EATING BEHAVIOR IN-THE-WILD AND ITS RELATIONSHIP TO MENTAL WELL-BEING

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EATING BEHAVIOR IN-THE-WILD AND ITS RELATIONSHIP TO MENTAL WELL-BEING

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Somewhere, something incredible is waiting to be known.

Carl Sagan

To my wife Afifa Tasnim.

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SUMMARY

The motivation for eating is beyond survival. Eating serves as means for socializing, exploring cultures, etc. Computing researchers have developed various eating detection technologies that can leverage passive sensors available on smart devices to automatically infer when and, to some extent, what an individual is eating. However, despite their significance in eating literature, crucial contextual information such as meal company, type of food, location of meals, the motivation of eating episodes, the timing of meals, etc., are difficult to detect through passive means. More importantly, the applications of currently developed automated eating detection systems are limited.

My dissertation addresses several of these challenges by combining the strengths of passive sensing technologies and EMAs (Ecological Momentary Assessment). EMAs are a widely adopted tool used across a variety of disciplines that can gather in-situ information about individual experiences. In my dissertation, I demonstrate the relationship between various eating contexts and the mental well-being of college students and information workers through naturalistic studies.

The contributions of my dissertation are four-fold. First, I develop a real-time meal detection system that can detect meal-level episodes and trigger EMAs to gather contextual data about one's eating episode. Second, I deploy this system in a college student population to understand their eating behavior during day-to-day life and investigate the relationship of these eating behaviors with various mental well-being outcomes. Third, based on the limitations of passive sensing systems to detect short and sporadic chewing episodes present in snacking, I develop a snacking detection system and operationalize the definition of snacking in this thesis. Finally, I investigate the causal relationship between stress levels experienced by remote information workers during their workdays and its effect on lunchtime. This dissertation situates the findings in an interdisciplinary context, including ubiquitous computing, psychology, and nutrition.

CHAPTER 1

INTRODUCTION AND MOTIVATION

Human activities can provide a deep insight into a person's behavioral pattern and can be used to model individuals' mental and physical well-being. One such behavioral pattern is one's dietary patterns, often associated with a variety of mental health indicators such as depression [102], anxiety [212], stress [90], mood [31]. For example, irregular meal patterns, such as skipping breakfast, negatively correlate with mental well-being [14, 211, 179]. Hence, understanding an individual's dietary patterns can be a relevant measure of mental well-being.

Despite the known relationship between dietary patterns and mental well-being, measuring dietary habits is challenging [3, 208]. Most dietary pattern assessment methodologies rely on retrospective self-reports by individuals to reflect on different aspect of meals their meals [95, 85]. Self-reported food consumption quantities are under-reported or over-reported, even when logged within a period of as little as 24 hours [60]. This issue poses a challenge for regular and accurate dietary assessment.

Human activity recognition using passive sensing can address some dietary assessment methods' challenges. For example, knowing when individuals are eating can infer whether individuals are consuming food at a regular or irregular time. Researchers in the Ubiquitous Computing community has formed a subcommunity around eating detection, primarily showing various ways to infer when an individual is eating. However, the dietary patterns of an individual are not exclusively related to the individual's interactions with the food.

Several contextual factors are related to eating and, indirectly, to mental well-being, including with whom a person is eating [256, 234], where they are eating [232], what other activities are being performed while eating [98], or mood around the time of eating [31]. Hence, it is valuable to understand in what context people eat to assess their mental well-being. Several eating detection approaches utilize passive sensing methods to detect when an individual is eating [8, 9]. However, using current technology, it is not feasible to passively and reliably detect relevant contextual data (e.g., company, kind of food, nutrition value of food, etc.) regarding eating without being intrusive (e.g., camera, microphone, etc.). Furthermore, current eating detection technologies perform poorly in terms of detecting snacking episodes.

A less intrusive and widely adopted [153, 119, 191] way of collecting subjective contextual data is using Ecological Momentary Assessment (EMA). EMAs are short questionnaires that can capture, through self-report, relevant contextual information from individuals [207]. However, self-reports about life experiences are prone to recall bias if the experience is asked to recall happened too long after the actual event [95, 60]. Hence, EMAs are most effective when asked near real-time of the actual event of interest [206, 207].

Based on that motivation, I will demonstrate the development, evaluation, and usage of a wrist-mounted real-time eating detection system that can passively detect eating moments in real-time and gather further eating-related contextual data with EMAs (Chapter 3). Furthermore, using this real-time eating detection system, I will demonstrate the correlations between passively and actively sensed eating behavior with mental well-being for college students, informed by a three-week-long study in the wild with 28 participants (Chapter 4).

One of the limitations of a wrist-mounted system is detecting short and sporadic eating episodes that are present in snacking. Based on this limitation, I will demonstrate the development of a snacking detection system leveraging Inertial Momentary Unit (IMU)-instrumented earbuds based on a semi-naturalistic user study conducted with 18 students (Chapter 5).

Finally, based on a month-long observational study with 49 participants, I will share my findings on how stress can affect the deviation in mealtimes through computational and casual methods (Chapter 6). My dissertation will pave a pathway to gather and leverage eating-related insights from various combinations of sources and situate their relevance in the context of mental well-being in diverse communities.

1.1 Thesis Statement

By combining the strengths of EMAs to capture contextual information with passive sensors to detect when people eat, we can gather rich contextual data about an eating episode, and such data can help us investigate the relationship between eating behavior and mental well-being.

1.2 Research Questions (RQs)

- **RQ1:** Can we detect meal-level episodes in real-time and capture meal-time context using a smartwatch? (Chapter 3)

  Several kinds of eating detection technologies exist that can help researchers passively detect when an individual is eating. However, such technologies have three major limitations. Firstly, most of these technologies are offline systems that pose a challenge in real-world deployment to study eating behavior in the wild. Secondly, some technologies (e.g., smart glasses, neckbands, etc.) pose issues with adoption and scalability, which poses a challenge for longitudinal data collection. Finally, most passive detection systems can detect when an individual is eating. However, important contextual information such as meal company, type of food, location of the meal, etc., are difficult to detect through passive means.

  To address these limitations, I build on a baseline recognition system for passively recognizing eating events using a smartwatch's 3-axis accelerometer to capture eating movements. A machine learning pipeline aggregates predicted segments of individual hand-to-mouth movements to infer meal-scale eating episodes. I substantially extend this system with a focus on (near) real-time analysis and improve overall accuracy, which allowed me to recognize eating episodes within minutes—typically while a person is still having their meal. With the availability of such a (near) real-time eating recognizer, I am then able to prompt the eater for relevant contextual information that is crucial for the assessment of eating behavior with regards to mental health and well-being, while at the same time remaining privacy-preserving and minimally intrusive as required for real-world deployments.

- **RQ2:** Does meal-time context correlate with the mental well-being of college students? (Chapter 4)

  My second work is an application of the real-time eating detection system (Chapter 4) to investigate the relationship between various eating behaviors "in-the-wild" and mental well-being. As part of demonstrating the application of the meal detection system, I recruited 28 Georgia Tech students for three weeks, during which they used the eating detection system and answered questions about their eating behavior and mental well-being through EMAs. I found that students skip more meals during weekdays as opposed to weekends, and students are less depressed, anxious, and stressed for days when they do not skip major meals. Irregularity in meal timing is associated with mood changes and changes in stress levels. Furthermore, I show that family meals are positively related to better mental well-being outcomes.

- **RQ3:** How can we detect short and sporadic eating episodes such as snacking? (Chapter 5)

  One of the limitations of current eating moment detection systems is lack of focus on short and sporadic chewing episodes. Snacking is an example eating episode where chewing can happen in short bursts. Snacking has been a difficult problem for the eating detection community to solve because snacking episodes are sporadic. With technologies like wrist-mounted smartwatches, it is challenging to detect such episodes since many hand-to-mouth movements are confused as eating gestures [109, 150]. Hence, I argue that wrist-mounted solutions leveraging IMUs are not a feasible direction for detecting snacking. As an alternative, I explore Nokia eSense earbuds [145, 96], which are instrumented with accelerometers and gyroscopes to address the difficult yet essential problem of snacking detection. After conducting a semi-naturalistic user study, I found it difficult to generalize a chewing detection system to detect short and sporadic chewing episodes for unseen participants. Hence, I also explored the role of personalization. I demonstrate that by using only 2 minutes of chewing samples, the chewing detection system can detect short chewing episodes with reasonable accuracy.

