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Reciprocal Markov modeling of feedback mechanisms between emotion and dietary choice using experience sampling data

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Abstract

With intensively collected longitudinal data, recent advances in Experience Sampling Method (ESM) benefit social science empirical research, but also pose important methodological challenges. As traditional statistical models are not generally well-equipped to analyze a system of variables that contain feedback loops, this paper proposes the utility of an extended hidden Markov model to model reciprocal relationship between momentary emotion and eating behavior. This paper revisited an ESM data set (Lu, Huet & Dube, 2011) that observed 160 participants' food consumption and momentary emotions six times per day in 10 days. Focusing on the analyses on feedback loop between mood and meal healthiness decision, the proposed Reciprocal Markov Model (RMM) can accommodate both hidden ("general" emotional states: positive vs. negative state) and observed states (meal: healthier, same or less healthy than usual) without presuming independence between observations and smooth trajectories of mood or behavior changes. The results of RMM analyses illustrated the reciprocal chains of meal consumption and mood as well as the effect of contextual factors that moderate the interrelationship between eating and emotion. A simulation experiment that generated data consistent to the empirical study further demonstrated that the procedure is promising in terms of recovering the parameters.

Hundreds of food related decisions - often nutrition sensitive - are typically made by an individual every day (Wansink & Sobal, 2007), and habit is an important underlining force shaping such repeated decisions (Ouellette & Wood, 1998). For example, the nutrient intake of meals systematically differs across occasions in a day (i.e., breakfast is healthier than lunch and supper; de Graaf, 2000). Being referred as baseline habit (Khare & Inman, 2006), such routine are formed in a stable psychosocial environment (Gallimore & Lopez, 2002), and to follow habits is "default" as minimum cognitive effort is required for such decisions (Wood, Quinn, & Kashy, 2002). Furthermore, daily routine are adaptable to changes (Jastran, Bisogni, Sobal, Blake, & Devine, 2009) as decisions are made under the influence

of contextual factors; if context does not dramatically vary across occasions, a decision heuristic is to make similar choices as prior occasion (Aarts, Verplanken, & van Knippenberg, 1998). Such decision momentum sets the healthiness decision for meals (Khare & Inman, 2006), unless there are “unusual” antecedent and/or contextual factors motivate individuals to make change.

Emotions facilitate decisions in responses to the dynamic feedback mechanism between prior behavior and further actions (Campos, Mumme, Kermoian, & Campos, 1994). Particularly, individuals in a positive emotion (PE) state typically avoid cognitive effort and employ decision heuristics (such as keeping habit or decision momentum) to guide behavior (Bless, Bohner, Schwarz, & Strack, 1990). On the other hand, negative emotions (NE) are typically associated with elaborate, goal-oriented processing, goals that often consists of alleviating the unpleasant states through emotion regulation. For example, a field observational study of everyday life eating and emotions demonstrated that when negative emotions are momentarily dominant, individuals are more motivated to eat irregularly and eat for emotional comfort as compared to eating under the influence of positive emotions (Macht & Simons, 2000).

The decisions regarding food healthiness and resulted healthy or less healthy food consumption often influence emotions, but literatures have revealed mixed findings. It has been shown that consuming palatable (usually unhealthy) food had stronger effect of improving mood than less palatable alternatives (Macht & Mueller, 2007), whereas a recent study found eat-induced emotional change was insensitive to the type of consumed food (Wagner et al., 2014). It has also been demonstrated that high-caloric comfort food consumption, despite the negative emotion alleviation goal, sometimes lead to increased negative emotions such as guilt (Dubé, LeBel, & Lu, 2005).

In terms of the location of the meal, it has been shown that the nutritional quality of food is healthier at home than away (Guthrie, Lin, & Frazao, 2002) but such trend has been questioned recently due to the general increase in high-fat and high-sugar foods in packaged meals typically consumed at home (Ries, Kline, & Weaver, 1987). However, recent study (Lu, Huet, & Dubé, 2011) showed that the protective mechanism of home environment lies in emotional reinforcement of healthy meal; particularly, home is the place that PE experience is constantly paired with and reinforces healthy food consumption. Built on the hypothesis that PE keeping decision momentum, we expect that home environment should selectively enhance the PE effect on keeping healthy decision momentum but not on less healthy choice momentum.

Research on the relationship between emotions and behavior primarily study either how mood moderate behavior or how behaviors trigger emotions. By using a sophisticated model, namely, reciprocal Markov model, this study aims to describe, in an everyday life setting, the intertwining feedback mechanisms between emotions and food decisions made for meals. To capture whether a meal was consistent to or deviated from one's baseline habit, this study took a relative measurement, that is, less healthy, healthier or the same as compared to one's “usual” meal at the same occasion (a breakfast episode compared to the

“usual” breakfasts). Such relative measurement allows this study to focus on the analyses of the healthiness decisions of meals, rather than the actual nutrition content of the meal.

METHODOLOGY CONSIDERATIONS

Empirical research on emotion and eating often encounter design and methodological challenges. Emotions of individuals tend to fluctuate throughout the day, and food intake is notoriously difficult to measure. Recent advances in data collection method such as Experience Sampling Method (ESM; Csikszentmihalyi & Larson, 1987; Wheeler & Reis, 1991; Stone & Shiffman, 1994) provide new tool sets for collecting momentary emotion and food intake data. As a novel psychometric technique, the ESM emphasizes the recording of temporal emotions and behaviors while “in the moment.” Data are often collected directly by the individual through devices such as a mobile phone or more traditional means such as journal. More advanced tools that include modern sensing and computational technologies that could automatically trigger sampling events are now beginning to emerge as well (Context-aware Experience Sampling Project, 2012). An advantage of ESM is that the intensively collected data could be used to pinpoint the moment when a behavior - for example food consumption - occurs, and the emotion immediately before or after the specific moment.

In this paper, our goal is to examine the relationship between meal decision and emotion - both before and after the specific episode of meal consumption using ESM data. While the ESM has the promise to gather highly granular data, the analysis of such data also poses important methodological and computational challenges. First, the ESM collected intensive longitudinal data that may not be amenable to standard statistical models that assume independence between observations. Second, because the reciprocity between eating behavior and emotion could be mediated by social environment and personal differences, the feedback mechanism between the two needs to be captured in the social and psychological context - for example whether or not the food is consumed at home or away-from-home (AFH). Although important tools such as system dynamic modeling, which involves difference equation or differential equation, do exist for capturing feedback mechanism, the dynamic between the interaction of eating and emotion is subject to substantial day-to-day, if not meal-to-meal, random fluctuation both in direction and magnitude. For example, there could be abrupt changes of emotion over a short sequence of food intake occasions.

