Network Analysis of Ecological Momentary Assessment Data for Monitoring and Understanding Eating Behavior

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Abstract. Ecological Momentary Assessment (EMA) techniques have been blooming during the last years due to the emergence of smart devices (like PDAs and smartphones) that allow the collection of repeated assessments of several measures (predictors) that affect a target variable. Eating behavior studies can benefit from EMA techniques by analysing almost real-time information regarding food intake and the related conditions and circumstances. In this paper, an EMA method protocol to study eating behavior is presented along with the mobile application developed for this purpose. Mixed effects and vector autoregression are utilized for conducting a network analysis of the data collected and lead to inferring knowledge for the connectivity between different conditions and their effect on eating behavior.

Keywords: Ecological momentary assessment · Mixed effects · Vector autoregression · Network analysis

1 Introduction

Nowadays, rapid technological advancement has allowed the introduction of modern devices (PDAs, mobile devices, electronic diaries, smartphones, etc.) into the collection and study of -almost- real-time data from real-world environments. These processes provide researchers with a harness of data that need to be analysed in an effective way. Ecological Momentary Assessment (EMA) [16] is an umbrella term for all methods used to repeatedly assess individual subjects in daily life. Reports can be created either randomly (e.g. selecting some time moments per day) or can even be event triggered. EMA has a number of advantages over more traditional methods [14] for the assessment of different measured values and a broad field of applications [13] (such as substance abuse, psychopathology, levels of pain, levels of physical activity, emotional states).

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Another field that EMA can provide more insight is the predictors of unhealthy eating behavior, and thereby can contribute to a better understanding of the mechanisms of eating behavior. The insights gained using this method can be used for developing ecological momentary interventions (EMI) [7], which consists of intervening in real-time, right in the situations in which it is most important, and most likely to have an effect. Furthermore, an open problem is the analysis of these predictors: How the different predictors (e.g. emotions, cognitions) are interrelated, change over time and are related to eating behavior.

In this paper, we present a method for analysing data collected using EMA utilizing a smartphone application and how mixed effects models (ME) with vector autoregression (VAR) can help reveal the network dynamics of how predictors like emotions affect each other but also eating behavior.

2 Related Work

2.1 Mixed Effects Models (ME) and Vector AutoRegression (VAR)

Mixed effects models refer to a variety of models which have as a key feature both fixed and random effects [5]. Fixed effects are ones in which the possible values of the variable are fixed across all samples (e.g. age) whereas random effects refer to variables in which the set of potential values can change (according to the individual). Mixed effects models are utilized in looking into research data where users are organized at more than one level. More specifically, a level-1 submodel describes how individuals change over time (fixed effects) and a level-2 submodel describes how these changes vary across individuals (random effects). The main advantage of mixed effects models is that they take into consideration variation across individuals that is not generalizable to the independent variables.

Mixed effects (ME) models can capture the multiple levels of organisation of EMA data but are not able to show evolution over time or how variables affect each other from one time point to the next. Vector autoregression (VAR) is an econometric model used to capture these interdependencies among multiple time series [18]. VAR models extend the univariate autoregression (AR) models by allowing for more than one evolving variable. Each variable is represented by an equation explaining its evolution based on its own lags and the lags of all the other model variables.

2.2 Studies on EMA Data and ME-VAR Models

EMA research methods use mobile technology (diaries, PDAs, smartphones etc.) in order to collect repeated measurements on the same unit (i.e. humans, plants, samples depending on the study) over time. Variables measured depend on the kind of study (agriculture, medical health, physical sciences, engineering) and can hold continuous, binary or ordinal values. An EMA framework allows the researcher to ask subjects to answer questions or to perform certain actions when predetermined conditions are met. These conditions can be anything from a certain time of day to the occurrence of events of interest, such as being about to eat or being tempted to eat.