- **RQ4:** For working adults working remotely from home, what is the causal relationship between their stress level changes and deviation in lunchtime? (Chapter 6)

  In Chapter 4, I will demonstrate a significant correlation between deviation in mealtime and higher instantaneous stress levels in a student population. Though there was diversity among the participants, the working context was different for my participants. Furthermore, the relationship between stress and mealtime deviation is not causal in Chapter 4. However, by carefully designing an observational study, I can infer the causal relationship between stress level and mealtime deviation.

  Based on this motivation, in my final dissertation chapter, I study the causal relationship between stress and mealtime deviation while controlling for other confounds. Note that I will not use any passive sensing technology for detecting eating moments in this study since I aim to understand how stress levels affect mealtimes for remote information workers. However, I will leverage passive and active sensing technologies through participants' work machines to account for the covariates to study the causal relationship between stress and mealtime deviation. In particular, I will demonstrate that individuals are likely to deviate twice as much from regular mealtime while experiencing high stress.

1.3 Research Contributions

Through this dissertation, I make the following research contributions:

1. Development of eating detection systems that can be used to detect meals (Chapter 3) and snacking episodes (Chapter 5).
2. Investigating the correlations between meal-time context and mental well-being for a college student population (Chapter 4).
3. Establishing a causal relationship between instantaneous stress levels of remote information workers and mealtime deviation (Chapter 6).

1.4 Organization of the Dissertation

In Chapter 2, I discuss the background work relevant to this thesis. Throughout Chapter 3, I highlight the development and evaluation study of a real-time eating detection system that can collect contextual data during eating episodes. In Chapter 4, I discuss how the system developed in Chapter 3 was leveraged in a three-week study to gather different contextually relevant information regarding an eating episode and understand the relationship between a variety of eating behaviors and the mental well-being of college students. In Chapter 5, I discuss the development of a chewing detection system that detects short and sporadic chewing detection present during snacking. In Chapter 6, I present the results of a causal analysis between stress levels and deviation of meal times for remote information workers across the US. In Chapter 7, I discuss the future directions, limitations, implications, ethical, and privacy considerations of my dissertation.

CHAPTER 2

BACKGROUND AND RELATED WORK

In this chapter, I review relevant literature from various disciplines: psychology, nutrition, and computing. First, in Section 2.1, I review the computing literature on the mental well-being of college students and information workers and identify how my thesis contributes to this body of work. Second, in Section 2.2, I identify the relevance of eating behavior in understanding the well-being of individuals from computing and non-computing domains. Furthermore, based on this literature, I demonstrate the need for understanding eating behavior through computational to assess and improve the well-being of individuals. Finally, in Section 2.3, I focus on current dietary assessment strategies from the computing and nutrition domain and highlight their limitation. In light of the limitations, I identify how my thesis addresses some of them.

2.1 Mental Well-Being Of Situated Communities

"Situated communities consist of geographically co-located, diverse, and close-knit communities of individuals, who share distinctive social ties" [195, 153]. Multiple disciplines (organizational science, psychology, nutrition, computing, etc.) have studied various aspects of both communities' mental and physical well-being. My dissertation focuses on two such communities: college students and information workers. In particular, I gather eating behavior through various computational means and investigate how such behavior is correlated or casually associated with multiple mental well-being measures. In this subsection, I reflect on relevant literature from computing that focuses on using computational means to understand various aspects of an individual's mental well-being.

2.1.1 Mental Well-being, College Students, and Computing

Due to the growing concerns about mental well-being in college students, computing researchers, in recent years, have focused on both online (e.g., social media [196]) and offline (e.g., physical activity [242]) activities of college students and showed promise for assessing their well-being based on these activities. Wang *et al.* showed how various kinds of passively sensed information can be used to infer students' well-being [242]. The research team gathered passive data from various sensors available on the students' smartphones and well-being data through EMA (Ecological Momentary Assessment) [207] questions. Other researchers have widely adopted such an approach to gauge other kinds of well-being-centered questions. For example, Sefidgar *et al.* investigate how passively sensed information can be used to understand mental and physical well-being around discrimination events of college students [204]. Morshed *et al.* investigated how passively sensed data from smartphones can be used to infer mood instability [153] and self-esteem [18]. Egilmez *et al.* investigated how a wristwatch can detect college students' stress levels through a lab-based study [47].

While most of these research approaches focus on client-centric (e.g., data is gathered from a device on a client) information, several research efforts investigated how infrastructure sensed data could be used to measure well-being in student population [220, 258, 244]. For example, Zakaria *et al.* used WiFi association logs collected by university administrations to detect stress in student population [258]. Ware *et al.* use similar information to detect depression in a student population based on their mobility pattern inferred from the WiFi association logs [244]. WiFi association logs have also been used to develop contact tracing tools to curb the spread of COVID-19 [74]. Apart from these sensing modalities, social media has been adopted for assessing the mental well-being of college students [191, 192, 193, 43].

While there has been growing interest in modeling the well-being of college students by investigating their offline and online behavior, one of the behaviors that are little studied—

yet important—is eating behavior. In my dissertation, I bridge this gap by studying the eating behavior of college students and remote information workers with (Chapter 4) and without (Chapter 6) an eating detection system respectively.

2.1.2 Irregularity in Work Rhythms, Meal Timing and Mental Well-being

Most research on work rhythms has focused on the time demand aspect of the work, such as the variability in time pressure [155] and work schedule [202]. Variability in sleep [169] and dietary habits [156, 169, 245, 151] such as mealtimes, have also been explored either as mediators or direct antecedents of poorer mental well-being at work. Watanabe *et al.* conducted a study with more than 3000 employees in Japan and found that long work hours do not directly affect workers' stress levels. However, the effects of long hours are mediated by lack of sleep duration and irregular mealtimes [245]. Tahara *et al.*, in their study with more than 4000 Japanese workers, found that irregular meal timing had a strong association with poorer mental well-being outcomes [221]. In particular, the authors found that irregularity of meal timing was significantly associated with nervousness, anxiousness, and depressive symptoms, among other mental well-being measures.

Several past works have demonstrated the relationship between irregular social rhythms and stress, depression, and anxiety, among other things [124, 77]. According to the "social zeitgeber" theory (Zeitgeber is German for "time-giver"), disruptions in times cues that regulate the body clock of biological behavior may result in adverse outcomes with mental well-being [67, 48, 49]. "Physical zeitgeber" compared to "social zeitgeber", are external physical cues such as sunrise, sunset, etc., that help us regulate our body clock [48].

An example of a "social zeitgeber" is workplace stress, which can affect the regularity of routines and disrupt physical cues such as mealtimes, observed with correlational studies. Biological or circadian rhythms that control functions like sleep are influenced by workplace stress, and their disruption has a direct impact on mental well-being [221, 245]. However, these studies are conducted through retrospective surveys, which poses a limitation in recall bias [57, 83]. In addition, information workers' daily work demands and resources available during the workday change frequently. With information workers, especially those who spend most of their time working on the computer (i.e., remote information workers), passive sensing to gather work-related data can be used to better understand their workplace rhythms study beyond correlational analysis and make stronger causal inferences. As all of the work done by the remote information workers' takes place on the computer, it only makes sense to account for covariates, discussed in the subsection below, that can help us explain the causal relationship between workplace stress and mealtime deviation. In Chapter 6, I explore the causal relationship between workplace stress and mealtime deviation through an observational study. However, workplace stress can affect a variety of outcomes. Hence, it is important to understand how workplace stress manifests through digital work signals. In the next subsection, I reflect on literature that focuses on workplace stress and computing literature.