Although specific classes of stochastic differential equation models are able to handle non-smooth changes and feedbacks, episodic changes of direction are not amenable to general system dynamic modeling. Methods such as structural equation modeling (SEM, Bollen, 1989) also have limitations in solving this kind of issue. It is true that the tools such as cross-lagged models (e.g., Finkel, 1995) and non-recursive models (e.g., Paxton, Hipp, & Marquart-Pyatt, 2011) are available for modeling reciprocal relationship. However, as special cases of the SEM, these models are often designed for continuous variables with a small number of time points.

To tackle these methodological challenges, this paper proposes using two discrete-time “intertwining” Markov chains - one latent and one observed - for modeling and computing the dynamic interaction between emotional states and food intake status. In other words,

emotion and food consumption assume a reciprocal relationship in which one influences the other over time as a Markov process. Pre-meal emotional state affects the healthiness decision of the meal, and the meal in turn affects post-meal emotion. A salient feature of the model is no smooth relationship between time and either emotion or meal is assumed. That is, emotion or food consumption is not modeled as a continuous smooth function of time, and these two variables can take specific states that are not necessarily ordered. We call the model a Reciprocal Markov Model (RMM). The RMM can accommodate both latent and observed Markov chains. In this sense, methodologically the RMM is an extension of the hidden Markov model (HMM) (Rabiner, 1990; MacDonald & Zucchini, 1997; Ip et al., 2010; Zhang et al., 2010; Ip et al., 2013a,b) which is in itself an important special case of the dynamic Bayesian network (Ghahraman, 1997). The model is a variation of the latent Markov model which has its root in sociological sciences (e.g., see Humphrey, 1998; Vermunt, Langeheine, & Böckenholt, 1999). The proposed RMM can also be considered a variation of the feedback model discussed in Zeger and Liang (1991), which featured an autoregressive model that involves two Markov chains and a generalized estimating equation (GEE) approach for parameter estimation. An important feature of the RMM is the joint estimation of the model. Instead of estimating individual submodels in a stepwise procedure – e.g., first estimate a submodel for one-way influence of emotion on eating over time, and then a separate submodel for the influence of eating on emotion based on the result of the first submodel – the simultaneous estimation has an advantage of yielding a global likelihood function for inference. This statistical advantage, which also exists in SEM (Bollen, 1989), allows a full range of tests and model assessments that are not possible by using the stepwise approach.

A second advantage of the RMM is its focus on modeling transition between different states of being. Specifically, the social context such as role of the eating at home or AFH within which behavior occurs, together with other important individual characteristics such as that captured by measures of impulsivity can be examined. In other words, the RMM can delineate contextual factors that drive the dynamic in a reciprocal relationship between eating behavior and emotion.

The remainder of the paper is organized as follows. First we provide a description of the data and measure. Next, we discuss the model and estimation methods. The result of analysis of the real ESM data set is then presented. A small simulation experiment that evaluates parameter recovery from RMM follows. Finally we provide a discussion of the model, the empirical finding in this specific application, and limitations of the method.

THIS STUDY

Data for investigating the reciprocal relationship between emotion and eating behavior were collected from 160 White adult nonobese women in a large North American city. Participants were recruited through local advertisement. All participants signed an informed consent form before engaging in the study and each participant received a small incentive for participating. The study protocol was approved by the human subjects ethics committee of McGill University, Canada. The ESM method was used to assess individual eating patterns and both concurrent (after meal) and lagged (before meal) emotional experience on

repeated episodes. Participants received instructions about the ESM protocol in a one-on-one training session conducted at a laboratory. During 10 observational days, a beeper would prompt a participant 6 times/day to fill out a short paper-and-pencil questionnaire at the next available moment. Data were collected over a period of 20 days, with systemic alternation between observational and nonobservational days. Participants were beeped every 2 hours during the typical waking hours (0800 to 2100) of a day. Thus, ideally there would be a total of 60 episodes collected for each participant. At each episode, a participant was asked to report on their eating behavior, including meals and snacks, in the preceding 2 hours and on their momentary emotional states. The reported emotions in this study were participants' current emotional feeling at the moment they filled the questionnaire for each episode. Participants were asked to "indicate the degree to which you experience each of the following emotions at the present moment." For reporting episodes that entailed a meal, each participant was asked to report on the nutritional quality of the meal, i.e., whether it is healthier, the same as, or less healthy than their baseline corresponding meal for breakfast, lunch, dinner, or snack. The baseline dietary habits were established in a face-to-face interview conducted by a nutritionist in the training session, and the protocol was described in detail by Lu, Huet & Dube (2011). In the interview, each participant first described her "typical" food choice for breakfast, lunch, and dinner. The nutritionist then provided information of the nutritional and caloric quality of the described food choices. Participants were explained that they should report the nutritional quality of each meal in this study by indicating how the meal compared with the "typical" meal they had just described. By providing a summary measure of perceived nutritional quality of each meal, the relative dietary measurement approach has the advantage of being highly efficient. The measure has been validated and used in the consumer and food research literature (Block, 2004). The ESM also asked the participant to report the social setting of the meal - whether the meal was consumed alone or with others, whether the meal is consumed at home or AFH, and whether the day on which the meal was consumed was a weekend day.

For measure of emotions, we followed Lu, Huet & Dube (2011) and used the following components: Positive Emotion (PE)-general; PE-peacefulness, Negative Emotion (NE)-general, NE-shame, NE-worry (See also Richins, 1997). Derived from these five observed continuous variables of emotion measurements, the present study operationalized the momentary emotional state as a latent variable with discrete states to reflect the dominant emotions for each episode. In a similar ESM study investigating female participants' emotions and eating in everyday life (Macht & Simons, 2000), the momentary emotions (6 emotion-related items) were classified by cluster analysis, which yielded four emotional states characterized by the dominant emotions of a given episode (Anger-dominance, Tension/fear, Relaxation/joy, and Unemotional state). In the present study, the number of latent emotional states was determined by using an HMM, and resulted only two states, namely positive or negative emotion state.

In order to control individual differences in their sensitivity to positive or negative life experiences, individual measures of aversive and appetitive motivation were assessed before ESM data collection.. The measures of Behavioral Inhibition System (BIS) and Behavioral Activation System (BAS) were derived from standard validated instruments (Carver & White, 1994). Two other demographic and anthropometric measures that were deemed

relevant - age and BMI (self-reported height and weight) - were also measured and included in the analysis.

