Developing Behavioral Interventions and Visual Intervention Displays for a Mobile Health Application

A Major Qualifying Project
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By

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Abstract

A previous MQP group (MQP CR-1502) created an app called 'SlipBuddy', an Android application that collects data about overeating episodes, identifies patterns in users' behaviors and provides interventions when they are likely to overeat. Our project was committed to improving and adding to the application's existing functionality.

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1. Introduction

According to the Center for Disease Control and Prevention, 36.5% of US adults are obese (Prevention, 2016). Obesity is an epidemic spreading across our country as a result of eating too much, exercising too little and the convenience of high-portion, high-calorie fast foods (Stewart, 2006). According to Marion Nestle, PhD, MPH, chair of the department of nutrition and food studies at New York University, corporate competition encourages higher portion sizes, which results in overeating, and the spread of obesity (Stewart, 2006).

But how do you counteract such a widespread problem?

The National Heart, Lung and Blood Institute believes that watching portion size is a key component in the fight against obesity (National Heart, 2012), which supports Nestle's claims, in addition to healthy exercise and dietary habits. Also, the American Obesity Treatment Association (American Obesity Treatment Association, 2008) believes that behavior therapy is a very useful and viable method to implement those attitudes.

This is not new territory. There is a plethora of dietary apps on the market. They mostly take in users' calorie counts to tell them when they are overeating. But this has three major drawbacks. Firstly, the user does not want to input data to the application, particularly of their failures. Secondly, the apps focus too much attention on the 'when' instead of the 'why'. Thirdly, 'overeating' may be different or subjective based on the person. For example, if someone is trying to accumulate muscle mass, eating four chicken legs might not be considered overeating, but eating eight Oreos might.

In response, a previous MQP group developed the SlipBuddy app, an Android application that records simple data like sleep and stress, and overeating episodes to find patterns in overeating. Overeating episodes are recorded when the user presses the in-app 'Oops' button after an overeating episode. The app takes this data, mines for patterns with machine learning, and presents a rough pattern to the user, so they can self-correct their own behavior and prevent future overeating episodes.

The app was useful and functional for the purposes above, however much of the app either needed fine-tuning or implementation, which is where our group began our project.

This MQP has been geared towards moving SlipBuddy another step further in its evolution. Whereas the last MQP built the app's foundation, this one focuses on patching its problems. Much this project's emphasis has been on improving the user experience through two categories: 1) Functionality and 2) Clarity. 'Functionality' involves granting the user additional and more effective tools for navigating the application; while 'clarity' involves making the users' data transparent and easy to understand without being overwhelming.

Through the two categories listed above, the SlipBuddy app has been enhanced to better utilize data and augment the User's experience.

2. Background

SlipBuddy is an application designed to help users identify and counteract their own overeating habits. This section will serve as a review of what came before our project, both the research and the justification. However, as this project is the continuation of a past MQP, this section will be two-fold. Firstly, it will review the foundation of research supporting the initial project. Secondly, it will explain the ground covered during the last MQP.

2.1 Current Dietary App Market

There is a significant number of dietary apps on the mobile market. While it is difficult to come up with an exact figure on their popularity, physical self-improvement applications have certainly established themselves as a popular genre in the mobile application market. However while these apps are flashy and consistently reviewed on several websites, more official sources have higher doubts of their quality. The Diabetes Prevention Program (DPP) conducted a study with the top on hundred free and non-free weight-loss applications from both the Android and iOS markets (Direito, 2014). The purpose of the study was to decide whether there was ample usage of behavioral strategies within these weight-loss applications. The study concluded that there is a harrowing vacancy in the market for applications that properly use effective behavioral strategies to reform behavior (which as we have covered in the Introduction, is an important method for losing weight). A similar study was conducted with the top forty applications, with very similar results (Direito, 2014). We also conducted our own study (see Findings 4.3) where we evaluated popular and well-researched apps for their data mining and behavioral modification capabilities. Like the DPP's study, we did not find anything substantial within that realm.

2.2 Why SlipBuddy works in this market

Fortunately, smartphones and behavioral modification synchronize very well with each other. The primary challenge of behavioral modification is the collecting, crunching, and upkeep of each users' data, which cell phones, with their convenience and processing power, excel at. In *Psychology & Health*, Susan Michie details forty strategies for creating effective behavioral change (Michie, 2011). Most of her techniques discuss when and how the information should be presented, all of which result in the following general summary. First, the user must understand their current circumstances, the consequences of their actions, and a general idea of the 'norm' of others. Next, the user is prompted to set goals and plan future steps. Finally, the guide (in this case, the app) provides the user with information as to the progression of their goals.

In theory, the purpose of SlipBuddy is to guide users away from overeating habits, and towards their goals. While the collecting, crunching, and upkeep of users' data was present, the guidance was often not. Users receive a message when they are likely to overeat, however the messages were customized by the programmers for each unique situation, and as such were not scalable as a model for message generation. In addition, there was not any infrastructure for goal-setting. Users could record their weights in-app, but any goals would have to be entirely internal. In short, while the application worked for the data, it did not guide users in the direction it needed to. This purpose makes up the crux of our MQP and the MQP that preceded ours. We strove to make SlipBuddy more usable and functional for its users, as well as expanding its use of data to other areas (such as intervention timing). We will cover our process to approaching these challenges in the Methodology section.

2.3 Decision Tree Technique

The primary method utilized by the SlipBuddy application to generate interventions is the decision tree method. Decision trees are graphs that use branching methods to illustrate every possible outcome of a decision. In **Figure 1** below, the population of the Titanic is analyzed through a decision tree (Milborrow, 2011) to determine which combinations of attributes resulted in the deaths of its passengers (where sibsp stands for 'spouses or siblings aboard').

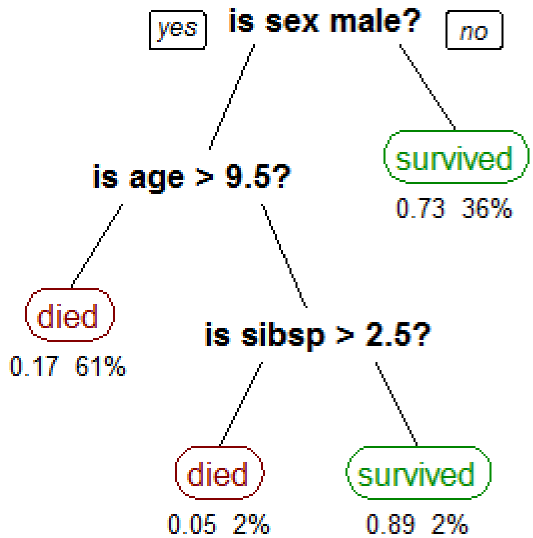

Figure 1: Depiction of Decision Tree for Titanic survivors

The task of the decision tree is to determine with maximum certainty which combinations of data can most determine the target outcome (Kingsford, 2009). In the above example, the outcome is whether passengers survived. In SlipBuddy, the outcome is whether its user overate.