2.1.3 Workplace Stress and Computing

Stress is a significant and growing issue in modern society. Prolonged high levels of stress have been shown to increase medical and insurance costs [66] as well as contribute to a wide variety of physical and psychological health issues such as high blood pressure [239], gastrointestinal problems [86], depression [146], mood disorders [17], and suicidal ideation [115]. One of the major sources of daily stress is workplace stress which can be defined as the reaction that people may experience when they are subject to high demands and pressures at work that do not correspond to their past experience and/or coping capabilities [29]. Some of the main contributing factors include, but are not limited to, juggling between professional and personal life, a perceived lack of job security, interpersonal issues with colleagues, and high workload [253]. When experienced over long periods, workplace stress has been shown to impair decision making, negatively affect productivity, and decrease job dissatisfaction [253] as well as lead to significant business costs (around $300 billion per year in the U.S. alone [143, 17]).

A wide gamut of factors can trigger workplace stress. While stress is more frequently associated with a negative response, specifically known as "distress," it is also well known that there are positive forms of stress, known as "eustress." In the context of work, distress might arise from a "toxic work environment, negative workload, isolation, number of hours worked, role conflicts, role ambiguity, lack of autonomy, career development barriers, difficult relationships with administrators and/or coworkers, managerial bullying, harassment, and organizational climate" [38]. Eustress is a "force that stimulates us to productively work through challenging situations and tasks" [38]. Examples might include a promotion, a successful project presentation, a deadline, or a positive but intense meeting.

While technology may not be the sole solution to helping people manage all of these sources of stress, researchers have explored its potential use to better understand and address some of the sources. For instance, studies of information workers have found that distractions can lead to higher reported stress and lower productivity [125, 127, 126] and there are promising opportunities for technology to support workers' well being, through reflection [137], intelligent agents [72] and interventions [167]. These solutions need to be designed carefully [248].

In a relevant study, Mark *et al.* [128, 127] presented a framework for how engagement and challenge at work were related to focus, boredom, stress, and rote work. Overall, they found more focused attention was present in the workplace than boredom. They also found that focus peaks mid-morning and mid-afternoon, while boredom is highest in the morning. People were happiest doing "rote", or easy work, and they showed that focused work *can* involve stress. Their study was the first to show that rhythms of attentional states are associated with context and time, even in a dynamic workplace environment. A subsequent empirical study [129] in the workplace found, using physiological sensors (heart rate monitors), computer log data, and ethnographic methods, that stress (as measured by heart rate variability (HRV)) was lower when not using email. Both qualitative and quantitative data corroborated the stress findings around email use [130]. More recently, McDuff *et al.* [136] analyzed facial expressions of information workers longitudinally to also reveal that passive sensors could pick up similar diurnal patterns in affective experience with displays of negative affect increasing monotonically on average over the day.

In a separate effort, Lopez *et al.* [116] have looked at real-time automatic stress detection for information workers but within a controlled setting. Using physiological data gathered by an Empatica E4 wristband for registering EDA, they examined an arousal-based statistical approach and compared their stress detection model to self-reported stress in quiet office environments versus when their participants were exposed to different kinds of emotional triggers. Though they had some success with this approach to detecting stress, it was still not studied in a realistic, natural setting. Similarly, Ide *et al.* [87] utilized multiple physiological signals to predict stress in daily life. However, this research also used a laboratory method to induce stress in various ways. Using electrocardiogram, pulse wave, breathing rate, and skin temperature, the authors predicted four psychological states: relaxed, normal stress, monotonous stress, and nervous. They used the integration of nine physiological features identified as related to stress leading to 87% accuracy for stress detection and 63% accuracy for stress type.

In an extensive survey examining stress detection in daily life, mainly using wearable sensors, Can *et al.* [29] reviewed the reported accuracy of various combinations of sensors across different environments, including office workplaces. They found that office environments provide an excellent bridge between controlled laboratory settings and mobile settings since office workers tend to be seated at their desks and quiet more often. In their review, research that employed EDA and HR had the highest performance in the office setting. They concluded that different human emotions could often result in similar physiological signals making classification difficult. They also discussed problems with identifying key contextual features and the artifacts that result from physical movement. Finally, the authors discussed the problems involved in getting subjective ground truth from users who might exhibit the same physiological markers but rate their stress levels in distinct ways. I acknowledge all of these phenomena that can get affected by changes in one's stress level should be accounted for while designing a causal study to investigate the causal relationship between workplace stress and mealtime deviation, which I address in Chapter 6.

2.2 Eating Behavior and Well-being of Situated Communities

In the previous subsection, I have highlighted that eating behavior has been studied little through computational means to analyze its relationship with mental well-being. In this subsection, I will reflect on literature from computing and non-computing domains that focus on the importance of understanding eating behavior in the context of understanding the well-being of individuals.

2.2.1 Lessons from Non-Computing Domain

The relationship between eating behavior and mental well-being is significant, and indeed, several research studies have shown strong associations between dietary habits and the mental well-being of individuals [212, 94, 210]. The primary dietary habits of most modern cultures refer to three main meals: breakfast in the morning, lunch at noon, and dinner in the evening. As with any such cultural habit, a complement exists of individuals who do not adhere to this meal pattern. Irregular meal patterns, such as those that skip breakfast, have been shown to be negatively correlated with mental well-being [178, 212]. On the other hand, several studies found that regular breakfast consumers are less stressed, anxious, and depressed than those who skip breakfast [212, 211]. Similar findings have been made for lunch consumption [94, 210].

Beyond main meals, snacking between meals is another common yet potentially problematic dietary habit. Although the term snacking can be used in the context of consuming healthy and unhealthy food between main meals, increased snacking frequency is often considered an irregular meal pattern [172], which in turn can result in or be indicative of poor mental well-being.

Apart from meal consumption, several other contextual factors are related to eating behavior and, indirectly, to mental well-being. For example, one's company during meals is associated with their mental well-being. Specifically, family meals are indicative of better mental well-being outcomes [256, 234, 157]. For these reasons, Maurer and Sobal noted "food and nutrition as social problems" [133]. In addition to the company during mealtime, activities are also associated with mental well-being. An aspect of healthy eating behavior is mindful eating [92], which translates to eating without any distraction such as watching TV [92], and eating without any judgment of the food (e.g., good, bad, etc.) [147]. Distracted eating, the opposite of mindfulness, often leads to overeating and, eventually, weight gain [19]. In addition, mindful eating significantly correlates with a variety of mental well-being measures [2, 98]. Khan and Zadeh found that individuals with mindful eating behaviors showed significant positive mental well-being outcomes [98]. On the other hand, irregular eating patterns are known to be related to the brain's reward mechanisms in regulating stress [215]. It is well known that disordered eating is accompanied by difficulty in regulating emotional states [236]. Several studies have also reported that obese people frequently perform "emotional eating," which is defined as eating for reasons other than hunger and consuming large quantities of food in response to emotional states [249]. Since physiological reactions to negative emotions or stress mimic the internal sensations associated with feeding-induced satiety, loss of appetite, and decreased food intake have been considered natural physiological responses to negative emotions [200].

The young adult age group (18-25 years old) is particularly susceptible to negative eating habits. During this transition period from adolescence to adulthood, young adults often start living independently, staying away from their parents for the first time, studying at university, or working, often resulting in irregular or inconsistent lifestyles [172]. Such lifestyles lend themselves to dietary pattern changes such as skipping breakfast and increased fast food consumption [159, 41]. Individual health behavioral patterns developed during this transition persist throughout an individual's lifetime, influencing the health of the individual and those around them [166, 251]. Moreover, although a balanced diet can help students increase energy levels, promote a functioning immune system, improve their ability to cope with stress, and increase concentration and performance in school, erratic eating behaviors remain a significant challenge.

However, very little has been done in the computing domain to understand how eating behavior can be used as a proxy to gauge student well-being. Hence, I focus my work on the young adult population and various contextual factors around eating to understand their mental well-being in Chapter 4.