Reciprocal Hidden Markov Model

The setup for the RMM is rather general in that the model can accommodate multiple chains of both observed and hidden Markov processes. For the sake of illustration, we focus on the current application in which one chain (eating) is directly observed and the other chain (emotion) is not. Consequently, the momentary eating measure and the emotional states were modeled as two intertwining reciprocal Markov chains, respectively observed and hidden. Momentary eating pattern relative to baseline habit, was modeled as an observable Markov process - i.e., the discrete variable indicating eating pattern X_t , for the meal at time t , $t = 1, \dots, T$, only depends on the status of the eating pattern of the previous meal X_{t-1} at time $t-1$. Mathematically, given X_{t-1} , X_t is conditionally independent of eating pattern of earlier meals X_{t-2} and so on. For ease of reading, the subscript for individual is not included here. On the other hand, an HMM was used to model emotional pattern. The HMM is a generalization of the latent class (mixture) analysis, which applies to cross-sectional and longitudinal data. Like a latent class analysis, the HMM delineates latent momentary states using five measures of specific emotions (observed continuous variables: PE-general; PE-peacefulness, NE-general, NE-shame and NE-worry). Given latent state, the observed measures are assumed to be conditionally independent. However, HMM uses data from all time points and “links” data from consecutive time points using the Markov assumption. Specifically, the latent momentary emotion state Z_t of an individual also follows a Markov process. Indicators such as PE-peacefulness and NE-shame, denoted by Y_{jt} , $j = 1, \dots, J$, where j is the subscript for the indicator variable, were used to fully capture the construct. The two Markov processes (one latent and one observed) were linked through their reciprocal relationship in the RMM.

An important feature of the RMM is that it captures the feedback mechanism inherent within the human emotion-behavior system. In other words, a variable X in the first chain at time t is modeled as having an effect on the variable of the second chain Z at time $t+1$, whereas the variable in the second chain at time $t+1$ has an effect on the variable of the first chain at $t+2$ and so on. The interacting chains thus allow a feedback loop to form for each variable; for example, $X_t \rightarrow Z_{t+1} \rightarrow X_{t+2}$. Generally, the RMM does not impose any restriction on the variable type of the respective Markov chains - i.e., the data type of the Markov chain could be discrete or continuous. They could also be either latent or observed. As described above, in the current application, emotional state was modeled as an HMM of which the hidden (discrete) variable is indicated by several continuous observable outcomes, whereas eating pattern is modeled as an observed Markov chain of discrete outcome variable. In the study, the emotional states data collected using ESM were regularly spaced throughout the day. Thus, they were not necessarily aligned to the number of meals consumed. Indeed, the number of reported meals varied substantially across individuals. We attempted two methods to align the emotion and the meal data. The first was to fix the number of daily reported time points to be identical to the number of ESM reported emotion -- i.e., 6 times per day. We then aligned the emotion data that was closest to after a meal. When an emotion state did not have a corresponding meal, we treated the variable for meal as missing-at-

random (MAR). On the other hand, if there were more meals than the ESM time points, then we extended the number of time points and used last-value-carried-forward (LVCF). The second method was to label the meals breakfast, lunch, and dinner according to their occurrence in the day – e.g., breakfast was within the time window between 0800 and 1000, and then align the six time points according to the three labeled meals. As a result, each meal was associated with two ESM emotion states.

Figure 1 shows the structure of the model and the time points. For example, at 0900 the question about the last meal (breakfast, of which the variable was labeled X_1) was asked and the momentary emotional variables were recorded and derived as Z_1 . At 1100 another episode of momentary emotion variables were recorded and derived as Z_2 , and participant reported she did not have a meal in the past two hours. Lunch occurred at 1200 and recorded as X_2 , and the emotional state for that meal was captured at ESM episode 1300 as Z_3 . For episodes that participants indicated there was “no meal”, the meal value was treated as missing-at-random (MAR). MAR implied that the observation of “no meal” did not enter into the likelihood equation. Note that “no meal” is not truly missing in this context and the MAR was used as an operative procedure to implement the likelihood. For a total of 235 episodes (2.4% of 9600 possible episodes), however, participants did not returned the questionnaires, hence we did not have data indicating whether or not they had meal in the past two hours. The MAR assumption was also used when participant missed the entire ESM survey. In other words, the missing observation did not enter the likelihood equation.. Note that Fig. 1 shows a slightly modified cross-lagged structure that reflects the design of the study. The indexes for emotion and meal do not exactly match because of the difference in sampling frequency – emotion was assessed approximately two times as often as meal. A restructured time index thus is required to accommodate the experimental design, as follows. The eating variable X_t was deemed to be influenced by both eating status from the last meal X_{t-1} as well as emotion at the preceding time point Z_{2t-2} . Similarly, Z_t was influenced by Z_{t-1} as well as $X_{\lceil t/2 \rceil}$ where $\lceil . \rceil$ is the ceiling function (e.g., $\lceil 3.5 \rceil = 4$). In this approach, daily data were concatenated into a vector so dinner from the previous day influenced breakfast on the next assessment day the same way as lunch influenced dinner on the same day. We made comparison between the two methods and accepted the second methods as the more realistic method. This is also the approach reported in this paper.

For the HMM for emotion, we first determined the number of latent states (details to be provided later). Given the number of states, the RMM defines two sets of transition models for the RMM: $P(Z_t|Z_{t-1}, X_{\lceil t/2 \rceil})$ and $P(X_t|X_{t-1}, Z_{2t-2})$. Both sets of models are assumed to be homogeneous, i.e., the transition probability from one emotional state to another emotional state is assumed to not vary across time points. The same could be said of eating states. Logistic regression models were also fitted to model the transition between states by incorporating a set of relevant covariates. The contextual covariates included in the RMM were (1) the social variable, eating alone or with others; (2) the location variable, eating at home or AFH; and (3) the weekend variable (weekday or weekend). Personal characteristics included BIS and BAS and demographic and anthropometric variables, and none of the personal characteristics variable was significant in the tested model. Because of the reciprocity structure of the RMM, a collection of conditional models needs to be specified.

In general, if there are S and M states respectively for emotion Z and eating X , there will be $S \times M$ different combinations of conditions. As an example, if there are two states of emotion status and three states of meal healthiness decision, then there are $3 \times 2 = 6$ regression models for each of emotion and eating. Given the emotion status $Z = s$ and eating status $X = m$ at the previous time points, we model the emotion and eating statuses at the current time point using the logistic formulation for ordinal outcomes. Formulations for unordered categorical outcomes are also possible and they are described later. To clarify model presentation, the subject subscript $i, i=1, \dots, n$, is now included. Furthermore, we present the combination of conditions as superscript in parenthesis to highlight cases in which the term is specific to the condition prior to the current outcome.

