Integrating geographic activity space and social network space to promote healthy lifestyles

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Abstract

Obesity is the most critical issue in public health today, the proposed project uses mobile technology to gather information from smartphone users among college freshmen so to construct activity space and behavioral patterns of individuals as related to weight changes. College freshmen tend to be living on their own for the first time in their lives. They are in a critical stage of forming life-long behavioral patterns of food consumption and physical activity. Based on the theoretical construct of activity space in time geography and social influence by social networks, the proposed project will integrate individual behavioral patterns into grouped behavioral trends. The research outcomes are expected to assist in better planning of built environment and better designing of intervention programs on college campuses to reduce obesity. Specific aims to be accomplished are (1) to develop cellphone applications (apps) to collect location information and information of the levels of physical activity of the participating students, (2) to analyze individual behavioral patterns by reconstructing activity space of the participating students over the proposed study period, and (3) to statistically model the association between weight changes and behavioral patterns. Expected research outcome will include quantitative and predictive models for the directions and strengths of the association between weight changes and how college freshmen live their lives in areas on and around college campuses.

1 Introduction

The prevalence of obesity, which is expected to reach 213 million globally, including 113 million Americans by 2022, has become an important social issue [1]. Obesity confers health risks and is associated with diseases and conditions including heart disease, stroke, diabetes and certain types of cancer, among others [2-3]. Often, by the time diseases are diagnosed, it is already too late or too difficult to reverse the trajectory of health outcomes. On the behavior side, individuals show relatively stable patterns of behavior and habits, which seem to maintain their own momentum, becoming resistant to change [4-7]. An individual's activity, such as lack of exercise and fast food consumption, once becoming routine, may directly lead to numerous health issues. In addition, the wide adoption of modern technology, such as mobile phones and online social networks, is increasingly shaping individuals' behaviors and behavioral outcomes and has been linked to poor fitness, inactivity, anxiety, and reduced happiness [8-9]. However, mobile phones and social networks can also be used to promote healthy behavior. For example, several apps are now available to assist individuals in recording paths and burnt calories while jogging. For metabolic and cardiovascular health, clearly behavioral strategies are needed to promote healthy choices. For better formulation of intervention programs and the design of a built environment favoring healthy lifestyle, we need to identify behavioral patterns that promote healthy lifestyles and those that lead to unhealthy lifestyles.

Behavioral patterns can be formulated using approaches suggested in time geography whereby geographical coordinates of the places where an individual visits are 'geocoded' to reconstruct an activity space. The range and temporal information of activity in an activity space provides the needed information to support analysis of an individual's behavioral patterns including food consumption and physical activity. The proposed study will use this approach to formulate behavioral patterns of college freshman. Given the popular belief of 'freshman 15', which suggests that many (not all) college freshmen experience weight gains in their first year living away from home for the first time, study of this population has excellent potential to identify individual differences in patterns of behavior associated with weight changes. Moreover, freshman year in college is a critical period when long lasting lifestyles are formed. Here, we propose to develop strategies to identify healthy and unhealthy behavior patterns using technology to track and define individuals' activity space and their levels of physical activity in the following Aims:

AIM 1: Develop cellphone applications to collect geographic coordinates and corresponding levels of physical activity
We will develop and perfect two cellphone apps to record geographic coordinates and the length of stay of a cellphone's location and to let students report their diets and physical activities. The developed apps will use mobile phone accelerometers to detect and record the levels of activity at each location. The collected information will be automatically uploaded to our server and merged into a database for subsequence analysis.

AIM 2: Analyze behavioral patterns using time geography
Upon the completion of data collection, we will analyze the locations and durations of participants' activity. An activity space will be constructed for each participant. Detailed analysis of locations, durations of stay, and levels of activity will be analyzed and quantified. Based on the collected data, a hierarchical cluster analysis will be carried out to classify collected data into a number of groups that have minimal in-group variation and maximal between-group variation. These identified clusters will form the basic classification of behavioral patterns.

AIM 3: Model the association between weight changes and behavioral patterns
With the classified behavioral patterns and reported weight changes, quantitative and predictive models will be constructed using multivariate regression models to assess the directions and strength of the association between weight changes and the patterns of activity spaces and the patterns of physical activity in each of the different types of behavioral patterns. We expect individuals with different behavioral patterns will likely be associated with different levels of weight changes. We will develop the behavior models and analyze relationships between behavioral patterns with health outcomes. We will publish the data and the software we developed, and we will create the database of information collected from project participants to be used for data analysis and for suggesting intervention programs and principles for better designing built environment on college campuses based on project's research outcome.

