DEPARTMENT OF INFORMATICS

TECHNICAL UNIVERSITY OF MUNICH

Bachelor's Thesis in Information Systems

# Analysis of Interaction Patterns in Healthy Eating Applications

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# Analyse des Interaktionsverhaltens in Apps für gesunde Ernährung


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| Submission Date: | 15.11.2018 |

I confirm that this bachelor's thesis in information systems is my own work and I have documented all sources and material used.

Munich, 15.11.2018 Florentin Wieser

# Abstract

With the incline of overweight and obesity, also the comorbidities are rising. Treatment is a huge financial burden, hence solutions are necessary. One approach to stop the prevalence is the usage of smartphone applications as a tool to support the transition to a healthy diet. An example for such an application is Nutrilize which provides, among others, diary- and feedback-functionality. Because electronic health interventions regularly suffer from high drop-out rates, measures to identify active and inactive users are necessary. Absolute measures of in-app activity were found useful to distinguish the users. On this basis, investigation was conducted how the functions of Nutrilize were used over time. The diary and various feedback screens were utilized most frequently and the overall usage declined over time. Because different functions have a similar structure, higher-level behavior change techniques were introduced. Afterwards, the functions were assigned to the abstract techniques and then analyzed. Techniques used often and over a long period of time were 'self-monitoring' and 'feedback'. Last investigated was the timeliness of diary entries. As meals are often tracked retrospectively, possibly occurring inaccuracies must be considered in future studies.

# Zusammenfassung

Mit der Verbreitung von Übergewicht und Adipositas steigen auch die auftretenden Begleiterkrankungen. Da die Behandlung dieser eine enorme finanzielle Belastung darstellt, sind Lösungen erforderlich. Ein Ansatz um die Verbreitung zu stoppen, sind Smartphone-Anwendungen die den Übergang zu einer gesunden Ernährung unterstützen. Ein Beispiel für eine solche Anwendung ist Nutrilize. Diese App bietet unter anderem eine Tagebuch- und mehrere Feedback-Funktionalitäten. Da elektronische Maßnahmen im Gesundheitswesen regelmäßig unter hohen Abbrecherquoten leiden, sind Merkmale zur Identifizierung aktiver und inaktiver Nutzer nötig. Für diese Unterscheidung wurden mehrere Merkmale der Aktivität in der App herangezogen. Basierend auf dieser Entscheidung wurde anschließend untersucht, welche Funktionen von Nutrilize wie im Zeitverlauf genutzt wurden. Das Tagebuch und verschiedene Feedback-Funktionen wurden am häufigsten gebraucht. Außerdem war eine Abnahme der Nutzung über den Zeitraum der Studie sichtbar. Weil verschiedene Funktionen eine ähnliche Struktur haben, wurden abstraktere Techniken zur Verhaltensänderung eingeführt. Anschließend wurden die Funktionen den Techniken zugeordnet. Die am häufigsten genutzten Techniken waren 'Selbstüberwachung' und 'Feedback durch die App'. Zuletzt wurde der Zeitraum zwischen dem Konsum von Mahlzeiten und dem Eintragen in das Tagebuch untersucht. Da der Großteil der Einträge nachträglich entstehen, müssen eventuell entstehende Ungenauigkeiten in zukünftigen Studien berücksichtigt werden.

# Contents

# 1. Introduction

## 1.1. Motivation

Currently, excessive bodyweight is at an all-time high, both globally and especially in the USA [13]. In the year 2016, for example, 39% of adults and about 18% of children worldwide were overweight with equal distribution between males and females [22]. Even though prevalence of obesity has leveled off in the USA in recent years, it still increases in many developed and developing countries [13]. Especially affected are low- and middle income nations. For example, the number of overweight children under the age of five increased by nearly 50% in Africa since 2000 [22].

With the rise of overweight and obesity, also the related diseases occur more often. These associated illnesses include type 2 diabetes, hypertension, dyslipidemia, cardiovascular diseases, and sleep apnea. These diseases make excess body weight the fifth most common cause of death globally [3]. Treatment is a huge financial burden, for direct health care cost as well as for indirect impacts like lost productivity due to absenteeism. In the USA, for example, obese individuals pay 42 % more for overall health care costs and spend 80 % more on prescription drugs than normal-weight individuals [13].

Next to physical health problems and financial expenses, excess bodyweight is also associated with a lower quality of life. This manifests along all groups of ages and sexes with loss of energy, sleep changes, poor performance in physical activity, and tiredness [3].

However, a moderate and longterm weight loss of 5% to 10% of the initial bodyweight has been shown to have a positive impact on the risk factors for the above mentioned diseases and on the quality of life [3]. With the reduction of weight, the comorbidities would decrease and ultimately the cost for health care systems would be reduced as well.

Many short term weight loss interventions already exist, including drug prescriptions and surgical procedures. Another approach for weight loss and retention of the reduced bodyweight is a change in the lifestyle. As many people struggle with the transition to a healthier diet, supportive tools are necessary. Smartphone applications (apps) could be a scalable and cost-efficient method to encourage change. Apps promoting a healthier lifestyle already exist for multiple issues like smoking cessation, birth control, healthy diet, and correct drug intake.

## 1.2. Goal

An example for a smartphone app targeted at healthy eating is Nutrilize. It serves primarily as an electronic diary but also includes feedback-functionality and a recommendation system. During a three-month study, participants were asked to log their diet with the app.

In this thesis, data derived from the study will be analyzed with focus on the used functionality and the timing of the logging.

High drop-out rates are common in electronic health (eHealth) interventions [9] and shouldn't be a reason to dismiss the data. Still, interesting usage patterns could arise amongst the active users. In order to differentiate between active and inactive users, decisive measures are necessary. One goal of this thesis is to find possible indicators of activity.

Nutrilize contains multiple functions. Analysis of the used features over time may yield interesting behavior patterns. As different features may provide similar functionality, the concept of behavior change techniques is introduced and then assessed.

The last investigation will address the timing of diary records. Questions addressed are: (1) to which extent does retrospective logging happen and (2) do differences between the distinct meals exist.

## 1.3. Outline

First described in chapter 2 are the general approaches of using technology and smartphone apps in health-related interventions. Further attention is paid to the factors influencing the effectiveness of an app - psychological theories, behavior change techniques, and the timing of logging. In chapter 3, Nutrilize itself and the available data are described. Also an overview of the study and the participants is presented. Chapter 4 provides information about the methods used to analyze the data. This includes additionally added features, different definitions and justifications of assignments. Next, chapter 5 explains the results and outcomes of the described analyses. The focus is placed on the differentiation between active and inactive users, used functions, perceived behavior change techniques, and the timing of the tracking. Afterwards, the results are compared with the findings by the literature in chapter 6. A conclusion is provided (chapter 7) and finally suggestions for future work in this field are given in chapter 8.

# 2. Related Work

## 2.1. Persuasive Technology for Health

Persuasive technology is defined as 'a computing system, device, or application intentionally designed to change a person's attitudes or behavior' [10]. Persuasive systems for health-related issues have evolved with the fast development and distribution of information technology. These technologies exist in different forms and ways of delivery - persuasive systems range from gamified approaches, web-based services, desktop applications to mobile apps. Equally vast as the types of the systems is the spectrum of addressed health-domains. The domains mainly targeted are physical activity, eating, dental health, disease management, and smoking [19].

To demonstrate the efficacy of these systems, Orji and Moffatt [19] evaluated 85 papers on persuasive technology. Their results made clear that 75% of the papers showed a complete positive impact on behavior, 17% demonstrated a partially positive influence, and only 8% showed a negative effect. When focusing on the domain of healthy eating, 91% of all studies reported fully positive results. These findings allow the conclusion, that persuasive technology in general is applicable and also delivers verifiable outcomes.

Although these findings promise good outcomes, it should be kept in mind that the effectiveness of interventions in general relies on multiple factors. Influential causes may include the quality of the implementation, the length/depth of the evaluation, or unexpected behavior of the target audience [19] [21].

Literature found that persuasive technologies in general are related to positive outcomes. However, a narrower distinction between the interventions is missing. Therefore, a lower-level investigation on the actually used functions should be conducted.

## 2.2. Diet and Nutrition Apps for Smartphones

As already mentioned, persuasive technology also includes smartphone apps. This is interesting, because the popularity of smartphones has grown extremely over the past years. With the distribution of hightech phones, also the market for mobile health (mHealth) apps grew. As many as 58% of US smartphone owners downloaded a health-related app [7].

Using smartphones as the fundamental platform for persuasive health apps brings many advantages. A major point is the constant presence of smartphones. The majority of users carry their telephone all day, 83 percent of US adults even use their smartphone while eating [7]. This information is particularly valuable for all kinds of diet apps, because prompt interaction may be intended. Another reason in favor of smartphones is the cost-effective process of enhancing a phones functionality with apps - no additional hardware is needed. The versatility of apps also allows the incorporation of personalized and persuasive features [16]. This is useful, as customization is reported to improve the results of persuasive technology [7] [15].

When nutrition apps include a diary-function, they profit even further. It has been shown that electronic diaries have high user satisfaction and are convenient to use [11]. Compared with paper-based diaries, data access for researchers/dietitians is more straightforward because the information is available faster and does not need to be transcribed. These advantages promote nutrition/diet apps and make them the fastest growing branch in health promotion apps [12].