Based on various user inputs during various times of day, SlipBuddy constructs a decision tree like the one above to determine which conditions result in each user overeating or not. In this way, we generate sets of conditions that are likely to result in overeating episodes. We use these conditions to generate interventions, to warn users when these conditions are met.

2.4 Previous Participation Analysis

While the previous MQP had 16 participants total that engaged in the user study last year, it is hard to conclude whether certain participants used the application actively or not. In order to understand the participant rate, we did an analysis on the data we collected from last year's user study.

The user study is divided into two parts, Phase 1 and Phase 2. Each phase is roughly a month long, with participants often having different start dates for the same phase. Phase 1 and 2 are usually two to three months apart. This was done to give participants time to rest in between phases. Of all participants, two participants dropped after Phase 1. The remaining 14 participants finished the study with varying levels of participation.

The participation data are divided into two categories, check-ins and episodes. Check-ins are data collected during the day to monitor the participants' statuses. Three check-ins occur throughout the day, during the morning, afternoon and evenings. They are available for participants to fill in throughout the day and the next day. The second category is episodes. Episodes are what we often referred to as "Oops incidents" - when the participants overeat, they are advised to record it using the "Oops button" within the application. A participant may have multiple Episodes each day. Using these two data sets (Check-ins & Episodes), we analyzed the participation rates for every participant.

2.4.1 Check-ins Participation Analysis

Check-ins data are collected during the day to monitor each user's stress levels, as well as their sleep hours, hunger levels and weight. They are clear indicators of whether or not a user used the application during that day, since check-ins are required daily for every user. We analyzed the participation of users on a daily basis compared between phases and times.

Phase 1 has a solid participation rate. With all 16 participants, the average Phase 1 length is 36.81 days with an average of 90.27% participation rate in check-ins. And among all of them, 6 participants used the check-in function every single day, 7 have used the function in more than 85% of the days assigned. The remaining 3 have the participation rate of 56.8%, 76% and 68.8%, including one participant that dropped out of the study after Phase 1.

Compared to Phase 1, Phase 2's participation dropped significantly. With all 14 participants in Phase 2, the average length is 42.14 days and the average participation rate is 63.30%, a significant drop from Phase 1. None of the participants used the application for check-in every single day. 6 participants have more than 85% days checked, 1 has more than 75%, the rest, 7 participants have less than 50% days checked. Using 85% as a threshold, Phase 1 has 13 out of 16 participants reach that goal, but Phase 2 has only 6 out of 14 participants.

Overall, with two phase combined, the average length of use is 73.69 days and the average participation rate is 77.10%.

Individual Participants	Phase 1 rate	Phase 2 rate	Overall rate
	56.82%	n/a	56.82%
	91.67%	94.74%	93.24%
	100.00%	98.15%	98.68%
	100.00%	95.45%	97.53%
	95.83%	75.47%	81.82%
	100.00%	97.44%	98.67%
	76.00%	87.80%	81.32%
	97.06%	n/a	97.06%
	85.29%	32.56%	55.84%
	94.74%	21.95%	56.96%
	92.11%	47.22%	70.27%
	68.75%	29.73%	51.76%
	86.05%	45.95%	67.50%
	100.00%	27.45%	61.86%
	100.00%	47.22%	73.61%
	100.00%	85.00%	90.48%
AVERAGE	90.27%	63.30%	77.09%

Table 1: Participation Rates by Phase

As mentioned above, as long as a day has one check-in, the day is counted as participated. However, in one day, we have three types of check-ins: morning, afternoon and evening. Each of them has different level of participation rate that are aggregated using the number of that specific check-ins compared to the length of the study to find out the rate of each person, then aggregate the number to get the average participation rate for each kind of check-ins. In Phase 1, morning check-ins have an average participation rate of 89.6%, afternoon check-ins have an average rate of 85.6% and those in the evening have an average rate of 76.2%. In Phase 2, morning check-ins have an average participation rate of 60.9%, afternoon check-ins have an average rate of 56.5% and those in the evening have an average rate of 51.8%. Clearly, the participation rate of those in the mornings is the highest, which is close to the overall participation rate. Afternoon and evening rate dropped down gradually, with afternoon is around 4.2% less than the morning and evening less than afternoon.

AVERAGE PARTICIPATION RATE	OVERALL	MORNING	AFTERNOON	EVENING
Phase 1	90.27%	89.60%	85.64%	76.19%
Phase 2	63.30%	60.88%	56.52%	51.79%

Table 2: Participation Rate by Phase & Time of Day

2.4.2 Episodes Participation Analysis

Episodes are the indicators of overeating activity. Since overeating could happen at different rates for different individuals, the degree of overeating or when the Episode occurs, do not necessarily align with the participation of the users. However, one interesting finding is that the episodes happen much less frequent than the check-ins. One extreme case for example, is found in one participant in Phase 1. He/She has checked-in every day for 22 days, but only has registered 2 episodes throughout that period.

3. Methodology

3.1 Overview

Our project was focused on enhancing the SlipBuddy application. This process consisted of two principles. First, we sought to find direction by studying the application and its place in the mobile app market. Second, we improved the application by adding or improving various features such as intervention messages, and user settings.

3.2 Intervention Messages

The intervention process involved three simple phases: the 'develop' phase, where an approach was designed and implemented, the 'talk' phase, where once the approach was implemented, the team reflected on its pros and cons, and the 'revise' phase, where the approach was either readjusted to fit its flaws, or was scrapped to begin the cycle again. We cycled through this cycle four times and developed a final implementation approach.

3.3 User Settings

We wanted to provide the users with the ability to input and update their information and give them a sense of customizability within the app.

The approach we decided to take for this portion of our project was to create a selection of potential settings to implement. Then, we implemented dummy settings that fit those parameters, and after a period of time, we returned to the list of settings and re-evaluated which settings fit the goals of what we were trying to achieve, and the theme of what we wanted our 'Settings' to mean.

3.4 Survey of Applications

As described in the Background section, it was important for our project to understand the current usages of behavior modification and data mining in the current market. To assess the potential need for and benefits of SlipBuddy, we reviewed several apps that were well-studied in the literature and were either extremely popular, had notable usages of behavior modification, or both.

Our approach for doing so was to scour various academic sources for reviews of apps that were noteworthy for their use of data mining or behavioral analysis. Apps that were well-researched, popular, and often both, made the cut, and only those that were noteworthy made the final reviews.

3.5 Graphing Participation

A common question that arose when people considered both our and past SlipBuddy projects is 'How is the Participation rate? Are users actively reporting their episodes in the experiment?'

To answer that question, we compiled the participation data according to the first two trial phases of the last SlipBuddy project's start and end dates. From the dates we got, we counted the number of check-ins and episodes in each phase as well as in between Phases 1 and 2. We used that data to visualize the participation of various participants. This includes a line chart detailing how the participants' check-in rates fluctuated across various phases. The charts can be found in section 5.4.