2.2.2 Lessons from Computing Domain

Research on analyzing eating behavior through automated means has been focusing on three main aspects: 1) understanding eating behavior [168, 36, 165]; 2) designing technologies to facilitate healthy eating behaviors [201, 71, 69]; and 3) designing eating moment detection technologies [227, 9, 150]. Such research, thus, covers investigating eating behavior in a continuum of disordered eating behavior to healthy eating behavior. Since I am not investigating disordered eating behavior, I will not reflect on this literature. Instead, in this subsection, I focus on computing literature on healthy eating behavior. I will focus on the *eating moment detection technologies* under the next section, which is also a method for dietary assessment (Section 2.3).

To promote healthy eating habits, Grimes *et al.* designed a game aimed at educating people about healthy food choices [71]. As mentioned before, eating behavior also comprises the context that an individual is situated in, and family meals play a significant role in the eating context. Based on that motivation, Grevet *et al.* designed a probe, EATProbe, that would provide social awareness when an individual is taking their meals with the motivation of facilitating family meals [69]. Lukoff *et al.* explored how family support can be leveraged for food journaling [121]. The authors found that individuals' food choices became healthier due to family involvement in the food journaling process.

Beyond family, Chung *et al.*, studied how peer support on social media can promote healthy eating behavior [36]. Besides meals, people tend to snack as well. Schaefbauer *et al.* designed a mobile application, Snack Buddy, to promote healthy snacking behavior and deployed the application in ten low SES families [201]. They found that the use of the application improved healthy snacking behavior for families.

Together, the above body of research in computing has primarily explored ways to encourage healthy eating, often adopting ecological approaches, such as technologies that can motivate the individual or technology that can mobilize peer support for the purpose. What is less explored is how these behaviors surrounding eating relate to an individual's mental health. This understanding is significant because the motivation for eating is not always hunger. Some people eat since they are in a social situation [7], some people eat when they are hungry, and some people eat as a response to emotions such as stress. HCI researchers have investigated how computing technologies can mitigate stress eating. In particular, Carroll *et al.* developed an intervention application on a smartphone that would recommend breathing exercises to reduce stress levels to mitigate the effect of stressed eating [31]. All participants in the study were emotional eaters [31].

Based on the implications that mindful eating has on the well-being of individuals, researchers have investigated how technology can be used to support mindful eating behavior. Khot *et al.* designed a smart spoon, SWAN, that can nudge users to pay attention to their food if they become distracted during eating [99]. Epstein *et al.* developed a mobile application, Food4Thought, to promote mindful eating behavior [56]. To provide personalized support for improving healthy eating behavior, one must understand how one can gauge an individual's dietary habits. In the next section, I reflect on literature focusing on dietary assessment strategies from the nutrition and computing domains.

2.3 Dietary Assessment Strategies

Despite the known relationship between dietary patterns and mental well-being [212, 172], regularly measuring dietary habits is challenging [3, 208]. Dietary assessment methods can be categorized into two groups [208]: *i)* objective observations; and *ii)* subjective reports. Well-trained researchers can observe and record food preparation and intake for several consecutive days as objective observations [64]. However, such a routine is not feasible for large-scale studies from a logistical perspective [208] because it would require a researcher to follow individuals for long periods, rendering studies of longitudinal dietary patterns very challenging if not impossible.

Hence, from a practical standpoint, subjective reports extracted from self-reports are the more widely used technique for assessing dietary patterns. Some of the methods that use subjective reports include 24-hour dietary recalls [95], dietary records [218], dietary history [27], and FFQ [85]. Data can be collected using these methods, with the help of an interviewer or through self-report [208]. However, due to the subjectivity of the data, dietary recall data is prone to recall bias [95].

2.3.1 Ecological Momentary Assessments of Eating Behavior

EMA questions are a popular, more recent technique that captures in-situ, real-time information about a person's experience and certain aspects of their daily living [207]. EMA questions are short questions that can be delivered on a variety of platforms such as text messages [78], voice calls [203, 209], or smart devices in general [182, 189]. In addition, the timing of when an EMA is administered can also vary depending on the research needs. For example, EMAs can be triggered after a particular time, after an event, or through a combination of both [230]. Hence, EMAs can sample relevant experiences of individuals at a higher frequency than traditional, survey-based approaches [207], which is true for studies in multiple domains [206, 230, 154]. Furthermore, since EMAs can be deployed on smart devices, they can be coupled with passive sensor data from that device to record other relevant contextual information (e.g., time, location, movement patterns, etc.).

Due to the advantages of EMAs over survey-based methods, they have been used to facilitate many eating-related studies, such as the analysis of the relationship between mood and binge eating [246], the relationship between environmental factors and obesity [225], exploring night eating [23], and understanding eating disorders [216]. However, such studies rely on individuals to self-report their eating episodes with a prompted EMA triggered at some time or times throughout the day, as the individuals usually may forget the context of their eating episodes if asked within as little as 24 hours after the eating episodes [60, 95]. My work in Chapter 3 and Chapter 4 is a natural extension of that body of research, where EMAs are triggered at the moment of eating detection.

2.3.2 Automated Eating Detection Using Passive Sensing

Research in the domain of automated eating detection can be categorized into three primary categories based on the sensing modality used to infer eating activities: *i)* acoustic sensing [255, 35]; *ii)* camera-based sensing [113, 160]; and *iii)* inertial sensing [228, 5].

Yatani and Truong presented BodyScope, which used a wearable acoustic sensor attached to the user's neck, and was able to classify four activities: eating, drinking, speaking, and laughing [255]. Cheng *et al.* also used a similar design for nutrition monitoring [35]. Liu *et al.* used a combination of a camera and a head-mounted microphone to predict whether an individual is chewing in real-time. Upon an affirmative chewing prediction, a wearable camera would take a picture of the food [113]. However, wearable cameras pose challenges concerning privacy and real-time image analysis. For addressing the real-time analysis limitation, Noronha *et al.* proposed Platemate, which is a crowd-sourcing platform for deriving nutritional information from food photographs [160]. However, privacy concerns remain an issue.

Hence, wearable inertial sensors are more practical in addressing privacy concerns than camera-based sensing. Most work leveraging inertial sensing for eating detection has been based on custom-made wearable devices [5, 10]. The motivation for such work is to explore different body areas that can be used as proxies for recognizing eating episodes.

Amft and Troster placed five inertial sensors on the body (wrists, upper arms, torso) for eating gesture detection [5]. [45] instrumented their participants' hands with a smartphone and developed a wrist-motion-based heuristic that could detect eating in real-world settings Dong *et al.* Bedri *et al.* used a custom wearable smart-glass to detect and log what kind of food an individual is having [9]. Due to the popularity and availability of wearable sensors, researchers have investigated various approaches for detecting when an individual is eating. Thomaz *et al.* designed an offline eating detection system using the IMU in a commercial smartwatch [228]. Several research projects use commercial devices to detect whether an individual is eating. A recent systematic review of publications, by Heydarian *et al.*, up to March 2019 reported that at least twenty-six studies have investigated how commercial devices can be used for detecting eating episodes [82].

Despite the relationship between the context surrounding an eating event (e.g., meal companions, activities while eating, meal location, etc.) and mental well-being [256, 54, 234], none of the eating detection research has used the eating event to trigger EMA questions to gauge the mental well-being of individuals. Biel et al. collected self-reported context information and investigated how it could be used for differentiating between meals and snacking [16].

A natural connection between real-time eating detection systems and EMA questions will prompt users with EMA questions as soon as the eating system detects an eating episode. The subjective reports of users about the context of their eating episodes can give us deeper insights into their mental well-being, given the relevance of context during meals. In my dissertation, I address this novel problem in Chapter 3.

2.3.3 Automated Snacking Detection Technologies

Despite the progress in eating moment detection research, prior work does not generally tackle detecting snacking episodes. In a recent review on eating detection systems developed and evaluated outside the lab environment, Bell *et al.* reported that only one study([45]) attempted to distinguish between meals and snacking episodes [11], which indicates limited prior work for detecting snacking. In addition, there is little consensus on the operational definition of snacking within nutrition literature [81, 91]. It provides me with a unique opportunity to operationalize the definition of snacking in the context of my dissertation. Hence, I propose the operational definition of snacking in Chapter 5 and describe a study protocol for gathering and modeling eating episodes that can be considered snacking episodes.