The full RMM is specified by the following set of equations:

For the mapping between the observed variables (Y_{ijt}, X_{it}) and the latent variables, we have for the emotional variables

$$Y_{ijt} \mid P(Y_{ijt} | Z_{it}=s) \sim N(\mu_{js}, \sigma_{js}^2), \quad (1)$$

where $s = 1, \dots, S$, and for the eating variable, an identity function was used in the mapping, implying that the observed variable X_{it} is directly used for the eating Markov process. The ordinal conditional food consumption transition model is given by:

$$\log \left(\frac{p(X_{it} \leq k)}{p(X_{it} > k)} \mid X_{i,t-1}=m, Z_{i,2t-2}=s \right) = \beta_{0k}^{(ms)} + \underline{w}_{i1}^T \underline{\beta}_1^{(ms)} + c_{ik}^{(ms)}, \quad (2)$$

for $k = 1, \dots, M-1$, and the transition model for emotion is given by:

$$\log \left(\frac{p(Z_{it} \leq q)}{p(Z_{it} > q)} \mid Z_{i,t-1}=s, X_{i[t/2]}=m \right) = \gamma_{0q}^{(ms)} + \underline{w}_{i2}^T \underline{\gamma}_1^{(ms)} + d_{iq}^{(ms)}, \quad (3)$$

for $q = 1, \dots, S-1$, where $\underline{w}_{i1}$ and $\underline{w}_{i2}$ denote the vectors of covariates, which are possibly time varying, for the respective transition models, $\beta_{0k}^{(ms)}$ and $\gamma_{0q}^{(ms)}$ denote the respective intercept terms, and $\underline{\beta}_1^{(ms)}$ and $\underline{\gamma}_1^{(ms)}$ denote the respective sets of regression coefficients.

For the data set that we analyzed, the same set of predictors were used – i.e., $\underline{w}_{i1} = \underline{w}_{i2}$ in (2) and (3), but this is not necessary in general. In order to account for individual differences in the strength of reciprocal influence between emotion and meal, we introduced a pair of individual-specific random effects into the $c_{ik}^{(ms)}$ for the transition of food consumption, and $d_{iq}^{(ms)}$ for the transition of emotion, with $c_{ik}^{(ms)} \sim N(0, \nu_c^2)$ and $d_{iq}^{(ms)} \sim N(0, \nu_d^2)$. These random effects account for intra-person correlation for the transition of psycho-behavioral conditions.

As a reviewer pointed out, in the equations (1)-(3), both the emotional and meal healthiness choice processes share the same discrete time line. While the meal healthiness choice process has missing values, the hidden Markov process, as a special case of the state-space

models, enables the application of elegant options, such as the restructured time index, to accommodate these missing values.

Several remarks need to be made about model (2) and (3). First, the ordinal models make use of the proportionality assumption, which leads to a more parsimonious model than one without the assumption. In other words, in both (2) and (3), the regression coefficients β and γ are not category specific (i.e., they are not function of either k or q), thus avoiding the need to include different regression coefficients for different categories. Under the proportionality assumption, it is assumed that the log odds ratio in the cumulative logit links in (2) and (3) only increases by a constant, as one moves from a lower-ordered to a higher ordered category. The constants are respectively by the category-specific intercept terms β_{0k} and γ_{0q} . Thus, when the states are ordered and the proportionality assumption holds, then the regression coefficients in model (2) and (3) can be interpreted as the conditional effect of a covariate in driving the outcome from a lower-ordered to a higher-ordered state, given the conditions at the time points prior to the current one. The proportionality assumption for ordinal regression can be tested using either exploratory or confirmatory methods (Harrell, 2001).

On the other hand, when the states are deemed not ordered, then models for categorical outcome would be needed to model the effects of predictors on transitions between the unordered states. This alternative – the multinomial mixed effects model – can be specified by the following equation:

$$\log \left(\frac{p(X_t=k)}{p(X_t=M)} \middle| X_{t-1}=m, Z_{2t-2}=s \right) = \beta_{0k}^{(ms)} + \underline{w}_1^T \underline{\beta}_{1k}^{(ms)} + c_{ik}^{(ms)}, \quad (4)$$

where state $X=M$ is used as a reference state. Similarly, the multinomial regression model for the food consumption outcome can be expressed as:

$$\log \left(\frac{p(Z_t=q)}{p(Z_t=S)} \middle| Z_{t-1}=s, X_{\lceil t/2 \rceil}=m \right) = \gamma_{0q}^{(ms)} + \underline{w}_2^T \underline{\gamma}_{1q}^{(ms)} + d_{iq}^{(ms)}, \quad (5)$$

where $Z=S$ is used as the reference state. Note that in Eqns. (4) and (5), unlike Eqns. (2) and (3), the coefficients $\underline{\gamma}_{1q}^{(ms)}$ and $\underline{\beta}_{1k}^{(ms)}$ are no longer uniform across the categories and depends on the modeled category. For the analysis of the real data set reported here, we used ordinal and binary logistic regression respectively for modeling eating and emotion outcomes.

It is possible to directly examine the transition probabilities within the Markov chain, which could be useful as a first step to understand the dynamic of the chains. Mathematically, this is equivalent to fitting a model without any predictor in (2) and (3). To see this, we use a binary logistic example for illustration. Model (3) for a binary outcome can be written as

$$\log \left(\frac{p(Z_{it}=1)}{p(Z_{it}=0)} \middle| Z_{i,t-1}=k, X_{i\lceil t/2 \rceil}=m \right) = \beta_0,$$

or equivalently, we have the transition probability

$$p\left(Z_{it}=1|Z_{i,t-1}=k, X_{i\lceil t/2\rceil}=m\right)=\frac{e^{\beta_0}}{1+e^{\beta_0}}. \quad (6)$$

In the result section, we present both the results for the transition tables without covariates and the conditional regression models for transitions.

There were altogether 2 (outcomes) $\times MS$ (previous conditions) models specified by (4) and (5). For example, if the number of categories in meal condition = 3, and the number of emotion state $S=2$, then there will be altogether $2 \times 6 = 12$ conditional regression models. When the meal and emotion variables are treated as categorical, additional sets for odds ratio of one category to a reference category would require additional significance testing. Because of simultaneous testing, we controlled multiple comparison to avoid “data fishing.” We used the Bonferroni procedure for adjusting the significance level for multiple models. To avoid being too restrictive and the loss of power, we use the total number of conditional regression models tested as the denominator in adjusting the nominal significance level – i.e., significance level = $\alpha^* / (\text{total\#models})$ where α^* is the nominal significance, which was set at 0.05.