3.6 Improving Application Input

While the old application is effective, some of relevant information about overeating episodes is not being collected, and portions of the design are not as user-friendly as they can be. In order to improve the current application and streamline the input experience, we added and change some features in the application.

3.6.1 Quantifying Overeating

While doing the data analysis of the current Episode data we have at hand, one thing we noted is that there is no way of quantifying how much a user overeats at each episode. It could be just one more bite on a cookie, or pounds of chicken wings. To deal with this, we added one more question to the survey that is triggered after each episode. This question asks: "On a scale of 0 to 10, how much did you overeat this time?". The application's local database on the cellphone and the central database on the remote server were both rebased to include this additional data.

3.6.2 Streamline Check-ins

During our discussion, we found that the application requires too much page-flipping in order to finish the morning check-ins. Unlike afternoon and evening check-ins, those in the morning have a total of five questions asked, including 'stress level', 'hunger level', 'sleep quality', 'sleep hours' and the users' current weight. In the original application, each question is represented in one page. This results in the users clicking the "next" button 5 times to finish the check-in. This is time-consuming.

4. Results

4.1 Intervention Messages

Over the course of the project and our design, talk, revise cycles, we developed four major approaches to how we wanted to handle intervention messages. The results of those approaches are listed below.

4.1.1 Intervention Messages: Sorting by Priority

Our first implementation of self-generated user messages involved sorting elements of the message by their importance (height) in the decision tree. In a decision tree, the higher the element is on the tree, the more statistically important it is. For example if the intervention occurred because of conditions A (root node), B (child of node A), and C (child of node B), the message would look something like: "You tend to overeat when you A, B, and C". The textual representations of A, B, and C resemble (with a few exceptions): (over/under)+(verb)+(degree)+(time of day). The degrees ranged from 'a bit' to 'a lot' depending on how far the occurrence was from the perceived 'norm'.

Also, as the conditions were arranged in a tree-like format, we generated message combinations for each iteration downwards. As the conditions were pre-sorted in order of importance, we generated (for a three condition example) messages for condition A-B-C, A+B-C, and A+B+C. That way the user could select the 'depth' of their intervention message. This would allow them to choose a brief message (based on just condition A), or a detailed one (based on conditions A+B+C), or anywhere in between.

The benefits of this approach were that the information was very explicitly communicated to the user. It also maintained the order of the conditions' importance. The trigger conditions are pre-sorted by order of statistical importance. Keeping them in that order made the users' reasons for overeating very clear. The problem with this approach is that it became clunky. To say: "You tend to overeat when you overstress a bit in the morning, undereat a lot in the afternoon, undersleep a bit in the morning, and overstress a bit in the afternoon" is annoyingly long and stilted. Even with a small depth, the repetition of the times of day makes for annoying read-throughs. To make this message more user-friendly, we developed a second approach.

4.1.2 Intervention Messages: Sorting by Time of Day

The second approach we took was sorting by time of day rather than priority. This solved the problem of brevity found in our last approach. The benefits of this strategy were that the information was easier to read through and more user-friendly. However, the messages appearing in order of the time of day made the importance of each condition invisible to the user. Here we chose readability over small pieces of information. And while to an extent we were able to combine the two (sorting each element in each time of day by priority), it did not have the thoroughness of the previous model.

4.1.3 Pre-Emptive Warnings

In the then-current implementation, interventions were triggered when every condition was met. In other words, if you overate when you did A+B+C, it would warn you about overeating. But this was a system we could improve upon. If A, B both occurred in the morning, perhaps it could warn you about doing C later, and overeating. While previous messages relied on interpreting the conditions for interventions, this new version demanded on constructing conditions differently.

When generating intervention conditions, a decision tree is built for each user. Each branch (or series of conditions) that results in a significant likelihood of overeating becomes an intervention. Every condition of that branch is listed in order, and those conditions are used to trigger interventions. For the new model, we had to add another step. We kept the standard interventions, but also broke them up into sections based on their time of day, so pre-emptive warnings would trigger in addition to the standard ones. So instead of printing out the branches, and having them become the trigger arguments for interventions, we reassembled the branches before they became passed as arguments.

The new message generation was similar in concept to the past versions. If you trigger every piece of the AM section of the original branch, it will trigger an intervention message citing the AM conditions, with a warning for the highest priority item of that original branch that occurs later on in the day (in this case, afternoon or evening). Alternatively, the AM&PM branches work the same way. (AM and PM are grouped together to utilize all data gathered by the afternoon).

This new message model was more proactive than past versions, but became programmatically complex. Through gradual design, it was not difficult to manage, however after reviewing it, we had realized how difficult it had been to make 'intervention messages' work, and how we still were dealing with the same fundamental issues.

The interventions were generated with the specific purpose of communicating important data to the user in an easy to understand way. However, we constantly ran into trade-offs with brevity vs complexity. Text is inherently flawed in that it cannot communicate large amounts of information in a dense, user-friendly space. To remedy this problem, we moved to our final intervention model: Graphical Interventions.

4.1.4 Intervention Messages: Graphical Interventions

Before we concluded our project, we decided to substitute user messages with a helpful graphic. While this meant that parts of our development had not come to fruition, it was a decision that was not made hastily, and supported by three primary reasons. The first was information density. User messages are flawed in that they cannot communicate complex information within a small space. Infographics, however, are much more efficient at storing dense information. The second reason was user engagement. We expect users to be more willing to observe and possibly return to a helpful infographic, than a message. The third reason was the complexity of tone. Prompting the user is difficult in that the program is fundamentally telling the user what to do. An effective program must be helpful and friendly while not coming across as annoying. And while this problem is not programmatically complex, it is one subverted by using images in place of text.

Pictured below, in **Figure 2**, we have an intervention represented graphically where an overeating episode is likely to occur if the user is hungry in the morning, stressed in the afternoon, and has medium stress in the evening. With our model, the user is able to view their top intervention at any point throughout the day, so they know what to watch out for.