Custom wearables sometimes pose a challenge regarding social acceptance, hindering the adoption of eating detection systems. The choice of earbuds is practical, as they are more suitable for integration within the technology ecosystem of a user. The promise of in-the-ear-sensing and the importance of snacking detection for understanding dietary habits motivate my investigation (Chapter 5) into the feasibility of eSense earbuds for detecting snacking. Using the same earbuds, Lotfi *et al.* explored the efficacy of detecting chewing episodes [117]. Several distinctions exist between my study and [117], including the participants' choice of food, class imbalance (eating vs. non-eating), number of participants (n=18 vs. n=5), and the duration per participant (60 minutes vs. 26 minutes).

Personalization In Developing Eating Detection Systems

A common concern for eating detection systems is their generalizability for detecting eating in unseen populations [259]. Hence, personalization has been explored for eating – [4] found that models for detecting chewing sounds based on audio data performed better with personalization. Thomaz, however, found inconclusive results for wrist-mounted eating moment detection and attributed it to the small number of participants (n=3) [226].

[237] utilized the Nokia eSense earbuds to detect individuals' facial action units, and determined personalization was vital for good accuracy. Given these studies, I hypothesize that personalization could improve the detection of chewing episodes due to individual differences in chewing patterns.

CHAPTER 3
DEVELOPING AND EVALUATING A REAL-TIME MEAL DETECTION SYSTEM USING A SMARTWATCH

Despite the known relationship between dietary patterns and well-being, measuring dietary patterns on a daily basis is challenging [3, 208]. Most assessment methodologies of dietary patterns rely on self-reports by individuals to reflect on their meals [95, 85]. Self-reported food consumption quantities suffer from under-report bias, recall bias [60]. This issue poses a challenge for regular dietary assessment. In addition, the dietary patterns of an individual are not exclusively related to their interactions with the food.

Several contextual factors are directly or indirectly related to eating and, consequently, well-being, including with whom a person is eating [234, 256], where they are eating [232], what other activities are being performed while eating [98, 122], or mood around the time of eating [31]. However, using current technology, it is not feasible to passively and reliably detect relevant contextual data (e.g., company, mood, kind of food, nutrition value of food, etc.) regarding eating without being intrusive (e.g., camera, microphone, etc.).

A widely adopted way of collecting subjective contextual data is by using Ecological Momentary Assessment (EMA) questions [119, 153, 191]. EMAs are short questionnaires that can capture contextual information from individuals [207], and they are most effective when asked near real-time of the actual event of interest [206, 207]. As such, a real-time eating episode detector can harness EMAs to gather insights about an individual's dietary patterns and use these insights to gauge the eating habits of individuals.

Motivated by the above, in this chapter, I address this research question: *"Can we detect meal-level episodes in real-time and capture meal-time context using a smartwatch?"* To address this question, I build on a baseline recognition system for passively recognizing eating events using a smartwatch's 3-axis accelerometer to capture eating movements.

Through a machine learning pipeline, I first predict individuals' hand-to-mouth movements and then obtain aggregated meal-scale eating episodes. By leveraging such a machine learning technique, I design an eating-detection system that not only focuses on real-time detection with high predictive accuracy but also allows me to recognize people's eating contexts. In particular, the real-time eating recognizer prompts eaters with EMA questions—designed after an online study—for capturing relevant contextual information while at the same time remaining privacy-preserving and minimally intrusive as required for real-world deployments. I deploy and validate the system in a college student population since young adults in the age group of 18-25 years old are likely to develop a poor diet for a variety of reasons: embarking on higher education or employment, beginning independent living, or starting to live with a partner(s), among others [159, 172].

3.1 Baseline Eating Detection System

Thomaz et al. [228] built and evaluated an offline eating detection pipeline for recognizing eating moments in 60-minute intervals. To detect an eating episode, the authors collected a dataset in a lab setting comprising 21 participants and containing both eating and non-eating hand movements. The data from an integrated 3-axis accelerometer was collected using a first-generation Pebble watch and transmitted to a companion smartphone application. After annotating the data, the authors employed an eating moment recognition pipeline similar to the conventional activity recognition chain [26].

Thomaz *et al.* used their system to collect samples of various eating-related movements, such as eating with knife and fork, eating with fork and spoon, and eating with hand. In addition, samples of non-eating related movements were collected, including watching a movie trailer, chatting, taking a walk, placing a phone call, brushing teeth, and combing hair. These non-target classes were collected to investigate whether the trained eating recognition model can differentiate between eating and non-eating movements.

These fine-grained activities were collected in the lab from 21 participants and named

Lab-21. The authors also collected another dataset in a semi-controlled setting outside the lab with only "eating" and "non-eating" labels and named the dataset Wild-7.

After collecting and preprocessing the data, the authors used a 50% overlapping, 6 seconds sliding window to extract five statistical features along each axis of the accelerometer: mean, variance, skewness, kurtosis, and root mean square – resulting in a 15-dimensional feature representation of the movement data. Figure 3.2a shows the recognition results on the Lab-21 dataset reported in the original paper.

The main focus of the original paper was on recognizing complete eating moments and not individual hand movements that contribute to overall eating moments. Consequently, individual movements were clustered (using DBSCAN) over varying context window lengths, and the results were integrated into the detection of eating moments. The authors found that using a 60-minute window yielded the best performance concerning both precision and recall of eating moment recognition.

3.2 Motivation for Changes in Eating Detection Pipeline

Thomaz *et al.*'s recognition system took an offline approach which can be used for passively logging eating episodes (typically at the meal level, i.e., a major eating event). However, for capturing the contextual factors of eating, as they are of relevance for the assessment of mental health aspects [256, 54, 234], I require a (near-) real-time recognition system, which can reliably recognize eating moments and then, with minimal delay, prompt the user to answer EMA questions about their eating episode – ideally while the eating episode is still in progress.

The baseline system of Thomaz *et al.*, while serving as an excellent starting point for my work, needs to be extended such that it can be used for my purposes as outlined above. The main directions of improvement are:

(Near) Real-Time Recognition of Eating Episodes: Since passive sensors cannot be used to infer contextual information, such as with whom someone is taking their meal or what kind of meal they are having, I wanted to gather such contextual information through subjective responses gathered using EMAs. Since EMAs are a tool for experience sampling, they work best when administered near the experience of interest. Ideally, the recognition system would trigger EMA questions while an individual was taking their meal.

Improved Accuracy of Automated Recognition: Higher-level analysis, such as the automated assessment of mental health and well-being through the proxy of eating behavior assessments, requires reliable low-level recognition of eating episodes. Thomaz *et al.* mentioned the need to improve their proposed eating detection by incorporating features that can represent the temporal aspect of sensor data since, in their study, that was one of the reasons for confusing non-eating gestures with eating gestures [228]. Hence, it was vital to improve the gesture recognition accuracy by improving the feature representation.

In what follows, I describe the technical details of the extended eating detection system that I have developed.

3.3 Real-Time Eating Detection System

3.3.1 Changes in Feature Representation

Before porting my system to analyze sensor data recorded through the smartwatch in real-time on smartphones, I extended the baseline system to aim for improved low-level eating detection results. The baseline system misclassified some non-target classes that appear very similar to typical eating-related hand movements, Examples include brushing, combing, talking on the phone, etc. Upon closer inspection, I concluded that this failure was because the feature representation could not capture the temporal aspect of the signal, which was also observed by [228].

