Modeling Dynamic Food Choice Processes to Understand Dietary Intervention Effects

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Abstract

Background Meal construction is largely governed by nonconscious and habit-based processes that can be represented as a collection of individual, micro-level food choices that eventually give rise to a final plate. Despite this, dietary behavior intervention research rarely captures these micro-level food choice processes, instead measuring outcomes at aggregated levels. This is due in part to a dearth of analytic techniques to model these dynamic time-series events.

Purpose The current article addresses this limitation by applying a generalization of the relational event framework to model micro-level food choice behavior following an educational intervention.

Method Relational event modeling was used to model the food choices that 221 mothers made for their child following receipt of an information-based intervention. Participants were randomized to receive either (a) control information; (b) childhood obesity risk information; (c) childhood obesity risk information plus a personalized family history-based risk estimate for their child. Participants then made food choices for their child in a virtual reality-based food buffet simulation.

Results Micro-level aspects of the built environment, such as the ordering of each food in the buffet, were influential. Other dynamic processes such as choice inertia also influenced food selection. Among participants receiving the strongest intervention condition, choice inertia decreased and the overall rate of food selection increased.

Conclusions Modeling food selection processes can elucidate the points at which interventions exert their influence. Researchers can leverage these findings to gain insight into nonconscious and uncontrollable aspects of food selection that influence dietary outcomes, which can ultimately improve the design of dietary interventions.

Keywords Food choice • Micro-behavior • Nutrition intervention • Relational event model

Introduction

In light of the public health burden associated with increasing rates of obesity [1], researchers have developed many interventions to improve dietary behavior. These efforts have shown some degree of short-term efficacy [2, 3], thereby establishing approaches to improve food choices. A number of studies suggest that educational approaches can be effective, and show that providing information about factors such as nutrition, weight reduction approaches, and health risks can promote healthier food choices [4–7]. Additionally, research has shown how socio-cultural norms such as beliefs about the healthfulness of certain foods, social pressure to make certain selections, and value negotiations about what constitutes “good” food, influence the ways in which people select

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food [8]. However, application of educational and social approaches has not shown enough success to dramatically alter obesity outcomes on a public health scale [9]. One potential reason for these shortcomings is that food selection may be driven by nonconscious and habitual actions that “fly below the radar” of most dietary intervention approaches [10, 11]. Indeed, a vast collection of micro-level actions make up food selection and consumption events [12]. Previous behavioral intervention studies have only examined influences on food choice at aggregate levels, investigating outcomes such as total calories on a plate or total amount of saturated fat eaten over a period of time. They thus fail to consider the micro-level food selection process that give rises to dietary selection actions and may be important targets for future interventions. The current study addresses this issue by demonstrating the utility of examining micro-behavior in the context of an intervention study, and by introducing a novel mode of analysis that could further this line of research.

The importance of understanding the behavioral process of food selection (i.e. the way in which people consider and make choices among foods and beverages), has been established in a handful of studies. One particularly relevant line of work demonstrates how design elements of cafeteria and buffet environments can influence, or “nudge,” food choices [13]. For example, organizing buffets so that the healthiest foods appear first leads people to make healthier selections [14], and physically distancing unhealthy snacks decreases intake without decreasing satiety [15]. Although these studies show how aspects of food selection are influenced by micro-level factors in the built environment, they still do not account for the entire selection process. Relatedly, research has shown that the mere availability of food options, even when they are not selected, influences the eventual composition of participants’ choices [16, 17]. For example, the presence of an extra vegetable option on a buffet can increase the likelihood that a single vegetable will be chosen during a meal [17]. These studies suggest that considering the placement of foods, variety of options, and the dynamics they engender is relevant for capturing the complex processes that constitute food selection.

Understanding the ways in which interventions alter food selection on a micro-behavioral level could help researchers identify points of leverage, and thus guide the development of more effective approaches for improving dietary behavior, both in terms of informational and environmental interventions. In this vein, there are two major open areas for researchers aiming to improve dietary behavior. The first is to understand how elements of the food environment and socio-cultural norms influence the micro-behavioral food selection process. Secondly, researchers may wish to know how dietary interventions influence the food selection process and whether this influence accounts for intervention effects.

