant
234 setting, which has only been observed in one previous study of food choices of vegetarian versus non-
235 vegetarian main dishes (Christie & Chen, 2018). Taken together, these findings suggest that modeling
236 of food choices is a robust phenomenon that exists outside of the laboratory.

237

238 We observed a modeling effect for starters and two of the starter subcategories (salads and mixed
239 starters), but not for desserts and none of the dessert subcategories. One reason why modeling was

240 observed for starters but not desserts may be that 93% of participants reported that they usually take
241 a dessert whereas only 54% reported usually taking a starter. In situations where people have clear
242 eating routines and/or strong pre-established preferences, social modelling is less likely to be observed
243 (Cruwys et al., 2015). Pliner and Mann (2004) observed social modeling for intake of
244 palatable/unhealthful cookies but not for unpalatable/healthful cookies. In addition, these authors did
245 not observe any influences of informational social norms on choice of cookies (participants chose the
246 palatable over the unpalatable cookies regardless of social information). These authors suggested that
247 one reason for these findings might have been because the participants were sure of their preference
248 for cookies and so did not look to others to guide their choices. In the present study it is possible that
249 choice of dessert was less susceptible to social influence than was choice of starter because the
250 participants were sure of their preference for these items. An additional explanation why choices of
251 starters were modeled, but not choices of dessert, may be the fact that the starter was the first item
252 to be chosen and this may have made the starter more visible on the tray of the person ahead in the
253 queue as it was the only item added on it. In addition, because the starter was the first item to be
254 chosen, choice of starter was not restricted by already having chosen other items. The choice of the
255 dessert (which was the second item to be chosen) may have been in part influenced by the choice of
256 the starter for the sake of having a balanced complete meal and makes it more susceptible to external
257 influences.

258 For the choice of starters, we observed social modeling of choice of the salads and mixed starters but
259 not for the cold meats. There are at least two potential reasons for this finding: 1) the cold meat
260 starters were not chosen very often and so it may be that there were insufficient observations for
261 modelling to be evident but it is also possible that 2) the participants were also more sure of their
262 preference for the cold meats than they were of their preference for the salads/mixed starters and so
263 while choice of the latter was susceptible to social influence the former was not.

264

265 Regardless of the specific explanation for this pattern of results, we did observe modelling of lower
266 energy “healthier” items (salads). This is significant because to date, the majority of studies on social
267 modeling have examined modelling of high energy foods and the effect of social context on the choice
268 of low versus high energy food items during a meal remains poorly studied. Robinson and Higgs (2013)
269 reported findings that differ somewhat from the present results. They found that participants choosing
270 from a buffet in the presence of an ‘unhealthy’ eating partner were significantly less likely to choose
271 and consume a low-energy-dense food item than when choosing alone or in the presence of a ‘healthy’
272 eater, suggesting that the presence of an ‘unhealthy’ eating partner may undermine intentions to
273 consume low-energy-dense foods (Robinson & Higgs, 2013). This study was conducted in a laboratory
274 setting and the fact that the participants knew they were taking part in an experiment may have
275 affected their responses. As argued by Robinson and Higgs (2013), it may have been that in the
276 ‘choosing-alone’ condition and the ‘healthy’ confederate condition, there was a social norm operating
277 to encourage the choice of at least some healthier items (perhaps because they thought their food
278 intake was being monitored), but this this norm may have been undermined in the ‘unhealthy’
279 confederate condition, leading participants to abandon the ‘healthy’ choice. The present results are
280 encouraging in suggesting that modeling could have a positive impact on healthier food choices in a
281 real life setting.

282

283 Social modelling of starter choice was unaffected by whether or not the participant reported **knowing**
284 the model. In other words, we observed modelling of food choices both under conditions of familiarity
285 with the model and when the model was not known to the participants. This is an important finding
286 because the majority of studies to date on modelling have involved testing of strangers. Reviews by
287 Cruwys and colleagues (2015), **and** Vartanian and colleagues (2015) found modeling in studies of
288 children eating with familiar models such as parents or teachers but to date only a few studies have
289 reported social modeling in pre-existing friendship groups of adults (Howland et al., 2012; Kaisari &

290 Higgs, 2015; Salvy et al. 2007). Taken together, these data support the suggestion that that modelling
291 within friendship networks may underlie the social transmission of food choices (Pachucki et al., 2011).