## 2.3. Decrease of User Activity in eHealth Applications

The attrition/drop-out of users in eHealth applications is very high. Attwood et al. [4], for example, experienced a decline of more than 50% after one week in an app designed to track alcohol consumption. Many factors may influence attrition. Eysenbach [9] proposed (among others) the following factors: demographics, usability issues, required time, and external events. Further mentioned factors are the so called 'push factors' (e.g. reminders or personal contact) by the research team.

However, the available data still could show significant behavior-patterns which need to be analyzed. In order to evaluate the results, a method to determine the commitment of users is necessary.

Related work already proposed different measures of user engagement. Two measures suggested by Rahman et al. [20] are the variables *longevity* and *number of records*. Further, Mohl [18] proposed the measure *interval* (in this thesis the feature will be called *mean time span*) as a good predictor for adherence as it omits the influence of familiarity and depicts the timeliness of tracking.

Nevertheless, further signs of activity should be considered and compared to the proposed indicators.

## 2.4. Psychological Behavior Change Theories

One remaining question is how persuasive technologies alter the users' attitudes and behaviors.

One approach to realize interventions, is to build on known psychological theories. There exist a large number of classical theories that try to describe the process and the stages of behavior change. It has been shown that interventions with a psychological foundation have a greater effect than ones lacking them [4]. The empirical review of 85 papers on persuasive technology for health by Orji and Moffatt [19] also confirms these positive effects: all studies based on known theories, besides one exception, either had a partial or a fully positive effect.

Despite the incorporation of theories in interventions is proven to have a positive influence, these concepts are not widely used [23] [19]. Stated as main reasons for the missing integration are the huge amount of applicable theories and the difficulties of implementing them for developers without psychological background.

When theories are included, the most common are the theory of planned behavior, transtheoretical model, goal setting theory, and social conformity theory [15] [19].

## 2.5. Behavior Change Techniques

While the psychological theories give rough layouts for change processes, behavior change techniques (BCTs) are more concrete tools to alter a user's habits.

They are defined as the 'smallest observable and replicable components of an intervention that have potential to bring about behavior change' [4]. Commonly found BCTs in health-related apps are 'instruction', 'encouragement', 'self-monitoring', 'feedback', 'information about consequences', 'goal setting', 'action planning', 'avoidance of cues for behavior', and 'social reward' [21] [4].

To bypass the still existing inconsistencies in naming and integrating BCTs [19], and to allow comparability between different studies, I am building on the 'taxonomy of behavior change techniques' proposed by Abraham and Michie [1]. An important detail of this taxonomy is the theory link. The authors analyzed the BCT-definitions and connected them to theoretical approaches of behavior change. Because different theories may include the same process of behavior change, multiple theories could be linked to one BCT. This link ensures the theoretical basis for all further analysis.

### Explanations of Selected BCTs

The next section provides a detailed description for selected behavior change techniques. Because this bachelor's thesis is focused on the analysis of interaction patterns, I will only highlight BCTs appearing in the app Nutrilize. Note that the definitions are based on the code sheet of the mentioned taxonomy [2].

**General information** describes the link between health and behavior. It includes mortality risk, susceptibility and general health education material.

**Information on consequences** focuses on the outcome of the decision whether to take action or not. In either case, benefits and cost are considered.

**Instruction** is defined as the action of telling a person how to perform the desired behavior. Forms of delivery could be either verbal or written.

**Self-monitoring** contains the tracking of own behavior, for example with a diary or a questionnaire.

**Feedback** provides previously captured data or evaluates a person's performance. Comparison could be done against standards, other individuals, or set goals.

**Intention formation** encourages a person to set a goal or resolution. It aims at rather general intents like 'more exercising next week' instead of highly specified goals.

**Goal setting** involves very specific planning of a person's future actions. The planning includes frequency, intensity, or duration and also names a context (e.g. where/with whom).

The differentiation between the last two BCTs may confuse at first glance, as they are pretty similar. The main difference is (besides the mentioned level of detail) that 'intention formation' encourages people to change. Instances of 'goal setting', in contrast, should be seen as applications of 'intention formation' [2]. However, the techniques are independent of each other and one doesn't imply the other.

Because different app features may represent the same BCT, a link between both should be established and the perception of BCTs over time should be analyzed.

## 2.6. Effect of Timeliness of Diary Entries

In diaries designed for food-tracking, the timing of logging plays an important role. The accuracy of recorded data is higher, when the entries are made timely. Upon reconstruction of previous events, retrospection errors can unconsciously be introduced [5]. Further, it has been shown by previous publications that timelier tracking is correlated with higher weight loss.

In order to validate the diary entries, the time-differences between intake and logging should be evaluated.

# 3. App Nutrilize and Available Data

This chapter will describe the layout and the major functions of the Nutrilize app and the available data.

## 3.1. Nutrilize

The app Nutrilize primarily provides a nutrition diary. The collected data are also visualized regarding the calorie and nutrient intake with different graphs. Nutrilize contrasts other diary-apps with a built-in recommendation function. Based on the user's preferences and missing nutrients, different recipes and dishes are recommended.

Following, an overview of salient screens of Nutrilize is shown. Due to the fact that the study was conducted in Germany, the language of the app is German.

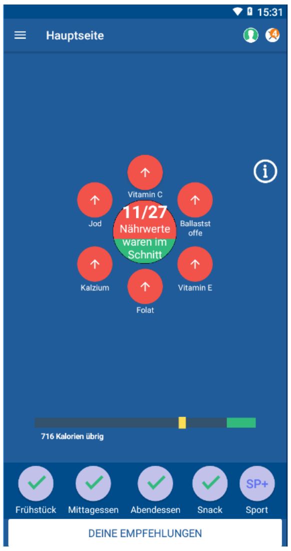



Figure 3.1.: Homescreen


Figure 3.2.: Profile

**Homescreen** The central element of the homescreen is feedback on the nutrient intake over the past three days. The biggest circle in the middle shows the number of nutrients in the optimal range. In total, 27 nutrients are considered in the app. Around this element, the six nutrients with most critical statuses (very high/low intake) are shown. The arrows indicate whether the intake of a substrate is too high (arrow points down) or should be increased (arrow directs upwards). An example is displayed in figure 3.1.

Another feedback-feature of the homescreen is the calorie bar below the nutrients. It basically shows the metabolic rate in dark blue, the calories burnt by activity in green and the actual calorie consumption in yellow. A click on the bar leads to the detailed calorie screen.

The white *your recommendations* button on the bottom links to the recommendations screen. Similarly the five buttons above the recommendation-link lead to the search and allow to add meals.

**Profile** The profile in figure 3.2 shows the key data of the user. The fields *height*, *weight*, *waist - & hip-circumference* can be altered by the user - body-mass-index (BMI) and waist-hip-ratio are then deduced. The physical activity level (PAL) describes a person's daily physical activity and approximates the energy expense. In Nutrilize, it is derived from the logging of athletic activities or a questionnaire. Unfortunately, edits of the field *my first goal* above the profile details are not saved and can't be tracked.

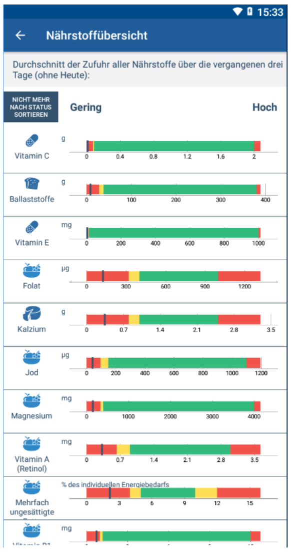



Figure 3.3.: Overview of all nutrients

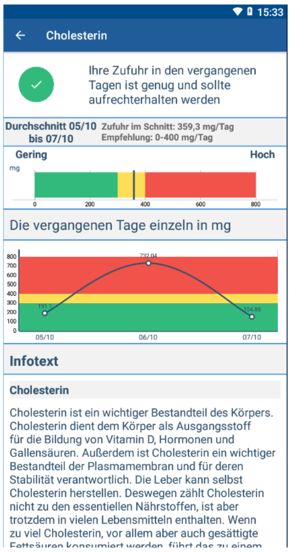



Figure 3.4.: Detail page of nutrient cholesterol

**Nutrient Overview** The overview in figure 3.3 shows all 27 nutrients examined by Nutrilize. Each bar is separated by three colors: red signaling an extreme deviation of the proposed quantity, yellow an intermediate discrepancy, and green an appropriate intake. The blue marker depicts the current consumption. Clicking on a substrate leads to the detailed nutrient description.

**Nutrient Details** The detailed screen again gives feedback with the colored bar. Additionally, a graph with the intake over the past few days is displayed. Below these visualizations, an information text is given. The text describes the body functions relying on the nutrient. Also described are the health consequences of inappropriate doses and the main occurrences in foods.

In figure 3.4 an example screen for cholesterol is depicted.


Figure 3.5.: Recommended dishes

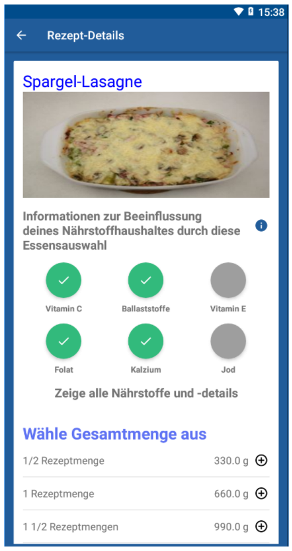



Figure 3.6.: Details of a selected recipe

**Recommendations** The recommendation screen (figure 3.5) proposes various dishes which have a positive effect on the user's nutrient-balance. The extent of the effect is differentiated by the colors - green is healthier than orange or red recipes. If a recipe is consumed, it can be added either directly with the ⊕-button or via the detail page of the recipe.