The long-term goal of this project is to use the identified behavior patterns to identify optimal strategies to promote healthy lifestyles in subgroups of people.

2 Research Strategy

2.1 Significance

Obesity is the most critical issue in public health today. Since the 1960s, the prevalence of obesity in adults age 20 and older has more than doubled, increasing from 13.4% to 34.9% in 2011-2012, with an additional

31.8% classified as overweight. Even more concerning, the prevalence of obesity in adolescents age 12-19 has increased to 20.5% [10]. Proposed explanations for the obesity epidemic include food price and quality [11-12], the consumption of nutrient-dense food and drinks [13], food stores and restaurants [14-15], neighborhood safety concerns [16-17], socioeconomic status [18-19], and the development of an obesogenic environment [20-21]. Though there are biological and genetic bases for obesity tendencies [22-23], we need to support healthy behaviors to maintain wellness. Part of that is determining which facets of people's living environments are problematic to long-term maintenance of health and wellness.

Obesity is an exceedingly complex public health problem. Biologically, weight gain is determined by calorie intake and expenditure, but what causes different people to alter their energy balance is much more complex, with hypothesized causes at multiple interacting levels that are embedded in the very structure of society. This complexity appears to be the reason that most one-dimensional, non-surgical preventive or therapeutic interventions have not met with long-term success [24]. Take, for example, the Foresight causal map prepared by UK Government Office for Science, which illustrates the inherent complexity of obesity as a public health problem [25]. The Foresight map was built around energy balance and mammalian physiology, but obesogenic policy determinants of the relevant physical, food, and built environments were excluded, which seems to limit the applicability of that approach. Obesity, per se, is only a small part of a larger public health problem that includes obesogenic policy, environments, and population characteristics.

Obesogenic policy, environments, and individual and population characteristics all interact to promote or support unhealthy lifestyles. These individual and population characteristics include unhealthy dietary habits, sedentary behavior, high prevalence of obesity, high obesity-related morbidity and mortality, and high rates of diabetes or cardiovascular diseases among historically disadvantaged groups. Poor health status is shown to spread through social connections [26-28], potentially contributing to the avalanche of obesity in our society in a relatively short period of time [26]. In addition, the wide adoption of modern technology, such as mobile phones and online social networks, is increasingly shaping individuals' behaviors and behavioral outcomes and has been linked to poor fitness, inactivity, anxiety, and reduced happiness [8-9]. Addressing these challenges requires new approaches that specifically incorporate associated built, physical, food, and socio-economic environments. Timely and rigorous analysis of these facets of obesity will open up a rich empirical context for the social sciences and policy interventions. Such highly topical subjects, however, increase the challenge and difficulty of deriving effective, validated, and convincing information. Problems of population, policy, and environment at the system-wide level can be attacked by gathering and analyzing data at the individual level.

Technology has increasingly been incorporated into research to allow for more individualized behavior to change or formulate intervention programs. Reviews conducted on technology-based interventions for healthy lifestyle demonstrate mixed effectiveness of technology in changing health behaviors and outcomes, partially due to highly variable study and intervention methods [29-35]. However, Khaylis et al. (2010) identify five key components for successful technology-based weight loss interventions, including self-monitoring, feedback and communication, social support, a structured program, and an individualized approach [31]. The potential effectiveness of tailored, technology-based communication was further supported by other reviews [36-37].

We propose to model the interplays between behavioral patterns and obesity as a health outcome by building a quantitative, predictive model to associate factors forming behavioral patterns to outcomes affecting obesity. We intend to focus on college freshmen who are mostly living on their own for the first time in their lives. The famous term 'freshman 15' suggests that weight gains are a common problem among first-year college students. We will simultaneously model both of these components using spatial hidden Markov models wherein there will be a pre-defined set of states that will be fixed to the model.