292 **Ninety-six percent** of our population reported that they were not influenced by others' choices in
293 making their own choices. Other research has found that people generally report being unaware of
294 social influence when it comes to food choices, although it may be that people are aware of social
295 influence under some circumstances, **but** are motivated to deny it (e.g. Spanos et al., 2014; Vartanian
296 et al., 2008, Robinson & Field, 2015). One explanation for a lack of awareness is that social influence
297 on eating could be operating on an automatic level. Indeed it has been argued that **an** automatic
298 mimicry process may underlie modelling at least in part (Bevelander et al., 2013; Hermans et al., 2012;
299 Higgs & Thomas, 2016; Huh et al., 2014). In their review, Cruwys and colleagues (2015) concluded that
300 the evidence suggests that while modeling can be automatic, it is also accessible to conscious control.
301 For example modeling has also been observed in studies using descriptive social norm-based
302 messages, which is unlikely to be explained by automatic mimicry process (Cruwys et al., 2015). More
303 research is needed to better understand mechanisms underlying social modeling.

304 This study has some limitations. Our study was observational and did not involve manipulation of food
305 choices, and so we cannot draw conclusions about causal effects in relation to modelling. Moreover,
306 the potential role of confounding factors cannot be ruled out, **such as the order of choice of the**
307 **different items for example as discussed above**. However, observational studies yield complementary
308 data and lend external validity to evidence obtained from laboratory studies conducted under
309 controlled conditions. Another point is that we recorded food choices, but we did not measure the
310 quantity of food actually consumed. Future work could examine whether modelled foods are more or
311 less likely to be wasted than are non-modelled foods.

312 This research has implications for interventions on healthy eating behavior. For example, it may be
313 possible to encourage choice of healthier menu items using social influence. Studies have already
314 succeeded in increasing the purchase of vegetables/salads in restaurants (Mollen et al., 2013, Thomas

315 et al., 2017) through the use of descriptive social norm messages and there is some evidence that
316 social-norm-based messages may be more effective than health-based messages (Collins et al., 2019;
317 Robinson et al., 2014), especially when using descriptive norms (information about what others are
318 eating) rather than injunctive norms (information about others approve of) (Mollen et al., 2013;
319 Robinson et al., 2014; Stok et al., 2014). Future studies could examine whether social-norm-based
320 message can also be applied to a wider range of healthier items and in a wider range of field settings.

321 In conclusion, we observed modelling of food choices in a real life setting but our data suggest that
322 choices in some food categories, such as starters, may be more susceptible to social modeling than
323 others, such as desserts, possibly because choice of dessert is habitual. Finally, we found that modeling
324 occurs both between familiar and unfamiliar participants, which suggests that social norms could be
325 used to promote healthier eating in a range of settings including friendship groups.

326

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331 **Author Contributions**

332 Armelle Garcia was responsible for the study design, data collection and analysis, and writing of the
333 manuscript. Nicolas Darcel, Suzanne Higgs and Olga Davidenko were responsible for the study design
334 and writing of the manuscript. Alya Hammami, Lucie Mazellier and Julien Lagneau participated to assist
335 with the data collection. All the authors approved the final manuscript.

336 The authors declare that there have no conflicts of interest.

337

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429

Starters		Desserts	
Salads	<ul style="list-style-type: none"> -Salads (grated carrots, beetroots, endives, cucumber and tomatoes etc) -Grapefruit 	Fruit	<ul style="list-style-type: none"> -Fresh Fruit - Canned fruit - Canned fruit salad - Fruit compote
Mixed starters	<ul style="list-style-type: none"> -Potato salad with ham and nuts - Salad and goat cheese - Mackerel - Salmon - Mimosa eggs (mayo) - Salmon pasta salad - Potatoes salad with bacon - Corn and chicken salad - Tabbouleh 	Dairy	<ul style="list-style-type: none"> -Plain yoghurt - Sweetened and flavored yoghurt - Full fat yoghurt - Dairy dessert - Cheese
Cold meat	Small plates with a variety of cold meat with butter	Pastries	<ul style="list-style-type: none"> -Traditional Basque cake - Fruit crumble - Custard pie - « Ile flottante » (whipped egg white with custard sauce and caramel) - Chocolate mousse - « Paris-Brest » (choux pastry filled with hazelnut flavored custard cream). - “Religieuse” (cream puffs with caramel) - Cherry pie - Lemon pie - Chocolate pie - Coconut pie - Apple pie - « Tarte tatin » (apple pie with caramel)

436 Annex 2: Perceived healthiness of food items (rated from 0 (unhealthy) to 7 (healthy))

437

Food categories	Mean perceived healthiness	Standard Deviation
Starters	4.60	1.97
Salads	6.58	0.75
Mixed starters	4.57	0.76
Cold Meats	2.64	0.61
Desserts	4.09	1.26
Fruits	5.22	1.56
Dairy Products	4.32	1.44
Pastries	2.73	0.46

438

439 An online questionnaire filled by 118 individuals with a mean age of 42 years old (which fit with our
440 population). They were asked to rate from 0 (unhealthy) to 7 (healthy) each items that were
441 proposed during our data collection.