Some of the main advantages of EMA methods are: (a) real-time assessments increase ecological validity and minimize retrospective bias, (b) repeated assessments can reveal dynamic processes, (c) multimodal assessments can integrate psychological, physiological, and behavioral data, (d) setting- or context-specific relationships of variables or events can be identified, (e) interactive feedback can be provided in real time and (f) assessments in real-life situations enhance generalizability.

During the last years EMA studies have been conducted in several fields like Tobacco use and relapse [15], social anxiety [9], mood disorders and mood dysregulation [4] and many more. There is also a great variety of EMA studies regarding eating behavior [3,8,12]. These studies demonstrated that by capturing eating behavior in everyday life, it is possible to reveal the factors affecting eating events like hunger experiencing, sorts of (non-)leisure activities undertaken, social circumstances and states of affective arousal (positive or negative emotions).

Combination of mixed effects models and vector autoregression is a technique which gains ground in analysing data (not only EMA). Brain connectivity has been investigated using ME-VAR techniques [6] from a functional MRI dataset. Besides graphical approaches, researchers are able to translate complex relations to tangible networks. For example, in psychopathology, symptom networks (created by interplay between symptoms) [1] can be used to extract useful information. Such network structures reveal that patterns of temporal influence allow symptoms to directly or indirectly connect and interact [2].

3 Description of the EMA Method

An iPhone application was developed in-house that allows people to report potential obesity-promoting factors in real time (see Table 1 for these factors), by filling in brief questionnaires. Such relatively unobtrusive on-line self-monitoring can yield more accurate results than retrospective (questionnaire) assessment. Ecological momentary assessment was performed in two ways: (a) *Event sampling*: participants were instructed to use the application immediately prior to eating something and (b) *Random sampling*: Limited input was requested at pseudo-random time points throughout the day (pseudo-random means that day is divided in 8 boxes and samples occur at random times in each of the boxes aiming at covering all day intervals).

In detail, the application is a logbook, which is used every time the user eats something and when the user is prompted (randomly) to report his/her status. The latter data points are used to generate a baseline by assessing user's status at random moments throughout the day. When an eating moment is about to happen, the user is required to provide short feedback about the emotional state, the food product, the thought that preceded food intake, and the circumstances. In addition, the user is also asked to add a picture of the food intake.

Table 1. Data collection using iPhone application

Variable	Format
Date saved *	date-month-year hour-min-sec
Craving *	VAS item (0–10)
Emotion worried *	VAS item (0–10)
Emotion angry/annoyed *	VAS item (0–10)
Emotion stressed/tense *	VAS item (0–10)
Emotion relaxed/at ease *	VAS item (0–10)
Emotion cheerful/happy *	VAS item (0–10)
Emotion sad/depressed *	VAS item (0–10)
Emotion bored *	VAS item (0–10)
Specific craving *	Selection from a table of 19 images
Location	Free text
Circumstances	Free text
Specific eating *, +	Selection from a table of 19 images
Thoughts regarding to eating +	Free text
Food intake image +	Image file in .png format

(*) denotes variables used in current paper analysis
(+) denotes variables present only in event-contingent samples

The ESM study followed 100 participants (equally divided to healthy-weight and obese, as defined by objective Body Mass Index (BMI) measurements) over the course of 14 days. Every day subjects were randomly notified by a beeper (random sampling) between 0730 and 2230 with an interval of two hours. Besides that, when they are about to eat something they fill out a similar questionnaire but containing the food information. This process resulted in an average of 10 responses (including random samples and eating events) per user per day. The dataset is multi-level and complex containing information about users and their eating events, emotions, circumstances, locations for several time moments during the days they participated in the study. In detail, the information collected using the application are presented in Table 1.