A special function on this screen is the *why should I eat this*-button. When clicking on the blue bar of a recommendation, a pop-up appears. It names the nutrient the user lacks and the recipe is rich in. The message also includes the info-text from the nutrient detail screen.

**Details of a Recipe** After selecting a recipe in the app, this screen opens. Six nutrients can be seen, each with three possible states: a green check indicating a positive influence on the nutrient-balance, a red exclamation mark implying a negative impact, and a gray circle attesting no effect upon consumption of the meal. To see the influence on all 27 nutrients, a click on the text *show all nutrients and details* is necessary.

Not seen on the screenshot in figure 3.6 are a list of ingredients and the cooking instructions. This information can be found when scrolling further down on the screen.

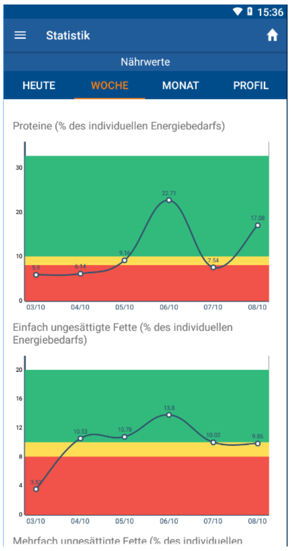



Figure 3.7.: Statistics

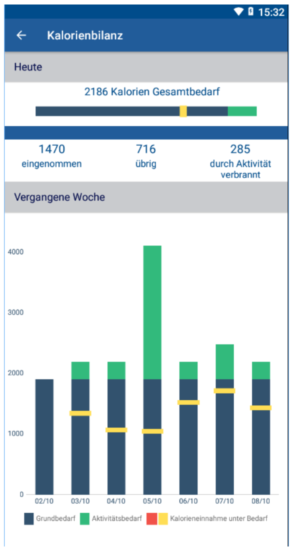



Figure 3.8.: Overview of ingested/burnt calories

**Statistics** Figure 3.7 shows the statistic screen. Plots of today's, last week's or last month's intake of all nutrients are displayed. In the profile page the developments of weight, PAL, hip-waist-ratio, and BMI are represented.

**Calorie Balance** When accessing the calorie balance, an extended view of the calorie bar on the homescreen is given. As seen in figure 3.8, the same colorscheme is used.

## 3.2. Study Design

The process of acquiring participants consisted of the following steps. Initially, a screening survey was conducted. It ensured that the technical and medical requirements are met. When all criteria were fulfilled, a questionnaire asking for physiological measures, physical activity, and eating habits was executed. After completion of this survey, Nutrilize was made available to the participants.

The analyzed study included eleven persons and was designed for a duration of three months. Access to the app was given in two waves: one in November and one in December. The users also were able to use Nutrilize after the three months. After the end of the study, a final survey was conducted and optional telephone interviews were held.

## 3.3. Structure of Available Data

The following section will introduce the available data. Three main sources were used: tracking data, questionnaires and data from the Nutrilize diary. Transcripts of telephone interviews with selected users were also available.

### 3.3.1. Tracking Data

| # | UserID | VisitID | Time | Action | Screen | Event | Object | Referring Action | Ref. Action Time Spent |
|---|---|---|---|---|---|---|---|---|---|
| **1** | [redacted] | 5379 | 19.11.17 12:58 | lunch | /home | Click | Add meal button | /home | 12 |
| **2** | [redacted] | 5379 | 19.11.17 12:59 | searchQuery=dam | /search | Info | Search executed | /search | 0 |
| **3** | [redacted] | 5379 | 19.11.17 13:00 | mealType=Lunch | /search | Click | All results item | /search | 4 |
| **4** | [redacted] | 5379 | 19.11.17 13:01 | portionWeight=23 | /food_details | Click | Add item button | /food_details | 6 |
| **5** | [redacted] | 5385 | 19.11.17 16:07 | percentage=107% | /food_details | Scroll | Scroll View | /food_details | 6 |
| **6** | [redacted] | 5401 | 20.11.17 11:39 | /diary | /settings | Click | Navigation Item | /settings | 8 |

Table 3.1.: Example data provided by the Piwik system; Entries 1-4 are coherent

Nutrilize was equipped with the analytics system Piwik 3.0.4. It allows the tracking of user interactions inside the app. Table 3.1 shows six sample rows of the data. The tracking-system delivers more information, but these additional entries were considered useless for this analysis.

Following is a short definition of the non-trivial columns.

**VisitID** identifies each visit. A visit is defined either as a first access or as a visit at least 30 minutes after the last visit [17].

**Screen** is the name of the page the action was tracked on. The names mostly correspond to the listing in chapter 3.1.

**Action** contains additional data of the tracked function. When a new screen is opened, for example via the sidebar, the target screen can be found here. Another instance is the registration of the position during a scrolling event (given in percent of the complete screen).

**Event** depicts the type of action a user conducted. Possible values are *click*, *info*, *swipe*, and *scroll*.

**Object** specifies the button/location on the screen where the event was tracked.

**Referring Action** describes, in contrast to it's name, the screen of the previous interaction. This field and the next one are necessary due to limitations of the Piwik-system.

**Referring Action Time Spent** describes the time spent on the previous screen in seconds. It is the only provided measure of time spent on a screen.

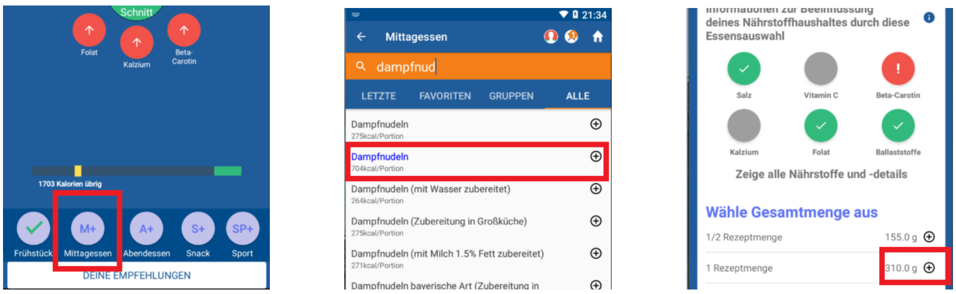



Figure 3.9.: Three steps of adding a lunch to the diary

To give an example how an activity in the app is depicted in the data, the addition of a lunch will be examined. The three steps are shown in figure 3.9 and the corresponding data is found in the rows **1-4** of table 3.1. Row **1** matches the clicking of the *lunch*-circle on the homescreen. The *referring* fields indicate that the user spent twelve seconds on the homescreen before. The second row represents the search for the dish. Row **3** is the data representation of accessing the recipe details from the search results. The fourth row indicates that a meal was added with the ⊕-button from the food details screen. Additionally, the column *action* includes data about the portion size.

### 3.3.2. Diary Data

| | UserID | Diary Date | Meal | Name | Typ | Amount (g) | Date of Record | kcal |
|---|---|---|---|---|---|---|---|---|
| **1** | [redacted] | 19.11.2017 | Breakfast | Kaffee | FoodItem | 150 | 2017-11-19T17:03 | 3 |
| **2** | [redacted] | 19.11.2017 | Lunch | Pizza | FoodItem | 250 | 2017-11-19T17:07 | 550 |
| **3** | [redacted] | 19.11.2017 | Dinner | Hühnersuppe | FoodItem | 7,5 | 2017-11-19T17:08 | 11 |
| **4** | [redacted] | 21.11.2017 | Breakfast | Vollkornbrot | FoodItem | 25 | 2017-11-21T13:08 | 49 |
| **5** | [redacted] | 21.11.2017 | Breakfast | Hummus | Recipe | 114 | 2017-11-21T13:09 | 223 |
| **6** | [redacted] | 21.11.2017 | Lunch | Laugenbrezel | FoodItem | 160 | 2017-11-21T13:11 | 612 |

Table 3.2.: Diary data

A sample of diary entries collected by Nutrilize is shown in table 3.2. The three valid types of entries are: 'FoodItem', 'Recipe' and 'SportItem'. An important difference exists between the columns *diary date* and *date of record*. The first term refers to the date the item was consumed on. *Date of record*, on the other hand, relates to the timestamp of the actual data entering. The rest of the columns should be self-explanatory.

### 3.3.3. Further Data Sources

Further available information sources are questionnaires. Multiple surveys were conducted during the duration of the study. They were executed twice: at the beginning of the study and three months after. The subject matter were questions on the lifestyle (type of work, hours of sleep, etc.) and basic information regarding the participants (gender, age, weight, height).

In addition to the questionnaires, the transcripts of optional telephone interviews were available. They were also held after the study and each lasted about 30 minutes. Because of the voluntary nature, there are only few available and those available were run with active participants who didn't quit the study.

