Exploring AI-based personalization of a mobile health intervention and its effects on behavior change, motivation, and adherence

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To Johana, Ada and Oliver

Abstract

Medical treatments are traditionally personalized in a manual process by healthcare practitioners. Personalization starts with a one-size-fits-all treatment adjusted for each patient in a lengthy trial and error process. Unfortunately, this process can result in unnecessary treatment, exposure to side effects, and patient loss of interest due to treatment ineffectiveness. Mobile health (mHealth) researchers have investigated ways to decrease ineffective treatment exposure by personalizing health interventions using Artificial Intelligence (AI). AI methods like contextual-bandits are often used for personalizing content (*i.e.,* which health advice to provide) with promising results. However, content personalization approaches alone are underpowered by lacking personalization of time of treatment: an active component that delivers health advice in the form of alerts or reminders at appropriate times (e.g., time, location, and activity). State of the art work has shown that reminders alone can increase treatment adherence but have not resulted in behavior change yet.

In this thesis, I developed and tested a method for personalizing mobile health interventions' content and timing of treatment. I tested this approach in a real-world deployment (n=30, spring 2019) of a behavioral sleep intervention. I found that this personalization approach improved sleep duration, motivation to improve sleep-related behaviors, and adherence to sleep advice. In addition, I discovered that contextual factors and participant intrinsic characteristics have a significant effect on adherence to treatment. Building on these results, I implemented a machine learning classifier that predicts next-day adherence to treatment with promising performance.

Following up on the results from the sleep intervention, I deployed a larger (n=80) to investigate further the marginal effects of personalization of content and treatment timing. The intervention was deployed sleep days before the beginning of the 2020 pandemic. This intervention did not result in behavior change. In this part of my thesis, I investigate this 2020 deployment and the specific causes of the null intervention results. I compare the behaviors

of the participants in the 2020 and 2019 studies using behavioral logs, phone usage, and sensor streams and surveys. I found that a lack of motivation caused by anxiety and stress induced by the pandemic and a drastic change in phone use and daily routines were the most likely reasons for the null intervention results. I close this thesis with recommendations on preparing for abrupt changes in their daily behavior and how they interact with computing devices used for intervention purposes.

In summary, this thesis contributes 1) A novel, effective, and sample efficient approach for the simultaneous personalization of content and timing of treatment using AI, sensors, and human feedback, 2) A deployment and test of a system using the personalization method mentioned above, 3) Findings on contributing factors that change adherence to treatment in the context of a behavioral intervention, 4) A machine learning classifier for the prediction of intraday adherence and 5)The development of a framework for understanding contributing factors that lead to null results during a pandemic and may generalize to pandemic-like events.

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Contents

Abstract v

Acknowledgements vii

Contents x

List of Figures xiv

Chapter 1 Introduction 1

1.1 Aims 3

1.2 Contribution 5

Chapter 2 Preliminaries 6

2.1 The elements of a mobile health intervention 6

2.1.1 Distal outcomes 8

2.1.2 Proximal outcomes 8

2.1.3 Decision points 8

2.1.4 Intervention points 9

2.1.5 Available treatments 11

2.1.6 Tailoring variables 11

2.1.7 Treatment selection 12

2.2 Dimensions of personalization in mhealth interventions 12

Chapter 3 Sleep health and interventions 15

3.1 Sleep Definition and Motivation 15

3.2 Sleep in Human-computer interaction 16

Chapter 4 The SleepU app 19

4.1 App description and walk-through 20

4.1.1 Design principles and connection to behavior change theories 23

Chapter 5 Personalization of time of treatment: Mobile-receptivity detection 25

5.1 Related work 26

5.2 Mobile-receptivity and interruptibility 27

5.2.1 Detecting interruptibility 28

5.2.2 Features 28

5.3 Mobile-receptivity detection 31

5.3.1 Data collection and features 31

5.3.2 Machine Learning Pipeline 32

5.3.3 Classifier and Performance evaluation 32

5.3.4 Receptivity detection during intervention 33

Chapter 6 Personalization of time and content of treatment 34

6.1 Related work 34

6.2 Personalization of content 36

6.2.1 Contextual bandit 36

Chapter 7 Study 1:Exploratory trial of the SleepU App 39

7.1 Method 39

7.1.1 Study design considerations 41

7.1.2 Participants 41

7.1.3 Measures 42

7.1.4 Analysis plan 43

7.2 Results 44

7.2.1 Behavior-RQ 45

7.2.2 Adherence-RQ: 46

7.2.3 Context-RQ 46

7.3 Discussion 47

7.4 Limitations 51

7.5 Conclusion 52

7.5.1 Scalability 52

7.5.2 Broad access 53
7.5.3 Privacy 54

Chapter 8 Adherence to treatment prediction 55
8.1 Related work 56
8.1.1 Time-length 56
8.1.2 Features 58
8.2 Intraday adherence prediction 60
8.2.1 Data collection 60
8.2.2 Features 61
8.2.3 Machine Learning Pipeline 61
8.2.4 Evaluation and results 61
8.3 Discussion 62
8.4 Limitations 63

Chapter 9 Study 2: Deploying an mHealth intervention during the 2020 pandemic 64
9.1 Method 64
9.1.1 Participants 66
9.1.2 Measures 66
9.2 Analysis plan 68
9.3 Results 69
9.3.1 Personalization of content 69
9.3.2 Personalization of time of treatment: Adherence 70
9.3.3 Personalization of time of treatment: Behavior change 72
9.4 Discussion 72
9.5 Conclusion 74

Chapter 10 Understanding the effect of the pandemic in study 2 75
10.1 Quantitative analysis: Comparison of study 1 (2019) and study (2) 75
10.1.1 Sleep and related behaviors 76
10.1.2 Phone use, location and activity 79

10.1.3 Conclusion 80
10.2 Qualitative Analysis: Understanding participants thoughts and feelings during study 2 81
10.2.1 Method 82
10.2.2 Results 82
10.2.3 Conclusion 84
10.3 The disruptive-events framework 85
10.4 Implications for pandemic-like events 86
10.4.1 Personalizing during pandemic-like events 86
10.5 Discussion: Three pandemic-like case scenarios 88
10.6 Conclusion 91

Chapter 11 Conclusion **92**
11.1 Unresolved questions 93
11.2 Future work 94
11.2.1 Personalization of time and content across different intervention domains 94
11.2.2 Beyond receptivity 95
11.2.3 Health interventions across devices 95
11.2.4 Language-style (a.k.a., Message Framing, tone) 96
11.2.5 Emotion-sensing 97
11.2.6 Self-tracking+sensing+receptivity 97

Chapter 12 Appendix **99**
12.1 Sleep Duration GMM 99
12.2 Study 1: Effect of context and intrinsic characteristics 101
12.3 Study 2: Personalization of content comparisons 102
12.4 Study 2: Personalization of time of treatment comparisons 103

References **104**

List of Figures

2.1 Traditional vs mobile health intervention cycle. 7

4.1 a)Fogg Behavior Model adaptation of the recommendation "avoid caffeine 6 hours before bedtime". The horizontal blue and red rectangle shows how the ability to enact a recommendation depends on time of day b) General process followed by the SleepU app. 19

4.2 Different screenshots from the SleepU app. Left to right: a) SleepU diary entry, the user gets a reminder at 9 am to fill out the diary. If they checked their phone earlier than that, the receptivity classifier could trigger a notification to fill out the sleep diary. b) The app pushing a notification to the user about a new sleep recommendation available; note that the actual recommendation text is omitted in the notification. c) A sleep recommendation viewable *after* the notification is clicked on. d) Main screen of the app which gives the user access to the sleep recommendations selected for her for the current day, with the other sleep recommendations hidden. 20

4.3 a) Process of checking a sleep recommendation in the SleepU App. b) Probability over time to pick at random receptivity detection or a random time for triggering a notification to read a sleep recommendation 22

5.1 Machine learning pipeline for training and deployment of the receptivity detector 32

7.1 Study design 40

7.2 a) The plot shows the adherence to the sleep recommendations provided by the app over time during the app-intervention phase. b) The plot shows the odd ratios intrinsic and contextual factors on adherence. c) Adherence rates for all the trigger mechanisms $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ 47

9.1 Study design 65

9.2 Adherence rates comparison between study 1 and 2. 70

9.3 Odd ratios comparison for the BMMs in Study 1 and 2. Values in red represent a decrease in odds $OR < 1$ and probability, while blue values represent an increase in odds and probability. For motivation, the confidence interval of the odd ratios includes 1 and for that reason it is not significant. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$ 71
9.4 Likelihood of adherence over the course of study 1 and 2. For study 2 (left) the likelihood decreases over time while for study 1 (right) adherence increases over time. 71
10.1 Smoothed standard deviation (rolling window, n=7 days) of sleep duration during the 2019 and 2020 studies. Higher values mean higher variance across individuals 77
10.2 Smoothed cognitive activity and percentiles 78
10.3 Smoothed cognitive activity before bed for different days of the week 78
10.4 Comparisons between motivation of 2020 and 2019 84

CHAPTER 1

Introduction

Personalized medicine (i.e., precision medicine) [**19**] is an approach where health treatment is adjusted to an individual's genetic, environmental, and lifestyle factors. This national initiative was introduced in 2015 by United States President Barack Obama [**19**] and later renamed to the All of Us program [**112**], a project that is currently active in the United States. The value of personalized health interventions comes from improved health care outcomes from trying only treatments that are most likely to succeed by reducing time to achieve improved outcomes, decreasing costs, and minimizing side effects improving quality of care [**58**]. However, despite the advantages, genetic-based personalized medicine is at a basic research stage, and it is not used yet in clinical practice [**76**].

Personalization has traditionally been a process in which both the patient and physician are involved: A clinician first provides treatment based on experience, patient's preferences, and treatment goal; after acquiring evidence [**2**] of success or failure in achieving the desired outcomes, the clinician proceeds to adjust treatment. The need for personalization comes from two primary sources that are not necessarily exclusive: Gaps in medical and personal knowledge. Medical knowledge may be insufficient to understand adherence or treatment effect for an individual. Personal knowledge means an individual may not be aware of her preferences, treatment adherence (compliance with treatment), or treatment side effects (unaware of allergies). This gap in personal knowledge means that even when the science is precise, the only way to personalize treatment is trial and error. In summary, this manual personalization is not only inefficient, but it may also be unavoidable.

Another problem is that patients are on their own when it comes to self-monitoring and self-managing their treatment, two crucial components of self-efficacy: an individual's belief

in their innate ability to achieve goals (*e.g.,* take medication on time, exercise more). Without self-efficacy, behavior change is not viable. Mobile health technology has emerged as a promising path to personalized medicine, not only to collect and monitor 24x7 and to collect previously unavailable data but also to support real-time interaction with the patient that could potentially improve engagement and empowerment.

Mobile health (mHealth) researchers have approached this challenge of personalization by using a combination of wearable sensors, user feedback, and AI. Researchers have investigated various personalization aspects [**107, 95, 139, 113, 109**] like content [**107, 95, 139**] and timing of treatment [**53, 71, 86, 139**]. Respectively they have been shown to generate behavior change for motivated individuals [**107, 139**] and increase adherence to treatment [**53**]. More recently, Kunzler *et al.,* [**71**] observed that "being receptive to interventions helped participants achieve intervention goals." However, a receptivity detector tuned for each individual with a minimal amount of data did not perform better than baseline approaches like providing recommendations at random times [**86**]. Overall, personalized content or timing alone is limited as it only optimize a single dimension of personalization. A possible approach to overcome this limitation is to combine the personalization of content and timing. This idea has been explored [**95**] resulting in promising outcomes, but it did not change participants' behavior. I posit that this joint personalization of (*i.e.,* using a single method) timing and content [**95**], suffers from high computational complexity resulting in a partially personalized intervention that does not achieve its full effect.

In this work, I explored an approach that reaps the benefits of personalizing content and time of treatment without incurring high computational complexity. First, I explored disjoint personalization (*i.e.,* estimated at the same time but separately) of timing and content. To personalize content, I used a contextual-bandit that uses sensor data, user's adherence to treatment, and the user's context. Second, to personalize the time of treatment, I built a mobile-receptivity detector from a group of people instead of a single individual [**86**] to create a more robust yet group-personalized mobile-receptivity detector. I then merged this approach with a standard sleep intervention into -SleepU- an Android app that provides sleep recommendations personalized in content and timing to college students. Finally, I selected

sleep as the domain for health intervention to validate this approach due to its essential role in physical [**42**] and mental health [**4, 42**]. SleepU delivers sleep recommendations after detecting receptivity in real-time from smartphone sensor streams. SleepU then uses a contextual-bandit running on a smartphone to personalize content by selecting a sleep recommendation, among a set of recommendations, that is best for the user according to wearable data, user's previous adherence to treatment, and the user's context.

1.1 Aims

I explored the potential of SleepU for promoting behavior change through a pilot study conducted as a real-world deployment ($n = 30$) in the spring of 2019 (Study 1). During the first four weeks, the participants did not receive an intervention while a background app passively collected sleep and smartphone use and sensor data. In the fifth week, participants were randomized to interact with SleepU for four weeks (app-intervention) or receive standard care (control-intervention). At the end of this first phase of the intervention, participants were assigned to the other intervention (control or app) for the remaining four weeks. During the app-intervention, participants could receive sleep recommendations when they were detected as mobile-receptive or at random times, and also, they could check recommendations on their own. In this exploration and as suggested by [**66**], I investigate proximal outcomes (*e.g.,* motivation and treatment adherence), distal outcomes (*e.g.,* sleep duration, efficiency, number of awakenings, and time in bed), and the effects of intrinsic characteristics of the participant (*e.g.,* baseline motivation and regular sleep duration) and context (*e.g.,* period of the day, number of days in intervention). I now present the guiding research questions of this thesis:

- *What is the effect of personalization of timing and content in behavior change and motivation?* I found that the participants' sleep duration increased significantly while interacting with SleepU compared to their sleep during the first four weeks of the study (*i.e.,* when there was no intervention) and compared to when they were exposed to the control-intervention. This disjoint personalization of timing

and content of treatment approach is the first to result in significant sleep behavior change. I also found a marginally significant increase in motivation between baseline and the app-intervention.

- *What is the effect of personalization of timing and content on adherence to treatment?* I found that receptivity results in statistically higher adherence compared to recommendations delivered at random times and those checked by the user on its own. This mobile-receptivity detector is the first receptivity model used in an mhealth intervention that results in increased adherence in a behavioral intervention.
- *What is the effect of context and motivation of the participant in the likelihood of adherence to recommendations?* I found that participants, independent of time of the day and in the absence of a reminder, are not likely to follow a sleep recommendation. I also found that delivering recommendations in the morning resulted in the highest likelihood of adherence and the evening the lowest, which corroborate recent findings [**71**]. Further, I found that both the number of days in the app-intervention phase and participant motivation to improve sleep increase the likelihood to adhere to treatment. These results have important implications for the design and tailoring of mhealth interventions.
- *Can we predict future adherence to treatment using contextual factors and motivation of the patient?* I found that using a machine learning model and the contextual factors that affect adherence, it is possible to predict next-day adherence to treatment. Furthermore, this machine learning model is 38% more accurate than a naive classifier that only picks the majority class (69% vs 50% balanced accuracy).

The results, at large, show that there is a positive and significant effect of personalizing timing and content concurrently. However, it is impossible to establish whether the intervention's primary driver for behavior change was the timing or the content component given the experimental design. Understanding the difference in the contribution to the effect on behavior change of each personalization dimension can help in real-world scenarios to decide where research and development efforts should be focused. In addition, it may lead to the creation of more straightforward but effective interventions. To explore the marginal contributions of the dimensions of personalization, a second research study (Study 2) was designed and deployed

to 80 participants. Study 2 started a week before the 2020 COVID-19 pandemic became official. This second intervention resulted in null results for behavior change, motivation, and adherence. Given these null results, I used the data collected from this second study as an opportunity to understand why it failed and specifically to understand how the pandemic could have disrupted the AI-based personalization approach and the participants' daily lives.

1.2 Contribution

This thesis advances mhealth interventions by developing and testing the effect of AI-based personalization of content and time of treatment in a real-world deployment. This thesis also explores contextual factors and an individual's intrinsic characteristics (e.g., demographics, motivation, daily behaviors) on adherence to treatment. From these results, I investigated and evaluated a method for predicting next-day adherence using a combination of behavioral measures, previous-day adherence, and context. Last, this thesis explores and discusses pandemic-induced factors that resulted in behavioral changes that lead to null intervention results of deployment during the 2020 pandemic.

CHAPTER 2

Preliminaries

In this chapter, I present basic definitions of the elements of a mobile health intervention. These definitions, in most cases, follow previous work while others are defined in this thesis. At the end of the chapter, I introduce the different dimensions of personalization.

In this thesis, mhealth interventions are defined as interventions delivered via a mobile device and tailored dynamically, *i.e.,* changes to the health intervention are based on sensor data or user feedback and performed multiple times throughout the intervention. In comparison, traditional computer-tailored interventions are not dynamic (static): usually, tailoring occurs once at the beginning of treatment. Dynamic computer-tailored health interventions have an increased efficacy [**69**] in comparison to static health interventions. Besides the value provided by being more efficient than a static health intervention, mhealth interventions have the added benefit that they can accompany the patient at all times: An mhealth intervention can both reach (push) or be reached by (pull) the patient at any time and place [**115**]. Ultimately one of the most promising roles of a mobile health intervention is to support the patient at the time and place where treatment is put into practice, and this is a role that even the best medical care cannot provide.

2.1 The elements of a mobile health intervention

Mobile health interventions are defined by components that are not present in traditional health interventions due to the intrinsic capabilities of mobile computing devices that make health interventions readily available anytime and anywhere. Some of these elements are defined in the literature [**90**] while other elements are extended (*e.g.,* available treatments,

tailoring variables, treatment selection), or first defined (intervention points, initial treatment) in this thesis to better match the nature of mobile health interventions.

To better illustrate some of the elements, figure 2.1 shows a general mobile health intervention cycle compared to a traditional health intervention. In the next sections, I describe the elements of a mobile health intervention considered throughout this thesis.

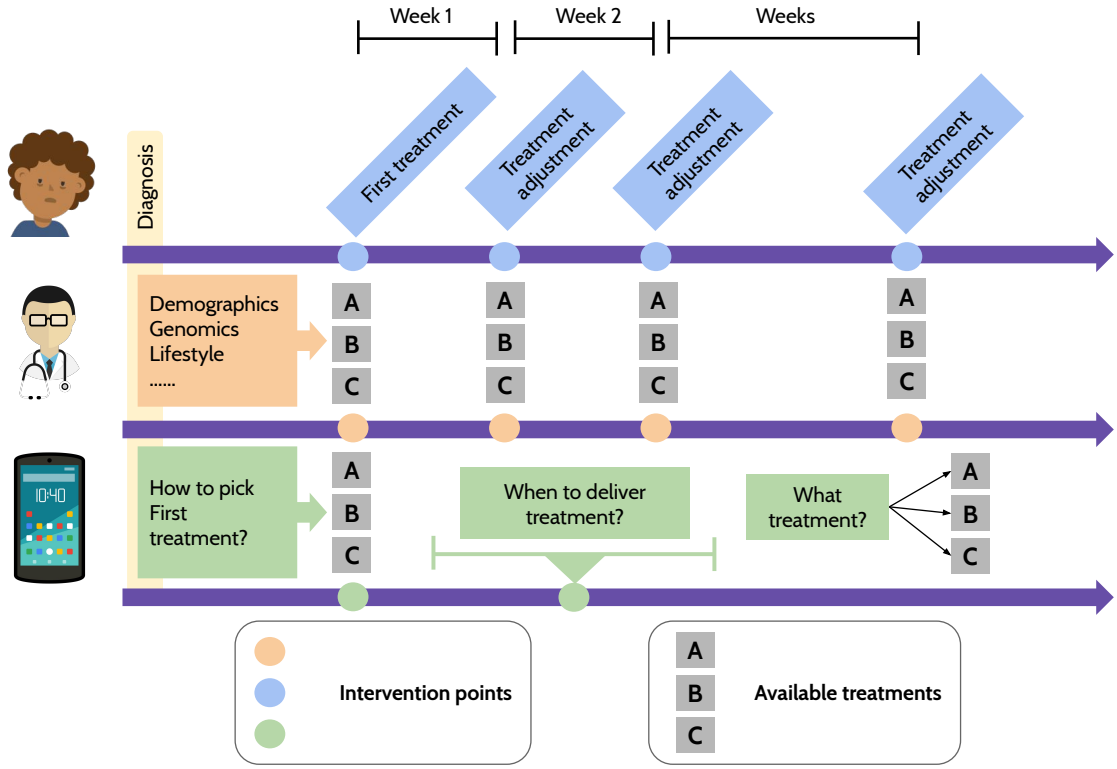


FIGURE 2.1. This diagram shows a basic health intervention cycle and each stakeholder. The patient first gets a diagnosis; afterward, the initial treatment follows, and then there are treatment adjustments sometime after. In order to select the initial treatment, the doctor needs to take into account the patient's demographics, genomics, lifestyle, and others. After the initial treatment, the patient goes back to the doctor, and depending on the health state; the treatment may be adjusted. In a mobile health intervention, the process is the same, but every decision is taken autonomously. Also, treatment adjustment does not have to occur at a fixed point in time; it can be adjusted in days or hours depending on the disease. However, this new model of health has three main challenges: 1) How to select the initial treatment?, 2) When to deliver the treatment, and 3)How to select a treatment.

2.1.1 Distal outcomes

Distal outcomes are defined as the set of outcomes that are the ultimate goal of the intervention [**90**]. This is also referred to as the primary clinical outcome. For example, in drug rehabilitation, the distal outcome is eliminating drug use; in sleep hygiene, it is the improvement of sleep health factors. Distal outcomes are essential to health interventions; however, they are usually tricky to use for day-to-day treatment adjustment: There is usually a long time between treatment administration and the observation of change. Distal outcomes alone are not sufficient to measure the intermediate success of a health intervention; however, they are crucial for designing a health intervention. Distal outcomes are usually domain-specific.