Understanding these two domains can guide efforts to change food environments and educate the public such that more healthful food choices are made.

The most likely reason for the scarcity of research on micro-behavioral processes in food choice is the complexity associated with modeling dynamic time-series events. The current article addresses this limitation by utilizing a generalization of the relational event framework for social action proposed by Butts to model micro-behavior [18]. We define “micro-behavior” in the same way that Butts [18] in the original development of the relational event framework defines actions as “discrete events in which one individual emits a behavior directed at one or more entities in his or her environment” (p. 156). In other words, a micro-behavior is a discrete event (of zero duration) in which some actor directs an action towards some target (e.g. another actor, a computer, a food item in a buffet, etc). Stringing records of a series of such actions together in time constitutes data on an event history that recounts how a particular actor behaved over some period of observation. The relational event framework is, thus, a theoretically motivated approach for thinking about, modeling, and making inferences about series of such discrete events, or micro-behaviors, unfolding in such event histories. At the most basic level, the relational event modeling framework allows the researcher to answer the question: What happens next in a series of events? In applying this model to food choice events, we aim to address the following research questions within an exploratory analysis: (a) Is it feasible to apply the relational event framework to food choice behavior? And, (b) Can the results from this exercise provide useful information about the micro-processes that underlie food choice that can be used to understand environmental and intervention effects?

The data for this exercise come from an experiment investigating the influence of behavioral and genomic risk information feedback on food choice selection in a virtual reality-based buffet [19].

Methods

Participants

The sample consisted of 221 mothers who met criteria for overweight or obesity and who had at least one 4- to 5-year-old child at the time of the data collection [19]. Eligible mothers were older than 18 years, had a self-reported BMI over 25, had a 4- to 5-year-old child without major food allergies or diet-related health conditions, and had the ability to read and write in English. Mothers also had to be able to report the child’s family history of overweight and obesity. Mothers were selected because of the influence they exert over children’s eating

[20]. Mothers with overweight and obesity were targeted so that messages indicating their child was at high genomic risk for obesity would be relevant to them. Mothers were recruited from the Greater Washington DC area using flyers posted or distributed in schools, daycare, web forums, listservers, and word of mouth. All actions were approved by the IRB of the National Institutes of Health.

Procedure

Through random assignment using a random number generator, mothers received either: (a) food safety information (control); (b) behavioral risk information about obesity; or, (c) behavioral risk information plus personal family history-based obesity risk information for their child [21, 22]. The food safety (control) module provided tips for enhancing food safety when feeding children. The behavioral risk information condition focused on the risks associated with obesity, the role of lifestyle in the development of obesity, and tips on developing healthy lifestyle habits. The behavioral risk plus family history-based risk information conditions began with the behavioral risk information module, then added

population-level absolute and relative risk of the index child becoming an obese adult based on the weight status of his/her biological parents. After receiving the information relevant to their assigned condition, mothers were asked to enter a virtual reality-based buffet environment to create a lunch meal for their child by choosing virtual servings of food and beverages. They were informed that the buffet should be considered fixed-price, and that they should assume the child would not eat again for several hours. The virtual buffet environment was identical for every participant in terms of the foods and drinks provided, ordering of foods and drinks, amount of food in serving dishes, etc. Calories chosen within this feeding scenario served as the outcome measure to assess the influence of risk information provided.

Virtual Buffet Environment and Data Collection

We chose to explore these research questions in a virtual reality framework because it provides several advantages for data quantification [23]; however, we posit that this approach would also be applicable to real-world food choices as well. Virtual reality simulations are increasingly used in experimental studies to investigate human behavior [24, 25]. This tool is particularly amenable to the current study because of the control that researchers have over the environment: all elements of the built environment remain identical for every participant including food location, distance between foods, amount of food in serving containers, etc. In addition, collection of the relevant data is automated, as every selection that a participant makes is time-stamped to the millisecond. Potential error associated with observer coding is therefore avoided. Finally, the virtual buffet design has spatial realism. Participants could move in the virtual buffet by physically walking around in space and make food selections by moving a handheld pointer. They were given a practice session before the primary buffet assessment so that they could learn how to effectively use the virtual reality environment and pointer. Fig. 1 illustrates a bird's-eye-view of the buffet with a hypothetical selection process superimposed atop the food options. The cool-to-hot color gradient along the path represents the flow of time between each discrete food selection event the hypothetical participant made as they navigated the simulation. This figure illustrates the precision associated with mapping a food selection event history.