## 3.4. Key Data of Participants

Eleven persons participated, nine females and two males. An overview of age, physical activity level (PAL) and BMI is given in table 3.3. It can be seen that the participants are rather old, they are aged between 28 and 65 at the beginning of the study. The high mean of the BMI corresponds the design of the study: only overweight persons (BMI in the range 25-40 $kg/m^2$) were included. The mean PAL is 1.5 which equals desk work with little to no exercise.

| | Age | BMI | PAL |
|---|---|---|---|
| **Mean** | 41.5 | 29.9 | 1.5 |
| **Standard Deviation** | 15.6 | 5.0 | 0.6 |

Table 3.3.: Key data of the participants

# 4. Approach

The analysis of the data was done with Python 3.6.5 and Jupyter notebooks. Visualizations were created with the Matplotlib within the notebooks and Tableau 2018.1 for more complex plots.

## 4.1. Introduced Measures and Aggregations

Prior to any analysis, additional measures were introduced and data were aggregated at different levels.

The study the data were derived from, enrolled the participants in two waves. Therefore, two starting dates exist: one in November and one in December. To avoid any unwanted shifts in later analysis, the measure *relative day* is introduced in the data generated by Piwik. It is defined as the difference between the actual date of action and the day each user got access to the app. This allows the analysis to be conducted over time courses.

Furthermore, aggregations of both datasets (tracking data and diary data) were formed. The challenge to be met by the aggregations is to deliver detailed data while simultaneously giving an overview of large-scale developments. To meet this requirement, two distinct levels of aggregation were formed: *per user per day* and *per user over the study*. These summarizations allowed the following features to be included into the Piwik data.

**Active Days** describes the amount of distinct days the user had any interactions with the app.

**Longevity** is defined by the number of days between the first and the last usage of Nutrilize during the considered period.

**Mean Time Span** describes the average time period between the first and last usage on a single day.

**Complete Day** indicates days with a logged intake of at least 1000 kcal.

Mohl [18] considered diary days with a summarized intake below 1000 kcal as incomplete. Another limit was chosen by Jimoh et al. [14]. They choose 500 tracked kcal per day sufficient to count as a complete diary day. But when considering the basal metabolic rate, this barrier seemed too low and therefore the limit by Mohl is adopted.

## 4.2. Differentiation of Active and Inactive Users

To enable the comparison between the interaction patterns of active and inactive users, two distinct groups were formed. All participants were split among these groups with the help of different variables.

Considered in the decision were the variables proposed by previous publications: *longevity*, *number of records*, and *mean time span*. Additionally, the variables *active days*, *count visits*, *mean time spent*, *count days with diary entry*, *count entries*, *complete days*, and *mean kcal* were considered as indicators for active or inactive behavior.

The decision itself was done by manually assessing each user's variables and then assigning him to one of the groups. From now on the active group will be referred as the adherence group and the inactive as the attrition group.

## 4.3. Detection of Function Usage

The first step of analyzing the Piwik data, is to filter the given data. Only interesting actions should be analyzed. Due to the different characteristics of features, the detection was approached using multiple methods. For the majority of functions, the detection was captured in the moment of clicking an object linked to the feature.

A straightforward action that should be detected is the opening of main screens like *details of a recipe*, *statistics*, *recommendations*, *calorie balance*, and the nutrient pages. Also the usage of the buttons *why should I eat this* and *show all nutrients and details* is tracked.

Another aspect which was investigated is the use of the electronic diary, since it is the central task of Nutrilize. This is accomplished with help of the *add item*-buttons (⊕). The data allows further distinctions: the type of entry (sport or food) and the site the entry was added from (*search results* or *details of food*). The acceptance of recommendations is tracked separately with the same rationale.

One special case is the detection of information that is placed on the lower fraction of the screen. To access this information, scrolling is necessary. Examples for this situation are the cooking instructions of a recipe and the info-text of the nutrient details screen. In order to differentiate between the content on top of the screen and the information on the bottom, the current position of scrolling is considered. One additional problem to consider when detecting scrolling are the many resulting entries in the tracking data - for each detected position, one entry is generated. To maintain valid information, an additional requirement for the tracking of this feature is introduced. The detection is

| Feature of Nutrilize | Mapped BCT |
|---|---|
| Add Item to Diary | Self-Monitoring |
| Accept Recommendation | Self-Monitoring |
| Open Recommendations | Instruction |
| Access Cooking Instructions of a Recipe | Instruction |
| Info-text of Nutrient Details | General Information |
| Why Should I Eat This | General Information |
| Open Details of FoodItems/Recipes | Consequence Information |
| Open Calorie Screen | Feedback |
| Open Nutrient Screens | Feedback |
| Open Statistics | Feedback |
| Spent 10+ Seconds on Homescreen | Feedback |
| Enter My First Goal | Intention Formation |

Table 4.1.: Mapping of app features and BCTs

only considered when at least three seconds were spent in one scroll position. This limit should be appropriate to differentiate between users skimming the text and users actually reading it.

Because the homescreen serves two functions at once, it is also tracked with a different method. On the one hand it serves as the starting point for all further functions of Nutrilize and on the other hand it provides feedback on consumed nutrients and calories. It is impossible to confirm whether people actually grasped the feedback or just navigated from the central screen. With only detecting stays which last longer than ten seconds, even slow users should have enough time to navigate away from the homescreen. On longer stays it is assumed that the user sees the feedback-circles. This solution seems like a good trade-off even though some feedback-perceptions may remain undetected.

As already mentioned, tracking functionality has not been implemented for the profile screen. Even though height, weight, hip- and waist-circumference could be accessed from other data provided by the app, the field *my first goal* can not.

## 4.4. Detection of BCT-Usage

With knowledge about the functions that were used, a link to the perceived BCTs can be formed. Basis of this connection is a mapping of features and behavior change techniques which can be seen in table 4.1.

The behavior change technique 'self-monitoring' includes all actions of adding entries to the diary. Distinction between the type of items was not done.

'Instruction' is the next considered BCT. As it is defined as tips on how to take action [2], two functions of Nutrilize are considered: access of recommendations and the cooking instructions of a recipe. The opening of the recommendations fulfills the definition, because it proposes dishes that improve the nutrient-balance of the user. The cooking instructions provide guidance on a more granular level.

'General information' is linked to the info-text on the nutrient details screen, because it includes facts about possible health threats when deviating from the proposed amounts. As the same text also is included in the *why should I eat this*-function, the same BCT is assigned.

The strict focus on the outcome of action and inaction differentiates the technique 'consequence information' from the technique 'general information'. The direct influence of an action can be found in the detail screen of recipes, when the *show all nutrients and details*-button is clicked. For each of the 27 nutrients considered in Nutrilize, the resulting effect on the nutrient balance can be seen.

Nutrilize includes many features with feedback functionality. Obvious are the calorie overview, both nutrient screens (the overview and the detailed screen) and the statistics-page. As already mentioned, the homescreen also provides some feedback. Therefore, longer stays on the homescreen are also linked to the technique 'feedback'.

The last BCT is 'intention formation', which is incorporated in the profile screen. Due to the missing ability to track entries here, this behavior change technique won't be addressed in the further analysis.

## 4.5. Time Course Analysis

As the usage patterns may alter over the period of the study, the temporal development of user's behavior is also analyzed. In order to conduct this investigation, plots of the absolute usage over time were generated for each function and BCT.

As the users show extremely different usage patterns over time - even inside the adherence or the attrition group - the visualizations were done in the form of stacked bar charts. In order to differentiate general developments and fluctuations produced by individual users, each participant had a distinct color assigned.

## 4.6. Retrospective Tracking

As mentioned earlier, the timeliness of diary entries plays an important role in terms of accuracy. Basis of this investigation is the diary-data. To check whether the study participants tracked their meals directly after consumption or not, the field *date of record* was inspected. An entry is considered as tracked retrospectively when the *date of record* doesn't correspond to the *diary date* or the meal is tracked outside the common periods for eating.

The definitions of ordinary periods are based on the analysis by Claupein et al. [8]. In their data, breakfasts were mainly consumed in the time between 6 and 9 o'clock in the morning, lunch between noon and 2 p.m., and dinner in the period between 6 and 8 p.m.. To relieve the strict limits, the usual time-periods were extended by 30 minutes in each direction.

# 5. Results

## 5.1. Classification of Active and Inactive Users

The classification of users based on their activity level led to six adherence users and five attrition users. Figure 5.1 depicts the outcome of the decision, the users considered as active are framed red. User-IDs were substituted with numbers to protect the participants' privacy. To emphasize the validity of the decision, color scales were created for each decisive variable. The boundaries for each scale are minimum and maximum of the considered variable.

It can be seen that the adherence users have many variables with higher values and are more consistent over the variables. The measures of users **2** and **3**, for example, aren't located in the high figures. But when considering the combination of all variables, they achieve consistent results in the middle range of values. Therefore, they are considered as active. In contrary, user **10** has a high longevity and a high mean of tracked calories, but the number of active days and the other variables are rather low. This distribution may hint at a usage with long interruptions, which shouldn't be considered as active.

The plot shows that the activity-measures proposed by the literature only partly coincide with the met distinction. *Longevity* and *mean time span* both show outliers. Only the *number of diary records* match the decision. Variables with better correspondence are the absolute measures *active days*, *visits*, *days with a diary entry*, and *complete days*.

These findings propose that the measures suggested by the literature shouldn't be used on their own. Instead, additional measures should be considered in order to get a valid result.

To better understand the participants of each group, an overview of the key data is presented. The corresponding result can be found in table 5.1. Compared to the outcomes of the core set (see table 3.3), the mean age and BMI of the adherence group is higher and the attrition group has lower figures in both measures. The disparity of the PAL values is conspicuous as well - the adherence group seems to be less athletic than the attrition group.