2.1.2 Proximal outcomes

Proximal outcomes are outcomes that can potentially lead to the desired distal outcome as mediating or direct factors affecting the distal outcome [**90**]. Typical examples of a proximal outcome are mediators of behavior change like motivation [**84, 37**] and self-efficacy [**5**]. Proximal outcomes apply not only to behavioral interventions but also to pharmacological treatments that rely on basic behaviors of the patient like taking pills at specified times; in this case, treatment adherence is a crucial factor: Patients' failure in adhering to medication regimes causes 33 to 69% of hospitalizations and accounts for $100 billion in annual health care costs [**94**]. Proximal outcomes are not domain-specific, but they are adapted to each intervention. For example, adherence to pharmacological treatment is measured by counting how many times a patient takes a pill on time, while in a sleep intervention, it is measured by the number of times the participant fills out a sleep diary. In both cases, the construct is the same, but the measure is specific to the intervention.

2.1.3 Decision points

Decision points are the points in time or, more generally, context (*e.g.,* location, time of day, mood), where a health intervention is adjusted [**90**]. Such adjustment could be based on a combination of sensor input, patient feedback, computational feedback (*i.e.,* estimates of

future outcomes from a model), or even physician's feedback. These decision points may or may not be of importance depending on the application. Decision points can be decoupled from delivery when estimating the next decision does not rely on real-time data. For example, in a sleep intervention using sleep-related outcomes, decision points could occur every day after waking up, or they could be computed right before the moment of delivery. Assuming the sleep treatment depends only on the previous night of sleep, there is no difference between computing a decision right before treatment is delivered or as soon as the night of sleep data is available (after waking up). In contrast, in an intervention for increasing physical activity based on steps, right before delivering an intervention, an estimate of the current number of steps is necessary to suggest the number of steps left to meet a predefined goal. In general, interventions where the target of the intervention involves an ever-changing process (like a step count), will require a decision point close to delivery.

2.1.4 Intervention points

Intervention points are the context of delivery of a health intervention. An important differentiator of intervention points is whether they are vulnerable or opportunistic states [**90**]. Vulnerable states lead to undesirable or dangerous outcomes; as an example, a stressful situation could be a vulnerable state for a person going through drug rehabilitation since such an event could lead to relapse. Opportunistic states are contexts used to improve health outcomes without a necessary connection between the health outcome and treatment. For example, the same individual going through rehabilitation may benefit from reminders to engage in positive social interactions and exercise. A key construct to find the best intervention points is *receptivity*: "an individual's transient ability and/or willingness to receive, process and utilize just-in-time support". This construct, rooted in the dual-process model for supportive communication, states that [**12**] supportive communication (*e.g.,* a sleep recommendation) can result in positive changes in behavior when the recipient is motivated to process and enact the message. The identification of receptivity is crucial for finding opportunistic intervention points. Although there has not been work looking at detecting receptive states from sensor

streams or data in general, researchers in human-computer interaction (HCI) have a well-established body of work on a similar concept called interruptibility and engagement. There are multiple definitions of interruptibility, but for this thesis, I refer to interruptibility as the idea that people have moments during the day when they are available to be interrupted. At such times, an interruption has a low enough cost, and an interruption is acceptable [**49, 91**]. Interruptibility has been studied around computer use and, more recently, mobile phone use, and as such, all of this body of work is centered on finding interruptible states when an individual is interacting with a computer or a mobile phone. More recently, HCI researchers have looked at engagement detection [**98**], an extension of interruptibility detection, where the goal is to detect not only when an individual can be interrupted but also when the individual further engages with the content of the interruption. An easy way to differentiate the two follows: When an individual receives an SMS and does not even look at it, the individual is not interruptible; when the individual glances at the SMS, the individual is interruptible; lastly, when the individual looks at the SMS, opens it and even replies to the sender or further engages in a task related to it, the individual is engaged. In this work, I use engagement detection (*i.e.,* mobile-receptivity) as a proxy for detecting receptivity. Despite the importance of receptivity and its related constructs of engagement and interruptibility, there is no work using receptivity to trigger the delivery of a health intervention. However, some researchers have already started including receptivity in their study protocols for future studies [**68**].

2.1.4.1 Initial treatment

In this thesis, I further refine the definition of intervention points to include the initial treatment. The initial treatment refers to the state in which the intervention starts and is delivered to an individual. There are two possible options to start an intervention: 1) Random: A treatment is picked at random among the possibilities for treatment. Although not ideal, it is realistic when there is not enough knowledge about the patient to perform any personalization. Also, this could be an option for interventions that are trying to fulfill research and clinical goals and as such, this initial treatment, if uniformly randomized, is a micro-randomized trial [**65**] and the data generated from this stage could be used for causal inference. At later decision points, the intervention could move away from a uniform probability distribution; however,

the data generated from that point forward cannot be used for causal inference because treatment is not provided randomly and is biased towards the clinical goal. 2) Tailored: The intervention starts with a treatment picked using variables that identify the subset of treatments that have a higher chance of succeeding at achieving the target outcome of the intervention. This treatment selection uses expert knowledge where a physician could look for specific demographic variables or other factors. In addition, this treatment selection could use computational models that can estimate, from clinical health records or biological databases, possible outcomes based on demographics or genetic makeup. Another possibility is to use a mixed approach where physicians rely on computational models and their knowledge to determine the best course of treatment.

2.1.5 Available treatments

Available treatments are referred to as intervention options in the literature and are the different types of treatment available for delivery at any given point. Here, I decided to add "Available" to highlight the changing nature of the context of the patient and how that context ultimately changes her ability to put into practice health treatments. Nahum-Shani [**90**], further defines as part of the available treatments the media of delivery (*e.g.,* SMS, email, phone call), the type (advice, feedback), or even the quantity of the treatment (*e.g.,* dosage of a medication or how many times to provide a heath recommendation).

2.1.6 Tailoring variables

Traditionally, tailoring variables are about the patient receiving the interventions, and as such, these variables revolve around the individual[**90**]. However, it is crucial to notice that, from a mobile health intervention point of view, intervention options must be dependent on the context of the individual receiving the intervention and the computational resources available (*e.g.,* battery levels, data available, internet connection). The context of the individual can define the content of the intervention; as an example, reminding a person to exercise when

they are ready to go to bed is not only counter-intuitive, it is frustrating. Tailoring variables are domain and system-specific.

2.1.7 Treatment selection

Treatment selection or decision rules (Nahum-Shani et al., 2018) are the underlying mechanisms to select intervention options. The decision rules pick the intervention treatment (intervention options) based on the variables tracked during the intervention (tailoring variables). More broadly, these rules are not necessarily static and can adapt to evidence of treatment or patient feedback to increase treatment efficacy, engagement, or any other proximal or distal intervention outcomes. In mobile health interventions, treatment selection may not be static and instead is updated using data. An example of this approach is MyBehavior [**106**], a system that uses a stochastic method to determine the best intervention to provide based on sensor data and personal preferences.

The elements of a mobile health intervention presented here are not too different from traditional health interventions. However, the nature of a mobile health intervention provides new challenges and opportunities for improved health care. The first such difference is in the initial treatment selection. In traditional health interventions, the physician uses her expertise and medical knowledge to decide. However, in a mobile health intervention, the initial treatment could be selected based on previously collected data. Another difference is that in a mobile health intervention, intervention points are not fixed and neither limited by the availability of a physician, time of day, or even geographic location. Instead, a mobile health intervention can provide treatment on a need basis. Last, a mobile health intervention could select a treatment at any intervention point in an objective manner by using available data. In the following section, I discuss all of these challenges and their possible solutions.

2.2 Dimensions of personalization in mhealth interventions

Although there is not an official taxonomy of the different dimensions of personalization at the time of this writing, some recent literature reviews summarize [**40, 124**] the results of

individual dimensions of personalization. In this section, summarize all those findings into a single taxonomy in the context of this thesis:

- **Content** [**40, 90**]: The information delivered to the patient which may contain a behavior (*e.g.,* avoid carbs), activity(*e.g.,* walking 15 minutes) recommendation or any other type of information related to the health intervention. Traditionally, content personalization meant changing the pronouns, activities, illustrations, among others of a health recommendation, to reflect the patient's demographics. In the context of this thesis, content personalization translates into delivering recommendations to the patient that are most likely to result in the desired outcome [**40**].
- **Timing** [**124, 90**]: The time, location, current physical (e.g., running, static) or social activity (*e.g.,* in conversation, alone), or situations (*e.g.,* opportunistic, vulnerable [**90**]) selected for the delivery of treatment. All of the different variables can be used in combination or separately. In this thesis, I refer to the personalization of timing as the process of selecting a time for delivery of treatment using contextual variables that include physical activity, transitions between activities, phone use, time of day, day of the week, among many other variables. I describe the contextual variables in chapter 5.
- **Message Framing**[**102**]: The language used to communicate with the patient (*e.g.,* supportive, authoritative, negative, positive). It can be found in previous work as tone or language style.
- **Delivery Channel**[**124**]: The media through which information is delivered (*e.g.,* text, voice message, email)
- **Goal** [**40**]: A target quantity to reach in a specific amount of time.
- **Dosage** [**124**]: The amount of support and the frequency of intervention delivery (*e.g.,* send notifications 3 times per day).

The above list is not exhaustive, and the dimensions are not mutually exclusive. For example, the content and message framing may be personalized at the same time by suggesting the same behavior recommendations but phrased in supportive vs. negative language. In this thesis, I decided to focus on only two of the most used dimensions of treatment: content and

timing. Content of treatment is an almost mandatory aspect of intervention in that it contains the behavior to recommend. Timing of treatment, although explored by mhealth researchers, has produced mainly mixed results [**95, 86**]. Overall, reminders have a positive effect on adherence to treatment [**53**]. Other approaches based on receptivity are promising [**71**] but have not yet resulted in behavior change [**86**]. This thesis demonstrates that personalization of timing of treatment and content results in behavior change, improved adherence to treatment, and increased motivation.

CHAPTER 3

Sleep health and interventions

The method and system presented in this thesis are applied to a common sleep intervention called sleep hygiene. In this chapter, are introduced the motivation for working on sleep, basic definitions and sleep related work in human-computer interaction.

3.1 Sleep Definition and Motivation

Sleep in humans is defined as a natural state of unconsciousness where responses to external stimuli are reduced. Sleep is reversible and occurs at regular intervals that are independent of many other physiological processes. Sleep has a fundamental role for many essential processes in the human body that regulate learning [**119, 138**], memory [**110, 119**], weight [**88**], mood [**129**] and cardiovascular health [**136**] among other processes. Despite its importance over 60% of college students in the United States report having poor sleep quality [**79**]. Having a night of poor quality sleep, is equivalent to working or studying after drinking 7 beers [**134**], causing a 50% slower response speed, poor accuracy in a psycho-motor vigilance test and an increased risk of an accident while operating a vehicle[**31, 26**]. A common way to improve sleep health [**13**] is through Sleep Hygiene [**104**], a set of general recommendations that help improve habits that are conducive to healthy sleep. There are other sleep interventions based on different behavior change models that have shown different measures of success like Cognitive and Behavioral Therapy for Insomnia (CBT-I) [**121**], sleep restriction therapy [**118**], *etc*. In this work, I focus on sleep hygiene-based interventions since it is one of the most common treatments for college students [**38**] with sleep health problems that are not

classified as sleep disorders (narcolepsy, chronic insomnia, apnea, *etc*.) requiring specialized medical treatment.

In this thesis, sleep will be defined by multiple of its qualities since there is not an agreed single measure of sleep quality. Sleep is defined using the following sleep health [**13**] factors: **Sleep duration**, the total amount of sleep obtained in a 24-hour period; **Sleep efficiency**, the ease of falling asleep and returning to sleep calculated as the percent of time asleep of the total time spent in bed; **Timing**, the time of occurrence of sleep within a 24-hour day; **Alertness**, the ability to maintain attentive wakefulness; **Quality**: the subjective assessment of sleep.

3.2 Sleep in Human-computer interaction

In this section I present sleep interventions developed in Human-computer interaction (HCI) focusing on their intervention mechanisms and their connections to psychological or medical treatments. Sleep interventions in Human-computer interaction are relatively new and for this reason most of the results in this area are explorations and in all cases did not result in behavior change.

One of the earliest work in HCI related to sleep intervention is ShutEye [**8**], a smartphone application that shows Sleep Hygiene recommendations at appropriate times in the background of the home-screen of a user's smartphone. ShutEye modified the background of the home-screen to display activities that were encouraged or discouraged depending only on the time of the day and sleep hygiene recommendations, and did so without sensing sleep-related parameters. Although the study was exploratory, there was a decrease in subjective sleepiness score for 8 out of 12 participants.

Horsch *et al.* [**54**] demonstrate that the usage of reminders increased adherence to automated parts of a Cognitive Behavioral Therapy for Insomnia (CBT-I) based intervention. This intervention was delivered through a smartphone application that contained a sleep diary and a relaxation exercise. The app also provided reminders to use the sleep diary and perform the relaxation exercises. The reminders were either set by the participant or event based.

Event based reminders used three heuristics: sitting still for some time, ending a phone call or switching from interacting with a popular app to another one. Their main result is that reminders in comparison to no reminders improve intervention adherence but no difference was found between self-set and event-based reminders. They also found that both self-set and event-based reminders were perceived as "inconvenient and bothersome". Overall this work shows that manually-personalized and heuristic-based timing work but that a more refined approach such as a receptivity detector could potentially improve the user experience and lead to higher adherence and intervention outcomes.

Daskalova *et al.* presents SleepCoacher [**24**], a framework for self-experimentation with sleep recommendations. The system works by using the phone as a sleep parameters sensor (sleep duration, time to bed, time out of bed, awakenings, *etc.*). Sleep measurements are collected over a baseline period of five days and then correlations are estimated for observed sleep-related behaviors (time to bed, sleep environment, *etc.*) and sleep related outcomes (awakening, sleep duration, efficiency). SleepCoacher then selects the pair of sleep behavior-outcomes with the highest correlation, finds a corresponding template generated by sleep experts, and then asks the participant to follow this behavior for 5 days, followed by 5 days of no-intervention, then another 5 days of the same recommendation. The total duration of the final study was 3 weeks with 17 participants. This intervention only provides one recommendation to each participant. SleepCoacher, given its high correlation selection algorithm, operates by reinforcing the participant's behavior that shows the highest correlation with a positive sleep outcome. In terms of outcomes as an intervention, 2 of the 17 participants showed improvements (Hedge's $g >= 0.5$) in their respective target variable (frequency of awakenings, self-reported restfulness and time to fall asleep). In a different project, Daskalova demonstrates the usage of a cohort-based approach for sleep health intervention [**23**]. This method for providing recommendations is based on providing sleep recommendations for a new patient by looking at data from people with similar demographics. Once a cohort is identified for a new patient, sleep-related measures that are the most dissimilar (compared to the cohort's) are chosen as a sleep target. Then, the sleep recommendation with the highest positive effect on the sleep target selected is provided to the participant. Their results show that cohort-based recommendations resulted in an increase of 17 minutes in sleep duration

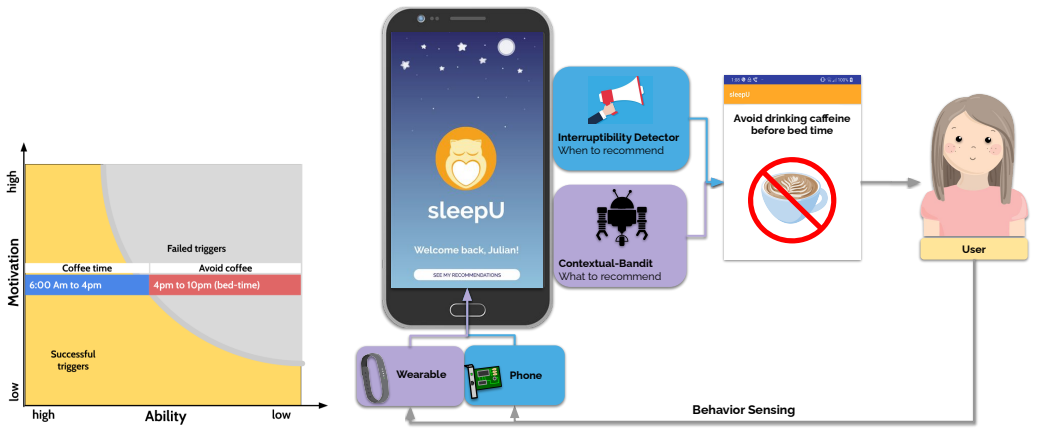
but this result was not statistically significant. More recently, Daskalova *et al.* [**25**] presents a series of design principles for self-experimentation systems. Although the results are in the context of a sleep self-experimentation study, they are applicable to other domains.

In summary, prior work used sleep hygiene recommendations and evaluated some form of personalization of content [**24, 8, 23, 25, 8**] or manual-personalization of timing [**53**] but not both. In terms of intervention outcomes, prior work reports positive outcomes (*e.g.,* increased sleep duration, increased adherence) but none of them reported significant improvements over baseline sleep measurements. These results may be explained by a common factor across all prior work: The lack of a dynamic strategy for personalization of content and timing. Although some level of personalization of content was part of all the interventions reviewed, they were all personalized only once at the beginning of the intervention. Also, the lack of a mechanism for triggering and delivering an intervention, or the use of a static method, may have greatly limited the effect of the intervention as well. In this thesis, I went beyond the static approach to personalization of sleep hygiene based recommendations. I personalize timing by using users' data to detect receptivity states and deliver sleep recommendations at those times. I personalize content of our intervention by measuring changes in sleep duration and efficiency.

CHAPTER 4

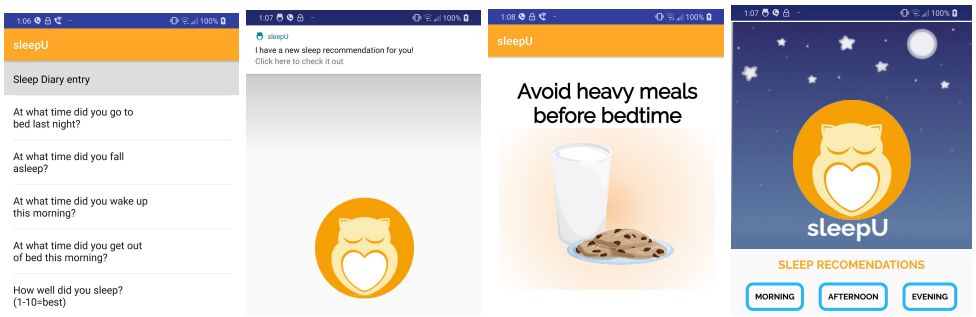
The SleepU app

For this thesis, I developed the SleepU app: An android application that performs on-device AI-based personalization of sleep advice using data from a wearable and the user's feedback. This app was used in both Study 1 (2019) and Study 2 (2020). The user interface for both studies remained the same; however, the internal mechanisms for personalization changed depending on the different phases of each study. In this chapter, I first make a walk-through of the installation and daily use of the SleepU app. Then, I explain the behavioral models and theories used to guide the algorithmic, visual, and information design choices of SleepU.



(A) (B)

FIGURE 4.1. a)Fogg Behavior Model adaptation of the recommendation "avoid caffeine 6 hours before bedtime". The horizontal blue and red rectangle shows how the ability to enact a recommendation depends on time of day b) General process followed by the SleepU app.



(A) (B) (C) (D)

FIGURE 4.2. Different screenshots from the SleepU app. Left to right: a) SleepU diary entry, the user gets a reminder at 9 am to fill out the diary. If they checked their phone earlier than that, the receptivity classifier could trigger a notification to fill out the sleep diary. b) The app pushing a notification to the user about a new sleep recommendation available; note that the actual recommendation text is omitted in the notification. c) A sleep recommendation viewable *after* the notification is clicked on. d) Main screen of the app which gives the user access to the sleep recommendations selected for her for the current day, with the other sleep recommendations hidden.

4.1 App description and walk-through

The general process followed by SleepU is shown in figure 4.1b: The app selects sleep recommendations from among a set of 15 recommendations commonly used in sleep hygiene interventions as shown in table 4.1 and delivers them at different times of the day. To select the time of delivery the app uses a receptivity detector described in chapter 5. To select the recommendation to show the app uses a contextual-bandit described in section 6.2.1. SleepU tracks sleep changes caused by the recommendations through a wearable and by asking the user if she has followed the recommendations.

At installation, SleepU asks the user to connect to her Fitbit account and asks for the necessary permissions to access sleep-related data automatically. The next day at 9 am, SleepU pushes a notification to the user asking her to fill out a standard sleep diary (Figure 4.2a) (*i.e.,* time to bed and wake up). After the user fills out the sleep diary, the app immediately uses the Fitbit data and diary responses to estimate which of all the sleep recommendations available should be shown at each period of the day: morning, evening, and afternoon; more details are provided in 6.2.1. In cases where the Fitbit data is not available, the app uses the sleep diary

responses. Once the estimation procedure is completed, SleepU pushes the morning sleep recommendation. SleepU provides at most one sleep recommendation at each time period. The user can check the chosen recommendations for the day at any time by opening the app's home screen (Figure 4.2d)).

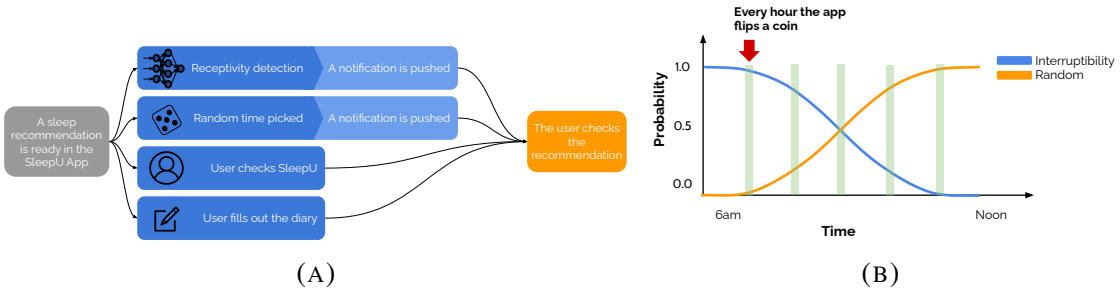
Notifications for each time period from SleepU stop once the user views a sleep recommendation. SleepU will push at least one notification per period (*e.g.,* morning, afternoon, evening) and a maximum of one notification per hour between 9 am and 12 am. To be able to detect when the user reads a sleep recommendation, rather than providing the sleep recommendation on the notification, all notifications always read "I have a new sleep recommendation for you!" (Figure 4.2b). When the notification is clicked on, the SleepU app opens and displays the suggested sleep recommendation. The next day after the first day of use, while filling out the sleep diary, the user is asked whether she followed the previous day's sleep recommendations. Sleep recommendations followed then cause an update in the contextual-bandit, keeping track of how good each recommendation is.