Model selection and estimation

We first determined the number of states for the emotional variables using an HMM without the meal variable and without any covariates. Then based on result of the model selection procedure, the number of latent states was fixed for the subsequent estimation procedure. This approach is consistent with the literature in latent class analysis (Huang & Bandeen-Roche, 2004). We used the Bayesian Information Criterion (BIC) for selecting the number of states in the observed emotional data. For jointly estimating the sets of parameters given the number of latent states for emotion, we used a maximum likelihood procedure. For the overall RMM, the components of the parameter set are as follows:

1. The set of prior marginal probabilities of food consumption at the first time point, denoted by $\alpha = (\alpha_1, \dots, \alpha_M)'$, where $\alpha_m = P(X_{i1} = m)$;
2. The set of conditional probabilities for food consumption given latent state at time 1, denoted by the matrix $\tau = (\tau_{ms})$, $\tau_{ms} = P(z_{i1} = s | X_{i1} = m)$;
3. The set of conditional means and variances of emotion outcomes given latent state respectively denoted by $\mu = (\mu_{js})$ and $\sigma^2 = (\sigma_{js}^2)$;
4. The set of regression parameters in the transition model $\beta = (\beta_0^{(ms)}, \underline{\beta}_1^{(ms)})'$ and $\gamma = (\gamma_0^{(ms)}, \underline{\gamma}_1^{(ms)})'$;
5. The set of variances $\nu = (\nu_c, \nu_d)$ specified in the distribution of the random effects.

We used a maximum likelihood (ML) method to estimate the entire set of parameters after the number of latent states has been determined in a separate step. The maximum likelihood procedure is based on an iterative EM algorithm (Dempster et al., 1977) and requires the intermediate step of estimating the following quantities:

- (a) The set of transition probabilities of food consumption given both food and emotion statuses at the previous time point $\xi = (\xi_{kms})$, $\xi_{kms} = P(X_{it} = k | X_{i,t-1} = m, Z_{i,2t-2} = s)$;
- (b) The set of transition probabilities of emotion given both food and emotion statuses at the previous time point $\zeta = (\zeta_{qms})$, $\zeta_{qms} = P(Z_{it} = q | Z_{i,t-1} = s, X_{i,\lceil t/2 \rceil} = m)$.

The basic idea is to derive the so called complete data likelihood as an objective function and maximum the objective function with respect to $(\alpha, \tau, \mu, \sigma, \xi, \zeta, \nu)$ through an iterative process. At each iteration, provisional values for $(\alpha, \tau, \mu, \sigma, \nu)$ are used, and the regression model parameters (β, γ) in the feedback submodels are then estimated by treating the estimated (ξ, ζ) values within that iteration as known. Details are given in Zhang et al. (2010), Ip et al. (2010), and Ip et al. (2013a).

Empirical data analysis

The mean age of the sample was 44.9 (range 18 to 83). In total, 9,365 observations were collected from $n = 160$ participants and an average of 24.7 meals episodes per participant were reported. The BIC values calculated from the HMM for 1, 2, 3, and 4 emotional states were respectively 133,071, 117,669, 100,816, and 179,219. The two-state model was used for its better interpretation. Fig. 2 visualizes the model. Each bar in a panel represents the distribution of the continuous conditional variable given state. The mean is represented by a dot whereas the length of the bar represents 2 standard deviations. We label the states Positive Emotion (PE) and Negative Emotion (NE). For the (observed) healthiness decision of meals, there are 3 states: Less Healthy (LH), Baseline (B), and Healthier (H). Tables 1 and 2 respectively show the conditional transition probabilities between different states for each of the intertwining emotional states and meal healthiness.

Baseline Habit, Decision Momentum and Antecedent Emotion—In terms of the healthiness decision of meals, participants generally were more likely to have baseline meals than H and LH meals, reflecting the adherence to baseline habit (Table 2). The results also revealed the effect of decision momentum, that is, the healthiness of previous meal tended to increase the odds that the same healthiness decision would be made for the current meal. Specifically, if the previous meal was healthier than usual (H), there was 30% chance that current meal would be reported as healthier (H). Comparing to the odds of having H meal (relative to the possibility of having Baseline meal) when previous meal was B or LH, a previous H meals tended to increase the odds of having healthier choice in current meal. If the previous meal was consistent to baseline habit (B meal), the probability of having a B meal (70% and 80% respectively for negative and positive emotions) was higher than that of other conditions (all $p < .001$). Likewise, if previous meal was LH, the odds of having LH meal were higher than the conditions that previous meal was H or B (all $p < .001$).

The results revealed in Table 2 further demonstrated that the antecedent emotions impacted the strength of momentum; and the momentum was stronger if the pre-meal emotion status was positive (PE) than NE. If the previous meal was baseline, the probability of having baseline meal in current eating episode was higher (80%) when the pre-meal emotion was

PE, as compared to when the pre-meal emotion was NE (70%, $p < .01$). If the previous meal was LH, the PE pre-meal emotion was associated with higher probability of LH meal (41%), as compared to when the pre-meal emotion was NE (and 31% of chance having less healthy meal, $p < .01$). When previous meal was H, the likelihoods of having H meal were not impacted by the pre-meal emotional states.

As for the location factor (home versus away from home), compared to eat away from home, the odds of eating healthier food (/baseline) appear to increase when eating at home across all pre-meal conditions (see Table 3: all the odds ratios are less than 1 in the first column). These results indicate that home meals tended to bias the decisions deviated from the baseline habit in a healthier direction.

Interestingly, home environment also moderated the decision momentum effect; as pre-meal PE was associated with stronger momentum effect, such effect was modified by the location of current meal. Specifically, when previous meal was H and pre-meal emotion was PE, home meals was more likely to be H (odds: 0.28) and less likely to be LH (odds: 2.61) than AFH meals. This indicates that while PE had an effect of sustaining H momentum, such effect was particularly stronger in home environment. On the contrary, if the previous condition was LH meal and PE states, current meal decision made at home was also more likely to be H (odds: 0.59) and less likely to be LH (odds: 2.61) than away-from-home. The pattern of these results indicates that although PE tends to sustain a LH momentum, such effect was alleviated, if not reversed, at home.

Emotional Momentum and Meal—Emotional states (PE versus NE) also demonstrated a momentum effect, that is, emotions were more likely to sustain (stays as the same as previous emotional states) than transit. Specifically, if the previous emotion was PE, the odds of experiencing PE (over NE) for current episode was higher than the condition that previous emotion was NE (See table 1). Furthermore, the likelihood of emotion states sustention (or transitions between PE and NE) was impacted by the healthiness of the most recent meal. This study was particularly interested in how meals that deviated from baseline habit (H or LH meals) influences emotional momentum. If the previous emotion was PE, the strongest PE momentum was associated with baseline meal (the highest odds of sustaining PE states: $0.84/0.16 = 5.25$), while having a healthier or unhealthy meal was associated with weaker PE momentum (odds of sustaining PE: H meal $0.8/0.2 = 4.0$ and LH: $0.75/0.25 = 3.0$). If the pre-meal emotion was NE, having an H meal was associated with a higher odds of sustaining NE status (odds: $0.8/0.2 = 4.0$), as compared to a smaller odds ($0.69/0.31 = 2.22$) of sustaining when the recent meal was LH. The pattern of these results indicated that while having a healthier meal could not weaken the negative emotion momentum, having a less healthy meal was associated with an increased probability of transition from pre-meal NE to post-meal PE (less healthy meal could ease the momentum of negative emotion).