In the current study, the buffet contained 15 foods, 11 beverages, and 3 condiments. Food and drink options were chosen to reflect a range of nutrient and calorie densities. Foods included in the buffet were: grilled chicken strips, macaroni and cheese, cheese pizza bagels, breaded chicken nuggets, peas, steamed baby carrots, green beans, corn, white rice, tater tots, orange slices, grapes, apple sauce, brownies and vanilla pudding. Drinks included

Fig. 1. Birds-eye-view of food selection process of a hypothetical participant. Directed arrows illustrate one route that a hypothetical participant might take to select food while immersed in the virtual buffet world as seen from overhead in this birds-eye-view capture. Red-to-yellow color gradient shading the arrows represents the flow of time as the hypothetical participant makes each discrete food choice. Circular arrow shows choice inertia. The participant begins the simulation in the center of the buffet (indicated by the red dot), walks around the area to choose food and drink, and finishes the simulation at the cashier (indicated by yellow dot). The colors of non-food components of the buffet have been reduced to grayscale for contrast.

were: water, diet and regular soda, milk (skim, 2% and whole), lemonade, 100% apple juice, and 100% orange juice. Condiments included were: ketchup, BBQ sauce, and butter.

Participants made selections by connecting their physical hand-held pointer in space with a virtual food and pressing a selection button to get a single serving of a given food (e.g. one teaspoon of cut corn). Participants could increase portion sizes by continuing to press the selection button. Participants chose beverages by first indicating their choice among cup sizes, then selecting a beverage to fill that cup. Participants indicated they were finished making selections by using their hand-held pointer to select a cash register located near the exit of the buffet area. For the purposes of the analysis, all beverages were collapsed to one item and all condiments collapsed to one item, though their individual caloric content was preserved.

Relational Events Model

The relational event framework for social action was first introduced by Butts [18] to analyze a series of micro-interactions unfolding in time between members of a social network. Since then, the framework has been generalized to model any series of events occurring in time and has been applied to a wide array of contexts including sleep interruption patterns in the elderly [26], reciprocity of food-sharing among birds [27], and the stability of inter-organizational communication [28]. Here, we use an ego-centered specification of the model per Marcum and Butts [26], which is ideal for addressing research questions about the dynamics of individual behaviors as they unfold in time.

Briefly, the relational events framework employs a continuous time proportional hazards model whereby the researcher specifies sufficient statistics that capture dynamic effects of interest in a statistical model fit using maximum a posteriori methods. Proportional hazards models are a class of survival/failure analysis [29], which is sometimes called event history analysis in the social sciences. While used in a completely different manner here (i.e. as a latent model governing the inter-event time rather than as a manifest model for the event accumulation as previously discussed [18, 26, 30]) there are many applications of this family of models to interesting social and behavioral phenomena [31]. The relational event model assumptions include: conditional independence between events (i.e. conditional on past history up to the focal event), a latent proportional hazards model between events, that the events transpire instantaneously and non-simultaneously, and that the entirety of the event history transpired within the period of observation (Our data meet these assumptions). Estimated effects may be global—such

as intercepts that model the rate of a particular type of event occurring in real time—or local, such as subsequences of events that model micro-behaviors as transitions from one event to another. Thus, one valuable use of the model is to evaluate the extent to which past history in a stream of events affects future behavior. While the model is fit to an entire event-history, the dependent variable is the next event, and thus each model term reflects changes in the hazard of what happens next.