TABLE 4.1. Sleep Hygiene recommendations used in the SleepU app

MAB	Sleep Recommendation
Morning	Keep record of your sleep with a diary (this app's diary counts!) Avoid exercising 4 hours before bedtime Always keep the daytime routine
Afternoon	Go to bed and wake up at the same time everyday Avoid caffeine 6 hours before bedtime Avoid alcohol 6 hours before bedtime Avoid naps Avoid heavy meals before bedtime
Evening	Sleep only when sleepy Get out of bed when not asleep in 20 mins and calm down until sleepy Use bed only for sleep and sex Perform a sleep routine Take a bath 1-2 hours before bedtime Avoid watching the clock Make the bed environment conducive to sleep

The recommendations in the SleepU app (Figure 4.2c) are a slight modification (for improved readability) of the sleep hygiene recommendations offered by sleep clinicians [**15**] and include an illustration related to the recommendation.

The SleepU app, as shown in Figure 4.3a has four different mechanisms for triggering the delivery of a recommendation: Diary, User, Random, and Receptivity. Diary-triggered recommendations are those checked right after filling out the sleep diary; in this case, the participant could check any morning, afternoon, or evening recommendations available. User-triggered recommendations are those the user checks independently without receiving a notification from the app and not read after filling out the sleep diary. In this scenario, the participant goes to the phone without receiving a notification and looks at any of the three sleep recommendations available for the day. Random-triggered recommendations are those delivered at a random time by the SleepU app. Finally, receptivity-triggered recommendations are pushed as a notification to the user after the receptivity detector identifies a receptive state. Although the primary goal of SleepU is to push health recommendations to the user during receptive states, those states are limited to times when the user is interacting with the phone. Because SleepU cannot detect receptive states when the user is away from the phone, every hour SleepU decides randomly to use the receptivity classifier or a random time during the next hour to interrupt the user. In addition, the probability of picking the receptivity classifier decreases over each time period, as shown in figure 4.3b. This approach guarantees that a recommendation is pushed in the last hour if the user has not seen a recommendation for that time period. In the chapter 5, I explain the implementation of the receptivity detector.



(A) (B)

FIGURE 4.3. a) Process of checking a sleep recommendation in the SleepU App. b) Probability over time to pick at random receptivity detection or a random time for triggering a notification to read a sleep recommendation

4.1.1 Design principles and connection to behavior change theories

The choices of an algorithm, information displayed to the user, and aesthetics behind SleepU are based on theories, and models like self-efficacy [**5**] theory, the Fogg Behavior Model [**37**], the COM-B framework [**84**] and closely follows the design guidelines for Just in time adaptive interventions [**90**]. Self-efficacy theory posits that behavior change occurs once the individual perceives success towards the execution of a task. For mobile health interventions, I posit that achieving high self-efficacy is context-dependent: Even if an individual has high efficacy for a given task, this task can only be executed under specific circumstances, so ultimately, success is dictated by the individual's ability and context. As an example, an individual may be able and willing to stop drinking coffee to improve sleep outcomes; however, due to habit, this individual may only remember to avoid coffee once inside a coffee shop, at which point surrendering to habit is easier than restraint. Under this scenario, a reminder that arrives with enough time to allow the individual to avoid this particular habit could succeed at avoiding this behavior.

Reminders driven by context and receptivity are also motivated by the Fogg Behavior Model (FBM). This model posits that behavior is composed of three different factors: motivation, ability, and triggers. Under the FBM, for any individual to succeed at behavior change, she needs to be motivated, needs a trigger to perform this behavior, and can actually perform the behavior. Take as an example, the recommendation to "avoid drinking coffee 6 hours before bedtime"; an individual's ability level to perform this recommendation varies during the day as shown in Figure 4.1a, where the morning and afternoon are among the best times to provide this recommendation, while an evening reminder cannot result in behavior change since the window of opportunity for succeeding has already passed, and it is too far away from the next occurrence of caffeine intake for planning. In the SleepU app, the FBM trigger is a notification delivered to the user's phone. COM-B [**84**], a behavior change framework, relates several causal factors (*e.g.,* capability, opportunity, and motivation) for the performance of volitional behavior, including the influence of extrinsic factors. The COM-B model is the result of an exhaustive literature review and the summarization of nineteen different behavior change frameworks. Compared to FBM, COM-B considers the role of motivation at a broader level

in the performance of behavior mediated by ability and opportunity (triggers under the FBM). However, COM-B goes further and suggests that motivation, capability and opportunity are also influenced by the performance of the behavior. This implies that motivation can increase as the patient engages more with behaviors resulting in a positive health outcome. In the context of SleepU, when the user follows a recommendation that results in better sleep, this outcome helps future executions of that sleep recommendation and may help the user explore the execution of other sleep recommendations. For this reason, SleepU, through a contextual bandit as explained in section 6.2, estimates which recommendations among the followed ones result in better sleep and shows them more frequently than those that are less likely to improve sleep. Last, SleepU does not have sleep tracking or other functionality standard in wellness and health apps to avoid any factors that could affect the intervention outcomes.

CHAPTER 5

Personalization of time of treatment: Mobile-receptivity detection

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Receptivity identification is crucial for the success of mobile health interventions [**90**], but it may be impossible to measure since it requires the sensing of constructs like willingness[1] which can change with context and are is not directly measurable [2]. Although there has not been any work looking at detecting receptive states from sensor streams, researchers in human-computer interaction (HCI) have a well-established body of work on a very close concept: interruptibility. This section summarizes the most prominent and recent work in interruptibility detection from mobile phone sensors. This body of work inspires the definition of mobile-receptivity as shown in section 5.2, a construct very close to receptivity adapted for mobile health interventions and constrained to be measurable through mobile phone sensors or similar technologies. Following this definition, I implemented and tested a mobile-receptivity detector. The detector is a machine learning model trained using mobile-phone data from 37 participants collected during four weeks. The performance of the receptivity detector is reported at the end of this section. This mobile-receptivity detector was used in a pilot randomized clinical trial as a trigger for the delivery of a sleep health intervention presented in chapter 7. Details about the mobile-receptivity detector implementation are provided in section 5.3.

[1] Willingness refers to the desire or volition towards treatment.

[2] Willingness could be measured through proxies like surveys however there are not any methods that could measure brain activity to determine willingness towards treatment

5.1 Related work

Intervention points are contexts (time, location, *etc*.) where treatment should be delivered. Following the definition of intervention points provided by Nahum-Shani *et al.* [**90**], this work is focused on the identification of opportunistic states defined as contexts where the patient is not in a vulnerable state but is in a state where she has the "ability or willingness to receive, process and utilize just-in-time support". There is not any prior work demonstrating the sensing of receptivity states as defined [**90**]. Instead, researchers working in receptivity [**86, 71**] have re-purposed interruptibility detection methods for detecting receptive states. The resulting receptivity detectors have shown promising results; however they either were not tested in a live deployment[**71**] or did not result in changes to intervention outcomes like treatment adherence or changes to the main intervention outcome[**86**].

Morrison *et al.* [**86**] explored the use of interruptibility to trigger the delivery of a stress-management intervention at receptive times on a mobile phone. Their interruptibility detector was trained using each participant's interactions with the stress intervention itself and using an Android interruptibility library [**97**]. Due to sample size, this exploratory study did not provide sufficient power to test group differences definitively and instead provides effect size results. These results were mixed but promising: "frequent notifications may encourage greater exposure to intervention content without deterring engagement, but adaptive tailoring of notification timing does not always enhance their use" [**86**]. They also found that the group of participants assigned to receive interruptibility-based recommendations appeared to take action at a higher rate than random timing ($d = 0.23$). More recently, Kunzler *et al.* [**71**] explored and found significant effects of contextual factors like time of day, phone battery level, physical activity, *etc.,* on receptivity. They performed an offline-only evaluation of a receptivity classifier on Android and iOS data using 10-fold cross-validation, resulting in a lower but similar performance reported for interruptibility detectors also evaluated with cross-validation. It is important to mention that cross-validation results from time-series data are over-optimistic since the independence assumption is broken. In comparison, work that splits the data according to users has lower but close to real-world performance results. For this reason, I use as a reference for my receptivity work the performance of the interruptibility

detector introduced by Pielot *et al*. [**98**]. For this thesis, I built a receptivity detector, tested it offline, and finally used it in a sleep health intervention to evaluate its effects on the primary intervention outcome and adherence to treatment.

5.2 Mobile-receptivity and interruptibility

Interruptibility is closely related to receptivity [**89**], however, there is not a single definition of interruptibility, and instead, it has been studied under different terms:

- Interruptibility [**91, 49**]: the idea that people have moments during the day when they are available to be interrupted. At such times, an interruption has a low enough cost such that an interruption is acceptable.
- Attention [**99, 100**]: The idea that people are busy and have moments of attention that they can direct towards something other than their current task.
- Boredom [**100**]: the idea that people intentionally seek information and ways to entertain themselves.
- Engagement [**98**] with the information presented: Users not only attend to a notification but click on it to find out more about it. Engagement detection is a step forward in the direction of receptivity detection, and it is well-differentiated with interruptibility work, which main focus is on finding a moment where the user is reachable by a notification or another type of alert [**98**]. Instead, engagement detection aims to estimate the user's states where she is likely to engage with the content provided.

All of the above concepts are related in the following way: interruptibility preludes engagement, and engagement preludes receptivity. Thus, Interruptibility is necessary but not sufficient for engagement. Likewise, engagement is necessary but not sufficient for receptivity, and receptivity implies an individual is interruptible and engaged. Unfortunately, despite the importance of receptivity, there is no work looking at the detection of receptivity to trigger the delivery of a health intervention. However, some researchers have considered including receptivity in future studies [**68**] as a fundamental part of mobile health interventions. In this thesis, I bridge interruptibility and receptivity under a new term, *mobile-receptivity*: A

state in which an individual has the cognitive ability to stop their current task to read and make sense of a notification related to health treatment in the context of a mobile health intervention. In practice, this can be measured by observing when the user clicks and reads through a push notification from a mobile phone application. Although mobile-receptivity is more constrained than interruptibility, many of the related work and lessons learned in building models of interruptibility can be used for building models of mobile-receptivity.

5.2.1 Detecting interruptibility

Although interruptibility itself is not sufficient for identifying mobile-receptivity states, many of the methods and features used are useful for detecting mobile-receptivity. The preferred method for building models of interruptibility is by using machine learning classifiers. Researchers have used different classifiers to build successful interruptibility detectors; however, the preferred classifiers are decision trees and random forests [**99, 49, 98, 60, 91, 29**] . The performance of models of interruptibility has been measured mainly in two different ways: leave a subset of users out at random or cross-validation in which data is randomized without taking into account time or user independence. The latter evaluation is the most prevalent in the literature and accounts for the best results. This is expected due to cross-validation's over-optimistic results in time series data where the independence assumption is broken, and as a result, work that splits the data according to users has a lower but more realistic performance estimate to those expected in a real-world deployment. Engagement work [**98**] shows the lowest performance; however, this is expected since engagement is only a tiny subset of interruptible situations and a much more challenging event for detection.

5.2.2 Features

In terms of the data used to build the classifiers, an ever-increasing number of features is being used by researchers to detect interruptibility. The number of features used has varied from 4 to more than 300, and there is no agreement on what features should be used. However, [**98**] presents an all-encompassing categorization of the different features used that is informative

Paper	Method	Evaluation	A	P	R	F1	Features selection
Didn't You See My Message? (Pielot *et al.* 2014)	Random Forests	Random cross-validation	0.68	–	–	–	Wrapper Accuracy
Using Context-Aware Computing (Ho *et al.* 2005)	Decision Tree	Data split into train and test	0.91	–	–	–	–
Beyond interruptibility(Pielot *et al.* 2017-09-11)	XGBoost	Cross validation randomizing over random groups of people	0.89	0.218	0.540	0.31	Features selection
People's interruptibility in-the-wild(Tsubouchi *et al.* 2017)	Linear regression	Live evaluation of the model, the performance metrics were reduced user response time 49%(54 to 27 minutes)	–	–	–	–	–
Continual Prediction of Notification(Katevas *et al.* 2017)	RNNs XGBost	Cross-validation including grid search for XGBoost	AUC 0.7	0.8	0.5	0.61	Features selection
Towards attention-aware (Okoshi *et al.* 2016-02)	Random forests	—	0.82	0.82	0.82	0.82	—
I'll be there for you(Dingler *et al.* 2013)	Random forests	–	0.79	0.77	0.82	0.79	—
When attention is not scarce (Pielot *et al.* 2015)	–	Random cross-validation	0.83	–	–	–	—
InterruptMe(Pejovic *et al.* 2014)	Adaboost	Random cross-validation	0.73	0.36	0.48	0.41	—
Using decision-theoretic (Rosenthal *et al.* 2011)	Logistic regression	—	0.9	–	–	–	—
Exploring the state of receptivity **iOS** (Kunzler *et al.* 2019)	Random Forests	10 fold cross-validation	–	0.3	0.27	0.29	—
Exploring the state of receptivity **android** (Kunzler *et al.* 2019)	Random Forests	10 fold cross-validation	–	0.35	0.65	0.45	—

TABLE 5.1. All the articles including method, evaluation and performance results. A (Accuracy), P (Precision), R(Recall), F1(F1_score)

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and allows for flexibility in implementation. Furthermore, all of the features used in other works fall into one of the categories described by [**98**], and so it is recommended to use them in any interruptibility:

- Communication activity: Computer-mediated communication. This group includes features that show how often a user uses the phone to communicate with others by, e.g., sending or receiving messages or making or replying to phone calls. For

instance, a user that just got distracted by an incoming phone call might not be open to further interruptions. Examples of Communication Activity features are number of SMS messages received in the past hour, time since the last incoming phone call, or category of the app that created the last notification.

- Context: Features related to the situation of the mobile phone user *i.e.,* his or her environmental context. The context of use often determines whether it is appropriate or safe to interact with the mobile phone. For instance, being at home during the weekend may indicate opportune moments for interruption, whereas being at work during the morning may indicate the opposite. Examples of contextual features are the time of day, estimated current distance from home, current levels of motion activity, or average ambient noise level during the last five minutes.
- Phone status: These features measure the status of the mobile phone. For instance, a device with screen status 'unlocked' indicates that the user is currently using the phone; thus, a notification might be interrupting a concurrent task. Examples of Phone Status features are the current ringer mode, the charging state of the battery, or current screen status (off, on, unlocked).
- Usage patterns: These features estimate the type and intensity of usage of the phone. For instance, a user engaged in playing a game or watching a video may be less open to an interruption, whereas surfing on the Internet might provide a better moment. Examples of Phone Usage features are the number of apps launched in the 10 minutes before the notification, average data usage of the current day, battery drain levels in the last hour, number of device unlocks, screen orientation changes, or photos taken during the day.

Demographics is another category used in the literature; however, it has mainly covered age and gender, and no other variables have been investigated. The importance of the features by category was studied by (Pielot et al., 2017)[**98**]; in that work, the ranking from best to worst features to predict interruptibility: Context (1), Communication (2), Usage Patterns (2), Demographics (3), Usage Patterns (3). A feature analysis was performed by (Pielot, et al., 2014)[**99**], using the same categorization as in (Pielot et al., 2017)[**98**] the ranking becomes

Communication (1), Context(2), Demographics(3), Usage Patterns(4). These results show that consistently both Communication and Context are the most important categories.

5.3 Mobile-receptivity detection

In this thesis, the mobile-receptivity detector is not claimed as a contribution since it is an extension of previous work [**99, 49, 98, 91, 60, 100**]. Instead, the contribution is in demonstrating how using a receptivity detector in a behavioral intervention improves adherence. The receptivity detector is a machine learning classifier that detects receptivity states from phone sensor data, statistics from user interface events, and the Google Activity Recognition API. In the next section, I explain how data was collected to build the detector, the machine learning pipeline used for training, performance evaluation, and integration to the sleep intervention.

5.3.1 Data collection and features

Data for building the receptivity detector was collected during the baseline phase (*i.e.,* first four weeks without any intervention) of our sleep intervention as described in section 7.1.3 chapter 7. A background app passively collected smartphone sensor data in the background and logged how the user interacted with all notifications received. SleepU's receptivity detector uses all of the features identified in [**98**], a total of 88 different features summarized as: Communication activity (*e.g.,* number of SMS received, time since last phone call); Context (*e.g.,* light, proximity, activity from Google's activity recognition API); Phone status ((*e.g.,* battery level, time since unlocked, number of times locked in the day); Usage patterns (*e.g.,* number of apps interacted with, number of UI events). The app computed and stored the features every second as long as the phone was not in sleep mode. For ground truth labels, I followed the methodology in [**98**]: if the user clicks on a notification within 10 minutes of arrival, the data collected between the arrival time and click are labeled as *receptive*. To detect when the participant clicks on a notification, I used Android's notification listener service and the accessibility service events log.

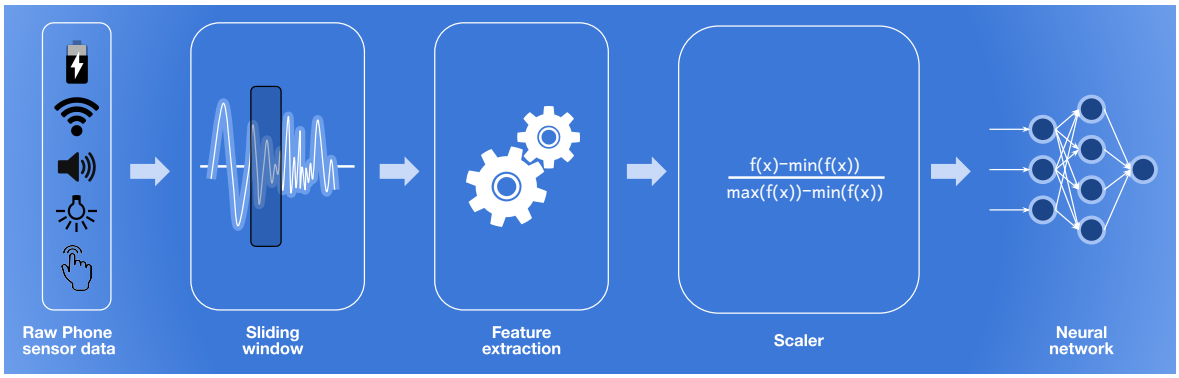


FIGURE 5.1. Machine learning pipeline for training and deployment of the receptivity detector

5.3.2 Machine Learning Pipeline

The steps to train the receptivity detector were kept simple to ease implementation and avoid computing overhead during our deployment. The first step was to compute statistical features (*e.g.*, mean, max, min, and standard deviation over each window) over a sliding window of 5 minutes. After that, values were normalized using a min-max scaler. The pipeline is shown in Figure 5.1.

5.3.3 Classifier and Performance evaluation

The classifier is a Multi-Layer Perceptron (MLP) from the scikit-learn library [**96**] for our receptivity detector. The classifier was trained from batches of data (online learning), allowing me to build a classifier as soon as data arrived from each participant instead of waiting for all participants to finish their baseline phase. This functionality is available for MLP but not for Random Forests or Decision Trees in scikit-learn. The MLP layers size are 88 (input), 50 (hidden), and 2(output) with an L2 penalty of 0.1, and trained using the ADAM solver. The hidden layer size and alpha values were optimized using grid search. To balance the number of observations per class was used SMOTE [**16**]. The MLP was trained using participant's data collected during the 4-week baseline period. The performance of the MLP was evaluated using leave-one-out-validation stratified by participant: $Accuracy = 0.88, Precision = 0.44, Recall = 0.74, F_1\_score = 0.54$. Our receptivity classifier has

a better performance than the state-of-the-art engagement classifier ([**98**]: $Precision = 0.2, Recall = 0.5, F_1\_score = 0.3$).

5.3.4 Receptivity detection during intervention

After training the receptivity detector, it was ported to Android-Java using sklearn-porter [**85**]. This detector was instantiated as an object inside an android service that checks for receptivity every second. The receptivity detector stops working once a recommendation for the current period is seen by the user as explained in section 4.1.

CHAPTER 6

Personalization of time and content of treatment

In this chapter, I first present related work that includes the personalization of content using AI alone or in conjunction with other dimensions of personalization. Then, I introduce the personalization of content approach used in this thesis and implementation details about how it was incorporated in the SleepU app.

6.1 Related work

Mobile health researchers have shown the feasibility of using Artificial Intelligence (AI) methods, and mobile sensors [**107, 95, 113, 109, 78**] to personalize health interventions. Yom *et al.* [**139**] present a system that uses a contextual bandit to personalize the type of message received to encourage physical activity for type II diabetes patients. The goal of their study was to increase physical activity to improve the health of people with type-2 diabetes. The results show a positive effect of the system in increasing physical activity and reduction of glucose levels. Mashfiqui *et al.* introduced MyBehavior [**107**], a mobile application that automatically generates recommendations for a healthy lifestyle. MyBehavior generates recommendations using EXP3 [**3**] multi-armed bandits. MyBehavior's main intervention mechanism is to extend current activities to increase calorie expenditure; for example, for someone who walks frequently, it will recommend walking a little more every day. MyBehavior was deployed to participants in ready or acting stages of behavior change. Participants using MyBehavior followed 1.2 more recommendations ($p < 0.0005$), walked for 10.1 ($p < 0.005$) more minutes, burned 42.1 more calories in non-walking exercises ($p < 0.05$), and consumed 56.1 less calories ($p < 0.05$) each day. However, MyBehavior is limited by 1) only extending current

activities without suggesting new ones that could result in higher calorie expenditure, and 2) MyBehavior does not push recommendations and instead relies on the user motivation and readiness to change look for recommendations on the phone. Mashfiqi *et al.*, followed MyBehavior with MyBehaviorCBP [**108**], which uses a very similar method for providing suggestions for pain management. Paredes [**95**] presents a stress intervention that uses a contextual bandit to provide stress recommendations through a mobile phone. Their results show a marginally significant decrease of perceived stress for participants in one of their experimental conditions, but there was no overall intervention effect.