For the purpose of the analysis presented in the next Section, we selected a number of items that captured the mood state of users and the items that captured their eating behavior (they are denoted by (*) in Table 1). Mood states are measured using seven emotions using Visual Analogue Scale (VAS). Regarding eating behavior, the assessment of user's craving (on VAS) was measured in each time point. Also, cravings for specific items have been included by allowing users to select an image (out of 19 possible choices) which is most similar to the craving they experience. There is also the option that users did not have a specific craving. The same idea is applied for specific eating: Whenever an eating event occurs, user selects an image (out the 19 possible) that is most similar to the food consumed. For random sampling events, users are considered to eat nothing at that moment. This broad selection (19 possible choices) allows us to categorize each specific item either to healthy or unhealthy food (where *unhealthy* refers mostly to high caloric food items and *healthy* to all other itmes). This categorization allows specific craving and eating to take three different values: healthy, unhealthy or nothing. So in total there are 10 variables: 8 continuous (emotions and craving) and 2 categorical (craving for healthy/unhealthy/nothing and eating healthy/unhealthy/nothing).

4 Description of the Model

Combination of mixed effects and vector autoregression leads to representations of the model variables based on all other variables' lags (itself included) and each lagged variable has both a fixed and a random effect. An exact description of the mixed effects vector autoregression model of order p (ME-VAR(p)) that captures the data described with (*) in Table 1 is the following:

$$\mathbf{Y}^i(t) = \left[\sum_{k=1}^{p} \mathbf{A}_k^i \cdot \mathbf{Y}^i(t-k)\right] + + \left[\sum_{k=1}^{p} \left\{\left(\mathbf{b}_k^i + \mathbf{c}_k^t\right) \cdot \mathbf{Y}^i(t-k)\right\} + \mathbf{e}^i(t)\right] \tag{1}$$

The explanation of the elements in this Equation is as follows.

1. $\mathbf{Y}^i(t)$ is the vector of variables for individual i at time t. Dimension of vector is R, where R is the number of different variables measured and used in this model, i.e. the variables referred at the end of previous Section.
2. $\mathbf{A}_k^i$ is the person-specific (i) direct connectivity matrix at lag k. This $R \times R$ matrix quantifies how $\mathbf{Y}^i(t-k)$ directly predicts $\mathbf{Y}^i(t)$. The first part of the Equation in the brackets represents the fixed effect part of the model.
3. $\mathbf{b}_k^i$ is the individual-specific random effect which describes the variability in the connectivity among different participants and that is defined by the superscript i.
4. $\mathbf{c}_k^t$ is the time-specific random effect which describes the variability in the connectivity in different time periods of data collection which are defined by superscript t.

   $\mathbf{e}^i(t)$ describes the per-person vector of error terms as Gaussian variables ($e_t \sim N(0, \sigma_\omega^2)$) and also satisfying the non-correlation condition over time.

Equation 1 demonstrates the importance of mixed effects models and how the connectivity matrix can be decomposed into fixed and random components:

$$\mathbf{A}_k^i = \mathbf{A}_k + \mathbf{b}_k^i + \mathbf{c}_k^t \tag{2}$$

where: $\mathbf{A}_k$ is the fixed effect connectivity matrix common in population from which persons are sampled, $\mathbf{b}_k^i$ is the random effect deviation of individual i from the common population connectivity matrix associated to lag k and $\mathbf{c}_k^t$

is the random effect deviation of time period t from the common population connectivity matrix associated to lag k. The elements of matrices $\mathbf{b}_k^i$ and $\mathbf{c}_k^t$ are modelled as mutually independent Gaussian random variables (like $\mathbf{e}^i(t)$).