Readers interested in the technical details of the model are directed to Butts [18] and Marcum and Butts [26]. Additionally, model specification and model fitting software are provided by the freely available *informR* [26] and *relevent* [18] packages for the *R* statistical programming environment [32], which we used here. These packages handle both time-ordered and exact timing (timestamped) event history data. When timestamped event history data are available (as are here), this approach allows the researcher to model the rate at which events occur, jointly with the inter-event waiting times between events.

Model Specification and Selection

In the current study, we are primarily interested in testing for two different types of relational event model effects: first, we want to capture the effects of built environmental structure and socio-cultural norms on the sequence of choices made as the simulation unfolds in time (here called dynamic effects); and second, we want to test whether the ways in which participants interact with the buffet vis-a-vis these dynamic effects differ by intervention feedback condition (here called experimental effects). To a lesser extent, we are also interested in understanding the rate at which particular foods are selected over the course of the simulation (called baserates) and how they may differ between control and feedback condition.

Baserate Effects

Food selection

We began the model of the food selection process with the trivial case that food is added and removed at some average fixed rate in time. However, some foods may be chosen more quickly than others by virtue of either exogenous factors (e.g. cultural preferences) or endogenous ones (e.g. their relative visual appeal or palatability). To capture potential differences in the rates at which each food is selected, we added a single statistic for each different type of food to the model ($n = 17$). The coefficients associated with these baserates are necessarily negative, as these are exact exponential time effects. They can

be interpreted as either waiting time effects or as rate-per-unit of time effects vis-a-vis algebraic conversion as described in Butts and Marcum [30].

Food removal

Participants were able to remove food that was previously added to their plates. As putting food back after it had been selected is not a widely-accepted behavior, this was very rare in our data (0.89% of all events). Still, as these removal events occasionally occurred, we control for them. Specifically, we add a single baserate statistic to the model that captures the effect of removing any food from one's plate. Additionally, we include an event-specific choice support constraint into the architecture of the model to ensure that the hazards for each selection and removal event were appropriately evaluated, such that removal events could only occur once that particular food had been selected.

Dynamic Effects

Spatial partial ordering

As the birds-eye-view of the buffet in Fig. 1 illustrates, options are not randomly encountered by the participant but are instead presented in a fixed spatial order on the buffet tables, just as in real-life scenarios. We can a priori expect this spatial ordering of the buffet to affect participants' decision making processes [33, 34]. In particular, we expect food encountered immediately adjacent to other food in the buffet to be selected prior to food found elsewhere. As the buffet is "double-sided" (consisting of two parallel buffet tables), and participants may choose to either start selection on the left or the right at any place in line, we specify two separate partial ordering effects: one statistic each to model the partial spatial ordering on the left and right side of the buffet, respectively. A significant positive coefficient for either of these effects indicates that, conditional on wherever a participant started selecting, the hazards for the food items immediately proximate to that choice go up (and are consequently more likely to be the next event). This is a "dynamic" effect as its associated sufficient statistic continues to be evaluated as participants complete the buffet. One may interpret this effect as a spatially conditioned first-order Markov process.

Healthy to unhealthy and entrée to vegetable

While partial spatial ordering is one dimension that may constrain the decision process, socio-cultural norms often prescribe appropriate behaviors for the order in which food is added to a plate. One might consider a host of effects for micro-sequences of putting different types of foods on the plate in different orders driven, in part,

by socio-cultural norms. For instance, individuals may feel that once they make a healthy food choice they are more free to select less healthy options next [35]. For instance, dessert items tend to be acquired and consumed last. Another example is the European norm that meals are built around a focal entrée [36], with vegetables added to play a supporting role on the plate after the entrée has been selected. Therefore, we add two statistics to the model that capture such effects. The first models the rate of less healthful options being selected immediately after healthier choices (categorized using the NHLBI Go, Slow, Whoa Heuristic [37]), and the second models the rate at which vegetables are chosen immediately following the selection of an entrée. Significant positive coefficients reflect evidence in support of the hypothesis that the decision-making process involves these norms. That is, a positive effect indicates that selecting healthier foods in the past increases the hazard of selecting less-healthier foods in the future.