Overall, all of the systems and methods[**107, 139, 95**], produce very encouraging results that show that personalization of content generates behavior change for participants with a high readiness to act [**107, 139**], and positive outcomes for participants at any readiness level [**95**]. Except for [**95**], prior work lacks a mechanism for proactively delivering health recommendations and instead relies entirely on the user's willingness or a predefined time to receive recommendations. This strategy potentially limits the effect of the intervention to highly motivated people, leaving out unmotivated participants. In Paredes *et al.,* work, although personalization of timing and content of treatment was pursued did not result in behavior change. I attribute this result to high computational complexity by solving two aspects of personalization with a single method.

Consequently, in this thesis, health recommendations are pushed to participants more proactively by displaying sleep recommendations relevant for the time of the day and when I detect that the patient is receptive. Also, treatment is personalized through contextual bandits that identify the best content (*i.e.,* sleep recommendations) for each person in their current context, including the time of the day. Also, to make this problem computationally tractable, I intentionally personalized timing and content separately. This thesis is the first work evaluating the disjoint personalization of timing and content of treatment in the context of a mobile health intervention.

6.2 Personalization of content

Personalization of content in this work is defined as a reinforcement learning problem [**120**] (*i.e.,* sequential decision making problem) in which an agent is interacting in an environment by taking actions, and the goal of the agent is to maximize some reward over a period of time. In this work, the agent is the SleepU app, the available actions for the app are the different sleep recommendations pushed to the user, and the reward is defined as the harmonic mean of sleep duration and sleep efficiency. In addition, treatment adherence is used to control updates to the estimates of possible rewards for each action; when a user reports that a recommendation was followed, an update occurs. Otherwise, there is no update since there is no new information. In summary, the SleepU app is selecting and displaying sleep recommendations to a participant while maximizing the following day's sleep duration and efficiency. Specifically, SleepU uses a contextual bandit as the reinforcement learning method for personalization of context.

6.2.1 Contextual bandit

This contextual bandit method [**73**] extends the bandit algorithm by adding the capability to deal with context. Contextual bandits are typically used in web advertising where the goal is to maximize click-through rates by deciding, for example, the on-screen location and topic of a web ad given a particular set of contextual features like user age, time of day, and season. For the implementation of SleepU, I chose contextual bandits instead of methods like Q-Learning or SARSA because of its ability to learn from a small amount of data.

To make the personalization of content computationally tractable, I divided the day into three different non-overlapping periods: morning (6:01am to 12pm), afternoon (12:01pm to 6pm), and evening (6:01pm to 6am). To decide in which period each recommendation should appear, I worked together with a sleep clinician. In addition, I took into account that some activities need planning. For example, for the recommendation "Avoid exercising 4 hours before bedtime", the goal is to remind the student to plan to exercise at a different time. Therefore, the best time to remind them about it is in the morning. More details on how these

recommendations were selected and displayed are provided in the study design section (7.1.3) chapter 7.

For each period, I use a different EXP3[**3**] multi-armed bandit (MAB). As defined in [**73**], this particular usage of multiple multi-armed bandits for different contexts corresponds to a *contextual bandit*. A similar approach could be taken for other health interventions where the contextual factor with the most weight in the intervention could be used to separate different contexts, and then a different MAB can be used for each context.

EXP3 works by selecting a recommendation at random from a multinomial distribution. The EXP3 algorithm is described in algorithm 1. There are many different multi-armed bandit methods such as the Upper Bound Confidence Interval, Thompson sampling, *etc*., however, EXP3 has been used in real-world deployments (*e.g.,* [**107**]) with successful results.

Initialization;
$w^{(0)} = \{w_n^{(0)} = 1\}, n = 1, ..., N$;
for *t=1,...,T* **do**
  $\beta = \sqrt{(}\log(k)/(k \cdot t))$;
  Select recommendation i;
  $\phi^{(t)} = \sum_{n=1}^{N} w_n^{(t)}$;
  $p_n^{(t)} = w_n^{(t)}/\phi^{(t)}$;
  $i \sim Multinomial(w^{(t-1)}/\phi^{(t-1)})$;
  Compute sleep score;
  $s^{(t)} = \mathbb{1}(i \in r^{(t-1)}) \cdot H(sleepD^{(t-1)}, sleepE^{(t-1)})$;
  Update;
  $w_n^{(t)} = w_n^{(t-1)} \cdot e^{(-\beta \cdot \ell(s^{(t)})/p_n^{(t)})}$
end

Algorithm 1: EXP3 algorithm adapted for the sleep recommendations problem. Where $w_n^{(t)}$ is the weight for recommendation n at time t, p_n is the probability of selecting a recommendation, $sleepD$ is the sleep duration in hours capped at 7 and divided by 7. Capping by 7 forces EXP3 to focus on increasing sleep to healthy levels without forcing the user to achieve a hard-coded sleep duration that may not be preferred. $sleepE$ is the sleep efficiency estimated as the sleep duration divided by the time in bed. $H(x)$ is the harmonic mean and $\mathbb{1}(i \in r^{(t-1)})$ is one if the recommendation i pushed by the app to the participant is reported as being followed.

EXP3 in the context of SleepU starts with a uniform probability for the sleep recommendations for each period. When a recommendation has a positive sleep outcome (high efficiency and/or high sleep duration), the probability of that recommendation is increased slightly while

all the other recommendations' probabilities are decreased. A short version of the sleep recommendations handled by each of the MABs is shown in Table 4.1. Our approach using a MAB naturally avoids learning the user habits. For example, a user could, even before using the app, already follow a sleep recommendation like "avoid exercising before bedtime." The participant then will answer at any time during the intervention that she followed the sleep recommendation. However, because "avoiding exercising before bedtime" is a habit (*i.e.,* it happens every day), following this recommendation will not have any effect on sleep, and so the bandit will decrease the probability of this recommendation.

CHAPTER 7

Study 1:Exploratory trial of the SleepU App

In this chapter, I introduce the first exploratory trial of the SleepU app. The goal of this study was to evaluate the feasibility of the personalization of content and time of treatment approach presented in chapter 6 and 5 as well as preliminary answers to some of the research questions posed in chapter 1 of this thesis.

7.1 Method

The SleepU app was deployed in a 12-weeks long, within-subjects research study with college students from Carnegie Mellon University (CMU) that followed the study design shown in figure 7.1. After screening, participants in the study were randomly assigned, while balancing gender across groups, to two different groups: **app-first** or **control-first**. The two different groups were created to counterbalance any possible order effects.

The eligibility requirements for participation were: 1) Participants had to be 18 to 25 years old and with an active undergraduate student status at CMU. 2) Participants could not have any on-going problematic substance use (*i.e.,* drugs, alcohol or nicotine) or sleep disorders (*i.e.,* apnea, narcolepsy, chronic insomnia). This latter exclusion criterion was necessary because participants with these issues need specialized sleep treatment.

All participants were exposed to three different study phases, each approximately 4 weeks long and phase order dependent on their group assignment. The different phases were:

- **Baseline**: This is the first phase of the study for all participants. Participants were given a Fitbit Flex2 activity tracker. During this phase, there is no intervention, and

only phone and Fitbit data are collected. I collected phone sensor data passively in the background using our logging app. This app was uninstalled after the baseline phase.

- **App-intervention**: In this phase, students were asked to install the SleepU app on their phones. Participants were sent a link from the research coordinator with instructions on how to install the app. During the study intake, participants were told that it was not mandatory to follow sleep recommendations provided by the app and that the only mandatory part of the study was to fill out the daily sleep diaries. After four weeks of this phase, participants uninstalled the SleepU app.
- **Control-intervention**: In this phase, students attended a sleep health consultation with a sleep clinician. This sleep consultation is part of the standard care provided by CMU at no cost. During the consultation, a sleep clinician covers the basics about sleep following recommendations from the Australian Centre for Clinical Interventions [**15**]. In addition, the clinician performs a sleep assessment using the Pittsburgh Sleep Quality Index (PSQI) [**14**], and creates a personalized plan for the student to put in practice sleep hygiene recommendations. The sleep clinicians

  The sleep consultations were scheduled with the university health center after a participant joined the study. The consultations occurred at the beginning of the control-intervention phase of the study. If the student was in the app-first group, they were asked to uninstall the SleepU app before the consultation.

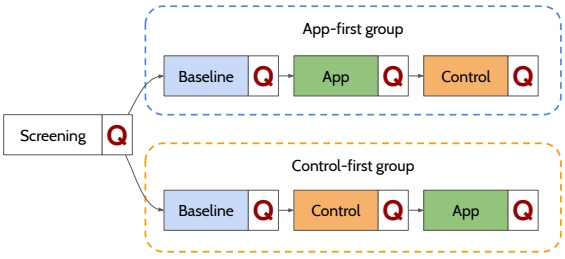


FIGURE 7.1. Study design. All study phases lasted four weeks except for screening. The Qs indicate times in the study when the participants filled out a battery of questionnaires as explained in section 7.1.3.

Due to the limited availability of sleep consultations, the study duration varied slightly among participants.

7.1.1 Study design considerations

Given the exploratory nature of this work, the purpose of this thesis is to identify components of a mobile health intervention to optimize for in future iterations as stated in the multi-phase optimization strategy (MOST) [**20**]. This study falls under the preparation stage of MOST, and as such, this study does not have separate groups evaluating each component of the intervention; instead, I exposed all participants to all components. Our study design follows recommendations by Onghena *et al*.[**92**] and Dallery et al.,[**22**] that argue for the use of single-case experiments: small scale, within-subject experiments. Single case experiments, despite using a small n can achieve statistical power through many repeated measures from each participant in the experiment. In our study, participants generate at least one behavioral observation per day from sleep measurements captured through the Fitbit and sleep diary, which amount to up to 84 days. In addition, the app captured up to 3 daily observations from adherence to sleep recommendations which amount to up to 252 adherence observations per participant. As suggested by Onghena *et al.*, [**92**], I used Hierarchical Linear Models in analyses that involved participants repeated measures. The sample size was determined following the guidelines for single-case experimental designs[**22**] which argues that $n \geq 4$ is sufficient for statistical power if enough repeated samples are collected per participant.

7.1.2 Participants

Participants were recruited using flyers and Facebook posts at university groups at the beginning of January 2019. After screening, 37 participants were invited to join the study. Of those, 30 participants (22 Female, 7 Male, 1 Undisclosed) finished the study. Seventeen participants were in the control-first group (3 Male) and 13 in the app-first group (4 male). Participants were compensated with 10 dollars (US) for each week of data logged in the study, and, as an extra incentive, those filling out 80% or more of the sleep diaries were allowed to

keep the Fitbit Flex2. The participants were explicitly not compensated for using the SleepU app's sleep intervention functionality (*e.g.,* checking or following sleep recommendations).

7.1.3 Measures

After screening, participants were asked to fill out a set of questionnaires related to sleep health and other related and proximal outcomes after each phase of the study. The questionnaires included measures of psycho-social or physiological processes that mediate health behavior change as suggested by Klasnja *et al.* [**66**]. The questionnaires used were: the Pittsburgh Sleep Quality Index (PSQI) [**14**], Sleep Practices and Attitudes [**43**], Sleep beliefs scale [**1**], Perceived stress scale [**18**], Morningness - Eveningness questionnaire [**52**], Readiness to change towards healthy sleep-related behaviors questionnaire(*i.e.,* motivation questionnaire [**10**]) .

I created the readiness questionnaire from a readiness ruler, a questionnaire that measures the patient's health stage as defined in the transtheoretical model of behavior change [**105**]. The readiness ruler has been used for smoking cessation [**10**] and alcohol rehabilitation interventions [**48**]. Our modification consisted of adjusting the text content for sleep hygiene recommendations and decreasing the number of options from 10 to 8 options for improved readability on a mobile phone, on which participants were filling out the questionnaire.

In our motivation questionnaire, I asked participants to rate their readiness for each of the 14 different sleep recommendations listed in table 4.1, excluding the sleep diary recommendation since I directly compensated participants for the diary entries. The readiness levels used a scale from 1 to 7: 1) Not ready at all, 3) Thinking about it, 5) Planning and making a commitment, 7) Actively/Already doing it, and a Does not apply to me option (*e.g.,* the coffee recommendation for participants that do not drink coffee). Additionally, participants were asked to fill out a standard sleep diary every day during the 12 weeks duration of the study. Participants received an email with a link to the sleep diary website form every morning during the baseline and control-intervention phases. In the app-intervention phase, participants received the sleep diary prompt on the SleepU app (via a notification) with three additional

questions asking whether the participant followed any of the three sleep recommendations generated by SleepU the previous day. All participants were provided with a Fitbit Flex2, a wrist-worn wearable with sensors that measure steps and sleep (awake *vs.* asleep). Sleep duration and efficiency were collected during the 12 weeks of the study except when the Fitbit was being charged. Participants in the study were instructed to wear the tracker at all times, including while taking a shower and sleeping. The device does not collect any data while recharging or at any time when the user does not wear it.

7.1.4 Analysis plan

In the next paragraphs, I describe the statistical analysis steps followed to answer the research questions (RQ) defined in the introduction. Moving further, to refer to each of these questions, I instead use the short name provided for each.

- **Behavior-RQ: What are the effect of personalization of timing and content in behavior change and motivation?** To explore this question, I estimated the effect of intervention by fitting a Generalized Linear Mixed Model (GMM) with fixed effects for phase, group, and phase-group interactions and a random effect for the participant. The data was not aggregated, given that GMMs can handle raw data directly. I controlled for factors like baseline amount of sleep (Type-of-sleeper[**75**]), and the number of days in the intervention [**95**] following data analyses and conclusions from previous work. A thorough explanation of why controlling for these factors is necessary is provided in the appendix section 12.1. I added the covariates sequentially [**35**] and compared them as shown in table 12.2 in the appendix. I also explored whether SleepU impacted participants' motivation to improve their sleep. I compared the effect of app-intervention in motivation against baseline values and the control-intervention. To measure this effect, I used the Aligned Rank Transform for Nonparametric Factorial ANOVAs (ART) [**135**] followed by pairwise comparisons using a Wilcoxon signed-rank test.
- **Adherence-RQ: What is the effect of personalization of timing and content on adherence to treatment?** To explore the effect of personalization on adherence,

I first looked at the adherence rate of each participant and compared it across the different notification mechanisms. I define *adherence rate* as the number of recommendations followed divided by the number of recommendations seen, aggregated over each period, and participant. Next, I compared adherence rates using a one-sided Wilcoxon-Pratt Signed-Rank Test.

- **Context-RQ: What is the effect of context and motivation of the participant in the likelihood of adherence to recommendations?** To explore the effect of context and motivation, I first aggregate the data into the different periods for each participant during the app-intervention phase. Then I used a Binomial Generalized Linear Mixed Model (BMM) with a random effect for the participant and fixed effects for day-of-intervention and period of delivery, and baseline motivation of the participant. Adding baseline motivation as a covariate is justified by the COM-B [**84**] health model that states how motivation directly influences behavior. COM-B has been used in many interventions ranging from hearing aid use [**6**], coaching for Latina moms with gestational diabetes [**47**], and sleep hygiene [**117**]. I added the covariates sequentially [**35**] and compared them as shown in table 12.3 in the appendix.

All p-values are adjusted within hypotheses using Benjamini-Hochberg to correct for type I error as recommended in [**9**] and following [**83**]. I used R 3.6.3, and the lme4 [**7**] and ggeffects [**80**] packages. Exploratory data analysis and hypothesis testing were conducted in Jupyter notebooks.

7.2 Results

Overall I found that our pilot study evaluating SleepU resulted in improved sleep duration, time-in-bed, treatment adherence for recommendations delivered when the user was receptive, and increased motivation. The next is a breakdown of these results, as guided by the research questions I posed earlier:

Delivery mechanism	Average adherence rate	(95% CI)		p-value	Cohen's d
Receptivity (Reference)	0.71	0.62	0.80		
Random	0.49	0.39	0.60	0.0029	0.40
User	0.39	0.31	0.48	1.39e-5	0.56
Diary	0.57	0.47	0.66	0.01	0.30

TABLE 7.1. Table of comparisons of adherence rates for all the different mechanisms. All p-values adjusted using Benjamini-Hochberg.

7.2.1 Behavior-RQ

I found that participants in our study improved sleep duration and time in bed. I also found that, on average, all our participants moved from a preparation stage to an action stage *i.e.,* they moved from *thinking about improving their sleep* to *actively trying sleep recommendations*. Out of the 30 participants that finished the study, I used the data from those that logged at least a week of Fitbit data during the app-intervention and the control-intervention leaving a total of 23 participants data for analysis.

I found an overall effect of phase on sleep duration ($\chi^2(4) = 28.8$,$p < 0.00001$). I then found a significant difference between the baseline and app-intervention phases ($app - baseline = 23\ minutes$,$CI(38, 10)$,$p < 0.005$, $d = 0.26$) and a significant difference between app and control-intervention ($app - control = 15\ minutes, CI(24, 7)$,$p < 0.005$, $d = 0.16$). I used the same model structure for different independent variables like time-in-bed, efficiency, minutes awake after sleep onset, minutes to fall asleep and minutes after wake up. I found a significant difference for time-in-bed of 15 minutes with baseline ($p < 0.005$, $d = 0.15$) and 25 minutes with the control-intervention ($p < 0.005$, $d = 0.25$). I did not find any other significant differences for other independent variables.

I found a change in average motivation as measured through our readiness scale for all participants from 4.6 in baseline to 5.17 during app-intervention ($p = 0.059$, $r = 0.55$). There was also a change for all participants from 4.6 in baseline to 5.11 during the control-intervention ($p = 0.086$, $r = 0.45$). There was no difference in motivation between the app and the control interventions ($p = 1.0$,$r = 0.07$). I looked at motivation before (4.5) and after (4.6) the baseline phase and found no difference ($p = 0.65$,$r = 0.13$). I found that motivation

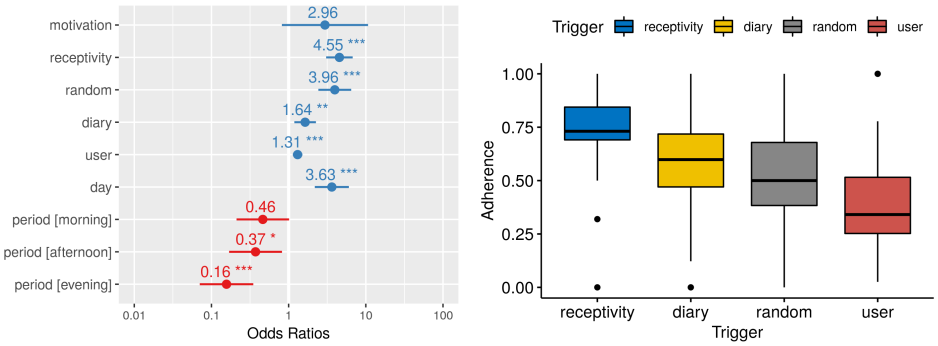
during the screening phase and by the end of the baseline phase did not change by a large amount. This result suggests that just filling out a sleep diary daily and being involved in a sleep study (without receiving any intervention) does not have a visible effect on participant motivation, and hence I would not expect to see a behavioral change as a consequence of the baseline phase alone.

7.2.2 Adherence-RQ:

I found that sleep recommendations delivered at detected receptive states result in higher adherence compared to delivered at random, after the sleep diary or those read independently by the user. Out of the 30 participants that finished the study, I used the data from those that logged at least a week of SleepU logs data during the app-intervention, leaving a total of 24 participants' data for analysis. On average, our participants logged 20 days during app-intervention ($sd = 7.0$). I found that the delivery mechanism (*e.g.*, receptivity, random, user and diary) had an effect on adherence ($\chi^2(4) = 67.7$,$p < 0.00001$). Planned comparisons revealed that receptivity had the highest adherence rate (75%) as shown in table 7.1 and figure 7.2b.

7.2.3 Context-RQ

I found that contextual factors and motivation have wide ranging and significant effects on adherence. I found that the period of delivery of recommendations has an overall negative impact on adherence, as shown in figure 7.2a . The odd ratios for the different periods are all less than one. This result indicates that any period causes a decrease in the odds of adherence of at least 50%. In terms of probabilities, assuming day 1 of the intervention and no recommendations the probability of adherence to a sleep recommendation is 0.58 in the morning, 0.53 in the afternoon and 0.32 in the evening. Under the same scenario, and with a recommendation delivered through the receptivity classifier, the probabilities become 0.86 in the morning, 0.83 in the afternoon, and 0.67 in the evening. Day in the intervention has a



(A) (B)

FIGURE 7.2. a) The plot shows the adherence to the sleep recommendations provided by the app over time during the app-intervention phase. b) The plot shows the odd ratios intrinsic and contextual factors on adherence. c) Adherence rates for all the trigger mechanisms *p<0.1; **p<0.05; ***p<0.01

significant and positive impact. While not significant, motivation has a mostly positive (higher than one odds ratio) impact and a wide confidence interval.

7.3 Discussion

In this section, I first discuss general results and their limitations. Then, I also discuss more specific aspects of the results about their significance outside the study and future research directions.

- **General results:** Overall, my exploration of the disjoint personalization of content and time of treatment through the deployment of SleepU is very promising. Participants in the study changed their behavior by significantly improving their sleep duration and time in bed compared to standard-care and baseline levels. They also moved from thinking about making a change to taking action towards improving their sleep. The results also show that receptivity generates the highest adherence to treatment. Similarly, contextual factors, motivation, and days in the intervention had an essential effect on adherence to treatment. I speculate that by considering motivation and contextual factors, it could be possible to maximize adherence to overcome

barriers typical of health interventions like low levels of motivation through simple strategies like delivering health recommendations in the morning.

- **Adherence and receptivity:** When receiving a sleep recommendation through the receptivity classifier, treatment adherence was 48% higher than at random times and 114% higher than user-initiated attempts at following a recommendation. It is, however, important to notice that real-world deployments of mHealth interventions outside research evaluations would most likely require the use of multiple delivery mechanisms. Although the receptivity detector produced the highest adherence, it can only detect receptivity accurately when the participant is interacting with or near the phone. Another important factor to consider when using receptivity is the way people use their phone. Our participants were all tech-savy college students. I expected this strategy to work well for them; however, populations like the elderly may not benefit as much from this approach to receptivity detection.