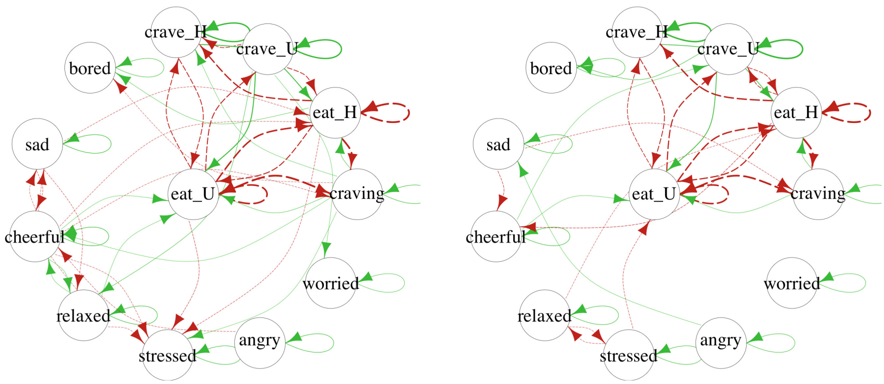
For the purpose of this study, a ME-VAR(1) model was introduced with the variables presented with (*) in Table 1. Because specific_craving and specific_eating are categorical variables, they need to be introduced as dummy variables in the ME-VAR model, by leaving one out as the reference level. Nothing was selected as reference level for both cases, allowing to compare healthy and unhealthy to this. By this coding, R is 12, thus there are 12 Equations (8 for the continuous variables and 4 for craving healthy/unhealthy and eating healthy/unhealthy).

Testing for Significance Among Obese and Healthy-Weight People and Further Remarks. One of our primary goals is to investigate differences in behavior between healthy-weight and obese people. Under the proposed model, this can be achieved by introducing two indicator factors for the two groups (obese and healthy-weight) and replacing connectivity matrix $\mathbf{A}_k^i$ with a formula $\left[\mathbf{A}_{k,ob}^i W_{ob}^i + \mathbf{A}_{k,hw}^i W_{hw}^i\right]$ where W_c^i are used to differentiate between the two groups ($c = \{hc, ob\}$) and $\mathbf{A}_{k,c}^i$ denote the connectivity matrices of each group. Equation 1 is now rewritten as follows:

$$\mathbf{Y}^i(t) = \left\{\sum_{k=1}^{p} \left(\mathbf{A}_{k,ob}^i + \boldsymbol{\Delta}_k W_{hw}^i + \mathbf{b}_k^i + \mathbf{c}_k^t\right) \cdot \mathbf{Y}^i(t-k)\right\} + \mathbf{e}^i(t) \qquad (3)$$

This way the parameter matrix $\boldsymbol{\Delta}_k$ (dimension $R \times R$) is directly tested via $H_0 : \boldsymbol{\Delta}_k = 0$ for $k = 1, ..., P$. Note that when $\boldsymbol{\Delta}_k \neq 0$ then the effective connectivity for the two groups is different at lag k. Using a similar formulation, one can also test for differences in effective connectivity across any other group or parameter than we want to include.

Regarding lagging the data, it should be noted that clock starts again at the beginning of the day, meaning that the last measurement of a day does not affect (or predict) the first measurement of the next day, something which is in accordance with literature (e.g. [11]). Regarding time, it is assumed that the time intervals between two consecutive measurements are approximately equal, but even without this assumption the introduction of time as a random factor (see the next Section for more) overcomes this issue. Stationarity was checked using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test [10] confirming that the data have a (weekly) constant mean and variance and no trend for every subject and every variable. Moreover, despite we present here results for lag=1 (ME-VAR(1) model), we also fitted models for lag=2 and lag=3, as well as a day-aggregated model (i.e. average of variables for one day) where 24 h was the lag. Space limitations do now allow the presentation of these results but since eating unhealthy can be very spontaneous, ME-VAR(1) model is considered to be the best choice for detecting the micro-level changes in people status.