Calorie accumulation

We also control for the changing calorie count on the plate as a first-approximation of plate monitoring. When foods are added, we increment the cumulative calorie count by the portion size of the particular selection, and we decrement the cumulative count as food is removed. As no participant leaves the simulation with an empty plate, nor starts the simulation with a full one, the parameter for this statistic is necessarily negative (reducing the hazard of making future selections as time transpires and more food is added to the plate); the magnitude of the coefficient reflects the impact of adding an additional calorie to the plate on the hazard of making a next food choice.

Choice inertia

In addition to the spatial partial-ordering and normative dynamic effects, we add an additional statistic to capture the tendency of past actions to be predictive of future behavior [38]. That is, we add one statistic to the model that captures the effect of picking whatever type of food was previously selected in the immediate past. This effect also captures effects induced by apparent small portion size of the foods because participants may be more likely to repeatedly serve themselves the same type of food since each spoonful yields a relatively small portion. Significant positive coefficients of this effect indicate the process that people are likely to make the same selection they just made.

Choose drink next-to-last

Finally, because drinks are located at the very end of the buffet, we add a separate statistic to the model that

Table 1 Demographic Factors by Condition, Mean (*SD*) or *n* (%)

	Control (<i>n</i> = 73)	Behavioral only (<i>n</i> = 73)	Behavioral + family health history (<i>n</i> = 75)	Total (<i>N</i> = 221)	Comparison
Age	38.5 (5.35)	36.84 (5.93)	37.20 (5.49)	37.50 (5.62)	$F(1,217) = 1.70, p = .18$
BMI	31.19 (5.09)	29.98 (4.26)	30.02 (4.90)	30.39 (4.78)	$F(1,218) = 1.51, p = .22$
College graduate	55 (75.3%)	49 (67.1%)	60 (80%)	164 (74.2%)	$\chi^2 = 3.28, p = .19$
White race	30 (41.1%)	31 (42.5%)	42 (56.8%)	103 (46.8%)	$\chi^2 = 4.45, p = .11$
More than one child	55 (75.3%)	54 (74%)	60 (80%)	169 (76.5%)	$\chi^2 = .82, p = .66$

Between-condition comparisons tested by ANOVA or chi-square test.

captures the effect of “cashing out” immediately following the selection of a drink. A significant positive coefficient indicates that the hazard of the last event goes up whenever a participant selects a drink.

Experimental Effects

Given that exposure to different types of information regarding causal factors for obesity shape aggregate food choice outcomes [7], the selection process itself may also be different based on feedback condition. Here, we use indicator variables to distinguish different processes for participants who received either causal feedback condition versus controls (who received no obesity-related feedback). These indicators are interacted with each statistic in the model (adding $pX2$ statistics to the model). Significant coefficients (in any direction) are evidence in support of the hypothesis that the dynamic choice process differed significantly by that amount between feedback group and control.

Each of the proceeding effects is captured by a sufficient statistic (a random variable that provides no more information than any other). All sufficient statistics except for the calorie counting effect were coded as a set of dummy variables indicating when the focal event involved by that effect transpired in the event history [26]. The calorie counting predictor was coded as the fraction of past calories accumulated as a predictor of the next event.

The Final Model

We fit several candidate models in our preliminary analysis in an exploratory fashion, varying the combinations of the effects described above in each candidate run, and report results from the model with the best fit evaluated by smallest Bayesian Information Criteria. Because we were interested in the experimental effects, we only considered candidate models that included interaction terms between the main effects (baserates, dynamic effects, and calorie accumulation) and the experimental feedback conditions. The final model contained 75 terms; for brevity, we report only the dynamic effects in the body of the text, separated out by each feedback condition.

Results

Mothers were on average 38 ($SD = 5.62$) years old with a BMI of 30 ($SD = 4.78$). Seventy-four percent ($n = 164$) were college educated, 47% ($n = 103$) were white, and 77% ($n = 169$) had more than one child. There were no differences in mothers' demographic characteristics by study arm; see Table 1. Mothers in the behavioral plus family health history information condition served an average of 45 fewer calories than those in the control arm ($p < .05$); those in the behavioral risk only arm filled the plate with 35 fewer calories than the control arm, although the difference was not significant. There was no significant difference in the amount of time spent in the buffet by intervention condition.