  In comparison to previous work on receptivity, [**86**] SleepU achieved a higher adherence rate despite using similar approaches in terms of classifier and sensor streams used. The key difference is that for SleepU, I used all mobile-phone interactions from all participants to build a single population-personalized receptivity classifier while Morrison *et al.*[**86**] built a detector separately for each participant. I believe the data I collected and combined resulted in more significant variance, increasing the generalization power of the classifier drastically. While in Morrison *et al.*work, relying exclusively on individual data may not provide good enough performance for short-term deployments. This counter-intuitive result where a population-based classifier is more effective than participant-based detectors was also observed in work by Hong *et al.*[**51**] for activity recognition. It is important to notice that increased adherence has important and well-documented downstream effects like increased patient autonomy, self-efficacy, and health outcomes [**55**], which further highlight delivering health recommendations during receptive times.
- **Context:** Our exploratory work highlights the critical role of context and motivation on adherence. All periods harmed adherence: Participants were most likely not to follow a sleep recommendation without a reminder for it. However, in comparison

to the evening, mornings and afternoons are the best times of the day to remind participants about putting a recommendation into practice. Although some of the recommendations chosen for the morning and afternoon may have been easier to execute for some of our participants, a morning recommendation like "Always keep the daytime routine" according to experts, is among the hardest recommendations to follow. Also, a similar result was found by Kunzler *et al*.[**71**] in a physical activity intervention: receptivity was highest between 10 am to 6 pm, and receptivity-related metrics do translate into adherence to treatment. This dependence on delivery time has several implications, *e.g.,* participants who are getting started with a sleep intervention (and when motivation may be low), should rely primarily on interventions in the morning and afternoon. Over time and as motivation and days of intervention increase, the probability of adherence will increase, making adherence to treatment in the evening more likely.

- **Motivation and days of intervention:** Although baseline motivation in the likelihood of adherence to treatment was marginally significant ($p < 0.1$), it has a positive and wide effect on adherence, increasing the odds from 1 to up to 10, I expect significance to increase with a larger population sample, and the general effect on adherence to narrow only slightly in range. The number of days in the intervention had a positive and significant effect and shows that the cumulative effect of the intervention is on par with receiving a recommendation at a random time every day. This effect shows that participants are making some of the sleep recommendations parts of their daily habits.
- **Self-motivation is not enough for adherence:** A striking result from this study is that even despite our participants' best intentions, their attempts at following sleep recommendations (self-initiated) were only successful 34% of the time. In comparison, through receptivity-triggered recommendations, our participants were successful 73% of the time, a 114% increase over the self-initiated adherence rate. I speculate that even when participants pursue behavior change, finding the right context and state of mind to enact or plan for putting in practice a health recommendation is difficult. This same result was observed in an intervention to

increase glaucoma medication adherence[**21**]. Participants were either reminded over the phone about taking medication or exposed to a motivational interview aimed at increasing their motivation. In that study, reminders resulted in a statistically significant increase in adherence while the motivational interview did not. Moreover, in a recent review [**64**] of strategies to increase adherence to medication, it was found that reminders are clinically practical and the best option with absolute improvements of 33% .

- **Comparison to medical sleep interventions:** HCI work in sleep interventions has not translated into significant sleep health changes. Our work is the first HCI intervention work to achieve significant behavior change. For this reason, I compared our results against standard care (control-intervention), and here I review our results against expected outcomes of sleep hygiene interventions according to medical research literature. The effect of SleepU on sleep duration and time in bed are well within expected values [**38**] for traditional Sleep Hygiene interventions (*i.e.,* not a mobile health intervention). For comparison, in a sleep intervention personalized content manually (*i.e.,* without sensing, mobile, machine learning or AI components) [**75**] with a comparable population, there was no difference between baseline and intervention for all participants (n=77). Although in Levenson *et al.* [**75**] content was personalized, and despite having several educational sessions, they had no component reminding participants to put the sleep recommendations into practice. Our results comparing standard-care with SleepU show a similar result and hints towards the same conclusion: personalization of content alone is not enough for behavior change.
- **Clinical significance:** The increase in sleep duration from using SleepU, may be clinically meaningful for a hypertensive population: In a 2013 study [**45**] with pre-hypertension patients, it was shown that an increase of 36 minutes in sleep duration resulted in a significant decrease in blood-pressure over a 6-week period. Further evaluations of sleep interventions could benefit from measuring other outcomes that may be affected by improved sleep like learning [**119, 138**], memory [**110, 119**], weight [**88**], mood [**129**] and cardiovascular health [**136**]. Although this clinical

significance result comes from a single study, it would be reasonable to expect that, given the profound connection of sleep to vital biological processes, changes in sleep could result in other clinically significant results.

- **Independent effects of content and time of treatment:** In this study, I followed the MOST framework to explore promising intervention components. The results suggest that this disjoint personalization of content and timing work; however, it is unclear which component has the most effect on the results observed. Evaluating these marginal effects has important implications for the deployment of mHealth interventions. In practice, and depending on financial and technological constraints, some of these components may be unfeasible. For example, to develop a contextual bandit that runs on the phone, hiring developers that know AI is necessary, and such talent is in short demand. In addition, deployment of this personalization technology in devices with low computing power may limit personalization to a single component but not both due to computing constraints. Under these scenarios knowing the marginal effects of different components can help decide which components to use given their cost-effectiveness. These marginal effects can be estimated by delivering each intervention component to different groups following a between-subjects design. Based on the MOST framework, this next step would encompass the optimization stage of the mHealth intervention.
- **Results connection to behavior change models:** According to the COM-B model, the changes observed in behavior and motivation in our pilot-study most likely also increased over time the capability of our participants and hence their self-efficacy towards improving their sleep. The changes in motivation and the positive effect of days-in-intervention point to capability and self-efficacy improvements.

7.4 Limitations

In this work, I explored the personalization of timing and content, intending to find the most promising ways forward in this domain. Although I only observed significant differences across phases in the study for sleep duration and total time in bed, it is possible that .our

choice of sleep tracker may have underestimated measures like sleep efficiency and sleep onset. In the study I used, the Fitbit Flex2, which has been found to report sleep duration and time in bed at accuracy levels comparable to actigraphs *i.e.,* Sensewear or Actiwatch) [**32**] however, sleep onset, time to wake up, and other measures may be less reliable [**32, 46**]. In general, moving forward with this line of work, it is recommended to use wearables capable of tracking different sleep stages and have shown promising performance [**46**] in accurately detecting most sleep measures.

Another limitation of this work is the homogeneity of the sample. All of our participants were young, healthy, attend the same university and have access to healthcare as mandated by the university. Although I would expect the results to carry over to similar populations, it is unclear whether the results will hold against samples with higher variance in age, location, and socioeconomic status. This is an important limitation of the results because mHealth interventions are very promising to populations under-served by the health care system. It is highly encouraged to further investigate this work with those populations.

7.5 Conclusion

AI based personalization of content and time of treatment is still a nascent research direction in mobile health. In this chapter, I have shown promising results for AI-based personalization. I demonstrated how this approach results in behavior change with better outcomes than standard-care provided by a sleep clinician.

There are several advantages of using AI-based personalization in comparison to traditional computer tailored approaches like scalability, broad access, and privacy.

7.5.1 Scalability

AI based personalization as described in this chapter (*e.g.,* the SleepU app) is scalable since it does not rely on a central server for AI, data storage or processing. Data is processed upon arrival locally in the user's device and AI based estimates and training is also executed locally

using a minimum amount of computing resources. Even the wearable's data although provided through the cloud is handled by the wearable's maker for free which allows for seamless scalability. Another important factor of scalability is its cost-effectiveness. The approach presented in this thesis does not rely on any external human supervision which means that the cost of use of the intervention app goes up linearly with the amount of users. In comparison, health treatments personalized by clinicians usually rely on different levels of supervision and management that adds up quickly when trying to scale up health treatments. Ideally however, AI-based personalization is supervised by human health care practitioners. AI, like any man made system can fail and in some time unpredictable ways. for this reason ideally AI-based personalization should be combined with a clinician's supervision and guidance. Such supervision could be done on a need basis and based on statistics of performance and hopefully this supervision is minimal and does not increase costs substantially so that AI-based personalization can still be cost-effective and scalable. Last, one of the only elements that could make this AI approach cost prohibitive is using a wearable device to track sleep. However, personalization is still possible without using a wearable for example by asking the patient to input sleep data by hand which is currently a common practice in sleep therapy.

7.5.2 Broad access

The AI models in SleepU run entirely on the phone and do not require internet access, making them suitable for broader adoption by users of different socioeconomic statuses. This personalization approach is accessible: with median mobile phone ownership varying from 45% for developing economies and 75% for developed economies [**122**]), mobile phone interventions like SleepU have the potential to reach most populations in the world independent of culture, socioeconomic status or constant internet access. Although our deployment was limited to sleep hygiene, I foresee it producing similar results in other health interventions where personalization can significantly affect behavior change, motivation, and adherence.

7.5.3 Privacy

All the computing necessary to achieve AI-based personalization takes place in the user's phone. Due to this, the user is in complete control of her data and inferences resulting from the AI models never leave the phone making the approach and system presented in this thesis completely self contained and private. Additional measures like encryption of files stored, password protected access to the app among others can easily be added to the system without incurring in drastic or costly changes.

CHAPTER 8

Adherence to treatment prediction

Adherence to treatment is defined as a patient's compliance with health professionals' recommendations [**28**]. Despite its importance, non-adherence is widespread, averaging 25% across different medical treatments. Non-adherence results in negative outcomes like therapeutic non-response [**50**], decreased long and short-term benefits [**141**], and in substance use rehabilitation, it can result in relapse [**141**]. An approach to decrease non-adherence is to predict overall adherence to identify high-risk non-adherent patients and then modify the intervention. Intervention modifications vary: incentives, reminders, simplified regimes, among others [**127**].

In other words, adherence prediction can be used to personalize an mHealth intervention. Most work in adherence prediction has focused on overall or weekly adherence, with only a few works looking at daily adherence, and no work in the literature has reported results on intraday adherence prediction. Intraday adherence prediction is important because it could help interventions that have multiple treatments a day (*e.g.,* one health condition with multiple treatments or multiple health conditions with multiple treatments). In such cases, intraday adherence could help boost times of day when following treatment may be difficult for the patient. Such boosts could be in the form of incentives (*e.g.,* monetary), changes in the intervention mechanism (*i.e.,* call to the patient, visit from a nurse), among others. In this chapter, I present multiple intraday adherence prediction classifiers that build on the findings from chapter 7. The adherence classifiers have promising performance with up to 0.7026 *balanced accuracy* and 0.7548 *f1_score*. The results from this exploration warrant real-world deployments; also pave a way forward to use adherence to treatment prediction as another dimension for personalization of treatment.

8.1 Related work

Adherence prediction mostly consists of estimating a classification model that uses different sets of features and looks at different time lengths for the prediction. There are three different time lengths reported for adherence prediction: Overall, weekly, and daily. Also, researchers have used a wide range of features which are summarized and described in this thesis. In this section, I first review the results of the different time spans used for adherence prediction (*e.g.,* overall, weekly and monthly). Then, I present a feature categorization created in this thesis to understand better the different features used for adherence to treatment prediction. The intervention domain (sleep, physical activity, cardiovascular health, among others) is ignored, and instead, the focus is on generalizable aspects of each work.

8.1.1 Time-length

Different time lengths have been used in related work with results within the same range in classifier performance. The most prevalent time-length is overall adherence prediction, followed by weekly and only a few works explored daily adherence prediction.

8.1.1.1 Overall adherence prediction

The main goal of overall adherence prediction [**116, 67, 130, 70, 74, 61**] is to predict whether the patient is going to comply with treatment, and usually, this prediction is made before starting the intervention. A way to predict adherence is by making it into a regression problem where the goal is to estimate the average compliance rate. A second approach is to treat adherence prediction as a classification problem where adherence is defined as compliance of at least some defined threshold. As an example, the threshold could be set to 80%, and a patient adhering to 75% of treatment is then labeled as overall non-adherent.

Overall adherence prediction classifiers and regressors rely on data that is available before the beginning of the intervention, like demographics, socioeconomic status, health state and

Paper	Type	Method	Evaluation	Accuracy	Precision	Recall	AUC	Feature selection
Son 2010 [**116**]	Overall	SVM	LOOCV	0.77				Brute force
Koesmahargyo 2020 [**67**]	Overall remaining adherence based on first week	XGBoost	5 folds leave one group out validation	0.722	0.76	0.74	0.8	None
Koesmahargyo 2020 [**67**]	Overall remaining adherence based on first two week	XGBoost	5 folds leave one group out validation	0.7666	0.78	0.78	0.83	None
Lee 2013 [**74**]	Overall	SVM, LR	Testing was done on training set	SVM=0.973, LR=0.711				None
Wallert 2018 [**130**]	Overall	random forest	Random cross-validation	0.64				None
Kumamaru 2018 [**70**]	Overall adherence to statins	LR and Poisson model					c-statistic= 0.695	Lasso
Killian 2019 [**61**]	Intervention outcome: cured-complete vs died, lost, failure	RF, LSTM, linear regression	Random cross validation				DL = 0.743, RF = 0.722	

TABLE 8.1. Articles on overall adherence prediction. *SVM = Support vector machine, LR = Logistic regression, RF = Random forest, LSTM = Long short term memory*

knowledge, health condition and knowledge, the initial frequency of treatment, and possible side effects. A summary of the articles found is shown in table 8.1.

Accuracy varies from 0.64 to 0.77, and although Lee *et al*. [**74**] reports 0.97 accuracy this value is likely from an overfitting model since it was trained and tested on the same dataset. AUC scores, equivalent to c-statistic values, vary from 0.695 to 0.83. Many different machine learning methods were used with very similar performance.

8.1.1.2 Weekly and daily adherence

Although overall adherence prediction is helpful, it relies on many population-based assumptions and ignores all of the day-to-day variability in patients' lives. In addition, adherence can change drastically during treatment due to factors like unexpected side effects, change in preferences, changes in routine [**101**] among others. To overcome these challenges, researchers have investigated methods for the prediction of daily and weekly adherence to treatment [**141, 27, 101, 67, 11, 61**]. The most typical pipeline uses similar features to those used in the overall adherence prediction approach plus features that aggregate previous adherence,

Paper	Type	Method	Evaluation	Accuracy	Precision	Recall	AUC	Feature selection
Zhou 2019 [**141**]	Weekly	SVM, LR	First weeks training, last weeks testing	0.85	0.52	0.86	0.9 (LR), 0.88 (SVM)	None
Dermody 2018 [**27**]	Daily	Multilevel structural equation modeling	Model fit					None
Platt 2010 [**101**]	Daily	LR with generalized estimating equations	Model fit: $R^2 = 0.319$				0.66 c-stat	None
Koesmahargyo 2020 [**67**]	Weekly	XGBoost	5 folds leave one group out validation	0.813	0.82	0.82	0.87	None
Koesmahargyo 2020 [**67**]	Daily	XGBoost	5 folds leave one group out validation	0.81	0.82	0.84	0.87	None
Blumenthal 2015 [**11**]	Daily	LR	Separate training and validation sets				0.702	None
Killian 2019 [**61**]	Weekly	RF, LSTM, linear regression	Random cross validation				LSTM = 0.775, RF = 0.724	None

TABLE 8.2. Summary of daily and weekly adherence prediction related work. *SVM = Support vector machine, LR = Logistic regression, RF = Random forest, LSTM = Long short term memory*

previous activity, previous side effects, and other related data for a period of time (*e.g.,* a week, a month, baseline), and then predict for the next time period (*e.g.,* day, week, month). A summary of the articles performing weekly or daily adherence prediction is shown in table 8.2.

Accuracy values range from 0.81 to 0.85, and AUC scores from 0.66 to 0.9, which is an improvement of over 10% for the best accuracy and 8% for the best AUC compared to the overall adherence prediction approach.

8.1.2 Features

Previous work uses different measures captured through health questionnaires, self-reports, sensor measurements, and app interactions. The only common feature is a measure of previous adherence. In this section, I created a categorization of the different features used in related

work to understand which aspects of the patient's health and the problem are being covered. I also created new categories that cover other aspects of the participants' everyday lives and hopefully can increase the predictive power of the adherence prediction model. Following are the different feature categories created:

(1) Adherence [**141, 27, 101, 116, 67, 74, 130, 11, 70, 61**]: This set of features usually capture whether the participant has complied with treatment in the past. This measure assumes that the participant has experienced the intervention during some baseline period and, in some cases, uses adherence from similar interventions as a proxy. These features also may be an average of previous days, an average from the previous week, or baseline values. These features can also be combined with time features, such as previous adherence, previous month adherence, and previous morning adherence.

(2) Participant intrinsic characteristics [**27, 101, 116, 67, 130, 11, 70, 61**]: These features include demographics (age, gender, among others) and socioeconomic-status (spouse, healthcare insurance type, salary, education level). The main motivation for including these features is to capture risk factors for different segments of the population [**33, 82, 133, 132**].

(3) Intervention [**141, 101, 67, 74, 11, 70, 61**]: These features capture specifics of the intervention like the amount of time a participant or patient had to wait to get the intervention, experience with the intervention, self-efficacy, types of treatments, knowledge about the health intervention, and rewards received, among others.

(4) Health [**27, 101, 116, 67, 74, 130, 11, 70**]: This set of features capture several aspects of the participants' health like cognitive function, side effects related to the intervention, cravings during substance use interventions, perceived health status, general health assessments, and comorbidities. These features help to identify both intentional and unintentional non-adherence. Unintentional non-adherence, for example, could be due to forgetfulness, and it is captured through cognitive function tests. Intentional non-adherence could be due to strong side effects or not recognizing a health issue, and it is captured through perceived health questionnaires.

(5) Activity Types and amounts of activity [**51, 81, 77, 72, 36, 17**]: These features are critical as they capture the overall health of the elderly and other populations. Examples of these features are amount of steps in a single day, type of activity (*e.g.,* walking, running, on-vehicle), physical intensity level (*e.g.,* low, moderate or vigorous), among many others.

(6) Phone use [**41, 34, 39, 126, 140, 125**]: The way a user interacts with her phone has been found to correlate with many different health aspects like cognitive ability [**41**], stress [**34**], anxiety [**39**], mental fatigue [**126**], depression [**140**] and schizophrenia symptoms [**125**]. Including features that capture participant's phone use may then be helpful to passively sense health rhythms and mental state, which could affect treatment adherence.

8.2 Intraday adherence prediction

In this section, I introduce the data, preprocessing, and classifier used for predicting intraday adherence to treatment (IAT). Following the findings from chapter 7 the IAT classifier uses some of the features found. It was also explored other features that characterize different aspects of the participant's interaction with the phone and daily activity routines.

8.2.1 Data collection

The data used to train the IAT classifier was collected during study 1 presented in chapter 7. Demographics were collected during the four weeks of the baseline phase. Adherence-related data was collected during the four weeks app-intervention phase explained in chapter 7. Adherence data comes from the answers to the question: *Did you follow the recommendation ... that I gave you yesterday?*. Out of the 30 participants who finished the study, I only had 19 participants who completed at least a week of sleep diary questionnaires and at least a week of Fitbit data. The final data set has an average of 20 days of data per participant and 1158 observations.

8.2.2 Features

A total of 40 different features spanning all of the categories presented above was available to build the classifier. The complete list of features is presented in table **??**. Although it is not a high number of features, noisy and less informative features can affect the accuracy and other metrics, making it necessary to use feature selection. Feature selection was performed using L1 regularization, which makes zero the coefficients of features with low predictive power. Table 8.3 shows the different classifiers with their respective performance. The final set of features used in this work are:

(1) number of recommendations followed two days ago
(2) evening
(3) baseline time to fall asleep
(4) short
(5) baseline time after wake-up
(6) previous day activities-steps
(7) long
(8) number of recommendation followed the previous day
(9) previous day heavy cognitive activity before bedtime

8.2.3 Machine Learning Pipeline

Several classifiers were tested out; however, the best results were achieved using a multi-layer perceptron as shown in table 8.3. Besides the preprocessing involved for some of the features, the only other preprocessing done was to scale the data using a min-max scaler and using SMOTE to oversample and make the training data set balanced.

8.2.4 Evaluation and results

To evaluate the generalization performance of the classifier, I used group k-fold validation, which splits the data into k groups, each containing data from different participants. Training

Details	Avg f1	Avg acc	Avg balc
DummyUniform	0.5629 (0.029)	0.5124 (0.0867)	∼0.5000
DummyMajority	0.7675 (0.086)	0.6301 (0.1050)	0.5000
MultiLayer Perceptron	0.7548 (0.0743)		0.7026 (0.0785)
Adaboost without SMOTE Parameters: 'n_estimators': 7, 'max_depth': 3, 'learning_rate': 0.01	0.7659 (0.0769)	0.7156 (0.0374)	0.6595 (0.0429)
Adaboost without SMOTE Parameters: 'n_estimators': 20, 'max_leaf': 9, 'learning_rate': 0.01	0.7932 (0.0537)	0.7195 (0.0313)	0.6447 (0.0393)
Elastic Net with SMOTE Parameters: 'l1_ratio': 0.0001, 'C': 0.01	0.7207 (0.0981)	0.6914 (0.0792)	0.6755 (0.0790)

TABLE 8.3. Summary of performance of different adherence classifiers including dummy majority and dummy uniform used as a reference for baseline classification values. The values reported are the average across the different folds, and the () values are the standard deviation across folds.

is done on k-1 groups while testing on group k for k=5. For comparison with previous work, I present accuracy; however, this is not a good metric for this type of problem since the data set is imbalanced. Instead, as suggested in recent work [**44**] I report balanced accuracy and f1_score. The final set of results and models is shown in table 8.3.

8.3 Discussion

In this preliminary exploration of intra-day adherence to treatment prediction, I found that it is feasible and produces results within range for state of the art work. The final set of features found through L1 regularization does not contain any features that capture phone use; however, all other categories are represented. The absence of phone use features is surprising given their use in digital phenotyping work; however the granularity (only 20 days of data per participant) of the data may not be high enough to capture important patterns in the data.

The feature evening follows the pattern of findings from study 1 where knowing that it is the evening means the likelihood of adherence is low. In comparison, the likelihood of adherence in the morning and afternoon are similar and higher than in the evening. The features, short and long, which capture whether the participant is a short or long sleeper, made it to the final

features. This is an interesting finding because these features were also important for the analysis of participants' sleep duration, as shown in chapter 7. Due to time constraints, many other possible machine learning pipelines, features, and feature selection strategies were not tested, possibly increasing the prediction accuracy of IAT.