(a) Obese population (b) Healthy-weight population

Fig. 1. Fixed effects networks for lag=1: predicting time (t) from time (t–1) (crave_H= craving healthy, crave_U=craving unhealthy, eat_H=eating healthy, eat_U=eating unhealthy). Green solid line implies that originating item's value at time (t–1) positively predicts endpoint item's value at time (t). Red dashed line implies that originating item's value at time (t–1) negatively predicts endpoint item's value at time (t). Only significant connections are shown, thicker arrows imply stronger relations (Color figure online)

5 Experimental Analysis

5.1 The Population Network

We construct two networks based on the population of obese and healthy-weight people and the ME-VAR(1) model described before. The networks are based on the connectivity matrix $\mathbf{A}_1$ of Eq. 1 as modified by Eq. 3 for the two groups (index 1 will be skipped from now on when referring to ME-VAR(1)). Each network is represented by a graph G comprising a set of $V = 12$ nodes (one for each variable) together with a set of E edges, which are 2-element subsets of V. More specifically, an edge is related with two nodes i and j and its weight is a direct reflection of the coefficient $A(i, j)$, which expresses the strength of the relation between item i at time $t-1$ and item j at time t. To clearly demonstrate positive and negative effects respectively, edges are drawn green when $A(i, j) > 0$ and red when $A(i, j) < 0$). Also, the thickness of edges is relative to the value of $A(i, j)$, meaning that the thicker the edge between two nodes, the stronger the relation between these nodes. These networks (based on connectivity matrices $\mathbf{A}_{ob}$ and $\mathbf{A}_{hw}$) are depicted in Fig. 1. Only significant connections are depicted (i.e. p-value of the t-statistic is smaller than 0.05).

A few general conclusions on the dynamical network structure between the twelve variables can be derived. Obese people have a more dense structure (which implies more complex relations between emotions and eating related events).

Self-loops or autoregressive effects are mostly positive indicating for example that the current experience of stressed predicts future feelings of stressed. The only case that self-loops are not positive is for eating healthy and eating unhealthy, probably because when an eating event occurs, that inhibits the same eating event to happen at the next data point.

Table 2. Predictors for eating events

Predictor	Obese people		Healthy Weighted people	
	eat_unhealthy	eat_healthy	eat_unhealthy	eat_healthy
Craving (crv)	++	++	++	++
Worried (worr)	-	-	+	+
Angry (ang)	-	-	+	+
Stressed (stsd)	-	-	- -	-
Relaxed (rlx)	++	-	+	- -
Cheerful (chrf)	++	- -	++	-
Sad (sad)	+	- -	-	+
Bored (brd)	+	-	-	+
crave_H (crvH)	- -	++	- -	++
crave_U (crvU)	++	- -	++	- -
eat_H (eatH)	- -	- -	- -	- -
eat_U (eatU)	- -	- -	- -	- -

(+) shows positive relation, (++) shows positive significant relation
(-) shows negative relation, (- -) shows negative significant relation

Table 2 demonstrates all (regardless their significance) positive and negative predictors for eating healthy and unhealthy for the two groups (obese and healthy weighted). Some remarks given this Table are:

- Craving positively affects eating either healthy or unhealthy.
- Craving for something healthy (or unhealthy respectively) positively predicts eating healthy (or unhealthy respectively).
- Positive emotions (relaxed and cheerful) positively predict eating unhealthy with relaxed being more significant for obese people.
- Stressed appears to inhibit eating for both groups.
- Sad, bored, worried and angry have an opposite effect on eating for both groups, demonstrating the differences in the two groups.

5.2 The Random Effects Networks

This individual variability can also be immediately observed in the networks of individual subjects. For this purpose, the matrices $\mathbf{A}_1^i$ and $\mathbf{b}_1^i$ of Eq. 2 are utilized. Figure 2 illustrates the individual networks for two persons randomly selected from the obese people sample.