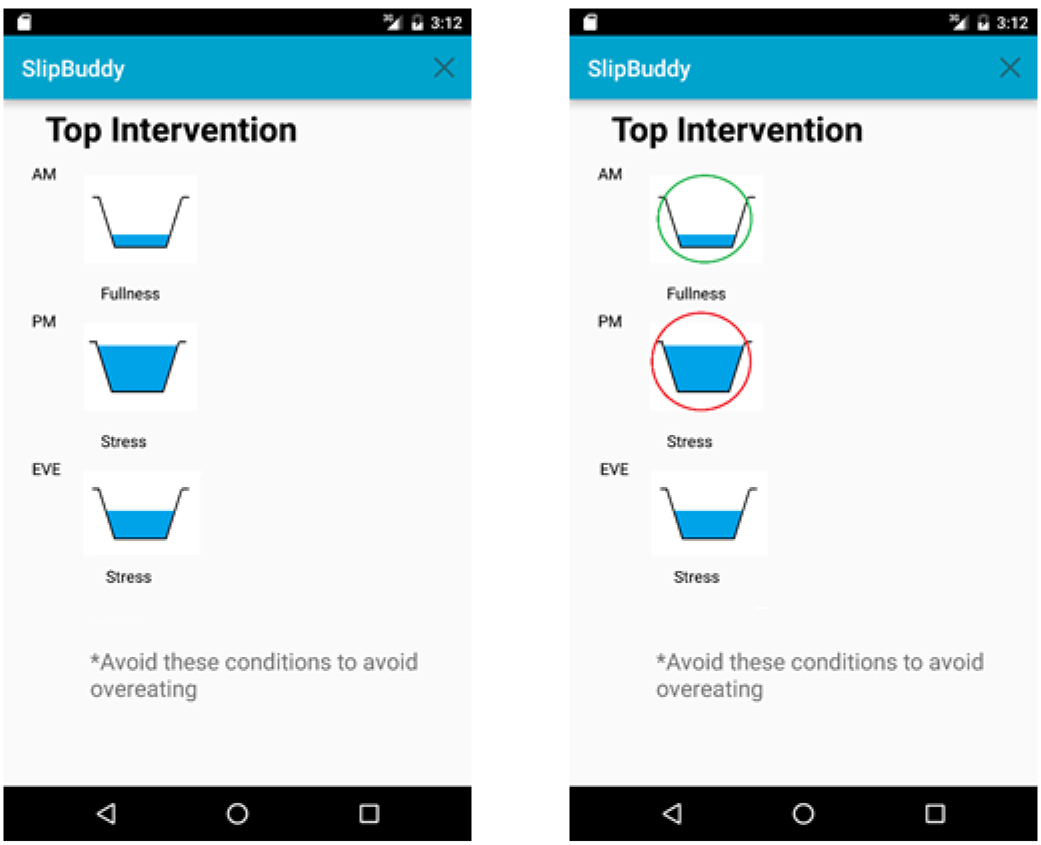

Figure 2: Graphical Intervention Model with and without checkpoints

We also implemented checkpoints into the graph. This means that as the users' day progresses through the morning, afternoon, and evening, they are able to keep track of their progress in avoiding behavior that triggers overeating. If they admit to enacting a behavior in their check-in that is associated with overeating, that behavior is circled in red in the graph. If they successfully avoid said behavior, it is circled in green. In the above example, the user successfully avoided his morning hunger, but failed to avoid afternoon stress.

By enabling graph-based interventions instead of text-based ones, we are able to provide users with very information-rich experiences that would have been impossible with simple text.

4.2 Settings

We integrated settings for Age, Height, and Ethnicity among others. We also added a Message Depth setting so users could customize the level of detail in the intervention messages. However this setting does not align with the new message model, and was thus removed. We also removed settings that took in user information, as we were not sure if that information would be utilized in the big-picture.

The remaining settings consisted of preferred check-in times for the user. This means that in future versions, the application will be able to notify the user that they should check in at a time that is convenient and customizable for them.

4.3 Survey

The results of the survey of existing weight loss apps on the market are both discouraging and heartening. The applications reviewed do not use behavior modification and data mining to the extent that SlipBuddy does. While it is unfortunate these techniques are not being utilized to their full potential, it does mean that there is a spot in the world of Health & Fitness apps for an app like SlipBuddy, which could potentially carve a niche as an application that employs data mining to a more full and thorough extent.

Below is the results of that survey, conducted on various Health & Fitness apps on the market which were well researched, and either very popular or notable for their usages of behavior modification (in several cases both). The simplified results of the survey can be found in the table below. Afterwards, more thorough reviews can be found.

Application Table

Name	Data Measured	Extent of App's Analysis	Other	Studied?
MyFitnessPal	Calories, weight, calorie composition	Graphs over time	Scans food	Yes
Jawbone Up	Sleep, calories, physical activity	Graphs over time	Plug-in for MyFitnessPal Add-on wristlet	Yes
Vegathon	Vegetable intake	Provides focused feedback and behavior modification	None	Yes
Lark	Diet, sleep, physical activity	Comparative graphs, personalized feedback on progress above or below average	No	Yes
8fit	Weight, calories, workout difficulty	Adjusts workouts based on user performance and enjoyment	No	Yes
Fooducate	Weight, calories	Daily calorie and weight counts	Rates the health value of various foods	Yes
Lose It!	Calories, weight, projected time to goal	Graphs over time, projected goal date	Calorie index of various foods	Yes

Table 3: Survey Results

4.3.1 MyFitnesssPal

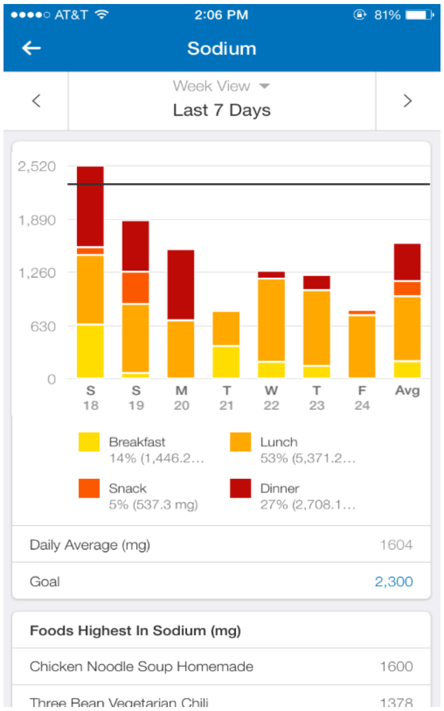

Figure 3: My Fitness Pal daily chart

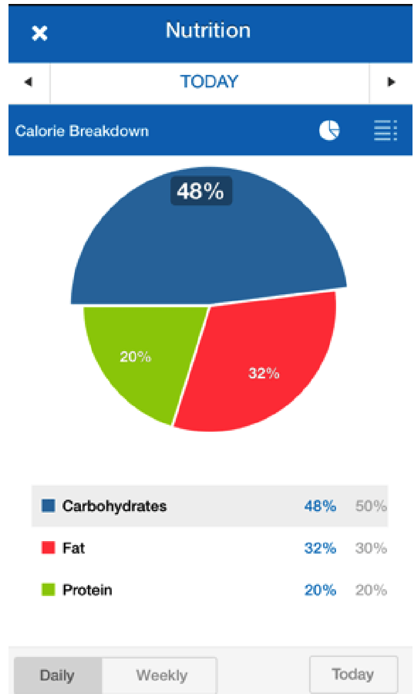

Figure 4: My Fitness Pal Nutrition chart

Data Measured: Foods you have eaten (remembers), Records meals

Tracked: Calories, weight, and calorie composition over time

Other capabilities: Scans food (determines health value of food via barcodes)

Study: (Ipjian, 2017)

The app was recommended in a study analyzing the potential benefits of using apps to modify dietary behaviors. The study determined that MyFitnessPal did, in fact, contribute to significant success in correcting their behavior metric (sodium intake).