Using this approach, we will be able to model the daily activities of the individuals using the spatial correlations between the locations. With participants' circles of friends (social networks), we will analyze the similarity in behavioral patterns among those in the same social groups. Understanding their behavioral patterns and how students settle into a new environment, the proposed study will provide a basis for addressing these issues and for better planning of daily activities and the design and layout of the built environment on college campuses. Using these research outcomes, appropriate interventions or educational efforts may be offered to freshmen to encourage developing a healthier lifestyle upon starting college. We will utilize the Poisson regression to model the association between estimated health outcome as measured by weight changes (dependent variable) and behavioral variables such as the types and levels of physical activity and geographic activity space, the types and frequency of food consumption, and memberships of social networks. Though outcomes from research on the 'freshman 15' referred to here are variable [38-41], we aim to identify relationships between those who do gain weight and how that is associated with levels of physical activity, patterns of food consumption as measured by frequencies of visits to different types of restaurants, and the influence from social networks. We do not argue 'freshman 15' as a certain consequence, nor a myth. The proposed project simply extends our research to examine variability of weight gain in freshmen.

2.2 Innovation

With the proliferation of cellphone use, many smartphone users have installed various applications (apps) to conduct a wide range of activity. At the same time, a smartphone's internal device may be used to passively record the locations, temporal durations, and levels of activity of the phone owners. The proposed project integrates the use of smartphones, social networking among phone users, and the concept of activity space from time geography, to study how behavioral patterns are associated with weight changes in college freshmen. In particular, our proposed new approaches include the following:

- Model behavior patterns and characterize individuals' behaviors in the presence of social influences.
- Identify key behavior factors and patterns for predicting health status.
- Leverage data collected by mobile device and identified social networks to effectively associate changes an individual's unhealthy behaviors and spread community-wide wellness.

The current literature on weight changes as an indicator of health outcome lacks systematic studies on large groups of college freshmen. Many of our target population are beginning to live on their own for the first time in their lives so it is critical to understand why and how sedentary lifestyles begin. By carrying out the proposed study, we will reveal the relationship between behavioral patterns and weight changes, as well as how social networking may impact such outcomes, as illustrated in Figure 1.

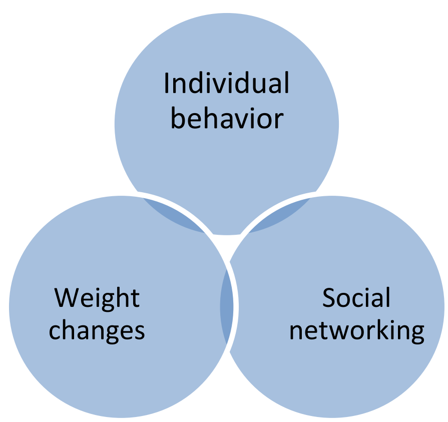

Figure 1: Behavioral patterns, social networking, and weight changes.

3 Approach

This research integrates mobile devices and social networks under the conceptual framework of time geography. Recent advances in mobile technology provide new opportunities to support healthy behaviors and to maintain wellness. The next challenge is to better understand human behaviors with social connections, identify key behavioral indicators affecting health status, and design effective social and community awareness and intervention approaches to reinforce an individual's healthy behavior and wellness. The reason for focusing on college students is not only because they form a well-recognized community and their activity is relatively easy to track and collect, but also many individuals tend to experience rather significant weight increase, such as the "freshman 15" phenomenon [38-41], and are particularly vulnerable to developing bad habits and addictions in their first experience living on their own. For most students, the period of college is the starting point of their lives independent from their parents. This is when they start to form their own behavior patterns and lifestyles. While not all freshmen gain weight in their first year in college, the mix of different lifestyles and weight gains provide an excellent setting for us to study the potential causes and health outcomes associated with individual differences in patterns of behavior. Understanding their behaviors in this period and providing early intervention may help them adopt a healthy and positive lifestyle potentially benefiting their entire lives. Finally, the approaches developed and findings discovered in the proposed project have the potential to be translated to other communities and populations as well. In this project, through modeling individual behaviors and understanding their relationship to health outcomes, new social-network based intervention approaches may be designed and introduced to help promote community-wide healthy lifestyle adoption.