Selected results of the relational event model are reported in Table 2. The lambda coefficients (–log hazard multipliers) are Bayesian Posterior Modes of the posterior distribution, and are represented alongside their associated standard deviations. The “ p values” are derived from the posterior quantiles about the mode under the assumption of asymptotic normality (as we use uninformative multivariate t -priors in the estimation these are equivalent to the assumptions held in Frequentist reasoning). The first column reports the main effects (the control condition) and the next two columns report the first-differences between these coefficients and the two feedback conditions. For main dynamic effects, we found significant positive effects for left and right side spatial ordering (1.156 and 1.709, $p < .001$), choice inertia (3.814, $p < .001$), entree-to-vegetable (3.394, $p < .05$), and drink selection to cashout (2.603, $p < .001$). These findings show that there are dynamic effects induced by the environment, such that participants tend to choose foods on the same side of the buffet where they just made a choice, continue making the same selection they just made (i.e. increase portion size), and select drinks last because drinks are placed at the rear of the food environment. These effects also have an exponential waiting time interpretation [29]. For example, the average baserate effect for selecting any food had a coefficient of -5.615 (not shown for brevity). This translates to an expected rate of selection, holding all

Table 2 Relational Events Model Effects Presented According to Intervention Condition

	Main effects (Control)		Behavioral + family health history		Behavioral only	
	λ	SD	λ	SD	λ	SD
Healthy to unhealthy	−0.0349	0.1041	0.0157	0.1453	−0.0188	0.146
Choice inertia	3.8143***	0.0554	−0.1729*	0.0784	0.0467	0.0783
Drinks-to-cashout	2.6032***	0.2855	−0.3226	0.4051	0.5744	0.3946
Calories	−0.0024***	3.00E-04	0.0012***	3.00E-04	0.0001	0.0002
Partial order left	1.1555***	0.1416	0.2623	0.188	0.0219	0.1951
Partial order right	1.7086***	0.0967	−0.0318	0.1353	0.0418	0.1372
Entree->Veg	0.3394*	0.1534	0.05	0.2096	−0.0054	0.2178

Null deviance: 75034.11 on 7048 degrees of freedom. Residual deviance: 54500.85 on 6973 degrees of freedom. Chi-square: 20533.27 on 75 degrees of freedom, asymptotic p value 0. AIC: 54650.85 AICC: 54652.48 BIC: 55165.39. Log posterior: −102324. Prior parameters: $\mu = 0$; $\sigma = 1000$; $v = 4$.

* $p < .05$; *** $p < .001$.

other effects constant, of about 0.22 events per minute ($\exp(-5.615) \cdot 60$) and an expected waiting time of about 4.6 min between events ($1/(\exp(-5.615) \cdot 60)$). Integrating the inertia coefficient into these calculations demonstrates how meaningful the effect is in the simulation: it reduces the waiting time between any two random selection events from over 4 min to about 6 s between two selection events of the same type of food ($1/(\exp(3.814 \pm 5.615) \cdot 60) = 0.101$). Such results add to previous studies which find aggregate effects of the built environment by investigating these aspects in a dynamic model. Furthermore, the entree-to-vegetable main effect suggests that plate-building norms influence selection processes above-and-beyond those induced by the built environment. Finally, we see that there is a significant effect of accumulating calories with every food selection on the hazard of any future selections (-0.0024 , $p < .001$). This result is perhaps unsurprising, since participants are by definition getting closer to terminating their food selection process as they progress through the buffet. There is no significant effect of transitioning from selecting healthful to less healthy food choices.