In terms of its data analysis, it tracks calories and weight over time, in addition to other miscellaneous diet help. In terms of data analysis and behavior modification, while it does provide some graphs to analyze (pictured above), it does not provide users with any specific paths to success aside from their own graphical analysis.

4.3.2 Jawbone up

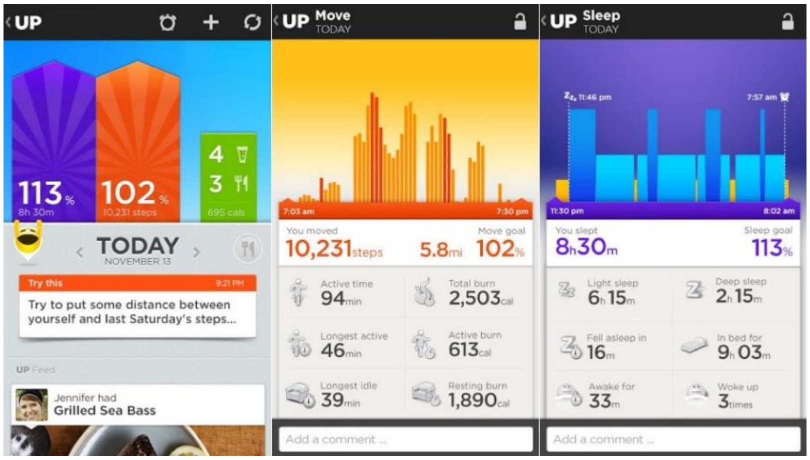

Figure 5: Jawbone Up charts

Data Measured/Tracked: Sleep, calories, and steps over time

Other capabilities: Mostly used as a helpful plug in for MyFitnessPal.

Add-ons: Wristlet (precisely measures steps)

Study:(de Zambotti, 2015)

This app was evaluated in a study that determined that it was able to nearly match polysomnography in its analysis of sleep behaviors. Its most significant claim to fame though is that of MyFitnessPal (the top fitness app on the Apple store)'s plug-ins, this one has the most data analytics.

Overall, this app adds sleep analysis and steps taken to the MyFitnessPal model. The metrics listed in the above graphs are also more varied. However, despite the 'Try this' tip on the layout above, it does not provide any consistent specific guidance for wading through the data and course-correcting.

4.3.3 Vegathon

Study: (Mummah, 2016)

This app was developed by Stanford to attempt to use several behavioral modification techniques such as goal-setting, feedback, social comparison, prompts/queues, framing identity. The study is actually very thorough in its uses. However, the app is not available to the open market.

Overall, the app uses analysis and personal comparisons to try and direct behavior. It does recommend particular changes so it is helpful in that regard. Speaking in terms of product viability though, it is much more specialized in its range over other apps, as its expertise begins and ends at vegetable consumption. It is an interesting example though of the different forms behavior modification can take.

4.3.4 Lark

Figure 6: Lark Daily Progress Image

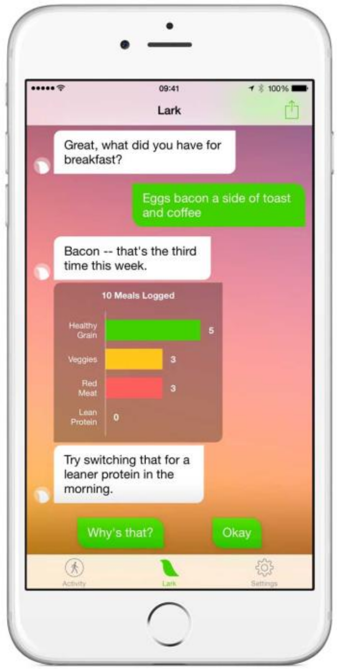

Figure 7: Lark Weeklong Progress Image

Data Measured/Tracked: Diet, Sleep, Physical Activity

Study:(McCormick, 2015)

The app uses 'compassionate' AI to encourage users to sleep, eat, and diet better. It tracks data, such as diet and physical activity and recommends very specific changes. It feels extremely customized in the way it 'chats' with you and personalizes advice. It certainly goes the extra mile in not only representing data, but recommending dynamic changes to the user.

4.3.5 8fit

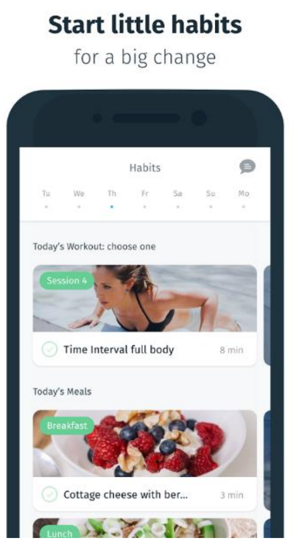

Figure 8: 8fit image - Habits

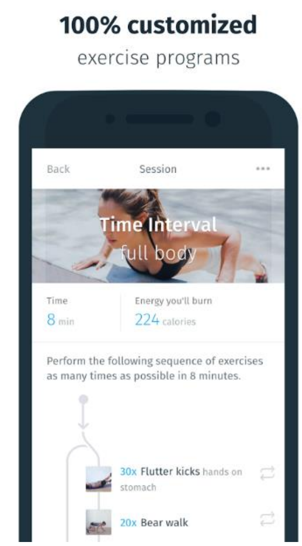

Figure 9: 8fit image - Custom

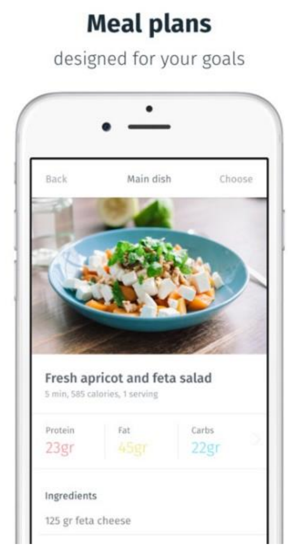

Figure 10: 8fit image - Meals

Data Measured: Physical attributes, goals.

Data Tracked: Weight, calories, workout difficulty/enjoyment.

Study: (Pan, 2016)

The app recommends very specific workouts and diets for you and your goals. Data is thorough and personalized. It takes in data such as your weight and goal (lose weight / gain muscle), and constructs customized diets for your size and goal. Additionally, it constructs personalized workouts and amends them based on difficulty and enjoyment. This process of self-perfecting recommendations allows for a dynamic process of modifying user behavior. That being said, (unless you want the apple watch plugin), none of the data collected is visually displayed to the user. In short, it recommends specific solutions, but it is difficult to view how to get there.