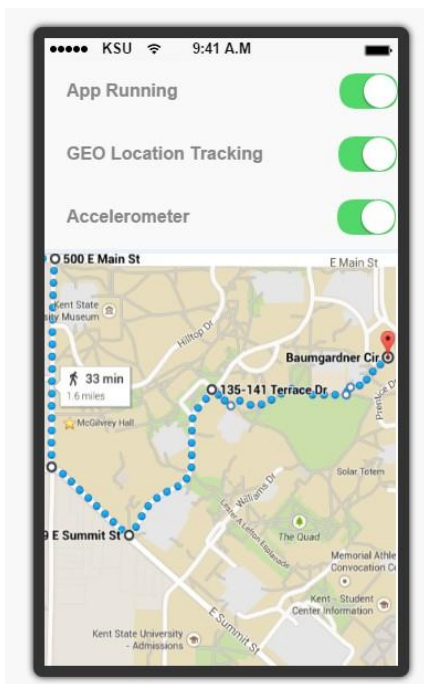

Figure 2: Prototype App

AIM 1: Develop cellphone applications to collect geographic coordinates and corresponding levels of physical activity.

Using the GPS and accelerometer units in smartphones, the apps to be developed by the proposed project will track the movements and levels of physical activity of the phone owners to facilitate the analysis of behavior patterns of individuals. Collected data will be used to support the analysis and modeling of the behavioral patterns of the phone owners.

Method: We will develop a smartphone application (app) to:
(1) passively record the coordinates and the lengths of stays at these locations by participants, and
(2) record the levels of physical activity of the participants at these locations.

Using detected levels of motion of the phones (by the accelerometers available in most smartphones), we can determine if the phone owners are mostly sedentary, moving around, or actively engaging in exercise at any location. The recordings will be extended to cover a semester in time. Collectively, coordinates of visited places will allow us to build a database to summarize individual behavioral patterns into grouped behavioral trends. Figure 2 shows a prototype of the cellphone app we have developed. It has the components for tracking movements and recording levels of physical activity. It also has a map that shows the geographic activity space. We will continue to improve it after field tests.

AIM 2: Analyze behavioral patterns using time geography
Rationale: The proposed study takes the approach of integrating individual behavioral patterns to form group behavioral trends. This bottom-up approach is effective in accounting for variations among individuals yet allowing integrated group trends to be discovered. The finding that geography can impact social contacts has been well documented in the literature of time geography [42-50]. Temporal changes in geography (or living environments) can be a key element in the ways people change their behavioral patterns (individually) and social behavioral processes (grouped). Time geography typically constructs paths of movements by individuals that trace the locations and durations of visits by individuals. Such paths are then aggregated to form grouped behavioral trends. In the process of aggregating individual paths into grouped ones, different aggregations can be applied based on the characteristics of individuals. This method offers a feasible approach to analyzing individual behavioral patterns and to derive social behavioral processes through integration of individual records.

Study population: Kent State University has a total student population of over 40,000, including all 6 campuses. The main campus, Kent Campus, which welcomes over 3,000 new students annually, will be our focused study area. Particularly suitable for recruiting participants to the proposed study is Destination Kent State (DKS), an orientation program held each summer before the freshman class enters the university. Requested funding will be used to compensate participating students and to support programming, data management, and data analysis. Most of the first-year students are required to live on campus at Kent State University, with only a small number of exceptions if their homes are within 5 miles from the campus.

- This study's initial recruits will be limited to 18-25 year old freshman students and segmented by self-reported biological sex, race, and ethnicity. We will sample an even distribution of self-identified males and females. We will recruit a stratified sample of self-identified racial and ethnic groups based upon the Status and Trends in the Education of Racial and Ethnic Groups report from the United States Department of Education which indicated the proportion of racial/ethnic groups represented in undergraduate American universities [51]. We will not control for the sex, race, or ethnicity of the friends, thus we will not estimate sample sizes of males and females or various races/ethnicities for the final sample. We expect a distribution representative of student population & will adjust if necessary.
- Students will be categorized as normal weight, overweight, obese, and severely obese by BMI data based on their measured weights. Participants will be divided into 4 subpopulations: those with BMI < 25 (normal weight), those with BMI between 25 and 29.9 (overweight), those with BMI between 30 and 39.9 (obese), and those with BMI equal to 40 or more (severely obese).
- The potential moderators (demographic variables) will be collected from each participant with a brief paper survey administered at the entry interview at the beginning of the Fall 2016 semester study period: age, gender, race, and ethnicity.