There were two dynamic effects that differed by experimental condition. Choice inertia in column 2 of Table 2 shows that the behavioral risk plus family health history feedback condition had a slower rate of choice inertia than control. Specifically, the hazard of selecting the same type of food one has just selected is about 45 times the rate of making another, different, choice ($\exp(3.814) = 45.331$, $p < .001$) among the control participants, while it is 38 times for that experimental group. Furthermore, there was an interaction effect of accumulating calories between the control and the behavioral risk information + family health history feedback group, such that the hazard rate modifier for the feedback group

Fig. 2. Expected rate of food choice selection per minute as a function of accumulated calories. Three lines are plotted representing expected participant trajectories exposed to the behavioral risk information + family health history feedback condition in blue, everyone pooled together in black, and the control group in green. Solid lines reflect observed trajectories marginalized over the model parameters and dotted lines represent out-of-sample projections. The figure demonstrates how the model expects that participants receiving behavioral risk information + family health history feedback are more quick to make selections than those receiving control and that they retain a faster rate of food selection through to completion of their final, lower calorie, plates than those receiving control (who slow down considerably as they accumulate a greater number of calories on their final plates). The dotted lines illustrate that these differences would be expected to continue even if participants from both arms eventually accumulated up to 1000 calories on their plates.

is lower than that of controls (0.0012, $p < .001$). This finding suggests that those in the experimental group made future decisions more quickly than control participants. To illustrate, Fig. 2 plots the expected rate of food choice selection per minute as a function of accumulated calories from the model marginalized over the observed data. This shows that: (a) the initial rate of overall food selection differs by feedback condition; (b) the experimental group accumulates fewer calories at a faster rate (they make choices more quickly) than control and, by corollary, the control group accumulates more calories at a slower rate than the experimental groups; and, (c) the effect of accumulated calories slows the rate of choice selection earlier for the control group than the experimental group.

Finally, in terms of model fit, our final model improved over the null with a 27.4% reduction in deviance $(75034.11 - 54500.85)/75034.11 \times 100$, which is akin to a pseudo- R^2 in a generalized linear model. Taken together with the chi-square of the model (20533.27 on 75 degrees of freedom, asymptotic p value $< .0001$), these results suggest that the final model fits well to our data.

Discussion

The current study applied relational event modeling to uncover micro-behavioral aspects of food selection that have broad implications for public health. Our results demonstrate process-level effects related to the built environment, socio-cultural norms of plate construction, and dynamic behavioral differences based on an information-based behavior change intervention. These findings reveal interesting and previously obscured ways in which micro-behaviors lead to aggregate differences in meal composition. Perhaps more importantly, our results highlight how a focus on micro-behavioral dynamics can aid in the development of behavioral interventions.

We turn first to micro-behavioral aspects of food selection that arise regardless of intervention condition: the analyses uncover several temporal patterns that expose how nonconscious and environmental variables exert their influence on food choice. Specifically, we found a significant effect of spatial partial ordering. While previous studies showed effects of manipulating large sections of a buffet [14], our model captures how placement of each food, one after another, on each side of a buffet influences selection. Considering the literature on nudging healthy choices based on placement, these results emphasize that careful consideration should go into the placement of all foods in any public eating environment, rather than considering only the “beginning” and “end.” Additionally, there was a sizable choice inertia effect such that once an individual had selected a single serving of a food, they were far more likely to again select that same food item as their next choice. This is tied to the need to

select a food multiple times to build up desired portion sizes. Previous work suggests that people tend to have difficulty estimating portion sizes precisely and conceptualizing what constitutes an appropriate portion [39]. In addition, portion control is a major barrier to weight management [40]. Thus, to the extent that choice inertia leads to nonconscious portion size increase, the current result identifies a micro-process that helps give rise to this issue. However, the operation of choice inertia also suggests that if one can attract individuals to a healthful food for a single serving, they may also encourage individuals to select more of that food, as opposed to moving to another, potentially less healthful food option. Even so, tendencies toward portion increases could become problematic even for healthy foods if they result in oversized portions. As such, this may be an important area to examine in future work. Finally, norms related to moving from entrée to vegetable in plate construction emerged. This suggests that social norms for food selection processes can influence behavior regardless of the built environment (i.e. whether or not entrées are presented first in a buffet), and should be considered when assessing how to encourage healthful selections. Such results show the limitations of built environment, and that any attempt to “nudge” participants toward more healthful food decisions should consider these embedded and automatic behaviors.