4.3.6 Fooducate

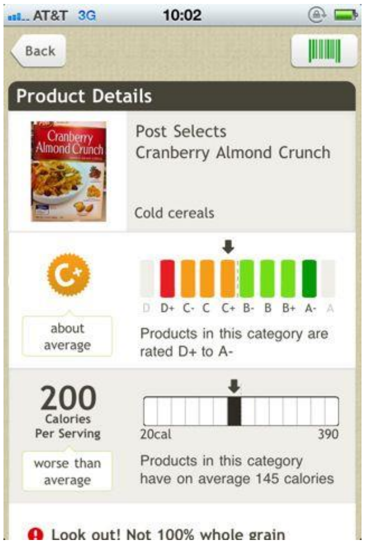

Figure 11: Fooducate Food Rating

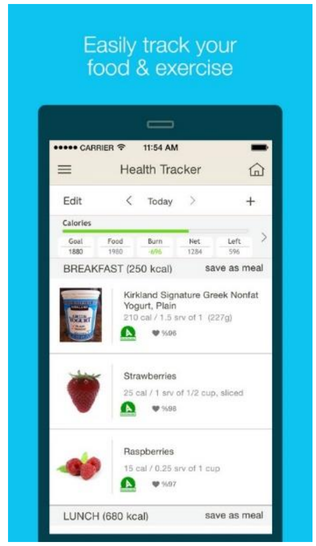

Figure 12: Fooducate Food Menu

Data Measured: Calories, ideal calorie count.

Data Tracked: Foods eaten, calories consumed, and weight.

Study: (Clary, 2017)

Other: Rates the health value of foods (by scanning barcode)

Overall, the app's primarily used for assessing the health of foods at supermarkets. It charts your weight over time so you can assess your own progress. And while it assesses the potential benefits of foods you scan, it does not give you any specific recommendations (aside from randomized foods to try) to improve your behavior.

4.3.7 Lose It!

Figure 13: Lose It! in-app menus

Data Measured: Calories, weight, goal-loss.

Data Tracked: Nutrient pie charts, weight over time, exercise, projected goal arrival time.

Study: (Wharton, 2014)

Overall, the app is reportedly very effective for losing weight. Not only does it provide you with charts of weight over time, but it also provides you with organized meals to lose weight, and a projected end time for your personal goal. However, while the charts do provide helpful information, they are generic and impersonalized. In short, while the graphics and data presented are helpful, they do not provide specific avenues for change aside from the user observing the graphs presented.

4.4 Graphing Participation

As described in the Methodology (3.5), we decided to graph the user study's participation data over time (Phase 1, between phases, Phase 2). Below are the graphical results of our analysis.

Figure 14 displays the trend of Episodes over time, by which we mean recorded instances of overeating.

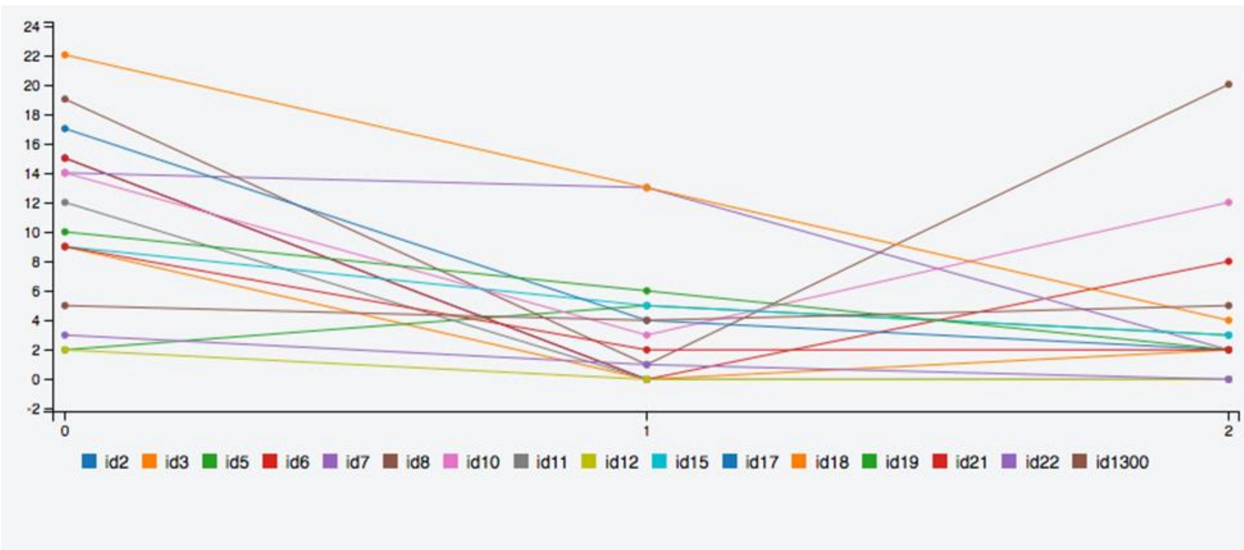

Figure 14: Graph of users' overeating episodes over time

And here, in **Figure 15** below, we have the graph of Check-Ins over time. Check-Ins are when the user inputs data about their day into the app. Check-Ins frequency is a metric of user engagement.