Model checking

We used both exploratory tools and sensitivity analysis to assess model fit and to check model assumptions. Evaluation tools for Markov models with discrete-valued outcomes and hidden Markov models are not as well developed as traditional autoregressive models for

continuous outcomes (MacDonald & Zucchini, 1997). The reciprocal relationships specified in the current model added another level of complexity for model checking. For example, for Markov models with discrete valued observed variables, Titman and Sharples (2008) proposed a modified version of the Pearson-type test called AH/F. The idea behind the test is to compare observed and expected cell counts where observed count is indicated by number of observations in the cross-classification (subscript i suppressed) $X_{t+1} = s$, and $X_t = r$, whereas the expected cell count $p(X_{t+1} = s | X_t = r)$ is estimated from the model. The problem with the procedure is that the discrepancy between expected and observed cannot be compared directly to a known distribution, say a chi-squared distribution with known degree of freedom (Titman & Sharples, 2008). In the current application, an additional complication is that there would be more than one conditioning variables – one of them latent- so the following comparison would be required: between the counts in $X_{t+1} = s$, $X_t = r$, and $Z_{\lceil t/2 \rceil} = k$ and the conditional probability $p(X_{t+1} = s | X_t = r, Z_{\lceil t/2 \rceil} = k)$. Again, no known distribution can be used for such comparison.

In the current analysis, we offered several alternative approaches for model checking. First, as suggested by the reviewers of the article, we provided exploratory analysis using plots for the sample data. Second, we used standard methods for checking assumptions by assuming simpler models, without directly resorting to the reciprocal model. For example, we plotted the autoregressive correlation function for the sample data in emotion and examined the Markov assumption. Most importantly, we evaluated the sensitivity of the inferential results to deviation of the assumption on equal sampling in the data. As a reviewer pointed out, the equal sampling assumption is questionable regarding the time interval between the final assessment on a day and first assessment on the next assessment day. The question is related to the first-order Markov assumption mentioned above. To assess the sensitivity of results to this major assumption, we used two simulation experiments to evaluate the robustness of the model to the equal sampling assumption.

Figures 3a and 3b show a small random sample of trajectories of the two selected individual measures – PE-peace and NE-worry - used to characterize the emotional profile. The mean values of the continuous variables for PE-peace and NE-worry are shown as respective dark lines across the time points, and the dotted lines indicate plus/minus one standard deviation (SD) from the mean curve. Fig.3 suggests that while the individual trajectories exhibit substantial fluctuations, the overall level of each individual tend to be generally stable – for example, individuals with low mean PE-peace scores tend to be low over time without exhibiting apparent time trend. Mean NE-worry scores are lower than PE-peace scores when converted to a common scale of 0-150. The mean curve and SD plots of all the characterizing variables for the emotion profile also show that the first two moments on average do not tend to change over time, suggesting stationarity of the process. The p-values for the Ljung-Box test (Ljung & Box, 1978) for NE-worry and PE-peace were respectively 8×10^{-8} and 0.05 (smaller p-value indicates stronger evidence of stationarity). The graphs of the other emotional domains look very similar and are not included here.

Figure 4a and 4b respectively show the sample autoregressive correlation function (ACF) of the PE-peace and NE-worry up to a maximum lag of 20 time points. Both graphs suggest

decreasing autocorrelations as a function of the time lag, suggesting that a first Markov model could serve as a sufficient first approximation for emotion.

Checking autocorrelation for the meal composition measure requires tools for handling discrete variables, of which the literature is not as well developed as that of continuous variables. Overall, the composition of the 3-category meal variable shows approximately 71.7% answered same as usual (baseline) (B), 14.4% selected healthier (H), and 13.8% selected less healthy (LH). Because there does not exist a standard method for characterizing autocorrelations for categorical variable, we used the following approach to derive a measure of correlation for the meal variable between the measure at t and $(t-k)$. First, the data at the two time points were cross-classified into a 3×3 table. Subsequently the chi-square statistic for testing independence, which approximately follows a chi-squared distribution with $df=4$, was derived.

Using the chi-square values as an indication of the strength of association, or the extent of deviation from dependence, the graph in Fig. 5 shows that within each consecutive 6 time points (one day), the association is declining. However, there appears to be a strong daily cyclic component in the dieting behavior. Further verification by using binary data Markov analysis (Goncalves, Cabral, & Azzalini, 2012) showed that the first-order odds ratios were significant ($p < .01$), where second-order odds ratios were not. The binary Markov model is based on logistic regression and can test both first and second-order Markov odds ratios. However, the model can only handle balanced binary data. In our analysis, we coded “healthier” as one category and tested the Markov assumptions against the two other categories combined. Thus, the binary analysis offers support that the eating variable exhibits cyclic behavior but within each cycle (day), the Markov assumption holds.

A related issue to the Markov assumption is that the reciprocal model assumed equal sampling – namely the relationship between assessments on the same day is the same as that between the last assessment and the first assessment on the next assessment day. We conducted two simulation experiments to evaluate the sensitivity of deviation from equal sampling on the parameter of interest – β in equation (2).

In the first experiment, we used a simple first-order Markov autoregressive model and changed the model parameter for selected paths. The autoregressive model that was used to generate the data is given by:

$$Y_t = \mu + \phi Y_{t-1} + a_1 X_{1t} + a_2 X_{2t} + \varepsilon_t,$$

where $\varepsilon_t \sim N(0,1)$; and when $t = 4+3(n-1)$, $\phi = \phi_1$, otherwise $\phi = \phi_2$, and n is a positive integer, $t = 1, 2, \dots, T$. In the experiment, we included two different covariates $X_1 \sim N(0,1)$, and $X_2 \sim \text{Bernoulli}(0.5)$. We set $T=150$, and 100 replications were used in each experimental condition to calculate average bias and root mean squared error (RMSE). The model is designed to mimic the unequal sampling scheme of which the coefficient associated with the last assessment of the day and the first assessment on the next assessment day may attain a different value ϕ_1 , than the value associated with other times ϕ_2 . The interest is on the effect of the deviation – as characterized by the difference between ϕ_1 and ϕ_2 – on the

regression coefficients a_1 and a_2 . Table 4 shows the bias and RMSE of a_1 and a_2 under different experimental conditions. Both bias and RMSE are moderate – for example bias stays small; in most cases the values are less than 4%.