For example, talking on the phone would require someone to take the phone with their

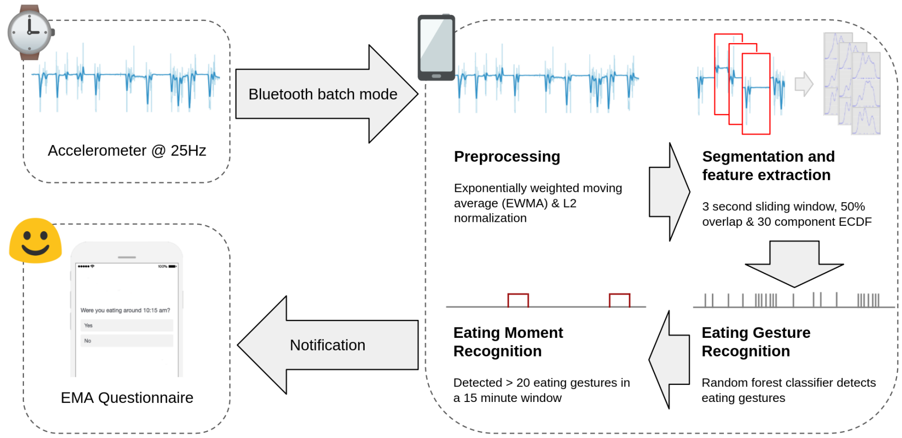
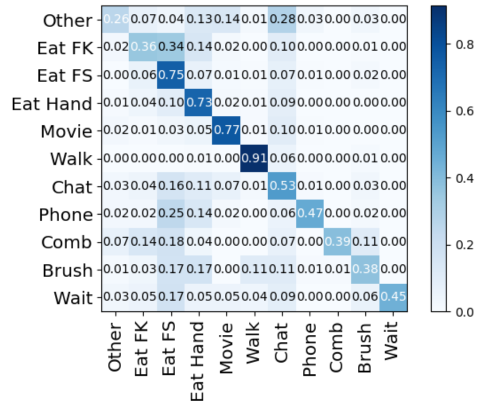


Figure 3.1: System architecture for (near) real-time eating detection using a smartwatch and smartphone. Upon detecting 20 eating gestures in 15 minutes, the smartphone prompts the user with EMAs to capture in-situ eating-related information. After I trained a random forest classifier offline using the Python package sklearn, I ported the best classifier to run on Android using sklearn-porter [148]. This model used for making predictions on the smartphone runs every 10 minutes. On average, when tested on a Google Pixel 2, the eating detection application consumed 30 megabytes (MB) of space on the phone while passively receiving data and 140 MB of RAM while the classifier was running. In addition, data was sent in batch mode from Pebble 1 smartwatch to conserve the device's battery life, which was approximately 36 hours.

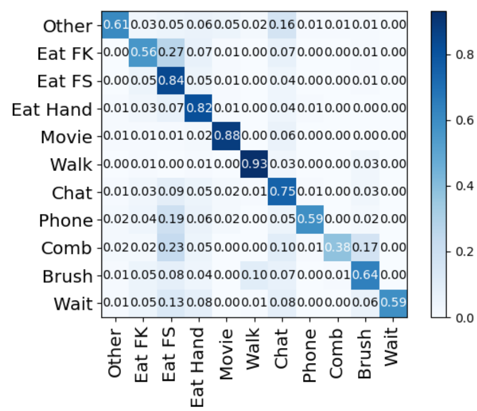
hand close to their head, which is similar to the hand-to-mouth movement during eating. If the feature representation does not capture the fact that the hand is not coming (back) down, as it is the case for eating, then both movements are very similar in the feature space leading to confusion.

Hence, my first point of investigation was whether I can improve the feature representation, and how changes in the feature space can affect the gesture recognition classification. In response to the observation of need to differentiate temporal dynamics, I employ the structural empirical cumulative distribution function (ECDF) feature representation [106], which specifically captures the temporal aspect of movement data at feature level. Structural ECDF is a variation of the distribution-based feature representation, ECDF [75].

Using a window size of 3 seconds with a 50 percent overlap generated best results (Figure 3.3) on the Wild-7 dataset made available by Thomaz et al [228]. The experimental results can be seen in Figure 3.2a and Figure 3.2b. 'Other' represents non-target classes in



(a) Confusion Matrix of Gesture Recognition Accuracy using the Original Features by Thomaz et al. [228]



(b) Confusion Matrix of Gesture Recognition Accuracy using Structural ECDF Feature Representation

Figure 3.2: Confusion Matrix for Gesture Recognition using features representation by Thomaz et al. [228] and ECDF features

both figures. 'Eat FK' represents eating with a fork and knife, 'Eat FS' represents eating with a fork and spoon, 'Eat Hand' represents eating with the hands, and the rest of the classes represent non-target classes. It can be seen that for non-target class detection (Other, Phone, Chat, Brush, etc.) the system based on structural ECDF features performed much better. Particularly for 'Brush', which was not well recognized by the baseline system, but through the structural ECDF feature representation I am able to classify this gesture with more than 20 percent higher accuracy. The recognition accuracy for 'Chat' also improved by more than 20%. The 'Chat' class contained gesticulation while the participant talked to other people. Recognition of the target classes ('Eat FK', 'Eat FS', 'Eat Hand') improved overall by 38%, with 'Eat FK' improving by 20%.

3.3.2 Moving Away from the Clustering Approach

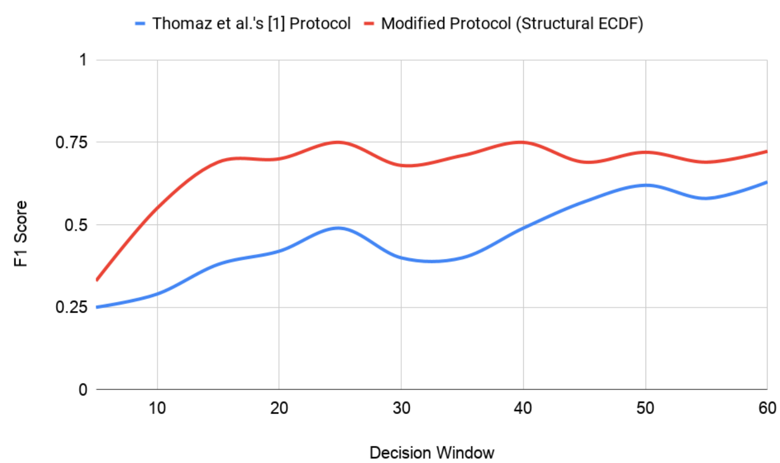


Figure 3.3: Eating moment recognition performance (F1 Score) using Thomaz et al. [228]'s proposed system and my system. This analysis was done on the same dataset that Thomaz et al. collected for his study.

Thomaz *et al.* indicated that they found best performance when predicted gestures were clustered within a window of 60 minutes, i.e., they needed at least 60 minutes of sensor data to infer whether an individual had an eating episode [228]. However, since the goal of my study was to assess the link between eating behavior w.r.t. major meals, I needed to gather eating related information from participants *after each meal*. Some of these insights about major meals can only be provided by participants. For example, whether the system predicted the meal correctly, since the system is not always accurate with meal predictions. If the detection was correct, one could ask a variety of questions that cannot be inferred passively. Since my goal was to use EMAs to understand various eating related information, it would be ideal if I could ask college students to reflect on their meal while they are taking their meal.

Hence, to maximize recognition performance and mitigate the effects of noisy frame-level classification, I aggregate the results of the frame-level recognizer with a window of size W accumulating the frame-level results. A threshold-based approach was adopted in which N frames within the window must be recognized as one of the target classes for the window to be considered an eating episode, thus triggering an EMA. I used Thomaz et al.'s window size of $W = 60$ as a starting point, and found that $N = 39$ frames produced the highest F1 score (71.38%). Since my goal was to make the detection system as real time as possible, I started reducing the prediction window W by increments of 5 minutes at a time and optimized for the F1 score. I found that at $W = 25$ minutes, the detection system performed the best ($F1 = 74.63\%$ with $N = 34$ frames). However, if I considered $W = 15$ minutes of sensor data, the F1 score was 69.44% ($N = 20$ frames), which is not significantly less than the F1 score at $W = 25$ minutes, but is closer to the actual eating episode for triggering the EMA. I finally decided upon using a window of $W = 15$ minutes with $N = 20$ eating gestures for detecting eating episodes.