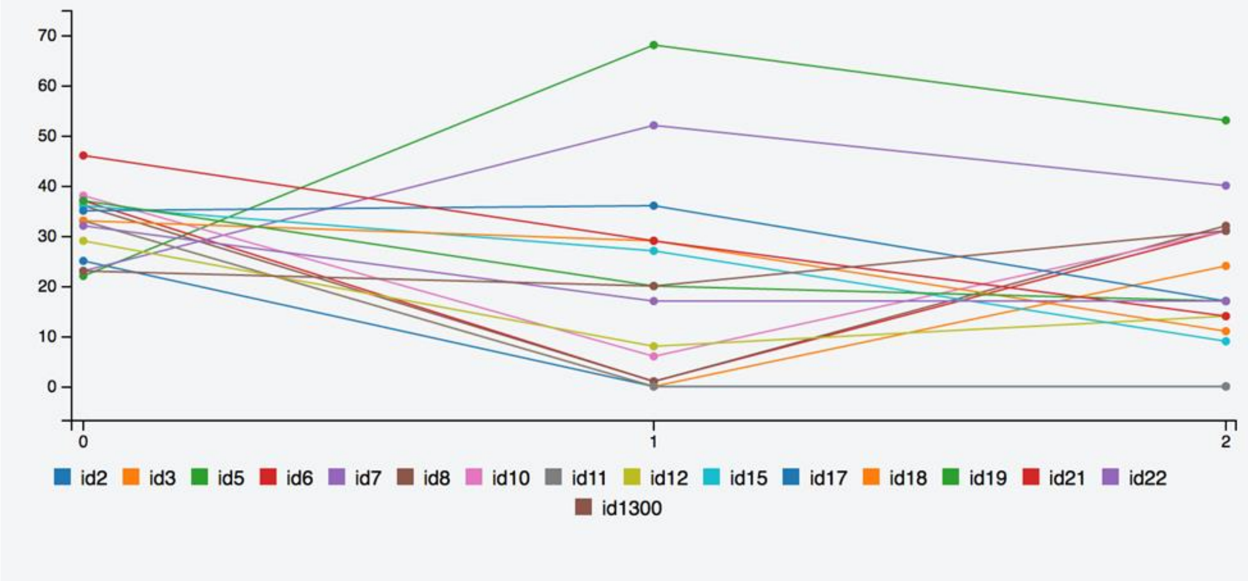

Figure 15: Graph of users' check-in frequency over time

4.5 Application History Visualization

During the summer of 2016, research students worked on developing appropriate visualization prototypes on the Android application to increase the effectiveness of using the SlipBuddy application. Four prototypes were developed, including the progress bar, overeating graph, weight over time, and the pie chart. In our project, we implemented three of them in the real application.

4.5.1 Progress Bar

It is important to keep track of users' overeating behavior. This can give users a sense of their progress over time. That is what the use of a progress bar is intended to achieve. During the summer research, three drafts of the progress bar were produced. The first prototype is a circular progress bar around the "Oops!" button, with circle decreasing as the episode number increases throughout the day. The color goes from green to yellow then to red, as the circle decreases. The second prototype is somewhat opposite. The circle increases with the number of episodes and the color goes from green to yellow then to red as this occurs. In the third prototype, the circle decreases as episodes' number increases. But the color of the circle changes as it decreases. When it is a full circle, it means that no episode has happened yet. At that point, the circle's color is gold. When 1 to 3 episodes occur, the circles' color changes to silver. Lastly, if more than 3 episodes occur, the circle's color changes to bronze.

The third prototype comes with various limitations. The choice of three colors is based on the understanding of how we rank gold, silver and bronze. It might not be well received by people from different backgrounds. Also, the silver color is really close to the background grey color of the circle, which could lead to ambiguity. The first and second prototypes are generally the same, only with the difference of a cut off or a complete circle. We expect that most people would like to see their circle as "complete" when no episodes happen. This can encourage them to keep the circle as complete as possible. Also, the first prototype gives a clear indication of how many episodes are left within the quota. With the second, users may feel as though it resembles a task of completing 5 episodes, which is against the logic of the application as overeating is an undesired behavior.

The first prototype is used as the final implementation in the application for its intuitive design.

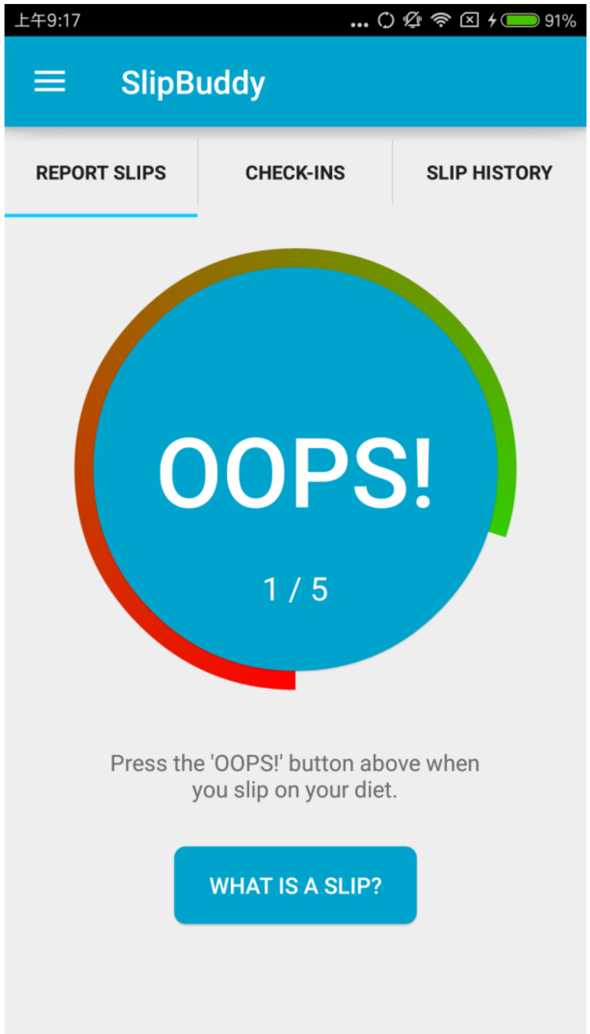

Figure 16: Slip Tracker first Prototype

4.5.2 Overeating Graph

The overeating graph displays how many episodes are in each level for each data point using a bar chart. There are a total of three data types available: Stress Level, Hunger Level and Overeating Level. The implementation used MP Android Chart library, a chart library for android in order to build the bar chart. A spinner at the top left of the page is the picker for selecting what data to show. The data gathered are from the application SQLite database, using the Java activity to filter and organize the number, then finally showing in the application.