8.4 Limitations

The adherence prediction technique presented in this work is likely to generalize to other domains; however, this method relies heavily on patient's feedback. For health conditions where the treatment consists of taking pills, there are solutions available that track that the patient is following treatment. For other health conditions, and especially for behavioral health interventions, like the behavioral sleep intervention presented in chapter 7 it is more challenging to get this automated treatment adherence tracking because the treatment consists of difficult to track behaviors. For this type of intervention, it is fundamental that patients are willing to track their behaviors.

CHAPTER 9

Study 2: Deploying an mHealth intervention during the 2020 pandemic

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The promising results from the deployment of the SleepU app in study 1 presented in chapter 7 show that personalization of content and time of treatment results in behavior change, increased adherence, and higher motivation in comparison to baseline measures and standard clinical care. However, the study design did not include a comparison against a non-personalized approach like random selection and timing that does not leverage AI or receptivity. In other words, it is unclear whether the personalization of time and content approach used in study 1 produces better outcomes (*e.g.,* behavior change, adherence, motivation) than a simpler approach. For this second study, the main aim was to compare a simple approach like random selection and timing of recommendations against personalization of content and treatment. This study was started a week before lockdowns, and other measures (*e.g.,* social distancing, minimized social gatherings, avoidance of indoor gatherings) related to the COVID-19 pandemic in Pennsylvania U.S. in 2020.

9.1 Method

The SleepU app was deployed in a 7-weeks long study with undergraduate and graduate students from multiple colleges in Pittsburgh, PA. In this study, the SleepU app was deployed under a different experimental design compared to the one used in 2019. This second study aimed to obtain marginal effects of personalization of time and content of treatment and its comparison against random content and timing. In order to compute these marginal effects, the experimental design shown in figure 9.1 was used. After screening, participants were randomized to the random-recommendations group or the AI-recommendations group. The

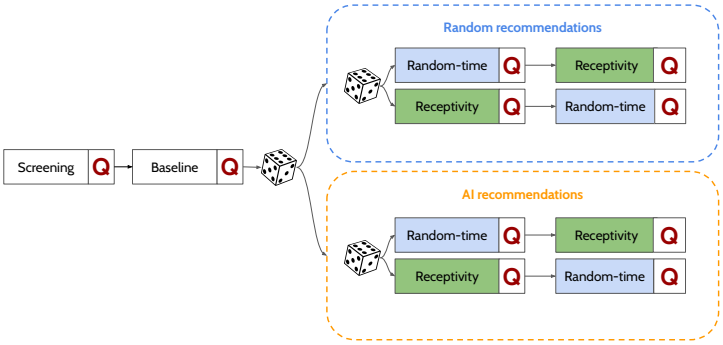

FIGURE 9.1. Study 2 experimental design. The baseline phase lasted 1 week and all other phases lasted 3 weeks. The Qs indicate times in the study when the participants filled out a battery of questionnaires as explained in section 7.1.3.

random group received recommendations selected randomly throughout the entire study. Participants in the AI-recommendations group received recommendations selected for them through the same contextual-bandit introduced in chapter 6. After the randomization for group, the participants were randomized to either start with recommendations delivered at random or receptive times to counterbalance any possible order effects. For receptivity, the same approach used in chapter 5 was used. In summary, all participants were exposed to time personalization and recommendations delivered at random times. Only half of the participants were exposed to AI-personalization of content, and the other half to recommendations selected at random. The eligibility requirements for participation were: 1) Participants had to be 18 to 30 years old and with an active undergraduate or graduate student status (only master's programs) at any Pittsburgh college. 2) Participants could not have any on-going problematic substance use (*i.e.,* drugs, alcohol or nicotine) or sleep disorders (*i.e.,* apnea, narcolepsy, chronic insomnia). This latter exclusion criterion was necessary because participants with these issues need specialized sleep treatment.

At the end of the study, a COVID-19 questionnaire was filled out by participants. This questionnaire was aimed to collect data related to how the pandemic affected sleep and several other aspects of the participants' everyday life with respect to the use of the SleepU app. Also, all participants were invited to participate in a final interview where particular themes identified through the surveys were further explored.

9.1.1 Participants

Participants were recruited using flyers, study recruitment websites, and Facebook posts at university groups at the beginning of January 2020. After screening, 78 participants were invited to join the study. Of those, 72 participants (32 Female, 39 Male, 1 Undisclosed) finished the study. The breakdown of participants for each group and condition is shown in table 9.1. Participants were compensated with 10 dollars (US) for each week of data logged in the study, and, as an extra incentive, those filling out 80% or more of the sleep diaries were allowed to keep the Fitbit inspire HR given to them at the beginning of the study. The participants were not compensated for using the SleepU app's sleep intervention functionality (*e.g.,* checking or following sleep recommendations).

9.1.2 Measures

In study 2 were used the same questionnaires used in study 1. After screening, participants were asked to fill out a set of questionnaires related to sleep health and other related and proximal outcomes after each phase of the study. The questionnaires included measures of psycho-social or physiological processes that are thought to mediate health behavior change as suggested by Klasnja *et al.* [**66**]. The questionnaires used were: the Pittsburgh Sleep Quality Index (PSQI) [**14**], Sleep Practices and Attitudes [**43**], Sleep beliefs scale [**1**], Perceived stress scale [**18**], Morningness - Eveningness questionnaire [**52**], Readiness to change towards healthy sleep-related behaviors questionnaire(*i.e.,* motivation questionnaire [**10**]).

Group	Condition	Number of participants
Random-recommendations	Random-times first	17
Random-recommendations	Receptivity-first	18
AI-recommendations	Random-times first	17
AI-recommendations	Receptivity-first	20

TABLE 9.1. Summary of participants that finished the study per group and condition

Additionally, participants were asked to fill out a sleep diary every day during the seven-week duration of the study and answer a yes/no question for each sleep recommendation available in the intervention. The complete list of questions used was:

(1) At what time did you go to bed last night?,
(2) At what time did you fall asleep?,
(3) At what time did you wake up this morning?,
(4) At what time did you get out of bed this morning?,
(5) How well did you sleep? (1-10=best),
(6) After falling asleep, How many minutes were you awake last night?,
(7) How many naps did you take yesterday?,
(8) How many caffeinated drinks (i.e., coffee, soda, energy drinks) did you have yesterday 6 hours before bedtime?,
(9) Did anything like noise/bed-partner/child/roommate disrupted your sleep?,
(10) Did you engage in cognitively moderate or intense activity (i.e., playing video games, studying, worrying about school) one hour before going to bed?,
(11) Did you avoid exercising 4 hours before bedtime,
(12) Did you maintain your usual daily activities?,
(13) Did you go to bed at your usual time?,
(14) Did you wake up at your usual time?,
(15) Did you avoid caffeine, nicotine or alcohol 6 hours before bedtime?",
(16) Did you avoid taking naps during the day?,
(17) Did you avoid heavy meals before bedtime?,
(18) Did you go to bed only when you felt sleepy?,
(19) Did you get out of bed after you could not sleep for 20 mins or more?,
(20) Did you use bed for sleep and sex only?,
(21) Did you perform any of these before going to bed: breathing exercise, meditation, mind-fullness?,
(22) Did you take a bath 1-2 hours before bedtime?,
(23) Did you avoid watching the clock before going to bed?,
(24) Did you make the bed environment conducive to sleep (e.g., cold, dark, noise-free)?,
(25) Did you avoid using an electronic device one hour before going to bed?

During the baseline week, participants answered the sleep diary questions directly on the SleepU app; however, no intervention was provided. After baseline, the app activated or deactivate the AI or receptivity detection depending on the group and condition assigned to the participant.

All participants were provided with a Fitbit Inspire HR, a wrist-worn wearable with sensors that measure steps and sleep phases. Sleep duration and efficiency were collected continuously during the seven weeks of the study. Participants in the study were instructed to wear the tracker at all times, including while taking a shower and while sleeping, with the exception of recharging. The device does not collect any data while recharging or at any time when the user does not wear it.

9.2 Analysis plan

In the following paragraphs are described the research questions and respective statistical analyses.

- **Personalization of content: Is there a difference between providing sleep recommendations at random or using AI?** To answer this question, a Generalized Linear Mixed Model (GMM) was estimated with minutes asleep as the dependent variable, fixed effects for day-of-intervention, and sleeper type (*e.g.,* short/long sleeper), and a random effect for the participant. The data was not aggregated, given that GMMs can handle raw data directly. Instead, I controlled for factors like baseline amount of sleep (Type-of-sleeper[**75**]), and the number of days in the intervention [**95**] following data analyses and conclusions from previous work. A thorough explanation of why controlling for these factors is necessary is provided in the appendix section 12.1. Covariates were added sequentially, making sure each increased the fit of the model to the data.
- **Personalization of time of treatment: Is there a difference in adherence to treatment between delivering sleep recommendations at random or receptivity detected times?** To answer this question, the data was aggregated into different periods (*i.e.,* morning, afternoon, evening) for each participant. Then, a Binomial Generalized Linear Mixed Model (BMM) was used with a random effect for the participant and fixed effects for day-of-intervention, delivery period, baseline motivation of the participant, and the type of time of treatment random vs. receptivity. Adding

baseline motivation as a covariate is justified by the COM-B [**84**] health model that states how motivation directly influences behavior. COM-B has been used in many interventions ranging from hearing aid use [**6**], coaching for Latina moms with gestational diabetes [**47**], and sleep hygiene [**117**]. Finally, covariates were added sequentially, making sure that each covariate increased the fit of the model.

- **Personalization of time of treatment: Was there a change in behavior between delivering sleep recommendations at random or receptivity detected times?** To answer this question, it was estimated a Generalized Linear Mixed Model (GMM) with minutes asleep as the dependent variable, fixed effects for day-of-intervention and sleeper type (*e.g.,* short/long sleeper), treatment (*e.g.,* random/receptivity), and a random effect for participant.

All p-values are adjusted within hypotheses using Benjamini-Hochberg to correct for type I error as recommended in [**9**] and following [**83**]. I used R 3.6.3, and the lme4 [**7**] and ggeffects [**80**] packages. Exploratory data analysis and hypothesis testing were conducted in Jupyter notebooks.

9.3 Results

9.3.1 Personalization of content

The AI-based personalization of content effect on behavior change (*i.e.,* minutes awake) was not statistically different from providing recommendations selected uniformly at random as shown in table 9.2. Evaluating other sleep-related measures was not warranted due to no change in minutes asleep. It is worth noticing that the AI group slept 5.5 minutes more on average than the random group. Similarly, the AI-based personalization of content effect on adherence to treatment was not statistically different from providing recommendations selected uniformly at random as shown in table 9.2. Although AI-based personalization did not result in a significantly higher adherence, it was 15% higher than recommendations selected at random.

Dependent variable	Null hypothesis	Estimate	Std. Error	z-value	Pr(>z)
minutes asleep	AI-random ≤ 0	5.504	13.077	0.421	0.337
adherence	AI-random ≤ 0	0.1536	0.2181	-0.704	0.241

TABLE 9.2. Statistical models estimated for personalization of content (AI vs random) effect on sleep duration (minutes asleep) and adherence.

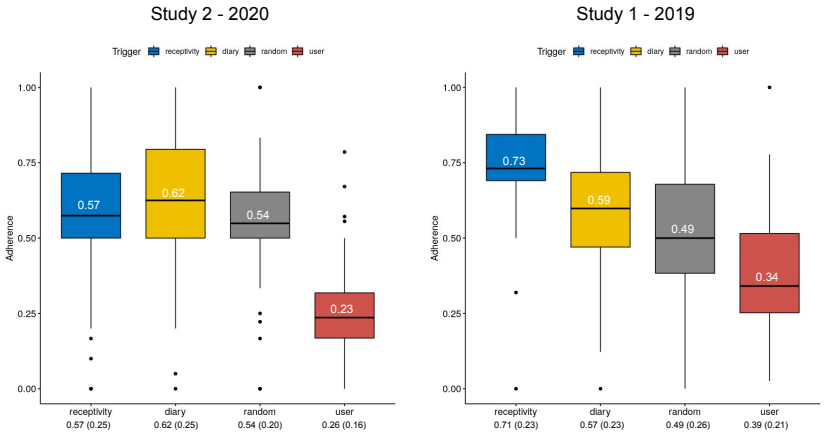

FIGURE 9.2. Adherence rates comparison between study 1 and 2.

9.3.2 Personalization of time of treatment: Adherence

The daily median of sleep recommendations seen by a participant was significantly different ($p < 0.008$) with 1.9 recommendations a day for 2019 and 0.8 for 2020. This difference translates into a median total of 45 fewer recommendations seen by a participant in 2020 in comparison to 2019 after adjusting for the different study lengths and using 42 (study 2 length) as the reference level. The adherence rates for the different delivery mechanisms (*e.g.,* receptivity, random, user, and diary) are shown in figure 9.2. I found that the delivery mechanism (*e.g.*, receptivity, random, user and diary) had an effect on adherence ($\chi^2(4) = 163.49$,$p < 0.00001$). Planned comparisons revealed that receptivity is only significantly higher than user ($p < 0.000001, d = 0.5898$).

The odd ratios of the BMM are shown in figure 9.3. In comparison to the 2019 values, the different odd ratios are very similar, and the conclusions are almost the same: Without a reminder, people are less likely to follow a recommendation; however, the morning and afternoon have a higher probability of resulting in adherence than the evening. Motivation

FIGURE 9.3. Odd ratios comparison for the BMMs in Study 1 and 2. Values in red represent a decrease in odds $OR < 1$ and probability, while blue values represent an increase in odds and probability. For motivation, the confidence interval of the odd ratios includes 1 and for that reason it is not significant. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

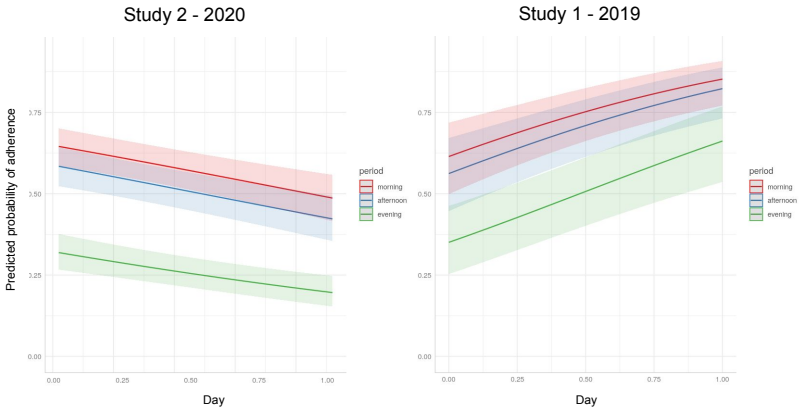

FIGURE 9.4. Likelihood of adherence over the course of study 1 and 2. For study 2 (left) the likelihood decreases over time while for study 1 (right) adherence increases over time.

is not significant, and it spans from $OR = 1$ to OR 10, meaning that there is a mostly positive but not significant effect of motivation. In terms of differences, random is higher than receptivity (for 2019, it was the opposite); however, both have the highest ORs. The day-of-intervention variable in 2019, as shown in figure 9.4 was positive, meaning as time passed, people adhered more to the intervention, for 2020 is the opposite as days of intervention passed, the likelihood decreased. Finally, diary in 2019 ($OR = 1.64$) was much lower than in 2020 ($OR = 3.88$).

Dependent variable	Null hypothesis	Estimate	Std. Error	Z value	Pr (<z)
minutes asleep	random-receptivity>=0	-4.539	4.281	-1.06	0.145
	baseline-receptivity>=0	-15.328	7.648	-2.004	0.045*
time in bed	random-receptivity>=0	-5.717	4.931	1.160	0.1231
	baseline-receptivity>=0	-16.8	8.807	-1.909	0.0563
minutes awake	random-receptivity>=0	-1.41	0.80	-1.71	0.039*
	baseline-receptivity>=0	-5.4788	1.4327	-3.824	0.000131***
efficiency	random-receptivity>=0	0.07	0.1596	0.496	0.6899
	baseline-receptivity>=0	-0.88	0.28522	3.089	0.00201**
minutes to fall asleep	random-receptivity>=0	-0.04	0.05	-0.791	0.927
	baseline-receptivity>=0	-0.13	0.09	-1.452	0.927
minutes after wakeup	random-receptivity>=0	0.04	0.07	0.552	0.45
	baseline-receptivity>=0	0.01594	0.12958	0.123	0.45

TABLE 9.3. Statistical models estimated for personalization of time of treatment (receptivity) vs random. All models used the same fixed effects (*e.g.,* treatment (receptivity/random), day-of-intervention, sleeper-type and participant as random effect). All p-values adjusted using Benjamini-Hochberg method. P-values: $p < 0.0001(***), p < 0.001(**), p < 0.01(*), p < 0.05(.)$

9.3.3 Personalization of time of treatment: Behavior change

Several GMMs were computed using different dependent variables related to sleep (*e.g.,* minutes asleep, time in bed, minutes awake, efficiency, minutes to fall asleep, and minutes after wake up) but with the same fixed and random effects. Dunnett's tests were then used to measure the statistical difference between the different groups (*e.g.,* baseline, random, receptivity) and sleep measures as shown in table 9.3. Minutes asleep for receptivity were higher than random (4.5 minutes) and significantly higher for receptivity (15.3 more minutes) compared to baseline. Minutes awake were significantly higher for receptivity (1.41 more minutes) than random and (5.47 minutes more) compared to baseline. Efficiency was higher for receptivity (0.88 higher) in comparison to baseline. All other results were not statistically different across groups and treatments.

9.4 Discussion

The results, in general, show that there was a null effect on sleep measures when comparing AI-based personalization and random. Similarly, there was no difference between personalization of time of treatment using receptivity vs. random. Despite the null results, there are a couple of good and interesting outcomes:

(1) Direction of effect mostly in favor of personalization content of treatment: Although the results were not statistically significant, in most cases, personalization had a higher outcome than either random time of treatment and random selection of content. Participants in the AI-based personalization of content group slept 5.5 more minutes than participants in the random group. For adherence, the participants in the AI-based personalization of the content group had a 15% higher probability of adhering to treatment. This result does not confirm the initial hypothesis, but considering the study occurred during a pandemic, it is surprising to see any effect at all.

(2) No best trigger for delivering treatment: In comparison to 2019, receptivity was not the best trigger for delivering sleep recommendations. The results show that receptivity, random, and diary have a comparable adherence rate, which means that even under pressing circumstances like the pandemic, the receptivity detector did not do worse than random. Based on 2019 results, it could do better than random under normal circumstances.

(3) Odd ratios are very similar: Despite the pandemic, odds ratios for the different factors used in the adherence model are very similar to those reported in 2019. Thus, according to the results, the receptivity classifier worked as it was supposed to, but Why did the intervention not work as a whole? This question will be answered in section 10.1.

(4) Only half of the recommendations from the 2019 study: Participants in study 2 saw only half the amount of recommendations participants saw in 2019. This is a drastic change, and it could indicate that participants in 2020 had half the interest of those in study 1, or participants cut their phone use by half, decreasing accordingly opportunities to receive notifications through the random and receptivity triggers.

(5) The pandemic made the intervention worst over time: As shown in figure 9.4, general adherence to the intervention decreased over the academic term for the 2020 study. This is the complete opposite of the 2019 study were participants' became more adherent to treatment over time. This effect will be further explored in the next section.

9.5 Conclusion

The pandemic decreased the intervention effects and may be the main reason behind the null results of the intervention. Particularly, the factor day-of-intervention in the adherence to treatment BMM models reveals a profound change in the way participants went through the study: In 2019, participants' adherence to treatment increased over time for 2020, the adherence decreased over time. However, all other factors of the adherence BMM model remained within the range of those of the 2019 study. These results show that when the receptivity and random mechanisms succeeded at delivering a sleep recommendation, their effect remained almost the same; however, they were triggered less than half the time compared to study 1, which would explain the lack of behavior change. In the next chapter, I explore the differences between the 2019 and 2020 studies with the goal of broadening the understanding of pandemic like events effect on mHealth interventions.

CHAPTER 10

Understanding the effect of the pandemic in study 2

The findings from chapter 9 show that the pandemic had a profound effect on the intervention. However, the underlying system, user and user-system interaction effects of the pandemic are unclear. In this chapter, through comparisons between study 1 (2019) and study (2020), quantitative and qualitative analyses I created the disruptive-event framework to further understand and generalize the factors and downstream effects of the pandemic in an mHealth intervention. For the quantitative analysis I investigated the behavioral (*e.g.,* sleep habits, before bed habits, time in bed and variance) and system level differences (*i.e.,* sensor streams, phone use and activities detected) between study 1 and 2. In the qualitative analysis I use surveys and interviews to understand the participants thoughts and feelings related to the sleep intervention during the pandemic. After these two analyses, I summarize all the findings into the disruptive-events framework to generalize these conclusions to other pandemic-like events. I close this chapter by exploring the application of the disruptive-events framework across pandemic-like events that occur much more often across the general population.

10.1 Quantitative analysis: Comparison of study 1 (2019) and study (2)

The results from section 9.3 show that there was no behavior change, and the receptivity and random triggering mechanisms in 2019 and 2020 worked very similarly. However, in 2020, participants saw half the amount of recommendations seen in 2019. This decrease in recommendation checking could explain the reason for no behavior change; however, it still hides the underlying reasons and conditions that forced that decrease. There are two possible

explanations for the null results 1) Participants lost their motivation for improving their sleep. 2) Participants changed their phone use, location, or daily activities resulting in a decreased phone use which in turn affected the SleepU app's ability to notify participants of new sleep recommendations. In this section, sleep and related behaviors, including motivation, phone use, location, and activity, are explored and compared to the 2019 study to uncover the reasons and conditions that caused the null results of the intervention. This section closes with a set of recommendations for deploying mHealth interventions to populations subject to drastic daily life changes (swift-work, relocation), and populations that are homebound.

10.1.1 Sleep and related behaviors

In this section are summarized sleep changes found between the participants in the 2019 and 2020 studies. These samples are comparable in terms of demographics; however, they are not similar. The 2019 study sample is composed exclusively of college students from Carnegie Mellon University. The 2020 study included students pursuing master's degrees and could be from any university or other undergraduate degree-granting institution in Pittsburgh. This means that the comparisons must be taken with caution, especially because across institutions, COVID-19 restrictions varied and may have affected students in different ways.