Data Collection:

- **Physical Activity, Sedentary Behavior, and Food Consumption.** Once installed, the cellphone app will record locations and levels of activity of the cellphones with a fixed interval of once every 15 minutes. We assume participants, as most cellphone users do, will keep their phones on with only brief periods of down time each day. The collected information will then be overlaid on a digital data layer that contains locations and types of stores, facilities, and structures. Through overlaying collected coordinates and lengths of stay, we will be able to reconstruct activity space of participants' behavioral patterns anonymously. This includes locations and frequencies of visits to food outlets, study halls, exercise facilities, parks, or time spent jogging along sidewalks of streets, for example.
- At the end of the semester, participants will be measured for their weight gains or losses, which will allow analysis be carried out in structuring collected records into control groups (those student whose weight changes are less than ±5 lbs) and the comparison groups (those students whose weight changes are more than ±5 lbs). Measuring the weights of participating students allows us to acquire more accurate information as it has been documented that it is possible for weights to be under-reported [52] if left for self-report. Regarding the measured weights, we intend to assure participants that their responses will be anonymous and to provide information to explain the value of correctly reported weights.
- Because this research will also focused on the influence of social networks on health related behaviors, each of the initial participant's social networks will be sampled. Each of the original 50 participants will provide a list of up to their ten best friends who are also registered students at Kent State University. Investigators will then recruit three friends for each of these initial participants leading to a final sample size of 200 (50 initial participants * 3 friends + 50 initial participants). If we are unable to enroll three friends into the study from the initial list of 10 friends, research personnel will obtain additional names of friends from the participant until at least three total friends are enrolled. We expect a distribution representative of student population and will adjust if necessary. This reported social grouping will be used to construct social networking to be integrated in the analysis of behavioral patterns [53].
- For the purpose of cross-references, participating students will be prompted daily to report physical activity, sedentary behavior, diet, and anxiety.
- After the completion of data collection over the semester, the apps will be removed from the phones, and participants will receive the balance of their payment.
- Data analysis and dissemination of findings will be ongoing until the conclusion of the project.

Data Analysis:

- **Data mining methods** will be used to analyze information collected via cellphone app to derive behavioral patterns of people's food consumption, physical activity, and lifestyles on campus. Such behavioral patterns will be used to assess and predict trends of obesity prevalence.
- **Modeling of collected data** will start with **Step 1**: constructing behavioral patterns for each individual by organizing the coordinates and physical activity collected via cellphone apps. These data will be structured into a set of independent variables, including (a) types and frequencies of visits to food outlets, (b) types and frequencies of visits to gyms or exercising facility, and (c) levels of physical activity. **Step 2**: hierarchical cluster analysis will be used to classify all individual behavioral patterns to create a typology of behavioral patterns. **Step 3**: Using the average and the standard deviations of the measured changes in weight as dependent variable, regression models will be conducted to detect the direction and strength of the association between weight changes and the independent variables for each classified behavioral pattern.
- This study will examine student behavioral patterns and health outcomes. Initial participants will be recruited for the 2016 Fall semester. Location information (coordinates collected by cellphone GPS)

will be overlaid over a digital data layers of stores, buildings, streets, sidewalks, parks, and other facilities in and around the campus. Financial incentives will be provided at the level of $400 over a semester, $200 at the entry interview and $200 at the conclusion interview. At the entry interview, each participant will have two cross-platform cell phone apps specially designed for this study installed on their cell phones:

The first application will record geographic coordinates and levels of physical activity of the phone user. The collected data will be used to perform analysis and to predict sedentary behavior and cardiorespiratory fitness [8]. **The second application** will prompt participants to complete daily measures of self-reported physical activity, sedentary behavior, diet, and anxiety. Participants will then receive a briefing on the apps, have an opportunity to explore their use, be assured of their privacy, and ask any questions they may have. Students will be measured for height and weight after being interviewed for basic information. Participants will then exit the lab and return in two weeks to ensure their understanding of the apps and their proper use of the apps. At the concluding interview, students will be re-informed of the anonymity of the data collected, provided with information about how the collected data will be aggregated and analyzed, and have their weights and heights re-measured.

- **With the data analysis, we wish to explore:**
  - How the types and frequency of visits to different food outlets may be associated with weight changes.
  - How the levels of physical activity may be associated with weight changes.
  - How the social networking among peers may be associated with weight changes.

The study approach outlined here allows us to measure the variables of interest in several ways. First, BMI and body composition will be objectively measured at the beginning and end of the 2016 Fall semester. Second, proprietary cell phone applications will record geographic coordinates and the length of stay of a cellphone’s location and prompt the participant to complete self-report measures for the behaviors of interest. Many validated behavioral recall surveys and/or studies that objectively monitor behavior (e.g., assessing alcohol consumption, eating, physical activity behavior) are designed to assess behavior for a brief period of time (e.g., one week) yet are accepted as accurate estimates of the behaviors under investigation [54-55]. Therefore, will plan to monitor the variables over a period of one semester is well within the standards set by previous studies and will provide an accurate estimation of behavior.