Taken together, these findings demonstrate that assessing micro-level patterns using relational event modeling is feasible and can reveal interesting behavioral patterns growing out of environmental and normative features. The particular patterns of behavior modeled here were chosen to fit with the data set employed in this exercise, and were based on the authors’ *a priori* anticipation of relevant behavioral processes that might impact food selection. Other behavioral patterns could certainly be modeled using this approach to address other research questions. For example, one might want to model moving from buffet to dining table, and back to buffet again. In this way, a wide variety of elements in food choice environments can be studied to inform consideration of potential intervention approaches.

Beyond the main effects found in our model, the current analyses also illustrate differences in micro-processes resulting from the introduction of an intervention. Specifically, we found that only mothers who were exposed to the highest level of the intervention (behavioral risk information *and* family health history-based risk information) differed from the control group with respect to model statistics. This group was far less engaged in choice inertia, suggesting that the feedback may have induced more sensitivity to portion control. No prior studies have investigated the temporal dynamics of portion construction, so this finding adds valuable insight into the point at which our intervention exerted its influence. Relatedly,

this group demonstrated a faster rate of making choices compared to control, despite creating plates with fewer total calories and spending similar amounts of time in the buffet environment overall. This suggests that the feedback facilitated efficiency in this group's food selection. Thus mothers in this group may have entered the buffet with a "healthy food" schema that required less intensive decision-making. It may also be that mothers in the control group took time to recall and attend to food safety guidelines, which may be more cognitively intensive than healthy food schema due to their comparative novelty. Regardless of the underlying psychological heuristic employed, these findings reveal, on a behavioral level, how decision-making differs by intervention condition. In the same way, our approach could be a tool in the evaluation of interventions that specifically aim to alter micro-behaviors.

Despite the insight garnered herein, the current work has limitations. First, the data analyzed here were collected in a virtual reality-based buffet. This simulation lacks some characteristics of a real food choice environment (e.g. food smell). However, the realism of the buffet simulation has been highly rated [19]. In addition, the virtual reality buffet has the added benefit of automated data collection, circumventing the labor and errors sometimes associated with human coders. A second limitation is that participants in the intervention trial were limited to mothers of 4- to 5-year-old children who were making food choices for their child. Future work should be expanded to examine food selection processes for the self to establish that the current findings apply to decision processes in the construction of one's own meal. Finally, the current analyses explored dynamic aspects of a static food environment. Future research should incorporate conditions wherein the ordering and availability of foods is varied.

Beyond the processes investigated here, this modeling approach has wide-ranging applicability for assessing the influence of many other intervention types on micro-level food choice processes. As the public health community approaches consensus about default options and choice architecture, and employs educational approaches to shift normative beliefs and behaviors around food [41, 42], it becomes increasingly important to model the complexity inherent in meal construction. One of the many potential uses of the relational event framework for research on food consumption include scenarios where researchers desire a model that handles dynamic processes involving people's food preferences and choices in real time where estimated effects have a rate of choice interpretation. Experimentally, the model would be ideal to evaluate how manipulations to food presentation (and even exogenous shocks) affect choices made in the immediate future. Thus, the model addresses research questions that modify behavioral dynamics unfolding on relatively short time scales (such as during an experiment

or observation period) but is not well-suited for addressing questions about long-term future behaviors. Through providing the means for such analysis, the current study brings us closer to optimizing the design of interventions that encourage healthful eating behaviors, and to understanding the manner in which health-related decisions are truly made. Only when we understand the process that gives rise to these choices can we begin to effectively alter them.

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Authors' Statement of Conflict of Interest and Adherence to Ethical Standards Authors Christopher Steven Marcum, Megan R. Goldring, Colleen M. McBride, and Susan Persky declare that they have no conflict of interest. All procedures, including the informed consent process, were conducted in accordance with the ethical standards of the responsible committee on human experimentation (institutional and national) and with the Helsinki Declaration of 1975, as revised in 2000.

Compliance with Ethical Standards

Ethical Approval All procedures were approved by the IRB of the Intramural Research Program at the National Institutes of Health, Bethesda, Maryland.

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