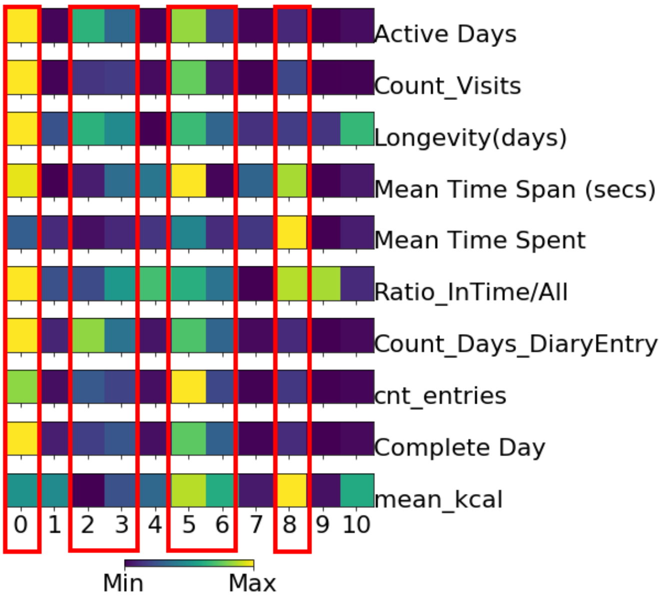



Figure 5.1.: Color scales for each variable; Active users are marked red

| | Adherence Group | Attrition Group |
|---|---|---|
| **Mean Age** | 46.2 | 30.8 |
| **Mean BMI** | 35.8 | 28.8 |
| **Mean PAL** | 1.3 | 1.7 |

Table 5.1.: Key data split on the assigned groups

## 5.2. Utilized App Functions

The usage of the attrition group is primary centered on the beginning of the study and has extremely low figures (see appendix, figure A.1). Therefore, only salient interactions of the adherence group are analyzed.

The first feature that will be analyzed is the addition of items to the diary. Figure 5.2 shows three plots: the general addition of an entry and the two methods of addition (from the details screen or directly from the search results). Even though only the adherence users are considered, the declining usage over time can be seen in the top plot. Also different usage patterns can be detected. Users **0** and **5** use the app often and consistent, participant **2** has long-lasting but lower usage. Another visible pattern is the interval usage: consistent activity for a few days, then a pause, and then again activity. Users **6** and **8** show this pattern from the beginning, **3** adopts this behavior after the

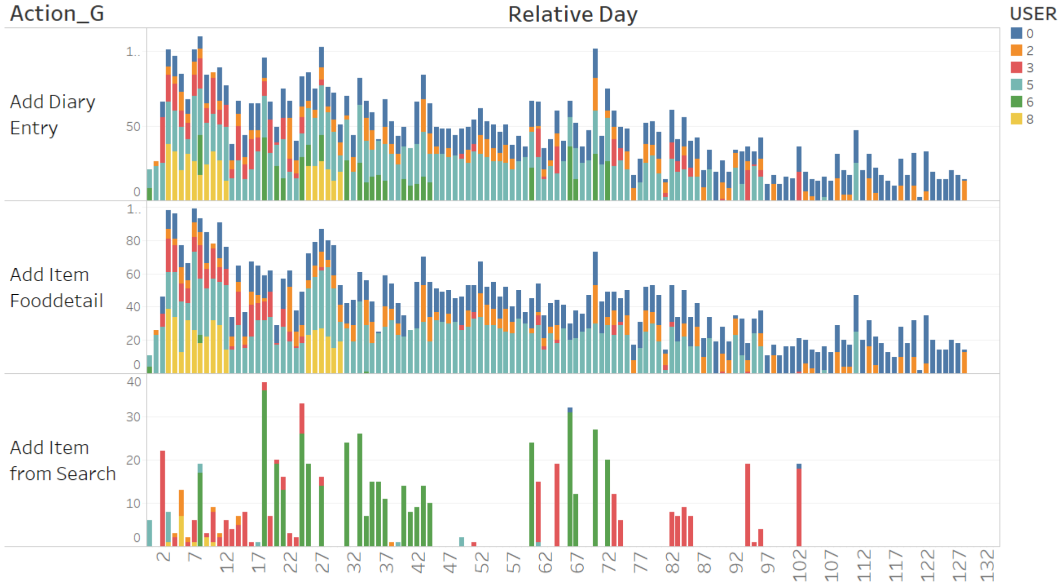



Figure 5.2.: Usage of the *add diary entry*-function by adherence group

first month of the study. The two plots on the bottom describe the source screens of the add-entry actions. Noticeable is the behavior of the users **0** and **6**. User **6** adds meals primary via the search function and not from the food details screen, user **0** shows the exact opposite behavior. One possible explanation for this behavior is that some users want to use Nutrilize as efficient as possible whereas others try to be precise.

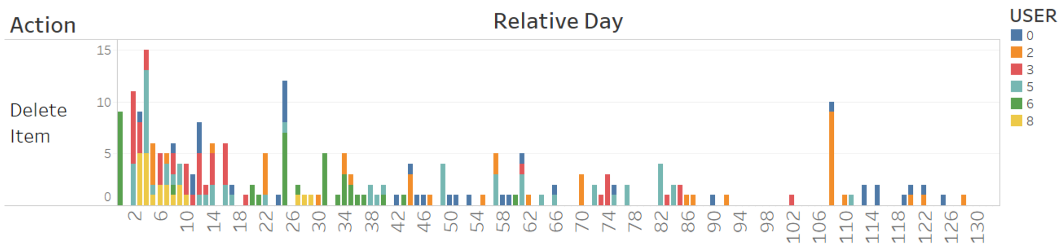



Figure 5.3.: Number of items deleted from the diary

As diary entries can be removed, this function is assessed too. In figure 5.3, a clear spike can be seen in the first days of the study. Further notable is that all users have activity in the first five days. A possible explanation is that users are exploring the features of Nutrilize. Before tracking their own behavior, people want to get a feeling for the app and add dummy-entries. Another possible reason is the user's unfamiliarity with the app, leading to mistakes in the beginning.

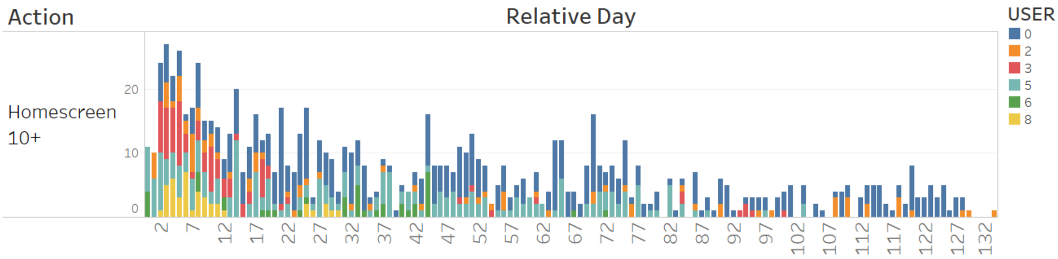



Figure 5.4.: Development of stays on the homescreen for ten seconds or longer

A feature used more often are the stays on the homescreen for ten seconds or longer. The development of the usage is displayed in figure 5.4. When comparing this plot with the graph of the diary entries (see figure 5.2), a steeper decrease is visible in the homescreen stays. Reasons for this finding may be the increasing familiarity of the users with Nutrilize. Knowledge about the location of desired features may reduce the time spent on the homescreen. Also, user **5** has a higher amount of absolute logging events in the diary than user **0** (see figure 5.2). But when analyzing the homescreen-stays, user **0** has much more detected activity. The disparity between both users may lay in different behavior patterns for receiving feedback. This probability will be analyzed later in this chapter.

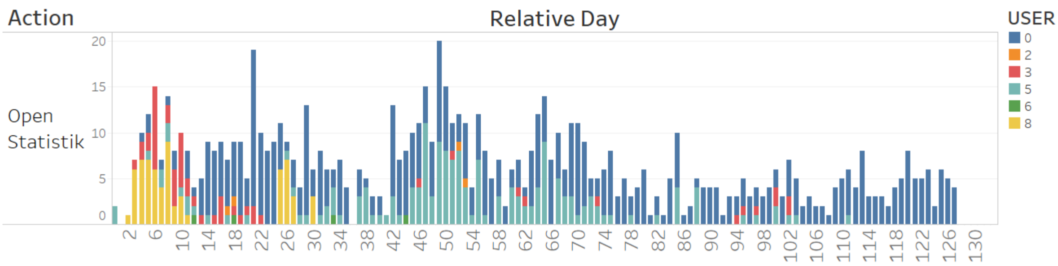



Figure 5.5.: Accesses of Nutrilize's statistics

The next feature under analysis is the access of the statistics. As seen in figure 5.5, this function was mostly used by the users **0** and **5**. The otherwise also rather active user **2** only has low usage of the statistics-screen. The majority of users show an intermittent usage. This may support the thesis that different users obtain feedback from various screens.

Figure 5.6 shows the accesses of three feedback screens - calorie overview, nutrient overview, and nutrient details. The first plot depicts the usage of the calorie feedback.