3.4 Study Design

Once I finalized on a functional "real-time" meal detection system, the next step was to use the system "in-the-wild" for evaluating its efficacy. Hence, I designed a three-week-long study to passively detect the meal consumption patterns of college students However, given that I wanted to capture relevant contextual meal related information using EMAs for understanding the context of an eating episode, it was necessary for me to understand what kinds of questions I should ask regarding an individual's meal. Hence, I first conducted an online survey study that addressed the following questions:

1. How long do students generally spend on each meal?

2. Why do students miss certain meals?

3. What are the factors that constitute "quality" eating experience of students?

I used the responses to this online survey to inform the design of the EMA questionnaire administered to the participants of the three-week-long study.

3.4.1 Online Survey Study

Survey Design

Since I was interested in the three questions mentioned above, I asked the following three open-ended and structured questions to the online participants. For the following question 2 and 3, I provided some pre-set options which were informed by conducting structured interviews with 25 students (15 male, 10 female) from the same university. I conducted qualitative coding on the interview data to derive themes and use those themes as available options for questions. In addition, the students had the option of giving their own responses. I wanted to validate whether the themes reflected the responses of a larger subset of students:

1. How much time do you spend on major eating episodes (e.g., breakfast, lunch, and dinner)?
2. If you ever miss some of your major meals (i.e., breakfast, lunch, dinner), please briefly mention why you miss these meals.
3. What does "quality" eating mean to you? We intend to learn about what you consider important as part of your eating experience. You are encouraged to come up with your own answer.

In addition to these questions, the students had to report their demographic information, which included their age, ethnicity, self-identified gender, and current academic status in the school. The demographic information was asked after the eating related questions. The demographic information was used to ensure that my data sampling was representative of the college campus. Recruitment for the survey was conducted through various online communication channels such as email, Reddit, Facebook groups, etc. The timeline for the survey distribution was throughout Summer 2018 and Fall 2018.

Responses from the Survey Study

Survey Participants' Demographics A total of 162 participants responded to the survey. Among these participants, 82 were female, 74 were male, 1 was non-binary, and 5 did not disclose their gender identity. Table 3.1 shows the demographic information (e.g., age, gender, education level, and ethnicity) of students who responded to the survey.

Time Spent Per Meal The average self-reported meal consumption times for breakfast, lunch, and dinner were 10 minutes, 20 minutes, and 25 minutes, respectively. Hence, I did not attempt to further improve the classifier since the minimum average meal consumption time was approximately 10 minutes for the student population of the target university.

Factors for Missing Meals I performed qualitative coding to extract themes from the responses to why students missed their meals. The themes found were: *workload, personal choice (i.e., intermittent fasting), eating disorder (i.e., anorexia), food insecurity, mental health (i.e., stress and mood).* The responses in this section were crucial for me to derive an exclusion criteria for the meal consumption and mental well-being study, which is explained in Section 3.4.5. I was unaware of the fact that parts of the student population may experience food insecurity. However, I did expect some students to miss major meals due to eating disorders. Some responses included self-identified stress and mood when skipping a meal. In addition, some responses identified academic and professional workload as one of the reasons for missing meals.

Perception of "Quality" Eating Experience I analyzed responses to this question with a similar process used for the previous questions. The emergent themes were: *contex-*

tual factors, perception of "healthiness" of the meal, and eating without distraction. Some of the contextual factors identified by the students were: taking a meal with family, the location where the meal is taking place, the noise around their eating location, etc. Some students mentioned that they would consider their meal as a "quality" meal if they were just taking their meals and doing nothing else while consuming the food. Finally, some of the students identified that if they took a healthy meal they would consider that as a quality meal.

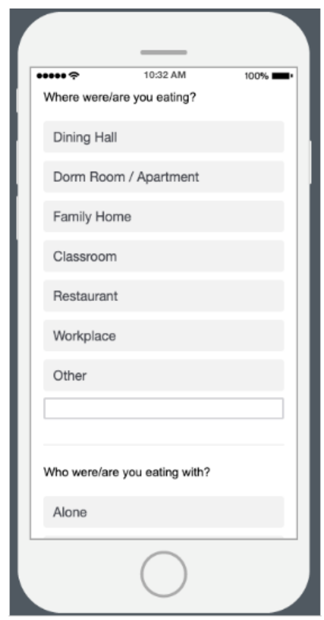
Table 3.1: Demographics summary of the online survey participants (N=162). The table below lists the demographic summary of the participants broken down by their gender, education, age group, and ethnicity.

Category	Count
Gender	
Female	82
Male	74
Non-binary	1
Prefer not to say	5
Current education level	
Undergrad students	111
Master's students	20
Ph.D. students	29
Age Group	
18-24	126
25-34	31
35-44	2
45-54	3
Ethnicity	
Caucasian	78
African American	10
Hispanic American	8
East Asian	26
South Asian	32
Middle Eastern	3
Prefer not to say	5

3.4.2 EMA Design for Capturing Contextual Factors for Eating Episodes

Whenever my eating detection system (Section 3.3) detects an eating episode, I prompt the user to answer questions on their smartphone (Figure 3.4a) to validate whether they were actually having an eating episode. If the user responded with ‘yes’ to the question, I asked them follow-up questions about: *i) what kind of meal (e.g., breakfast, lunch, dinner, etc.) they were eating; ii) with whom and where they were eating; and iii) what kind of activities they were performing while taking the meal (Figure 3.4b)*. In order to obtain the ground truth total number of eating episodes, at the end of each day, participants were asked which meals they had during that day.

(a) Sample prompt for validation from the user whether they are taking any meal



(b) Sample question users would get if they select yes on the left prompt

Figure 3.4: Sample EMA questions to capture in-situ eating experience upon detection of an eating episode by the eating detector

3.4.3 Passive Sensing from the Pebble Smartwatch

For collecting and sending the raw accelerometer data from the Pebble smartwatch to a companion Android device, I wrote a native Pebble watch application (in C) that sampled the watch's accelerometer at 25Hz and sent the data in batches to the phone approximately every five minutes. The battery of the Pebble watches lasted approximately 36 hours on a single charge.

3.4.4 Compensation

The timeline for the study was three weeks. If a participant participated for more than two weeks in the study, they received an AmazeFit Bip watch valued at $80. If they participated for more than one week and less than 2 weeks, they received a $25 Amazon Gift Card. If the participant did not participate for at least one week, they did not receive any compensation.

3.4.5 Exclusion Criteria

Results of the survey unveiled that some students miss meals for a variety of reasons. Two of these reasons were the presence of an eating disorder, or food insecurity. For these students such a pre-condition can trigger stress. For example, participants with an eating disorder may have a relapse when they journal food since it makes them more self-conscious. Given that I am not in the position to effectively intervene if it was ethically required, I did not include students with food insecurity in my study. I used a validated eating disorder questionnaire [120] and a validated survey for identifying food insecurity [231] in my participants.

3.4.6 Sample Size

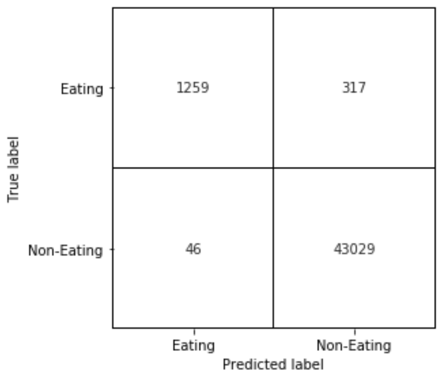
The motivation of my study was to investigate the feasibility of using a real-time eating detection system to investigate the relationship between eating behavior and mental well-being. Hence, I recruited participants in the manner that effectively replicates the protocol and enrollment numbers as they have been reported in comparable related feasibility studies that investigate well-being with respect to human behaviors, e.g., [1, 242, 173]. For example, Abdullah *et al.* recruited nine participants to understand the relationship between sleep and well-being [1]. Wang *et al.* recruited 48 participants to understand various well-being parameters (stress, depression, mood, etc.) with passively sensed physical activity, sleep, etc [242]. Rabbi *et al.* conducted a feasibility study of physical activity and well-being with eight participants [173]. Hence, my recruitment targeted a similar range w.r.t. enrollment numbers and I was able to recruit 30 participants. Arguably, this enrollment allows me to draw conclusions within the scope of my feasibility study. Yet, for generalizing my results across colleges in the US, even within the institution, a larger scale would be needed, which is, however, beyond the scope of this paper.