Analysis:
Using the **susceptible-infectious-recovered (SIR) model** [24], changes in weight will move a person between subpopulations of normal, overweight, obese, and severely obese categorization. We anticipate that freshman participants will show a weight increase in general, with the levels of changes associated with different behavioral patterns to be identified by the proposed study. Changes in weight may be due to dietary changes or changes in levels of physical activity. Changes in weight over the course of a semester as shown in the collected data will allow us to analyze how such changes occur in association with individual behavioral patterns by looking at the places visited, the duration of visit, and what levels of activity occur at these locations. We will build a quantitative model to describe the relationships between behavioral patterns and levels of weight changes.

Beyond this exploratory project, we plan to carry out additional projects in the future to explore the causes of obesity prevalence and ways to curb it. Using data collected over multiple years, we will be able to calibrate and fine tune the model for practical uses such as devising intervention programs to reduce weight gains, changing university policies regarding meal plans, and informing design of built environments.

AIM 3: Model the association between weight changes and behavioral patterns
Rationale: The proposed study will promote healthy lifestyles through a comprehensive and

accurate assessment and analysis of human behaviors and day-to-day activity. There have been many studies in computer science aiming to model and even predict human behaviors. For example, Eagle and Pentland [56-57] explored harnessing data collected on regular smart phones for modeling human behavior; Ziebart et al. [58] developed a conditional probabilistic model for predicting human decisions given the contextual situation; and Sadilek and Krumm [59] proposed a nonparametric method that extracts significant periodic patterns in location data, learns their associations with contextual features (e.g., day of week, holiday, etc.), and subsequently leverages the patterns to predict the most likely location at any given time in the future. In behavioral and social science, interpersonal-level and community-level theories that recognize the role of multiple levels of influence on behavior will be evaluated and applied to intervention efforts as appropriate, including Social Cognitive Theory [60], the Integrated Behavioral Model [61], theories of social networks and social integration [62-64], and theories of community intervention [65-66].

The aforementioned modeling approaches provided the conceptual foundation for the modeling processes in the proposed project. In the modeling processes, participating students will be asked to provide anonymous information regarding their lifestyle and individual attributes, with their consent. Individual attributes include age, gender, race, ethnicity, weight, and height. In addition, participating students will be asked to identify their activity space (locations of residence and daily activity). Finally, the proposed project will invite students to contribute information of their social networks (e.g., friendship circles, memberships in social groups, academic standings, majors, and the like).

For the purpose of observing and understanding the impacts of **social influences** on participants' healthy lifestyles, we assume that some students will function as opinion leaders and/or as activity organizers who receive and disseminate messages from both online and offline social networks. In addition, the proposed project will also assume that there will be events and intervention programs on campuses and nearby communities that may promote or demote agents' healthy lifestyle. For example, fast food promotions as well as social events such as traditional college parties may demote agents' healthy lifestyles, but interventional programs, such as those by student health centers and campus gyms, may promote agents' healthy lifestyle. These will be incorporated in the modeling processes and later on when analyzing collected data.

Lastly, we can analyze the impact of physical activity on weight gain. For example we can use regression and correlation analyses to determine if level of physical activity (acceleration per day) is negatively correlated to weight gain (i.e., if those who are more active resist gaining weight).

4 Evaluation Plan

For the individual behavior modeling, individuals' behavior records are divided according to time series. We will use the first few weeks of data to train the model and the rest of the days for testing (from both public and our own collected data). In addition, for the accuracy comparison, we will compare our approaches with a few baseline methods, such as Logistical Autoregression (LAR) and basic Gaussian Process (PGP) [67]. In other words, the models to be developed can be expressed as $\Delta C = f(f, p, s) + \varepsilon$, where ΔC is weight change, and f and p are two sets of independent variables representing behavioral patterns of food consumption and levels of physical activity. Finally, s is a set of variables indicating individuals memberships in circles of friendship and social media. In linking behavior to health outcome, we will utilize cross validation mechanisms on the data we will collect. Similar to the evaluation of user behavior models, the time periods will be suitably discretized and the final goal of the model will analyze the correlation between individual behavior and their health status as indicated by their weight changes.

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