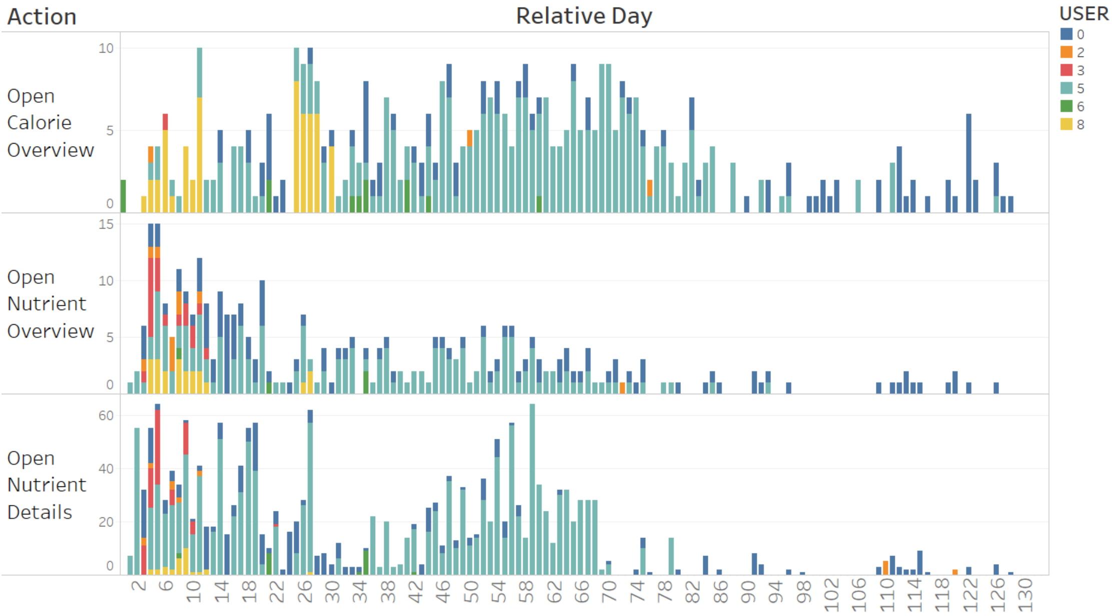



Figure 5.6.: Accesses of the feedback screens calorie overview, nutrient overview, and nutrient details

Eye-catching is the high and consistent activity of user **5**, the other users have low to decent activity. Also the often visible peak in the early period of the study is missing. These outcomes may result from the fact that the information of todays consumed calories is also available on the homescreen. Another possibility is user's unawareness of this feature.

In contrary to the calorie overview, the early peak is visible in both nutrient screens. Most users ceased usage after the peak. Notable is also the spike between day 45 and day 70 in access of nutrient details by user **5**.

When comparing the usage of the homescreen (figure 5.4) and the feedback screens (figure 5.6), one relation can be seen. User **0** is pretty active on the homescreen and has rather low figures in all feedback screens. User **5** shows the opposite pattern: high activity in the calorie- and nutrient-screens and relatively low figures on the homescreen. This disparity may hint at different ways of receiving feedback: on the one hand the quick overview on the homescreen and on the other hand the detailed insights on the according screens.

Comparatively high activity on the information text of the nutrition details is only shown by the user **5**. Graph 5.7 also shows that other participants used this feature in the early stage of the study but soon stopped the usage. A possible factor for this

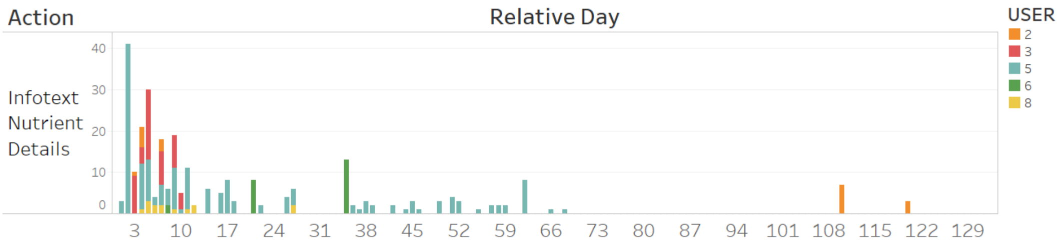



Figure 5.7.: Usage of the information text on the screen nutrient details

development is the static content of the feature - the texts never change and therefore never provide new information. Once a user read the text, future visits have no utility anymore.
User **0** is an extreme example, as he never accessed this information - even though he opened the nutrient details multiple times. A closer look into the data revealed that this specific participant uses a tablet instead of a smartphone. The bigger display dimensions make scrolling for this user unnecessary. However, this user is the only one using a tablet and the detection should work properly for the other participants.

## 5.3. Perceived Behavior Change Techniques

In the following section, the actually perceived BCTs will be analyzed.

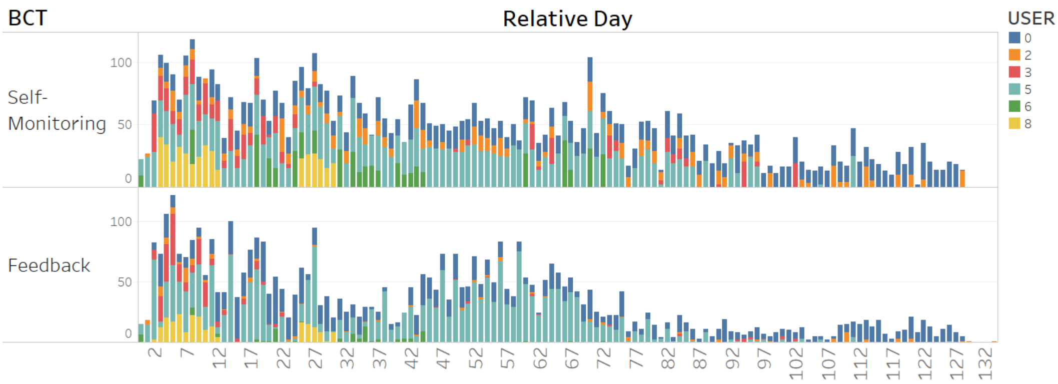



Figure 5.8.: Usage of the behavior change techniques 'self-monitoring' and 'feedback'

The two plots shown in figure 5.8 depict the BCTs 'self-monitoring' and 'feedback'. The first plot shows the vivid and steady usage of the diary-function. Two user-groups can be determined: the ones which log daily and the ones with intermittent logging. As consequent usage is the desired outcome, the reasons for the interruptions are of interest. For two of the irregular users, **3** and **6**, transcripts of the telephone interviews exist. During these conversations, illness (and subsequent altered eating behavior) and the big effort to log meals were stated as reasons to pause the tracking. While the first reason is hard to overcome, the second should be considered for future improvements.

The second displayed plot shows the technique 'feedback'. This technique is also regularly used by all participants, but less intensive. Also the decline of use is - besides the spike of user **5** - more pronounced than in the top plot. When looking at the activity by user **5**, a spiky pattern can be detected. This participant seems to check his stats every day, but with different intensity. A two-day interval may be a sufficient pattern for detailed feedback screens. According to the interviews, the implemented feedback features were useful and gladly used.

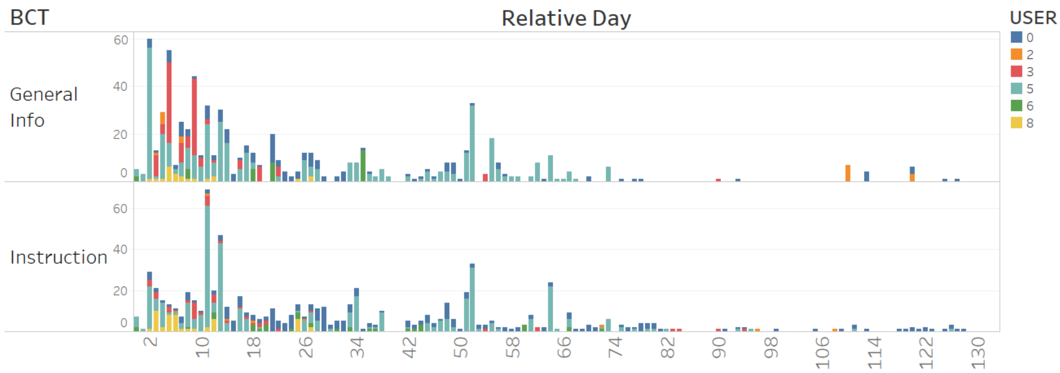



Figure 5.9.: BCT-Interactions of 'general information' and 'instructions'

Figure 5.9 contains the development of the techniques 'general information' and 'instruction'. The first named BCT is particularly affected from the spike at the beginning of the study. Near the end of the considered period the usage decreased to some single days. When looking at the development of both considered functions (*why should I eat this* and the info-text on the nutrient details), it can be seen that the accesses of the info-text have a steeper decrease. The *why should I eat this*-function retains a low but periodic use. The development of the info-text usage isn't so critical when one-time information provision on the nutrients may be sufficient.The usage of the *why should I eat this*-function could be increased with a shorter and more specific text.

The lower plot shows the BCT 'instruction'. The usage is spread across all users, but very irregular. Major contribution to this technique came by the recommendation function. During the telephone interviews, this feature also was topic of conversation. Users stated that the recommendation system has some shortages, for example the proposed portion sizes were inappropriate. These flaws led participants to lower or stop their usage. A way to increase the perception of this technique is to improve the system - even though this betterment is not trivial.

## 5.4. Timing of Logging

In the following sections, the diary-data will be investigated. Major points are the different logging-behaviors of the two user-groups adherence/attrition and the temporal distribution of tracking amongst the different meal types.