In order to compare sleep-related measures across studies, the same model structure used in study 1 as described in chapter 7 was used. This model used as an independent variable the sleep measure of interest (*e.g.,* minutes asleep, awake, after wakeup, to fall asleep) and has as fixed effects baseline sleep, the study phases, day-in-study, type-of-sleeper (*e.g.,* short, long), and year (*e.g.,* 2020, 2019 with 2020 measuring the effect of the pandemic) and used as random effects the participant ID. A model with a single fixed effect for year was used for sleep quality, and the participant's ID was used as random effect. The comparisons are summarized in table 10.1.

Participants' sleep in 2020 was worse than in 2019. Time in bed for 2020 was reduced by 31 minutes, distributed as a reduction in minutes asleep of 55 minutes and an increase in minutes awake, which account for awakenings and poor sleep, of 25 minutes. Despite the reduction in

Measure	Estimate (2020-2019)	CI (2.5%)	CI (97.5%)
Time in bed	-31.11 *	-58	-3.9
Minutes asleep	-55.62 ***	-80.4	-30.7
Minutes awake	25.0 ***	20.17	29.9
Minutes after wakeup	0.2	-0.04	0.4
Minutes to fall asleep	-0.13	-0.34	0.06
Efficiency	-0.3%	-1.3%	0.7%
Sleep quality (subjective)	0.63 ***	029	0.97

TABLE 10.1. Difference in sleep measures of the 2020 and 2019 studies. $p \leq 0.00005$(***), $p \leq 0.01$(*)

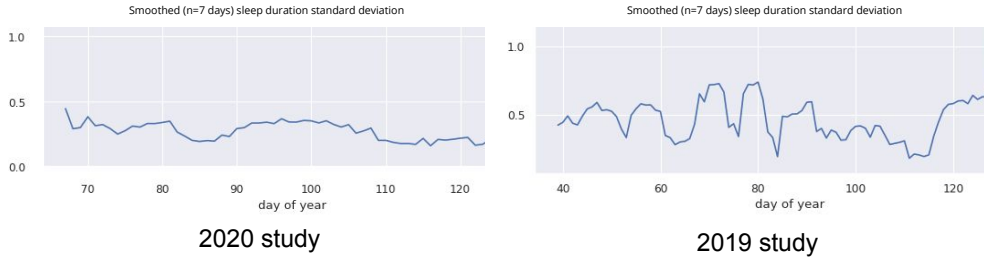

FIGURE 10.1. Smoothed standard deviation (rolling window, n=7 days) of sleep duration during the 2019 and 2020 studies. Higher values mean higher variance across individuals

sleep, participants in 2020 reported a sleep quality of 6.86, which is higher in comparison to 2019 (6.23). The change in sleep quality, although significant it not very meaningful given that sleep quality was measured on a 1-10 scale. Participants sleep in 2020 became more stable in comparison to 2019 as shown in figure 10.1. The standard deviation figure 10.1 shows an almost periodic signal that cycles between maximum and minimum values about every seven days for 2019. This periodicity was not visible in 2020.

Overall, the average standard deviation of minutes asleep in 2020 (108.6) was 19.1 higher ($p < 0.05$) than in 2019 (89.271). This pattern of higher weekly cognitive activity during the weekend is seen when comparing cognitive activity before bedtime both at a daily level 10.2 and at a weekly level 10.3. At the daily level, the percent of people per day of year responding that they were performing some cognitive activity before bedtime fluctuates in a weekly pattern for 2019, as shown in figure 10.2. This same pattern is much difficult to see for 2020.

At the weekly level, as shown in figure 10.3 there is only a slight increase in cognitive activity before bed in 2020, while for 2019, weekends have lower cognitive activity. The 2019 pattern could be due to increased social activity on weekends at night. In 2020, due to the lockdown, social and other activities may have been drastically reduced, and cognitive activity compared to weekdays stayed at a similar level.

In summary, sleep duration and cognitive activity before bed during the 2020 pandemic became more stable. Participants in the 2020 study reported a slightly higher sleep quality which this more stable rhythm of sleep may explain.

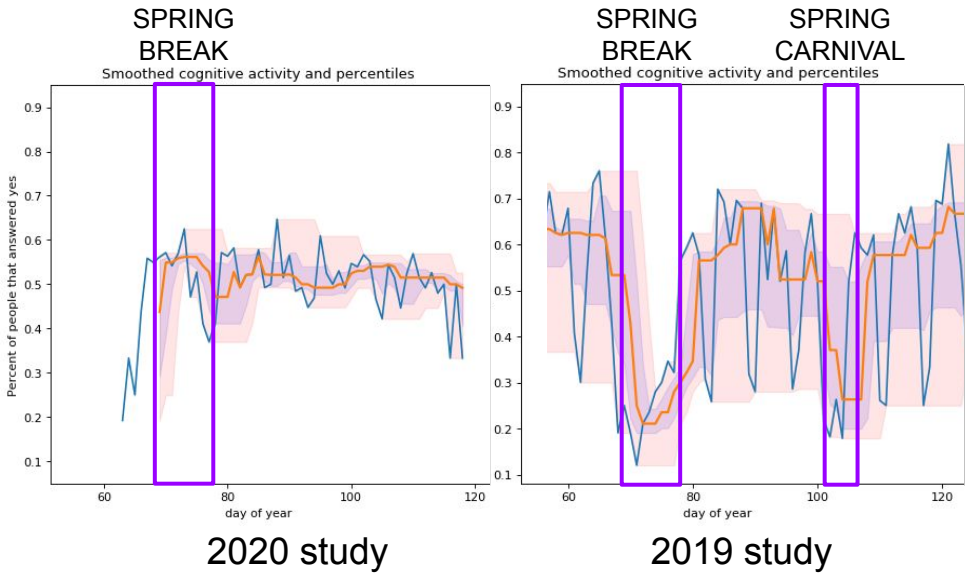

FIGURE 10.2. Smoothed cognitive activity and percentiles

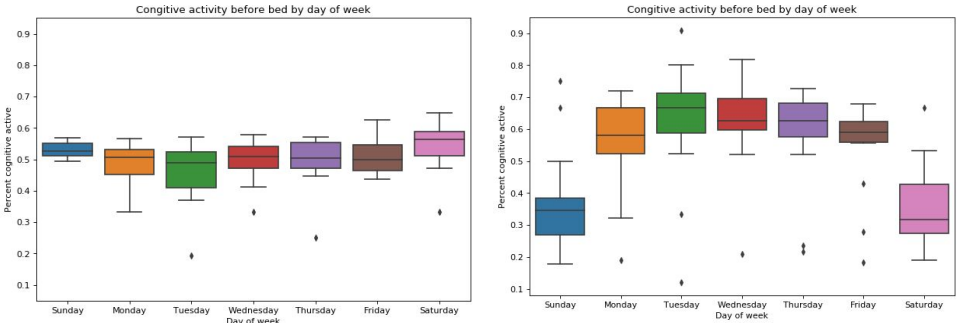

FIGURE 10.3. Smoothed cognitive activity before bed for different days of the week

Sensor-stream / event daily average counts	**median 2020**	**median 2019**	**difference (2020-2019)**	**p_value**
screen_off (.)	6.60	10.33	-3.74	p=0.02666
screen_on (.)	6.84	9.07	-2.23	p=0.04441
clicked_different	1.80	1.12	0.69	p=0.06141
interacting_false	10718.41	11729.52	-1011.11	p=0.18871
interacting_true	695.21	589.15	106.06	p=0.08822
event_notification_event	288.06	248.18	39.88	p=0.15063
event_foreground_event (.)	239.66	128.20	111.46	p=0.01438
foreground_different	16.44	16.33	0.11	p=0.42432
ringer_normal (.)	960.46	660.70	299.77	p=0.04586
ringer_vibrate	2049.79	5140.56	-3090.76	p=0.24698
ringer_silent (∗)	456.58	6871.41	-6414.82	p=0.00373
lock_true (.)	16.92	21.59	-4.67	p=0.02050
connection_mobile (.)	1.87	3.67	-1.80	p=0.01467
connection_wifi (∗ ∗ ∗)	1.59	5.93	-4.34	p=0.00000
connection_none (∗ ∗ ∗)	0.94	3.67	-2.72	p=0.00002
orientation_landscape (∗)	256.00	87.86	168.14	p=0.00991
vehicle	0.040	0.040	0.000	p=0.41844
bicycle	0.015	0.017	-0.002	p=0.08040
on-foot (∗ ∗ ∗)	0.050	0.121	-0.070	p=0.00000
still (∗ ∗ ∗)	0.720	0.585	0.136	p=0.00000
walking (∗ ∗ ∗)	0.050	0.120	-0.070	p=0.00000
running	0.012	0.011	0.000	p=0.21746
locations (∗ ∗ ∗)	3.022	7.212	-4.190	p=0.00000
entropy (∗ ∗ ∗)	0.480	0.619	-0.138	p=0.00000

TABLE 10.2. Different sensor streams and events comparing several aspects of smartphone usage in 2020 and 2019. $p < 0.0001(***), p < 0.001(**), p < 0.01(*), p < 0.05(.)$

10.1.2 Phone use, location and activity

After comparing several sensors and event streams collected from participants' phones in the 2020 and 2019 studies, I found that the participants in 2020 interacted with their phones in a significantly different way. A summary of all the different events and sensor streams evaluated and their comparisons are shown in table**??**

The number of screen_on , off, and lock_true logs, which are measures of how many times participants logged in and interacted with their phones, shows that there were fewer sessions in 2020. The number of notifications participants clicked on (*i.e.,* clicked_different, event_notification_event) was higher for 2020 but only marginally different. While participants' phone screen was on, the number of interactions for 2020 was higher (*i.e.,* interacting_true, screen touches). The phone ringer setting (*e.g.,* lower, normal, silent) shows that participants, in general, used the normal mode more than silent or vibration. Network

connection which indicates when the phone connects to a new network (*e.g.,* mobile, none and wifi), were significantly lower. Phone orientation logs (*e.g.,* orientation_landscape) for 2020 show participants were significantly more often in landscape mode.

There were also some differences in the activity-related events detected by the google activity recognition API. These values are also reported in table 10.2 as the average of probabilities. For example, for still, the 0.72 value reported means that, on average, participants were detected to be still with a 72% probability. Participants vehicle rides detected were not different in 2020, although bicycle riding was marginally lower for 2019. Participants (or their phones) were detected still more often, walking less and running about the same in 2020. Last, the number of locations visited in 2020 was significantly lower in 2020. The variety of locations visited, computed as the entropy of the locations visited per day, was also significantly lower.

10.1.3 Conclusion

Overall there were significant differences between the 2020 and 2019 studies. In terms of user behavior, participants in 2020 had worse sleep for most measures evaluated, with the exception of sleep quality and sleep duration stability. A markedly different pattern of behavior was found for cognitive activity before bedtime and sleep duration: during 2019, there is a clear difference between weekends and weekdays. For 2020, cognitive activity before bed and sleep duration difference between weekends and weekdays is much lower, making any day of the week similar to any other. For system and user-system interaction I found that participants opened their phones less, click on the screen more, and responded to notifications slightly more. Portrait orientation was logged more in 2020, which could indicate using the phone more often for full-screen apps to watch movies, tv, or playing video games. Also, it seems like participants may not have carried their phones on them given that they used less often the silent and vibration ringer mode: If they are away from their phones, they need the phone to produce sounds to be aware of notifications and others. Activity data logged also favor some of the above hypotheses. The probability of the activity still is much higher in 2020, which may not indicate that the participant was still but rather that the phone

was. Walking was also lower, and again it could be indicating simply participants not carrying their phone around. In terms of locations, participants visited much fewer places in 2020. In summary, all evidence points at changes with the the user, system and user-system interaction. Sleep and related behaviors, phone use, and activity, which affected the receptivity detector's firing rate, which in turn could have resulted in the null intervention results. All these results are well aligned with lockdown-related mandates that suggested people to remain indoors (*i.e.,* increased still, decreased walking, decreased network connections) and avoid social gatherings (decrease in locations visited and walking).

10.2 Qualitative Analysis: Understanding participants thoughts and feelings during study 2

Participants in the 2020 study answered a short survey where they were asked about their experience related to their sleep behavior and SleepU app usage during the 2020 lockdown. Some of the questions used a "strongly agree" to "strongly disagree" scale, while others were open text. The survey questions were the next:

- Did you experience any of the next symptoms during the study: Dry cough, shortness of breath, fever, loss of smell, loss of taste?
- How much do you agree with the next statements:
  - During the study, my sleep was positively affected by the lockdown
  - During the study, my sleep was negatively affected by the lockdown
  - During the study, my sleep was about the same as it was before the lockdown
- How do you think the COVID-19 lockdown affected your sleep (e.g., sleep duration, quality, awakenings) during the weeks you participated in our study?
- How do you think the COVID-19 lockdown affected the way you interacted with the SleepU app?

10.2.1 Method

The survey data collected was analyzed in two main ways: Likert-scale questions were analyzed by estimating counts. Open ended questions were coded, and affinity diagramming was used to find common themes across the responses.

10.2.2 Results

53 of the 72 participants responded to the survey. Only 3.7% (n=2) of the survey respondents reported experiencing any COVID-19 symptoms. 54.7% (n=29) of the participants disagreed (*e.g.,* disagree, strongly disagree) that the lockdown affected their sleep positively, and 13% (n=7) stated that it did not have any effect (*e.g.,* neutral). 56% (n=30) of the participants stated that the lockdown affected negatively (*e.g.,* strongly agree, agree) their sleep, and 17% (n=9) of the participants stated that it did not have any effect. 77.3% (n=41) of the participants stated that their sleep was not the same (*e.g.,* strongly disagree, disagree) as before the lockdown. In summary, most of the participants (54% to 56%) stated that the lockdown measures had a negative or did not have a positive impact on their sleep, and a majority of the participants (77%) perceived a change in their sleep.

For the question *How do you think the COVID-19 lockdown affected your sleep* I found four general themes:

(1) **The majority of the participants reported going to bed and waking up later than before the pandemic:** Participants attributed this to a less strict daily schedule allowed by measures like online classes, quoting one of the responses: *" I didn't have to stay with a strict bedtime and wake up time anymore so I didn't go to bed and wake up at the same time everyday like I normally would."*.

(2) **The majority of the participants reported more irregular sleep schedules compared to before the lockdown:** Participants shared that their "sleep became immensely irregular resulting in a perception of lower productivity.

(3) **Participants reported sleeping more each day:** Participants indicated that they were "getting a lot more sleep than [they] normally would. Usually [they] would get 3-5 hours of sleep, but since the lockdown [they got] 6-8 hours every day."

(4) **Many participants reported their sleep was affected by their anxiety or stress by the COVID-19 pandemic:** Several participants indicated that they were emotionally affected and had a negative effect on their sleep: "being in lockdown has been an emotional toll, as I literally did not go out for more than a month now ... I don't feel as tired as before lockdown, but everything is feeling sluggish" or that "COVID-19 did make me feel more anxious about my health, study and future, so during the lockdown I didn't sleep well, and I woke up early."

In general, participants reported both positive and negative impact on their sleep, daily schedules and routines, anxiety and stress among others.

For the question *How do you think the COVID-19 lockdown affected interaction with the SleepU app* the next were the patterns found:

(1) **My interaction with the SleepU app was not affected by the pandemic:** 37% (n=20) of the participants thought their use of the SleepU app was not affected by the pandemic. These participants did not elaborate further in their response.

(2) **I didn't follow advice because I was not motivated, found it difficult or ignored the app:** 41%(n=22) of the participants reported not following the recommendations a majority of the time due to changes mostly in motivation. These changes were brought out by pandemic related changes like lack of a normal schedule, messy sleep, higher work, attention devoted to pandemic developments. This may have resulted in a lower prioritization of sleep and hence a decrease in motivation. As part of the responses many of these participants stated that they would have followed or at least tried harder to follow the sleep advice under normal conditions.

(3) **The lockdown helped with my sleep:** 7.5%(n=3) of the participants stated that their new found lack of schedule as an opportunity to organize better their day. Recommendations that in normal times they found difficult to follow like "keep your

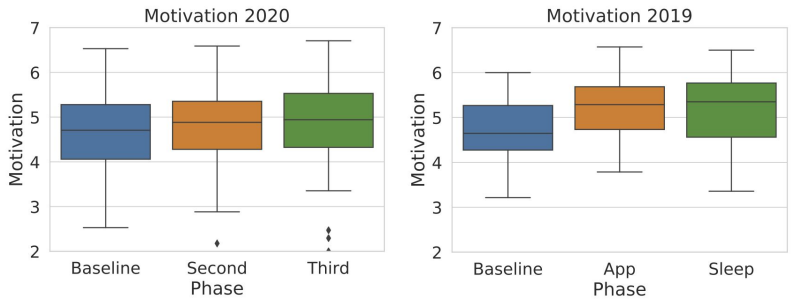

FIGURE 10.4. Motivation levels for the 2020 and 2019 studies. For 2020 the organization of the phases reflects the chronological order. For 2019 app and sleep phases happened at the same time

daily routine even after bad sleep" or "take a bath before bedtime" were easier to follow. This was however was a very small set of the participants

10.2.3 Conclusion

Most participants reported that their sleep was affected negatively by the 2020 pandemic. Participants were exposed to a lack of a regular schedule, flexibility to watch videos instead of attending lectures and a lack of a commute to class. In addition, a large subset (41%)of the students found that the pandemic caused stress, anxiety, and an increase in workload, which in turn decreased their motivation and prioritization of sleep. Another relatively large subset of the students (37 %) thought their interaction with the SleepU app was not affected by the pandemic; however, they did not elaborate on the details. This last subset of participants suggests that they may not have been interested at all in improving their sleep even before the pandemic. To investigate further, I explored the average total motivation towards improving sleep at different phases of the study as shown in figure 10.4. The plot shows that the initial median motivation is 4.4 for 2020, and although it is slightly lower than the 4.6 for 2019, it is not a meaningful difference. Thus, participants' initial motivation does not explain the null results of the intervention.

10.3 The disruptive-events framework

In order to understand how different factors affected the health intervention in study 2, I created the disruptive-events framework. The disruptive-events framework as shown in figure 10.5 connects changes caused by the pandemic to findings of study 2 and the COM-B [**47**] model of behavior change. The pandemic affected the participants emotions, daily routine and the way they interacted with their phone. The pandemic created negative emotions by increasing participants stress, worry about the future and the health of their older relatives. This feelings in turn hurt negatively their sleep by making it shorter and increasing the number of awakenings. All these feelings overcome their capability and motivation to improve their sleep. Changes in routine like virtual classes, lack of a commute, and flexibility for watching lectures made it difficult to attach healthy sleep habits to routines hurting their capability to achieve long-term behavior change. This lack of routine also affected time to bed times, time in bed and their physical activity. Since students didn't have to commute daily to campus, the amount of daily walking went down, access to campus's gym became more difficult causing a decrease in their physical activity levels.

Last, daily phone interactions between the participants and their phones, and their decrease in physical activity caused the receptivity detector to prompt rarely the participants about

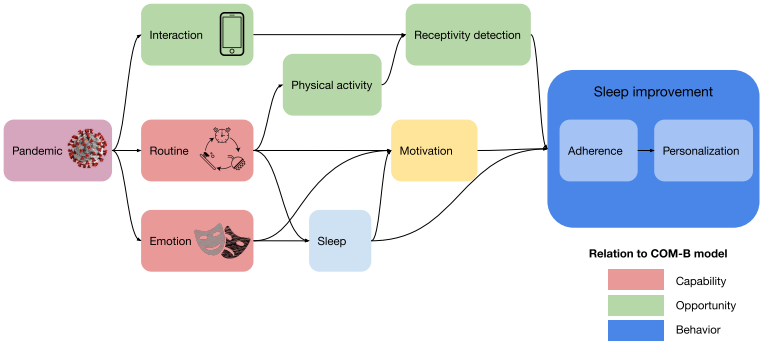

FIGURE 10.5. Main changes caused by the and its relation to different intervention components. The color of the different blocks indicate how each is related to the COM-B model of behavior change.

sleep recommendations. This decrease in prompts in turn reduced the opportunity window to achieve behavior change.

The pandemic affected the participants capability, motivation and opportunity to improve their sleep resulting in low adherence to the intervention. Low adherence as a result produced very few data points for the AI-based personalization approach to modify the intervention which ultimately led to the null interventions results.

10.4 Implications for pandemic-like events

The 2019 pandemic is an unprecedented event in its global reach, however at the individual level some aspects of it can be similar to typical life events like relocating to a new city, being or becoming homebound or doing shift-work. This implies that some of the results obtained during the 2020 study are likely to generalize. In this section, I first explore possible solutions that are centered around the three main issues caused by the pandemic and then I explore three case scenarios and derive ways to achieve personalization on each scenario based on the findings of this chapter.

10.4.1 Personalizing during pandemic-like events

In figure 10.5 it is shown how three main issues were found to disrupt personalization and behavior change during study 2. In general, most of the issues caused people to not adhere to sleep recommendations and this lack of adherence did not allow personalization to occur since the AI approach relies on people adhering to the sleep recommendations. In the next paragraphs I summarize the challenges that participants had at following recommendations during study 2, then I describe possible solutions that could allow to overcome those challenges:

- **Interaction:** When participants in study 2 changed the way the interacted with their phones, it rendered useless AI-based mechanisms that reminded them of following sleep recommendations. To overcome this issue, the health intervention should rely on more than one device and in more than one communication channel to reach

the participant. For example, in study 2 the intervention depended on interactions with the participant's phone and only used notifications as the main communication channel. To solve this challenge, the intervention by itself could have explored delivering the sleep recommendation to different devices (laptop, desktop computer, landline among others) and different communication channels like emails, voice messages, SMS or even calls. Both device and communication channel could also become additional personalization dimensions that may be included in an AI-based health interventions but that are only explored after failure of the main device and communication channel. This strategy is likely to work well across different case scenarios.