In the second simulation study, we mimicked experimental conditions that were similar to that of the real data set of ESM data. The simulated data contained 4 continuous standard Gaussian manifest variables for emotion, generated for 60 consecutive ESM measurements, together with a 3-category observed variable of food consumption. Three meals per day were also simulated for food consumption. The sample size was fixed at $N=200$ and transition probabilities given previous conditions were generated using the RMM described above. Specifically, transitions probabilities of latent states - i.e., the fixed effect component in the transition probabilities $\zeta_{qms} = P(Z_{it} = q | Z_{i,t-1} = s, X_{i,\lceil t/2 \rceil} = m)$, $m = 1, 2, 3$, $q, s = 1, 2$, and that for the observed meal conditions $\xi_{kms} = P(X_{it} = k | X_{i,t-1} = m, Z_{i,2t-2} = s)$, $k, m = 1, 2, 3$, $s = 1, 2$, were respectively simulated using mixed effects binary logistic model and mixed effects multinomial model. Besides the intercept, only one fixed effect w_{it} , sampled from a standard Gaussian distribution, was included. For random effects for the individuals, independent sampling values were drawn from a standard Gaussian variable.

To mimic possible deviation from the equal sampling assumption, at selected time points noise was added to the parameter of interest (β_1 in this case). The perturbed coefficient β_1^* at the last assessment of a day was specified by:

$$\beta_1^* = \kappa_N R + (1 - \kappa_N) \beta_1, \quad (7)$$

where R is a random variable that follows a standard normal distribution, and κ_N denotes the noise level. Three experiment conditions that corresponded to no, moderate, and high level of noise, were respectively represented by setting $\kappa_N = 0, 0.2$, and 0.8 for β_1^* in (7).

With the set of known parameters, for each experimental condition we replicated 100 times and obtained model parameters for each data set. We evaluated (1) bias, (2) RMSE, and (3) distribution of deviations of estimated parameters from the true value under the three different scenarios of no, moderate, and high levels of added noise to the coefficient that was related to the last assessment of a day. Figure 6 shows the distribution of the estimated parameter values across 100 replications by experimental conditions. The true value in each graph is indicated by the vertical line. The three vertical panels represent the conditions of no, moderate, and high level of noise. Because there are three categories in the multinomial response of the eating variable, we have two sets of regression coefficients β_0 (top two panels), β_1 (bottom two panels), respectively for $\log(p(X_t = 1) / p(X_t = 3) | X_{t-1}, Z_{2t-2})$ and $\log(p(X_t = 2) / p(X_t = 3) | X_{t-1}, Z_{2t-2})$. As expected, bias and RMSE increases with the level of “noise.” The deviation from the equal sampling assumption, however, appears to be largely affecting the intercept β_0 . On the other hand, even when moderate deviation exists (middle panel), the extent of bias and RMSE of the parameter of interest (β_1) appears to be minimal.

CONCLUSION

Using ESM data collected from a sample of women, this article presents an analysis that incorporates feedback mechanism between emotion and behavior. The analysis demonstrates the baseline habit by showing that baseline meals were more likely to be consumed across all previous conditions. As the healthiness of current meal was more likely to be the same as previous meal, such decision momentum is stronger when pre-meal emotion was PE. Furthermore, home environment enhances the effect of PE on sustaining healthier meal momentum and weakened the effect of PE on keeping less healthy meal momentum. As of the meal consumption influencing emotions, a less healthy meal is associated with higher likelihood of transition from NE to PE.

The RMM has the potential to be deployed in applications other than eating behavior and emotion. As a proven tool for analyzing intensively sampled longitudinal data, the HMM has advanced applications to areas including signal processing. In the social sciences, the HMM, as well as the RMM, can be used to analyze intensively collected ESM data, which are becoming more prevalent as mobile devices are increasingly used for momentary data collection. The RMM has the potential to be applied to other socio-behavioral situations in which multiple streams of momentary data are collected. One example is the collection of data related to alcohol consumption. The reciprocal pathways between influence of both positive and negative emotion on alcohol use and vice versa have been studied in depth (e.g., Cooper et al., 1995) and ESM data arising from such situation could be analyzed using RMM. Other potential applications of the RMM include situations in which behavior and psychological states are interrelated and some kind of feedback mechanism exists within such interrelatedness. One example is the self-regulation of health and illness behavior. Emotional processes such as anxiety and denial of disease could adversely affect health-related experience and self-regulation. On the other hand, health conditions such as physical symptomatology and related health behavior such as help seeking could be dynamically linked to depressive symptomatology (Cameron & Leventhal, 2003). The RMM could be used to answer important questions about such dynamic.

The RMM described in this paper is most appropriate for applications in which multiple Markov processes are characterized by either discrete latent or discrete observed variables measured over time. The manifest variables for the discrete latent states can be continuous or discrete. The current application illustrates the case when one Markov process involves a latent variable which is indicated by continuous variables (emotion scores) whereas the other Markov process involves a directly observed discrete variable (meal healthiness choice). It is straightforward for example, to generalize the model to include two latent Markov processes.

By demonstrating the utility of an extended hidden Markov model to model reciprocal relationship within intensively sampled longitudinal data, this paper also offers two methodological contributions. First, in this paper we propose a general Markov model that can accommodate both hidden and observed states. More importantly, we focus on a reciprocal mechanism that allows the examination of possible feedback loop between emotion and eating behavior. We view the proposed RMM model as an important addition

to the statistical toolkit for analyzing social behavioral data. With a few exceptions in methodologies developed by social scientists, traditional statistical models are not generally well-equipped to analyze a system of variables that contain feedback loops (Ip et al., 2013c). The lack of the capacity to incorporate feedback mechanism has long been viewed as a barrier for applying formal statistical models to complex systems. The feed-back RMM proposed in this paper is an attempt to mend the barrier.

A second methodology contribution is the treatment of episodic and rapidly changing processes such as eating behavior and emotion as reported in this paper. Important tools such as SEM and dynamic system exist for handling relatively smooth and linear changes and feedback mechanisms but may not be able to capture episodic events such as change of mood. Additionally, like SEM, the joint estimation of the transition model within the RMM allows global assessment of model fit and avoid potential shortcomings of multi-steps estimation procedures.

There are also substantive and methodological limitations to this study. In the RMM, the emotional states were modeled as dichotomized latent variable, which was linked to five observable specific emotional variables. Specifying individual emotions as continues variables in the model is of greater theoretical interests. Although our proposed model can be generalized to accommodate such specification, the current parsimonious model is motivated by some methodological considerations. First, we intended to demonstrate the capacity of our model in treating latent variables, and the dichotomized latent emotional status was the choice made under such context. Second, by including detailed emotions in the model, more reciprocal chains (within different emotions and between specific emotions and eating) must be specified in the model, which would exponentially increase the complexity of the model. Given the sample size and number of observations in this study, it is very difficult to make a robust testing on such a complicated model.