### 5.4.1. Timeliness of Tracking between Adherence and Attrition Users

| | **Adherence Users** | **Attrition Users** |
|---|---|---|
| **Mean days between record and diary** | 0.15 | 0.68 |
| **Fraction of items tracked in time** | 32.5% | 20% |

Table 5.2.: Amount of items traced in time grouped by active users

Table 5.2 shows the disparity in the usage of Nutrilize's diary between the active and inactive users. The measure in the first row describes the average difference between *date of record* and *diary date* over all entries. The second inspected feature is the percentage of all items, which were tracked in time (see section 4.6).

The results are very clear. Users with more activity in the app also tracked their meals sooner than the attrition group: the average number of days between logging and date of diary is way lower in the adherence group (0.15) than in the attrition group (0.68). The fraction of entries made in time yields similar outcomes. The active users logged nearly one third of all meals in the correct time-frame whereas the attrition users only accomplished 20%.

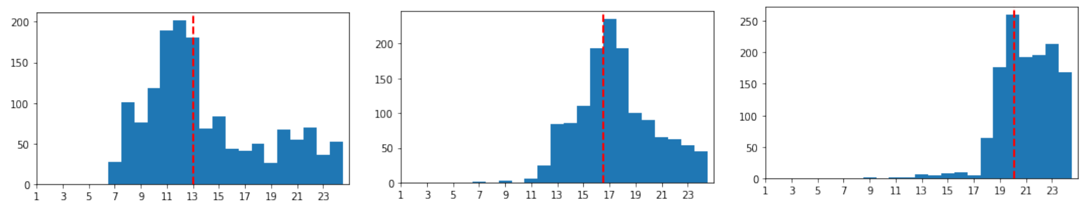
### 5.4.2. Timing of Tracking across Meal Types

| **Meal** | **Mean Hour of Record** | **Median Time of Record** |
|---|---|---|
| Breakfast | 13.03 | 12 |
| Lunch | 16.49 | 16 |
| Dinner | 20.06 | 20 |
| Snack | 17.61 | 18 |
| Sport | 17.89 | 18 |

Table 5.3.: Mean and median of the recording times for the adherence group

The next analysis assesses the different types of entries. In order to maximize the expected reliability, only the data of the adherence group were considered. As we are interested in the time passed between eating and logging, only diary-entries with matching dates of record and diary-dates are considered. Table 5.3 shows the five traceable meal types and the corresponding means of the recording time. To address the influence of possible outliers, the medians were also calculated.

It can be seen that median and mean coincide for most meal types. This indicates the absence of one-sided outliers. The only exception is the breakfast which seems to have a positive skew. Also visible is that breakfast and lunch are tracked rather late - both lay far beyond the earlier defined ordinary eating periods. The only meal that is averagely tracked in time is the dinner. Statements about the two groups *snack* and *sport* cannot be done, as it is impossible to define appropriate time periods for the events.



Breakfast Lunch Dinner

Figure 5.10.: Histograms of the time of record per meal; Mean is marked in red

The three histograms in figure 5.10 show the timing of the diary records per meal type. Again, only the data of the adherence group were used and the mean-values are marked with red lines.

Breakfast was tracked all over the day with most entries at noon. A clear peak can be seen between 10 a.m. and 1 p.m.. Another spike is also visible in the late evening around 9 p.m.. The second peak probably results from users logging the complete day's intake in one rush in the evening. This behavior was confirmed by multiple users in the telephone interviews.

The period for tracking lunches starts at 11 a.m. and lasts until midnight. Most entries were made after 3 p.m., thus a long time after the defined usual lunch times. Even though most of the tracking was done before the evening, still a large number of meals were tracked after 7 p.m..

Dinners are primarily tracked after 6 p.m.. As already mentioned, dinner is the only meal where many records lay in the earlier set time-spans. This trend could be explained by the fact that logging of meals in advance is uncommon and barely exists in this dataset.

# 6. Discussion

In this section the previous results will be interpreted and discussed. The order will be the same as in the last chapter.

## 6.1. Classification of Users

The variables suggested in the literature to identify active and inactive users were found to be only partly suitable for this specific dataset. More helpful were the absolute measures derived from the data. Especially the measure *longevity* would propose a different allocation. It seems intuitive to use the difference between the first and last day of usage as an indicator for user engagement, but the results could be biased by participants often pausing the usage. Particularly follow-up questionnaires or events which remind the users of the app may skew the results. However, lone variables never should be used to determine activity levels. To get a valid overview, always the compilation of multiple measures should be interpreted.

Comparison of the subgroup's key data showed that the adherence group is older than the attrition group. The finding that older participants are more active goes hand in hand with the results by Attwood et al. [4] and Rahman et al. [20].

The literature finds mixed results on the correlation between BMI and user engagement. In the considered study however, the users marked as active have higher BMI- and lower PAL-values.

## 6.2. Used Functions of Nutrilize

The first investigated function is the adding of diary-entries. Two users of the adherence group had high activity but stopped usage of the diary before the study-end. Therefore, seven out of eleven participants dropped out before the end of the study. This may seem like a large figure, but high drop-out rates are common in mHealth interventions [9]. In a similar 21-day-study on Nutrilize, Mohl [18] as well encountered a high drop-out rate (only 9/21 participants completed the study).

Another finding of the function-analysis are the different patterns of receiving feedback. Especially the relation between long stays on the homescreens and accesses of the detailed feedback screens (overview of nutrients and calories) is noticeable. Users which remain on the homescreen often, tend to have lover activity on the overview-pages. A possible explanation for this behavior is that the essential information of both overview-pages is already visible on the homescreen. This finding may introduce conflicts. On the one hand quick feedback should be given and on the other the feedback should also be detailed and useful. This may not be the case on the homescreen.

## 6.3. Perceived BCTs

Also analyzed were the used behavior change techniques. Average mHealth apps include six BCTs [1] [21]. Disregarding the not operable technique 'intention formation', Nutrilize incorporates five BCTs. Also the most implemented techniques in diet apps - 'self-monitoring' and 'feedback' [19] - are included. However, Nutrilize lacks the BCTs 'social comparison', 'goal setting', and 'general encouragement'. These techniques are among the most often implemented in weight loss apps [6].

First, analysis was done on 'self-monitoring'. Tracking is the most frequently and heavily used function by the users. This high activity is a good sign for the efficiency of Nutrilize, as regular and frequent monitoring of own behavior is a foundational component of weight loss [7]. Problematic is the intermittent use, as it creates periods of missing diary data or signalizes retrospective tracking.

The second-most perceived technique is 'feedback'. One factor not addressed in this analysis is that different feedback screens are counted equally. For example a look at the statistics screen contains more information than the calorie bar, but both are counted as one perception of feedback. This effect may influence the validity of the data.

One problem to keep in mind when analyzing the BCT-usage is that the quality of implementation could have a huge impact on the effectiveness and could undermine the intended purpose [21].

## 6.4. Timing of Logging

The final investigation concerns the timing of diary entries. Examination of the elapsed days between intake and logging supports the earlier met differentiation between adherence and attrition users.

When looking at the meals tracked by the active users in the ordinary meal periods, one third of all meals seems like a low fraction. One reason for this outcome are the tight time-periods considered as typical meal times. Further analysis revealed that the majority of meals are tracked on the same day, but after the defined periods.

It should be mentioned that the study which entailed the time-limits was conducted by Claupein et al. [8] in 2001 and that the considered data were from 1992. Nowadays, the time-schedules may have shifted in either direction.

The finding that most meals are logged on the day of consumption shows that Nutrilize indeed fulfills the 'near real-time'-tracking which was attributed to smartphone apps by Chen et al. [7]. However, the influence of retrospective tracking must be considered in future work.

# 7. Conclusion

One common problem in mHealth interventions is the high drop-out rate of participants. Anyway, analysis may lead to significant insights and therefore a differentiation between active and inactive users is wanted. Some measures of user engagement found in literature (*longevity* and *time span*) should only be used as supplements for absolute figures like *days of activity*, *complete days*, and *numbers of entries*. The splitting of the dataset with these measures led to an adherence group which was older and had a higher BMI than the average participant.

One further assessment targeted the used functions of Nutrilize over time course. Besides the natural attrition, the following functions stood out. The recommendation system was often opened, but proposed recipes only seldom were accepted. Also disparate users behaved different. Some added meals directly from the search results, others from the food details. Further, distinct behavior-patterns were detected on the various feedback screens. Some users perceived feedback on the homescreen and some used the detailed pages. Another development appearing primarily in less used functions is the spike in the beginning of the study. All users test the features in the beginning, but only few users maintain the usage.

When linking the features to BCTs, 'self-monitoring' and 'feedback' were most perceived by all users. In both some form of interval usage could be detected for some users (either in height or intensity). The BCTs 'general information' and 'instruction' were also perceived by all users, but they suffered from strong decline in usage after the first 15 days.

Finally, it has been shown that most logging is done retrospectively. Further disparities were shown between the two user groups. The adherence group tracked their meals timelier than the attrition group. Another salient result is that all meals are tracked rather late. The phenomenon of tracking the complete day in the evening is supported by the outcomes.

# 8. Future Work

This chapter presents possible improvements for the app Nutrilize. Also, potential topics for pursuing research in the field of healthy eating apps are proposed.

## 8.1. Technical Improvements

To prevent the attrition of participants, it may be helpful to improve the usability of Nutrilize. Findings by Zhao et al. [15] indicated a higher retention of users when the usability is increased. Especially the search and addition of dishes takes a long time, which also was criticized during the telephone interviews with the participants.