- **Routine:**Participants loss of routine during the pandemic led them to not follow a predetermined schedule since they didn't need to wake up at an specific time, or be in a specific place to full fill their academic goals (*e.g.,* delivering homework, attend lecture, attend labs). Participants mentioned that they could not turn the sleep recommendations into habit because they could not attach them to a daily routine. This finding is supported by habit formation theory[**137**] that states that to form a habit its needed a time, location, previous behavior or something (*i.e.,* context cue) that will trigger the habit. During the study participant's location was mostly the same, time was no longer a cue for starting or stopping activities and even lectures could be watched online anytime. Then, it follows that adhering to sleep recommendations and making them into a habit would be difficult. To overcome this challenge, namely to be able to personalize in the absence of a routine, the reliance on any contextual cue should be minimal or none, instead relying on participant-specified reminders could be the best possible solution and personalization could be used to fine-tune the time of the reminders. As an example, the participant could provide time ranges during the day to be reminded about the sleep recommendations. Then, using a Multi-armed bandit, those time ranges are split into smaller intervals that the bandit could pick at random initially but as the participant responds positively to them, the bandit could over time estimate which are the best to provide advice to the participant. This solution could generalize well not only across pandemic-like

scenarios but it may be used as an alternative to receptivity detection for non-pandemic scenarios. Another solution could be to provide reminders when activities that do not depend on routine occur like waking up, eating or cooking meals, and taking a shower. With the exception of detecting wake-up, most of these solutions depend on instrumenting the environment and may be unfeasible.

- **Emotion:** During the pandemic participants emotion went into different directions anxiety, stress, depression among others made sleep worse and also decreased the priority given to the sleep intervention. More generally, an emotion component separate from the intervention and related to being homebound decreased the priority of the health intervention. A possible solution to this challenge could be to adapt the health recommendations to highlight their value as a way to get good health and as a way to feel better while homebound. For example, for in the SleepU app the message and illustrations used in the sleep recommendations were designed to highlight how to perform the recommendations however they do not appeal to the emotions of the user to make a case for sleep and general well being. As a general rule, health recommendations should be adapted to the specific homebound event by connecting the value of the intervention with the participant's current environment and state of affairs. In summary, the health intervention should move from disease-directed to patient-value based care [**123**]. In the common disease-directed paradigm, health interventions are evaluated based on health measures of improvement like decrease blood pressure for people with hypertension or steps in a physical activity intervention. Under patient-value based care the goal is to improve something the patient cares about, in the case of a patient with hypertension she could have as a goal to be able to decrease fatigue levels to be able to participate in physical activities with family members.

10.5 Discussion: Three pandemic-like case scenarios

Although the covid-19 pandemic is a rare event, there are common life events that share characteristics with the pandemic. Using the findings in this chapter I now describe how the

personalization strategies described in the previous subsection can be used during common life events.

- **Being or becoming homebound:** 1.9 million adults age 65 or older in the U.S. are completely or mostly homebound, and another 5.3 million have limitations that makes it difficult to go out [**93**]. This does not take into account people who are temporarily homebound due to health problems or after treatments like major surgeries. This population is affected by all of the factors identified in section 10.2.3. The way this population interacts with their phones is different in contrast to younger populations for example their smartphone use is decreased in stable locations [**111**]. This finding together with results from study 2 related to smartphone use while homebound imply that receptivity and context based personalization of time of treatment may be difficult to achieve. A possible approach to be able to personalize time of treatment is by relying on other devices like wearables and smart speakers like amazon's Alexa who are increasing in popularity among the elderly [**59, 62**] and could help increase adherence. Similarly, using more traditional channels of communication (*e.g.,* SMS, phone calls) could work well with this population.

  Although this population is at home, they likely follow a routine unlike the participants of study 2. However, detecting routines at home without significant contextual changes is difficult to achieve without instrumenting the home. In this case the solution to overcome this challenge would be to rely on the patient's provided times for reminding them of treatment plus further time personalization using bandits. Finally for the challenge of emotion, the transition to patient value-based care should make the health intervention more important to the patient resulting in an increased adherence to treatment despite being homebound. As an example, among the elderly homebound population some of them are cancer survivors. This population is in great need of physical activity to decrease their sedentary behaviors and improve their cardiovascular health which is usually treated with physical activity interventions. While homebound, these population may experience frustration and depresion and this could greatly interfere with physical interventions. Using a patient value-based approach, the physical activity intervention could for example highlight to the patient

how her fatigue levels have been improving and how she could now engage in leisure activities and sustaining family relationships by joining on activities like being able to play and lift their grandchildren [**87**].

- **Relocating to a new city:** Relocating to a new city or country usually involves a complete re-evaluation and adjustment of activities and routines. Relocation then, at least for some amount of time, shares the lack of routine with the framework presented in figure 10.5. Unlike becoming homebound, relocation's lack of routine is only temporal and routines are established quickly overtime as the participants adjust to their new lives. Under such circumstances, AI-based personalization needs to adapt accordingly to the new situation. To do that, an anomaly detection module should be added to the personalization process. This module will then be in charge of making the probability distribution over the likelihood of showing health recommendations more uniform (*i.e.,* increasing entropy). In other words, the resetting mechanism should decrease the probability of recommendations with very high probability while increasing the probability of less likely recommendations. Through this approach, the system will be exploring more often among less likely recommendations and will be able to adapt to the relocation. Phone interactions under this scenario could change but not drastically and for this reason the receptivity detector is still likely to work.
- **Shift-work:** Among the 144 million wage and salary workers in the U.S in 2017, 16% worked a non-daytime schedule, (*e.g.,* evenings, nights, rotating shift, split shift, irregular schedule or some other schedule). Shift-work is challenging since it disrupts natural biological rhythms and leads to disease and chronic conditions like obesity, diabetes, compromised immune function, cardiovascular disease, and increased cancer risk [**57**]. Given the negative consequences of shift-work it is very important that any efforts at personalizing a health intervention succeed at their goal of maximizing adherence to treatment. Following the disruptive-events framework, shift-work is affected by the routine of this population. Although this population has a routine, their routine changes depending on the shift they are working. This means that when a participant is in her routine for the evening

shift, the health recommendations that she can follow and the contexts where she can execute them could be very different from her night shift. As a consequence, AI-based personalization may not rely on the divide and conquer approach used to achieve personalization were time of day was used to create three different bandits that handle recommendations separately for the morning, afternoon and evening. Instead, the shift occurring should be incorporated directly as a factor in the contextual bandit. Unfortunately, this approach increases computational complexity and requires of a higher amount of data for personalization or the use of other alternative strategies like leveraging data from multiple people to speed up personalization. An alternative could be to use separate bandits for each shift. This approach will retain the computational efficiency achieved in the approach presented in this thesis. However, whether using a single contextual bandits or multiple, in both cases is necessary that either the user inputs the shift occurring or a way to detect the shift automatically.

10.6 Conclusion

Despite the rarity of pandemic-like events, the findings of how an mHealth intervention could fail during a pandemic are likely generalizable to other more common events. These findings were used in this section to create the disruptive-events framework which can be used to understand how pandemic-like events could affect an mHealth interventions and as a template to draft a solution to the challenges posed by these type of events. Some of the solutions to these challenges are changes at the system level like modifying the contextual bandits, identifying changes in routine or using multiple devices in the interventions. Other changes like switching from disease-directed to patient-value based goals are a design guideline at the user level that requires understanding the user needs and wants to connect them to the mHealth intervention.

CHAPTER 11

Conclusion

In this dissertation, I have described the development and testing of an AI-based personalization approach for mobile health interventions. By creating this novel, effective and sample efficient personalization approach that combines artificial intelligence, wearables sensors and human-feedback, my work transforms behavioral data, and human-AI interactions into a decision making platform that facilitates behavior change and habit creation. This AI-personalization approach automatically adapts to context, patient outcomes and preferences, demonstrating the potential of contextual and AI-based digital health interventions.

Outside of the sleep intervention results I presented in this thesis, personalizing health interventions for content and time of treatment has real-world impact in specific domains like diet, physical activity for cardiovascular health and stress-management, and also in broad spectrum interventions like weight management, substance abuse and even as a way to enhance common behavioral intervention approaches like cognitive behavioral therapy.

More generally this thesis has made contributions in the domain of digital health interventions, context aware decision making, human-AI interaction and more broadly in human-computer interaction. My work on personalization of time of treatment contributes to the understanding of how contextual and patient's intrinsic characteristics can enhance or decrease adherence to treatment. My work on personalization of content contributes to the understanding of how context (*i.e.,* time of day), environment (*i.e.,* days of the semester) and health specific factors (*i.e.,* short vs long sleeper) affect behavior change. My work on intraday adherence prediction demonstrates the feasibility of fine grained adherence prediction which could be used as a further dimension of personalization. Last, my deployment during the pandemic resulted in the creation of the disruptive-events framework that can be used to understand

and formulate solutions to the challenges posed by pandemic-like events in the context of mHealth interventions.

In summary my thesis contributes to the understanding of the interplay of device use, context, environmental and health factors role in behavior change and adherence to treatment and how through digital sensing technologies and artificial intelligence these factors can be used to make health interventions more effective. These findings warrant further exploration as new dimensions of personalization to improve proximal and main intervention outcomes. Likewise, some of the findings from the disruptive-events framework can be tested both during a pandemic or in pandemic-like scenarios as those introduced in chapter 10.

11.1 Unresolved questions

From my investigation, it is still unclear whether the personalization methods and system used in the 2019 study can produce better or similar outcomes than simpler methods like showing everyday sleep recommendations selected at random and delivered at random times. Nonetheless the results presented evaluating the effectivity of this type of AI-based intervention across several intervention dimensions (behavior change, adherence and motivation) are very promising and warrant further exploration of this approach.

Another unresolved question is related to the effect of specific sleep recommendations and their (most likely conditional on demographic and contextual factors) effect on participants' sleep. Although, sleep recommendations affect people in different ways there could be sub-population or demographic based health outcomes to the recommendations that could be used as priors for AI-based personalization methods. For example, this priors can give broad estimates of how a demographic factor like age affects adherence and sleep related behaviors. With this information, the AI then does not need to explore all possible treatments and instead could narrow down its health treatment personalization to a few health recommendations possibly resulting in faster personalization. This reduction in time of personalization in turn can result in higher user satisfaction with the intervention, improved self-efficacy and adherence to treatment.

11.2 Future work

In this thesis, I demonstrated the value of personalization of content and time of treatment and its positive effect on health (*e.g.,* behavior change, adherence to treatment and motivation) in the context of a sleep intervention. These results are very likely to generalize across different domains and dimensions of personalization. The next is a breakdown of those promising paths:

11.2.1 Personalization of time and content across different intervention domains

The approach introduced in this thesis is most likely to generalize well for behavioral interventions that rely on providing health recommendations. Examples of such interventions are weight loss interventions where advise on which activities to perform or which foods to eat are provided. For both interventions, personalization of content (*i.e.,* selecting which recommendations to deliver) can be done using the methods described in this thesis. However, the selection of the reward signal to use as a measure of personalization should be selected carefully. For example, in this thesis I selected a score that captures both sleep duration and efficiency as both measures are equally important to achieve high sleep quality. However, data points from sleep duration and efficiency are scarce: one data point per day, limiting the quantity of data available for personalization. A possibility, to overcome this data scarcity is to instead of using the intervention main health outcome to rely on a proximal measure like adherence to treatment. An advantage of using adherence is that at least in the case of the sleep intervention presented in this thesis, it increases three fold the quantity of data available for personalization. Likewise, in a weight loss intervention, adherence to physical activity and eating recommendations will increase the amount of data linearly with the amount of recommendations available. Adherence has as a further advantage that it can be found in all health interventions independent of domain.

One possible challenge in this domain does emerge when the patient may be adherent to unproductive recommendations that are not going to significantly improve the patient's health.

Over a short time span this may not be bad as can be used as a warm period to get the patient comfortable with treatment (*e.g.,* increase self-efficacy). However, over time the personalization system should explore more effective recommendations and somehow re-evaluate the effectivity of recommendations based on the intervention end goal measure and not simply adherence to treatment.

11.2.2 Beyond receptivity

Unusual events (*e.g.,* the pandemic, cancer diagnosis and treatment, mobility loss) affects the way people interact with their electronic devices, rendering useless pre-trained models that rely on user-device interactions to trigger, manage or adapt interventions.

Training new or updating receptivity detectors although possible does not work very well[**86**] and requires at best weeks of data [**71**]. In the pandemic scenario, even the receptivity concept that hinges around discovering opportunistic states may be unfeasible. To overcome this challenge, the AI personalizing timing of treatment may need to try different communication channels (*e.g.,* chatbots, SMS, phone call, social networks, email). In this research avenue, it would be very valuable to explore multi-device (*e.g.,* phone, wearable, desktop) receptivity detection and multi-channel health interventions. The main goal would be to discover which device and channel work best for each patient using minimal data or feedback. Based on this thesis findings, it is expected that the device type and communication channel has an effect on adherence to treatment. For example, a user commuting home who is listening to music, may be open to hear about personal health advice and feedback through her earphones, but not through SMS, chat or text communications. A user browsing through a social network website may be willing to trade-off ads for health recommendations that may include text and video.

11.2.3 Health interventions across devices

Mobile health interventions have opened up a way to deliver health interventions in most places at almost any time of the day. However, people split their time across different devices

depending on contextual (*e.g.,* time of day, physical activity, current task), intrinsic (*e.g.,* age, gender, mobility) and other factors. The device-context dependence creates new affordances for health interventions. For example reading and watching videos may be easier on a desktop while listening to audio or impromptu short health recommendations is more convenient on a mobile phone. Overall the guiding research question in this area is **How can be leveraged the affordances and contexts of use of different computing devices to deliver different types of content of a health intervention?**. Another important aspect to investigate in this area is the embodiment of the health intervention: *What are the implications of perceiving a health intervention as a single entity moving across devices or as multiple entities across different devices?*. The perception of the health intervention as a single agency may be conflicting for the patient since she could expect then to receive the same information and treatment across different devices even though by design it would not be possible. The perception of the health intervention as separate agents may help with patient expectations of treatment but could create conflict by giving the illusion that the information across agents is not shared. Then, if agents do share information for some patients this could be a great feature that will help them have a more seamless interaction will all the health intervention devices. However, for patients with higher privacy expectations this could be problematic. For example the patient could provide sensitive information to an AI over chat that is password protected, if this information is available to a virtual assistant with voice interaction, the patient may be worried that anybody could get its hands on her private health information.

11.2.4 Language-style (a.k.a., Message Framing, tone)

The particular language-style used for communicating, has improved intervention outcomes in personalized health interventions [**103, 139**]. There are many different language-styles (e.g., empathetic, authoritative, supportive); however, figuring out the one that works best for each individual is time-consuming and current approaches rely on the response to questionnaires, which limits adaptation. In this research area, I envision the development of methods for the automatic adaptation of tone, based on health outcomes and context. Mhealth systems could learn over time which language-style works better and how context (e.g., time-of-day,

weekend vs. weekday) or intervention specific measures (e.g., motivation) affect health outcomes. For example, for participants with low motivation, empathetic messages could work better, while authoritative messages may be more effective at high motivation levels. Adherence could also be factor for personalization of language-style, for example participants that missed on treatment require an authoritative message right after to go back in track with the intervention while at any other time supportive messages work best.

11.2.5 Emotion-sensing

Emotion sensing is very challenging, despite many advances it is still difficult to find approaches that are robust enough to integrate in live deployments. Nonetheless, recent advances in deep learning specifically in self-supervised learning allow estimating from unlabeled data, features that can then be used to create classifiers with a small amount of data. This ability to create better and "cheaper" emotion sensing models then could allow for their usage in just in time intervention. Detecting high anxiety levels could for example trigger more intrusive interventions (phone call, visits). Stressful events detected after providing a treatment could be used as proxies for self efficacy and the ability to cope with the intervention which in turn can help with personalization of content. Overall adding real time emotion sensing as a proximal signal for personalization could greatly reduce the time necessary to achieve personalization of treatment.

11.2.6 Self-tracking+sensing+receptivity

Self tracking is an important part of health interventions that can increase patients self-efficacy[**5**] and enhance motivation towards behavior change. Despite this, current tracking technologies are at a very basic stage and may even hurt health interventions [**56**]. Recent advances in self-tracking technologies like Omni-Track [**63**], a tracking system that allows patients to create personalized tracking experiences, could be a further boost for mobile health interventions. In this area, it could be explored a way to enhance systems like Omni-track by incorporating sensing of stress, depression or even receptivity to trigger manual entries in

self-tracking systems. The goal would be to increase patient's self awareness of symptoms with the final goal to increase self-efficacy and adherence to treatment. Another important area to explore could be automated tracking customization through a recommender system approach, where from a large pool of people doing customized self-tracking, a system could then suggest elements for the customized tracking including triggers and measures reducing the effort and increasing time to optimal tracking. For example, from a pool of 20 to 25 years old patients, it could be that self-tracking is best when using reminder in the morning, receptivity triggers in the afternoon, and email entry in the evening. For a new user, falling in the above patient pool, it would be suggested to use this combination of reminders and triggers to self-track health.

CHAPTER 12

Appendix

12.1 Sleep Duration GMM

In our GMM for sleep duration I control the effect of type-of-sleeper and day-of-year by incorporating their respective covariates following observations observations from prior work [**75, 95**]. Type-of-sleeper refers to whether a participant in unconstrained conditions would sleep less than 7 hours (Short-sleeper) or more than 7 hours (Long-sleeper). A study by Levenson *et al.* [**75**] found differences in sleep intervention outcomes depending on whether a participant was a short or long sleeper. Type-of-sleeper in our data set was estimated from the baseline data. Day-of-year was also included as a covariate because I observed in the results from the StudentLife project [**131**] that day-of-year seemed to have a negative effect in sleep duration of college students. Intuitively this would not be surprising given the structure of academic terms were final example, projects, among others all are presented in the last weeks of the term, causing higher constraints in time to sleep for students. To further corroborate this hypothesis, I contacted the authors of several recent research projects were Fitbit data was collected. I gained access to sleep data sets from observational studies that occurred at the University of Washington [**114**], Carnegie Mellon University [**30**] and the University of Notre Dame [**128**]. In addition, I recruited 19 college students from Carnegie Mellon University and asked for access to their previously logged Fitbit data which included the Spring of 2019, Fall 2019 and Spring 2020. I fit a GMM for each data set with participant as a random intercept and day-of-year as a fixed effect with the goal of measuring the effect of day of the semester on college students' daily sleep duration. I only used data from the first day of classes to the last day of classes of the academic terms as stated in each school's official calendars, explicitly

excluding final exams to make the datasets comparable. I found that across most schools and academic terms (7 out of 9), there is a significant decrease ($p < 0.05$) in sleep duration from beginning to end of the term as shown in table 12.1. This decrease varies from -0.06 minutes (7 minutes/semester) a day to -0.3 minutes a day (36 minutes/semester). Based on these results, I included covariates to control for the effects of type-of-sleeper and day-of-year in our analyses. I added the covariates one at a time and confirmed that the GMM with the new covariate was better than the model without it as shown in table 12.2. Our final model has study phase as the main effect and type-of-sleeper and day-of-year as covariates.

University	Year	Term	p-value	Beta	Total subjects	Total observations	Wearable
Notre Dame	2018	Spring	*	-0.2	323	27744	Fitbit HR
	2018	Fall		0.03	204	15181	Fitbit HR
	2019	Spring	.	-0.06	168	12467	Fitbit HR
University of Washington	2019	Winter quarter	*	-0.17	179	11082	Flex 2
	2019	Spring quarter	*	-0.17	165	9362	Flex 2
Carnegie Mellon University	2017	Spring	*	-0.07	144	12866	Flex 2
	2018	Spring	*	-0.1	179	15647	Flex 2
Carnegie Mellon University	2019	Spring	*	-0.2	7	818	Various
	2019	Fall	*	-0.3	10	1044	Various

TABLE 12.1. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

	Dependent variable:			
	Minutes asleep			
	(1)	(2)	(3)	(4)
phase-sleep		-13.505^{**}	-15.457^{***}	-15.366^{***}
		(5.277)	(5.327)	(5.325)
phase-baseline		-7.011	-23.506^{***}	-23.719^{***}
		(5.333)	(8.556)	(8.540)
day-Of-Year			-0.366^{**}	-0.375^{**}
			(0.149)	(0.148)
sleeper-Type-short				-61.227^{***}
				(12.645)
Constant	410.116^{***}	416.788^{***}	451.631^{***}	476.331^{***}
	(8.740)	(9.232)	(16.895)	(16.498)
Note:				*p<0.1; **p<0.05; ***p<0.01

TABLE 12.2. Comparison between the different GMMs after adding covariates. Models 2 to 4 also include the intercept. The phase reference level is app-intervention with null: *other-phase* $-$ *app-intervention*$>= 0$

12.2 Study 1: Effect of context and intrinsic characteristics

	Dependent variable:				
	Adherence				
	(1)	(2)	(3)	(4)	(5)
random		0.987***	1.006***	1.376***	1.377***
		(0.235)	(0.238)	(0.250)	(0.250)
receptivity		1.234***	1.244***	1.508***	1.515***
		(0.191)	(0.192)	(0.203)	(0.202)
diary		0.529***	0.572***	0.489***	0.492***
		(0.169)	(0.167)	(0.164)	(0.164)
user		0.316***	0.336***	0.267***	0.267***
		(0.071)	(0.072)	(0.073)	(0.073)
day			1.282***	1.297***	1.289***
			(0.254)	(0.259)	(0.259)
morning				−0.249	−0.771*
				(0.255)	(0.400)
afternoon				−0.466*	−0.987**
				(0.259)	(0.403)
evening				−1.332***	−1.853***
				(0.263)	(0.408)
motivation					1.084*
					(0.656)
Constant	0.417*	−0.130	−0.632***		
	(0.214)	(0.205)	(0.233)		
Note:					*p<0.1; **p<0.05; ***p<0.01

TABLE 12.3. BMMs for adherence showing the null model (Constant only) and comparisons.

12.3 Study 2: Personalization of content comparisons

	Dependent variable:
	minutesAsleep
groupbandit	5.504
	(13.077)
dayOfYear	−0.276
	(0.171)
sleeperTypeshort	−34.093**
	(13.364)
Constant	404.188***
	(18.586)
Note:	*p<0.1; **p<0.05; ***p<0.01

TABLE 12.4. GMM for personalization of content comparisons using as reference level content selected randomly.

12.4 Study 2: Personalization of time of treatment comparisons

	Dependent variable:
	minutesAsleep
phaserandom	−4.539
	(4.281)
phasebaseline	−15.328**
	(7.648)
dayOfYear	−0.258
	(0.172)
sleeperTypeshort	−31.968**
	(12.522)
Constant	406.367***
	(17.681)
Note:	*p<0.1; **p<0.05; ***p<0.01

TABLE 12.5. GMM for personalization of time of treatment comparisons using as reference level sleep recommendations delivered at receptive times.

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