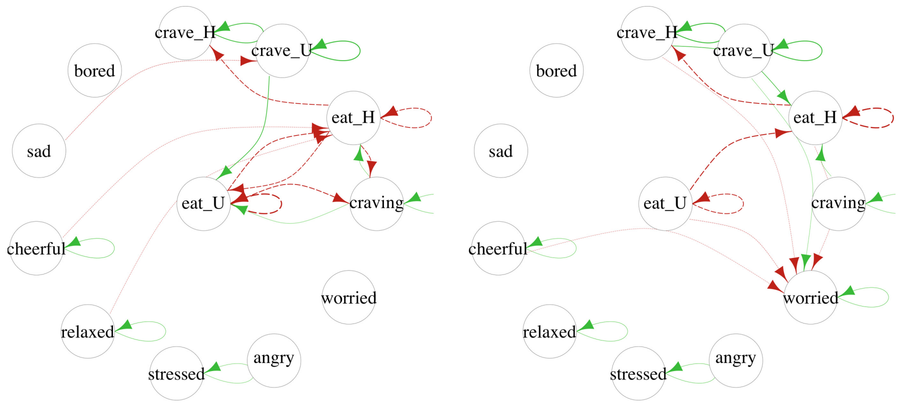
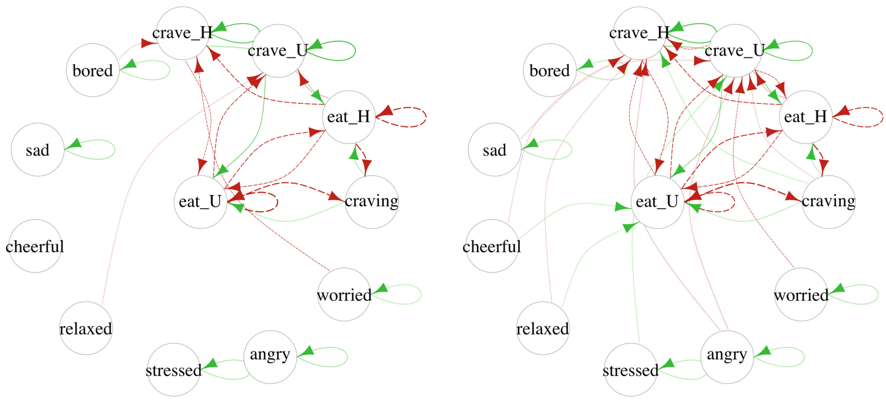


Fig. 2. Individual networks of two different (random, obese) users

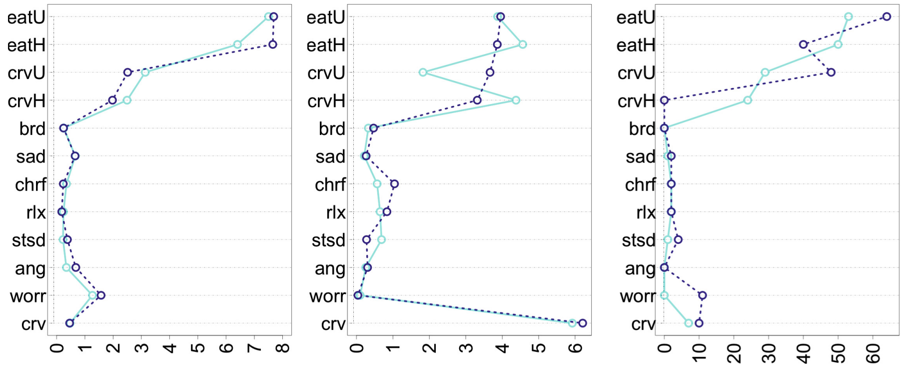


(a) Baseline network for 10:00-12:00 block (b) Baseline network for 18:00-20:00 block

Fig. 3. Networks for specific time periods of day

The network on the left has a quite strong self-loop for craving unhealthy and a strong connection to eating unhealthy, which means that this person has often unhealthy cravings (self-loop) but also tends to give in by eating something unhealthy. Also, the positive emotions have a negative affect on eating healthy. On the other hand, the network of the participant on the right implies that eating in general (healthy or unhealthy) has a negative affect on worried and also craving unhealthy predicts worried. Obviously, worried is an emotion which can be further monitored for this specific user.