In order to help users become acquainted with the features of the app, a tutorial on the first start could introduce the different screens and functionalities. This forced familiarization would entail a smoother user base and make the analysis of used app-features more meaningful.

In order to improve the effectiveness of Nutrilize, additional BCTs could be implemented. Especially the 'goal setting' technique should be considered. This special BCT was shown to be effective in a study concerning the reduction of alcohol consumption [4] and the basic structure already exists.

## 8.2. Scientific Improvements

The major limitation of the proposed analysis is the low number of participants. Only six persons were found to use the app over a period long enough to allow conclusions. Therefore, the findings in this thesis should be verified with larger datasets. Because attrition is strongly correlated to the duration of interventions, the analysis of studies of different lengths could also generate interesting insights.

The investigation revealed that most of the diary entries are made retrospectively. One question not addressed is to which extent this fact has an influence on the quality of the logged data. One opportunity could be to compare the meals recorded with delays (breakfast and lunch) with the timely tracked dinners.

Completely ignored in this thesis is the validity of diary entries. Related literature found that higher BMI-values are correlated with increased underreporting [11]. As the considered study only included overweight persons, this phenomenon should be further examined.

# A. Appendix

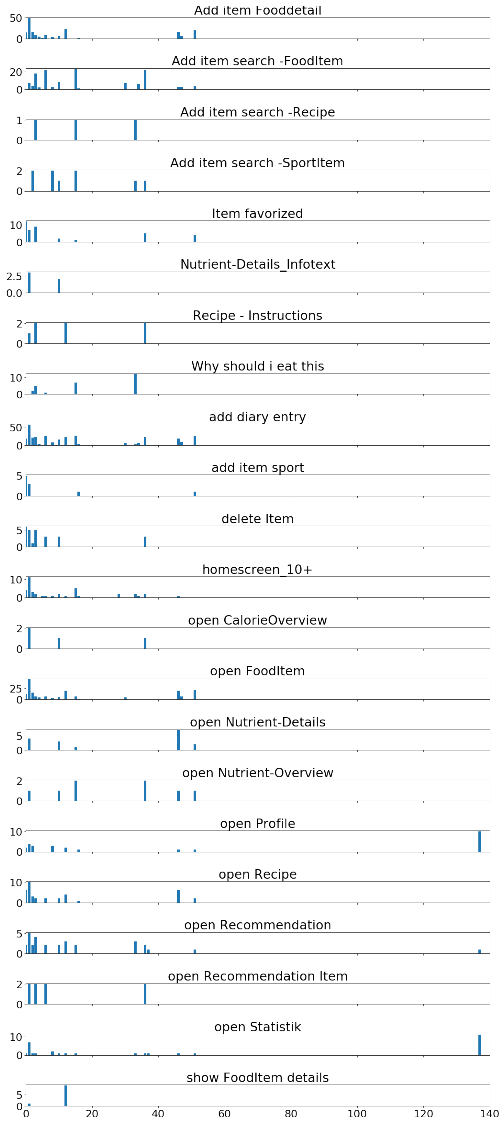



Figure A.1.: Some actions of the attrition group

# List of Figures

# List of Tables

# Bibliography


[1] C. Abraham and S. Michie. "A taxonomy of behavior change techniques used in interventions." In: *Health psychology : official journal of the Division of Health Psychology, American Psychological Association* 27 3 (2008), pp. 379–87.

[2] C. Abraham and S. Michie. "Coding Manual to Identify Behaviour Change Techniques in Behaviour Change Intervention Descriptions." In: (2008). Described in Abraham, C. & Michie, S. (2008) A taxonomy of behavior change techniques used in interventions.

[3] C. M. Apovian. "The Clinical and Economic Consequences of Obesity." In: *The American journal of managed care* 19.11 (2013).

[4] S. Attwood, H. L. Parke, J. Larsen, and K. Morton. "Using a mobile health application to reduce alcohol consumption: a mixed-methods evaluation of the drinkaware track & calculate units application." In: *BMC public health* (2017).

[5] L. E. Burke, S. M. Sereika, E. Music, M. Warziski, M. A. Styn, and A. Stone. "Using instrumented paper diaries to document self-monitoring patterns in weight loss." In: *Contemporary clinical trials* 29.2 (2007), pp. 182–93.

[6] J. Chen, J. E. Cade, and M. Allman-Farinelli. "The Most Popular Smartphone Apps for Weight Loss: A Quality Assessment." In: *JMIR mHealth uHealth* 3.4 (Dec. 2015), e104. ISSN: 2291-5222. DOI: `10.2196/mhealth.4334`.

[7] J. Chen, L. Gemming, R. Hanning, and M. Allman-Farinelli. "Smartphone apps and the nutrition care process: Current perspectives and future considerations." In: *Patient Education and Counseling* 101.4 (2018), pp. 750–757. ISSN: 0738-3991. DOI: `https://doi.org/10.1016/j.pec.2017.11.011`.

[8] E. Claupein, U. Oltersdorf, and G. Walker. "Zeit fürs Essen – Deskriptive Auswertung der Zeitbudgeterhebung." In: *Spektrum Bundesstatistik, Band 17* (2001), pp. 202–213.

[9] G. Eysenbach. "The Law of Attrition." In: *Journal of Medical Internet Research* 7.1 (2005).

[10] B. J. Fogg. "Persuasive technologies." In: *Communications of the ACM* 42.5 (1999), pp. 27–29.

[11] N. R. Fuller, M. Fong, J. Gerofi, F. Ferkh, C. Leung, L. Leung, S. Zhang, M. Skilton, and I. D. Caterson. "Comparison of an electronic versus traditional food diary for assessing dietary intake—A validation study." In: *Obesity Research & Clinical Practice* 11.6 (2017), pp. 647–654. ISSN: 1871-403X. DOI: `https://doi.org/10.1016/j.orcp.2017.04.001`.

[12] S. Gabrielli, M. Dianti, R. Maimone, M. Betta, L. Filippi, M. Ghezzi, and S. Forti. "Design of a Mobile App for Nutrition Education (TreC-LifeStyle) and Formative Evaluation With Families of Overweight Children." In: *JMIR Mhealth Uhealth* 5.4 (Apr. 2017). ISSN: 2291-5222. DOI: `10.2196/mhealth.7080`.

[13] C. C. Imes and L. E. Burke. "The Obesity Epidemic: The USA as a Cautionary Tale for the Rest of the World." In: *Current Epidemiology Reports* 1.2 (June 2014), pp. 82–88. ISSN: 2196-2995. DOI: `10.1007/s40471-014-0012-6`.

[14] F. Jimoh, E. Lund, L. J Harvey, C. Frost, W. James Lay, M. Roe, R. Berry, and P. Finglas. "Comparing Diet and Exercise Monitoring Using Smartphone App and Paper Diary: A Two-Phase Intervention Study." In: *JMIR mHealth and uHealth* 6 (Jan. 2018), e17. DOI: `10.2196/mhealth.7702`.

[15] M. L. Jing Zhao Becky Freeman. "Can Mobile Phone Apps Influence People's Health Behavior Change? An Evidence Review." In: *Journal of Medical Internet Research* 18.11 (2016).

[16] M. Klein, N. Mogles, and A. van Wissen. "Intelligent mobile support for therapy adherence and behavior change." In: *Journal of Biomedical Informatics* 51 (2014), pp. 137–151. ISSN: 1532-0464. DOI: `https://doi.org/10.1016/j.jbi.2014.05.005`.

[17] Matomo. *Analytics Glossary*. URL: `https://glossary.matomo.org/`. accessed: 25.10.2018.

[18] M. Mohl. "Machine Learning of Motivational and Behavior Change Stages from Nutritional Diaries." In: (Apr. 2018). Master's Thesis in Informatics, Technical University of Munich.

[19] R. Orji and K. Moffatt. "Persuasive technology for health and wellness: State-of-the-art and emerging trends." In: *Health Informatics Journal* 24.1 (2018), pp. 66–91. DOI: `10.1177/1460458216650979`. eprint: `https://doi.org/10.1177/1460458216650979`.

[20] Q. A. Rahman, T. Janmohamed, M. Pirbaglou, P. Ritvo, J. M. Heffernan, H. Clarke, and J. Katz. "Patterns of User Engagement With the Mobile App, Manage My Pain: Results of a Data Mining Investigation." In: *JMIR Mhealth Uhealth* 5.7 (June 2017), e96. ISSN: 2291-5222. DOI: `10.2196/mhealth.7871`.

[21] S. Schoeppe, S. Alley, A. L. Rebar, M. Hayman, N. A. Bray, W. Van Lippefelde, J.-P. Gnam, P. Bachert, A. Direito, and C. Vandelanotte. “Apps to improve diet, physical activity and sedentary behaviour in children and adolescents : a review of quality, features and behaviour change techniques.” In: *International Journal of Behavioral Nutrition and Physical Activity* 14.83 (2017), 10 S. ISSN: 1479-5868. DOI: `10.1186/s12966-017-0538-3`.

[22] WHO. *Fact sheet: Obesity and overweight*. Feb. 2018. URL: `http://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight`. accessed: 16.10.2018.

[23] C. Zhang, D. Lakens, and W. IJsselsteijn. “Connecting Behavior Change Theories to E-coaching Applications: A Review and A Unified Framework.” In: *Working Manuscript for Journal of Medical Internet Research* ().