442 Annex 3: Results of binary logistic regression for starter and starters' subcategories.

443

Variables	OR	CI 97,5%	p-value
Starter			
Choice of the person ahead	1.65	1.06-2.57	0.03
Age	0.97	0.96-0.99	< 0.01
Sex	1.35	0.85-2.13	0.21
BMI	1.22	0.49-2.12	0.70
Familiarity	0.97	0.60-1.56	0.91
Usual choices			
<i>Starter</i>	12.19	6.05-25.20	< 0.01
<i>Starter + Dessert</i>	18.75	11.32-32.22	< 0.01
Raw Vegetables			
Choice of the person ahead	1.78	1.08-2.93	0.02
Age	1.01	0.99-1.02	0.69
Sex	0.80	0.50-1.31	0.38
BMI	0.74	0.27-1.86	0.53
Familiarity	1.05	0.64-1.74	0.84
Usual choices			
<i>Starter</i>	10.75	4.48-26.11	< 0.01
<i>Starter + Dessert</i>	17.38	9.02-37.12	< 0.01
Mixed Starters			
Choice of the person ahead	2.98	1.42-6.05	< 0.01
Age	0.94	0.91-0.96	< 0.01
Sex	1.16	0.63-2.21	0.64
BMI	1.26	0.34-3.80	0.70
Familiarity	1.29	0.67-2.61	0.46
Usual choices			
<i>Starter</i>	5.09	1.84-14.00	< 0.01
<i>Starter + Dessert</i>	4.83	2.37-10.75	< 0.01
Cold Meats			
Choice of the person ahead	1.89	0.42-6.19	0.34
Age	1.00	0.97-1.03	0.84
Sex	2.43	1.05-6.37	0.05
BMI	1.64	0.36-5.34	0.47
Familiarity	0.57	0.27-1.21	0.14
Usual choices			
<i>Starter</i>	5.24	1.39-19.82	0.01
<i>Starter + Dessert</i>	4.69	1.87-14.29	< 0.01

444 OR: Odd Ratios, CI: Confidence Intervals

445 Annex 4: Results of binary logistic regression for dessert and desserts' subcategories.

Variables	OR	CI 97,5%	p-value
Dessert			
Choice of the person ahead	1.28	0.26-4.64	0.73
Age	1.01	0.98-1.05	0.56
Sex	2.28	0.99-5.36	0.05
BMI	1.80	0.30-35.75	0.60
Familiarity	0.77	0.28-1.92	0.59
Usual choices			
<i>Dessert</i>	18.31	6.91-54.92	< 0.01
<i>Entrée + Dessert</i>	12.73	4.97-35.70	< 0.01
Fruits			
Choice of the person ahead	0.97	0.69-1.38	0.88
Age	1.01	0.99-1.02	0.41
Sex	0.71	0.50-1.03	0.07
BMI	1.27	0.57-2.20	0.56
Familiarity	0.89	0.60-1.30	0.54
Usual choices			
<i>Dessert</i>	2.18	1.17-4.18	0.02
<i>Entrée + Dessert</i>	2.65	1.41-5.11	< 0.01
Dairy Products			
Choice of the person ahead	1.26	0.84-1.87	0.27
Age	1.02	1.00-1.03	0.02
Sex	0.81	0.55-1.20	0.29
BMI	1.83	0.81-4.05	0.14
Familiarity	1.33	0.88-2.04	0.19
Usual choices			
<i>Dessert</i>	1.48	0.76-3.06	0.27
<i>Entrée + Dessert</i>	1.38	0.70-2.97	0.37
Pastries			
Choice of the person ahead	1.42	0.97-2.07	0.07
Age	0.98	0.97-0.99	< 0.01
Sex	2.34	1.58-3.50	< 0.01
BMI	0.57	0.21-1.37	0.23
Familiarity	1.39	0.92-2.10	0.12
Usual choices			
<i>Dessert</i>	4.60	2.14-11.13	< 0.01
<i>Entrée + Dessert</i>	3.29	1.52-7.96	< 0.01

446 OR: Odd Ratios, CI: Confidence Intervals

Conflict of interest statement

The authors declare that they have no conflicts of interest.