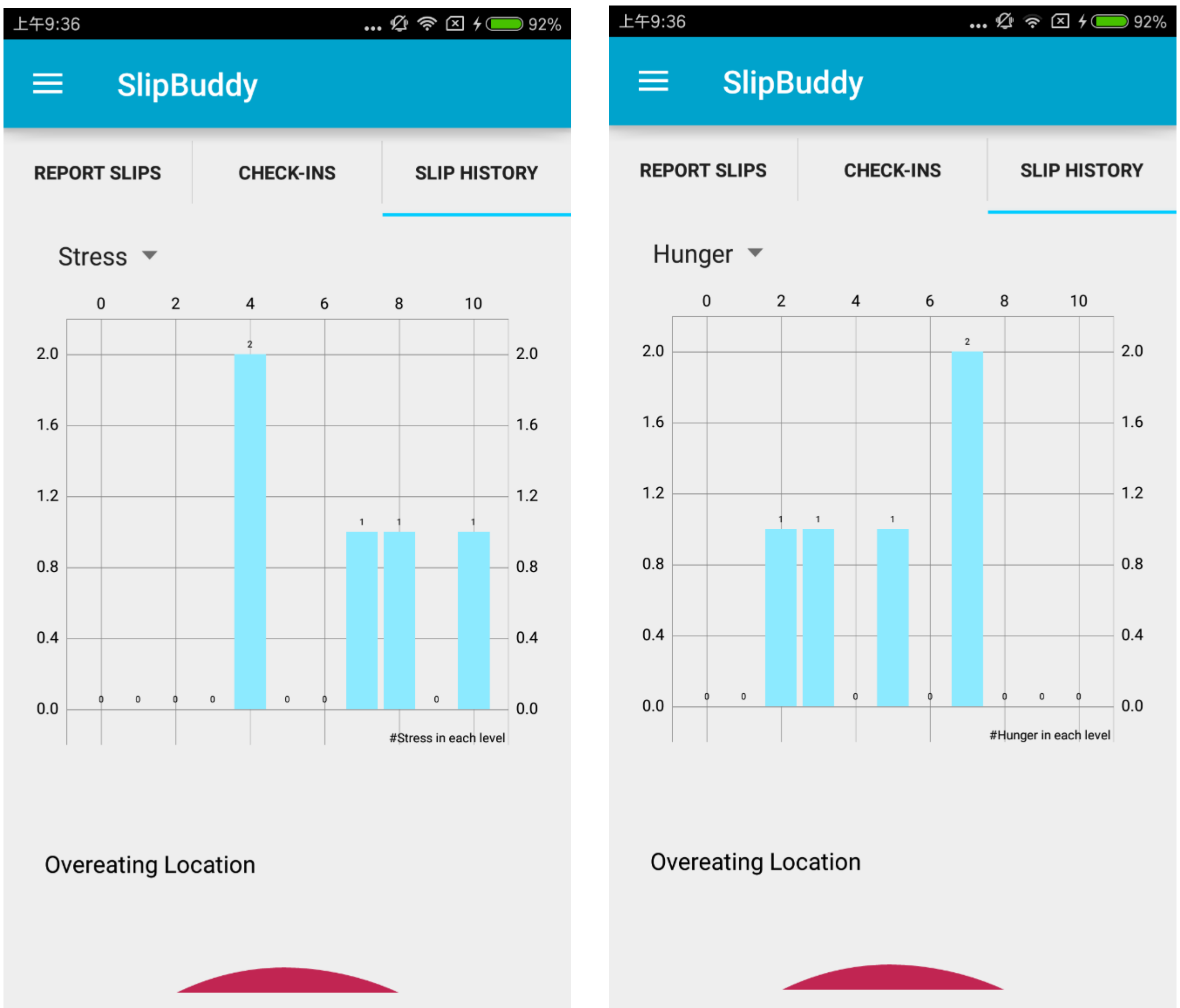

Figure 17: Data Charts for Hunger & Stress

4.5.3 Pie Charts

Two pie charts are implemented in the new application. One is the percentage pie chart for location where episode happened. The other is the percentage pie chart for Activity when episode happened. As with the Overeating Graph, both charts are implemented using MP Android Chart library. The data gathered are also from the application's SQLite database, followed by using a function to process and map the numbers to each arc of the pie.

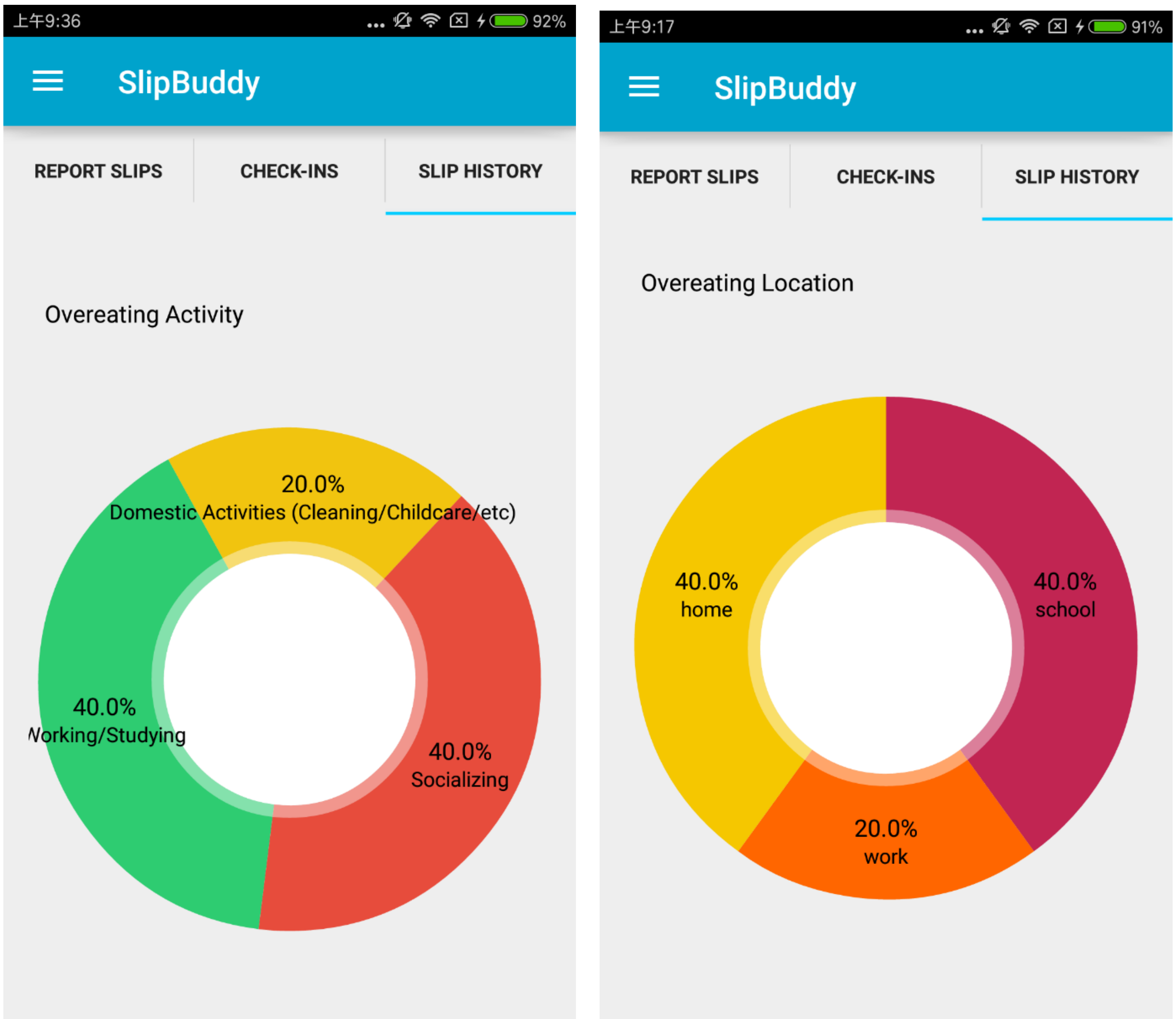

Figure 18: Overeating Location & Activity Charts

5. Conclusion

This MQP enhanced some of the functionality of the SlipBuddy app developed by a previous MQP. The app was missing features such as ‘Settings’, which makes the app more welcoming and customizable. Also graphical representations were added to the app to provide a more intuitive way of conveying information and feedback to the users.

Some aspects of the app could still manage to be refined. Visualizations of data over time would help the app display more complex information in a simple manner.

Obesity is a prominent problem worldwide and will continue to be for some time. However, through learning, improving, and studying the proven techniques of behavior modification, health apps like SlipBuddy can help take obesity a step back.

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