The rather homogeneous sample in terms of demographics makes generalization of our findings difficult. Also, we did not measure and control for participants' current healthy eating and dieting considerations, which may have impact on meal decisions. In terms of the decision regarding the healthiness of the meal, the measurement was based on self-perception of nutritional quality. Such a self-reported measurement enables the study to focus on the effect of emotions on decision momentum, but is with limitations associated with misconceptions regarding the healthiness of food. Future study would be benefit from a factual food intake measurement to strengthen health implication. The experience sampling data was collected through paper-and-pencil questionnaires, which are tied to some limitations, including the inconvenience for participants filling out the questionnaire when prompted and the difficulty to get precise "time stamp" for each episode (the exact time of filling a questionnaire was self-reported). To overcome such limitations, future studies may take the advantages of new advances on social media, mobile communication, and wearable technologies. The method did not distinguish possible within-day and between-day variations. The assumptions for aligning meals and emotion and of missing and additional meals other than breakfast, lunch, and dinner may not apply to all individuals. Also, the homogeneous transition probability assumption used in the current application can only be considered a first-order approximation, although we expect the fixed effects to capture some

of the heterogeneity in transitions. Because the number of parameters in a fully nonhomogeneous transition matrix grows rapidly as the number of time points, there only existed a limited number of studies that used fully nonhomogeneous transition matrices (e.g., Scott et al., 2000). Finally, Gollob and Reichardt (1987) pointed out the not taking into account length of the causal interval could lead to biased estimates. We expect that the effect of length of interval between assessments to have an effect on the outcome. Thus one needs to be cautious when interpreting the results; the sensitivity analysis provides some indication of the potential level of bias that can result if factors such as between-meal variations and different lengths of interval are not taken into account. Despite these limitations, this article represents a first-step to offer a formal statistical Markov model that captures two intertwining chains of intensively collected data. It also illustrates the complexity and challenges of modeling feedback loops that involve transitions between discrete states.

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Fig. 1.
Path diagram for a reciprocal Markov model.

Fig. 2.
Emotion states derived from a hidden Markov analysis.

(a)

(b)

Fig. 3. Sample trajectories and mean trajectories (solid) line for Positive Emotion (PE)-Peace (a, upper panel) and Negative Emotion (NE)-worried (b, lower panel). The dashed lines across the graphs indicate plus/minus one standard deviation from the respective mean trajectories.

(a)

(b)

(c)

(d)

Fig 4.
The autocorrelation plots for PE-Peace (a) and NE-worry (b), and partial autocorrelation plots for PE-Peace(c), and NE-worry (d)

Fig. 5.
Chi-squared values as a function of time lag for the meal composition variable.

Fig. 6.

Distributions of the estimated parameters for regression coefficients β_0 (top 2 panels) and β_1 (bottom 2 panels) for three levels of noise: low $\kappa_N = 0.0$ (leftmost panels), moderate $\kappa_N = 0.2$ (middle panels), and high $\kappa_N = 0.8$ (rightmost panels). The vertical line represents the true value of the parameter.

Table 1

Estimates of conditional transition (probabilities) table for emotion, $p(Z_t | Z_{t-1}, X_{[t/2]})$

<u>Previous Conditions</u>		<u>Emotional Consequences (Z_t)</u>	
<u>Emotion(Z_{t-1})</u>	<u>Meal ($X_{[t/2]}$)</u>	<u>PE</u>	<u>NE</u>
PE	H	0.8	0.2
PE	B	0.84	0.16
PE	LH	0.75	0.25
NE	H	0.2	0.8
NE	B	0.24	0.76
NE	LH	0.31	0.69

Table 2

Estimates of conditional transition (probabilities) table for diet condition $p(X_t | X_{t-1}, Z_{2t-2})$

<u>Previous Conditions</u>		<u>Meal Consequences (X_t)</u>		
<u>Meal (X_{t-1})</u>	<u>Emotion(Z_{2t-2})</u>	<u>H</u>	<u>B</u>	<u>LH</u>
H	PE	0.30	0.58	0.12
H	NE	0.30	0.57	0.13
B	PE	0.09	0.80	0.11
B	NE	0.16	0.70	0.14
LH	PE	0.10	0.49	0.41
LH	NE	0.11	0.58	0.31

Table 3

Significant odds ratio for the healthiness decision of meal after adjusting for multiple comparison at nominal $\alpha = .05$. The logistic regression models the outcome $\log(p(X_t = H) / p(X_t = S) | \cdot)$ and $\log(p(X_t = LH) / p(X_t = S) | \cdot)$, where $\cdot$ represents the values of the emotion variable Z_{2t-2} and the eating variable $X_{[t/2]}$ from the previous time point.

		<u>Factors:</u>	<u>away from home</u>		<u>with others</u>		<u>Weekend</u>	
Consequence:			H	LH	H	LH	H	LH
Previous Meal	Pre-Emotion							
	H	PE	0.28	2.61	0.55	1.34	1.8	
	H	NE	0.42	0.59	1.88			
	S	PE	0.35	0.34	0.32	1.93		0.62
	S	NE	0.64	0.31	1.7		1.63	0.12
	LH	PE	0.59	2.61				0.71
	LH	NE	0.63	0.62				

*reference category for Location, Social, and Weekend: eat at home, eating alone, and weekday

Table 4

Bias and RMSE of estimates of model parameters in first simulation experiment.

	$a_1=-0.8$				$a_2=0.8$			
	Bias	Bias%*	SD	RMSE	Bias	Bias%*	SD	RMSE
$\varphi_1=0.2, \varphi_2=0.8$	0.0225	2.81%	0.1091	0.1108	0.0468	5.85%	0.1072	0.1166
$\varphi_1=0.2, \varphi_2=0.5$	0.0250	3.12%	0.0916	0.0945	-0.0018	0.23%	0.0895	0.0891
$\varphi_1=0.2, \varphi_2=0.3$	0.0261	3.26%	0.0873	0.0907	-0.0085	1.06%	0.0846	0.0846
$\varphi_1=0.5, \varphi_2=0.8$	0.0264	3.30%	0.0944	0.0976	0.0252	3.15%	0.1066	0.1091
$\varphi_1=0.5, \varphi_2=0.6$	0.0263	3.29%	0.0866	0.0901	-0.0036	0.45%	0.0956	0.0952
$\varphi_1=0.7, \varphi_2=0.9$	0.0276	3.45%	0.0943	0.0977	0.0270	3.38%	0.1125	0.1151

Bias% = Bias/(true value of parameter) $\times$ 100%