Another target of the current approach was to investigate the effect of time of day in the networks but also to eating behavior. This can be achieved by taking into account the c_1^t of Eq. 2. Figure 3 illustrates networks for a morning period



(a) Outdegree of nodes (b) Indegree of nodes (c) Node betweeness

Fig. 4. Centrality analysis of networks of obese and healthy-weight people blue dashed line = obese people, cyan solid line = healthy-weight people (eat{H,U} = eat{healthy, unhealthy}, crv{H,U} = crave{healthy,unhealthy}, brd = bored, sad = sad, chrf = cheerful, rlx = relaxed, stsd = stressed, ang = angry, worr = worried, crv = craving) (Color figure online)

(1000–1200) and for an evening period (1800–2000) for the baseline model (fixed effects of the whole population).

Figure 3b is more dense (because it is dinner time for most people that participated in the study) and also positive emotions have a stronger affect on eating unhealthy compared to Fig. 3a which represents a time block when people do not usually eat. It is obvious that these time-period-specific networks can also be drawn for different groups (obese versus healthy-weight) but also for different individuals, assessing for example, when an obese person is more likely to eat something unhealthy.

5.3 Graph Analysis Measures

By treating these networks as graphs, it is possible to perform a graph-based analysis in order to reveal which nodes (i.e. variables) have stronger effect on the network. Figure 4 illustrates three centrality analysis measures (outdegree, indegree and betweeness values) for the networks of obese and healthy-weight people (see Fig. 1) but taking into account all connections (regardless of significance).

The outdegree is a measure of how a node connects to other nodes (thus it takes into account edges that originated from this node to all others) and shows how this node influences and affects other nodes. Figure 4a suggests that eating (either healthy or unhealthy) severely affects all other nodes (emotions) in the next time point. Outdegree value (for eating healthy or unhealthy) is larger for obese people which is in contrast to craving (for healthy or unhealthy) which takes larger values healthy people.

The indegree is a measure of how other nodes connect to a specific node (thus, it takes into account edges that end up at a specific node from all others) and shows how this node is influenced or affected by other nodes. Figure 4b suggests that craving (numeric value) is severely affected by other nodes. Healthy weighted people also have higher indegree for eating healthy than unhealthy, in contrast to obese people where the relation is slightly inverse. The same pattern applies for craving (either for healthy or unhealthy). Also, positive emotions (cheerful and relaxed) have higher indegrees for obese people, also meaning that they are expected to receive greater effect from other nodes.

Finally, the betweeness value is a measure which is indicative of which nodes are more central in the network, so they are important for defining the status of people at each time point (for more information see [17]). Figure 4c suggests that eating unhealthy is the node with the largest betweeness value (with eating healthy being second largest) and the difference between eating healthy and unhealthy is even larger for obese people, suggesting that unhealthy eating is much more important in defining obese people's situation and status. Other interesting findings are that craving (the numeric value) has larger betweeness value for obese people, suggesting that they eventually experience more craving (and possibly satisfy them more often). Finally, negative emotions (like worried and stressed) also have large betweeness values for obese people, which is also an indication that could reveal interesting dynamic relations between emotions and unhealthy eating.

6 Conclusion and Further Work

In this paper we proposed a mixed effects vector autoregression (ME-VAR) model to analyse EMA data related to eating behavior and emotions. Data were collected using an iPhone application developed specifically for this study and they represent almost real-time information about predictors of eating behavior. The ME-VAR model allows the combination of mixed effects (fixed and random) along with time lagging leading to insightful findings. Results presented suggest that there is a complex network affecting multiple variables and events which can vary not only according to groups of people (like obese or healthy-weight) but also to individual persons and to the time block of day.

Further analysis will involve finding ways to include more complex variables (like location, circumstances or thoughts) which will enhance the ability to monitor persons' behavior (through measuring their data) in order to (early) detect moments that each person will be more prone to eating unhealthy. Ultimate goal would be to utilize knowledge acquired from current analysis in order to accurately predict (person-specific) unhealthy eating moments.

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