3.5 Results

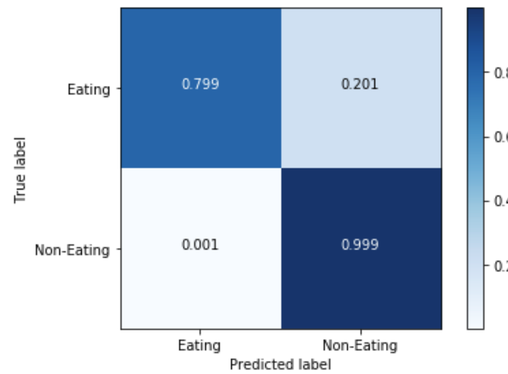
3.5.1 Performance of the Eating Detection System

In this subsection, I reflect upon the validity and reliability of the eating detection system that I deployed for approximately 3 weeks. I report the confusion matrix for the recognized eating events, explain in detail how I gathered the ground truth for eating and non-eating events, and what kind of eating episodes were particularly challenging for my system to detect.

Recall that the (near) real-time system (Figure 3.1) prompted participants with EMAs to capture eating related information whenever it detected an eating episode. The first question in the series of EMA questions was to understand whether the participants were having a meal (Figure 3.4a). If the participants answered "Yes", I considered it as a true positive, and if the participants answered "No", I considered that as a false positive. To capture false negatives, I asked participants at the end of the day which meals (e.g., breakfast, lunch, dinner, etc.) they actually had in that particular day. If my system did not detect that meal, then I considered that meal as a false negative. It allowed me to understand how



(a) Confusion Matrix with Number of Meals



(b) Confusion Matrix with Percentage of Meals

Figure 3.5: Confusion matrix of the (near) real time eating detection system.

well or poorly my eating detector performs compared to the ground truth. Figure 3.5a and Figure 3.5b show the confusion matrices for eating episodes.

The (unweighted) F1 score for predicting major meals was 87.3%. The false positive rate was 0.7%. The (unweighted) F1 score is particularly useful for cases where there is class imbalance. In my study, there were only 1,305 out of 44,651 instances that resembled eating episodes, which justifies F1-score analysis.

Table 3.2: Percentage of Meals that was Detected by the Eating Detection System

Meal Type	Total Episodes	Percentage of Detected Episode	Total Detected Episodes
Breakfast	294	90%	264
Lunch	410	99%	406
Dinner	601	98%	589
		Total	1,259

In addition, I investigated around which kind of activities the eating detection system is making wrong predictions (i.e., false positive, false negative). Hence, during exit interviews, I asked participants whether they could recall for which activities the eating detector was erroneously prompting them (false positives) or around what kind of eating episodes the eating detector was not detecting eating events (false negatives).

I analyzed the misclassifications as follows. For false positive predictions, I found that if participants performed hand movements similar to eating-related movements over an extended period of time (e.g., brushing teeth, trimming beard, etc.), then the eating detector was confusing these with eating episodes.

For false negatives, I found that short eating episodes (e.g., such eating a banana, taking a few spoons of yogurt in the morning as breakfast, etc.), were generally not detected by the eating detection system. Table 3.2 represents the percentage of eating episodes that were detected by the eating detection system throughout the study.

As it can be seen, breakfasts were the most frequently skipped meals by my participants throughout the study. It should be noted that seven participants self-identified themselves as individuals who did not have breakfasts. Lunches were skipped more than dinners.

3.5.2 Context During Eating Episodes

I now report the contextual factors that were captured by the meal detection system. The EMAs asked about various aspects that are challenging to be passively detected without invading an individual's privacy. These include the company of a participant during the meal, whether they were hungry when they had the meal, etc.

I found that 62.99% (793/1259) of meals were perceived as healthy and 31.05% (391/1259) of meals were perceived as unhealthy, and for the rest 5.95% (75/1259), the participants did not know whether the meal was healthy.

Since students generally operate on a busy and mobile schedule, I was interested to know where they were having their meals. I found that most meals were consumed either at the apartment/dorm room (393/1259, 31.22%) or family home (390/1259, 30.98%). Additionally, 14.54% (183/1259) of meals were consumed at workplaces, 10.25% (129/1259) were consumed at restaurants, and 4.13% (52/1259) were consumed in classes. Other than the predefined options, students could report places under the "other" option, and example responses included church, party, ministry, supermarket, and car.

The company during meals is strongly associated with well-being. By asking participants their company via EMAs, I found that participants had 54.17% (682/1259) of the detected meals alone, 24.17% (304/1259) with friends, 13.82% (174/1259) with family, 3.81% (48/1259) with partners, and 3.49% (44/1259) with colleagues.

Distracted eating is one of the most important factors behind many unhealthy eating behaviors, such as overeating, undereating, and binge eating. I gathered information on what concurrent activities students were doing while they were having their meal. The two most common activities during eating were using a smartphone (281/1259, 22.32%) and laptop (178/1259, 14.14%). Only 0.87% (11/1259) of meal episodes were without any distractions.

3.6 Discussion

In this chapter, I addressed my first research question of the dissertation: "*Can we detect meal-level episodes in real-time and capture meal-time context using a smartwatch?*" In particular, I showed the design, development, and evaluation of a wrist-mounted meal detection system that can be used to trigger EMAs to gather contextually relevant information about an ongoing eating episode, which has the potential for addressing recall-bias in retrospective surveys to collect eating-related information. I discuss the implications of my results in the subsequent subsections.

3.6.1 Principal Results

My work shows that major meal episodes can be detected using the meal detection system with an F1 score of 87.3%, a precision of 80%, and a recall of 96%. I demonstrated how an EMA-based design can augment a meal detection system to gather contextual information on eating behavior. This is the first-of-its-kind real-time meal detection system. When deployed for over a period of 3 weeks with 28 participants, my system showed a low false-positive rate of 0.7%, which is practical for daily usage considering that too many false positives may be bothersome to participants.

Among all consumed meals, 54.17% (682/1259) were consumed in isolation and 31.22% (393/1259) were consumed at apartment/dorm rooms. Most of the meal activities were often performed with another activity. Smartphone use and laptop use were the two most dominant activities (281/1259, 22.32% and 178/1259, 14.14%, respectively) during meals. Less than 1% (11/1259, 0.87%) of meal episodes were "only eating" episodes, which means for the rest of the cases, participants were engaged in some other activities during a meal. These findings uncover previously unexplored and difficult to glean information, namely college students' eating behaviors at a longitudinal scale. My work can inform the design of well-being interventions in student populations.

Engaging in non-eating activities during eating is considered as a distraction, and distraction during eating reduces the ability to assess internal sensory cues such as taste perception, which can lead to overeating [240, 241]. Given the high percentage of distracted meals, I argue that college students can benefit from healthy eating behavior technologies that can build on the meal detection system.

3.6.2 Implications for Eating Detection Technology Researchers

Researchers developing technology for detecting eating episodes have primarily shown the ability to detect when one eats, and to some extent, what and how much is being eaten. While the performance of these systems can always be improved, I believe that the technology has now reached a point of diminishing returns. Instead, I argue that my work is sufficient for detecting major meal frequencies at the group and individual levels, and only novel applications and end goals that require finer granularity of detection should motivate further detection work.

3.6.3 Implications for Dietary Assessment Research

Dietary assessment is important for person-specific interventions. However, dietary assessment is a challenging task since most of the dietary assessment methods are based on subjective recall [27, 85, 95]. Such recall can vary from a day to a few months [208]. Delays as little as 24 hours in answering questions related to dietary portions or contents can generate significant recall errors [60, 95]. Hence, the implication of my research also applies for research community that are investigating nutrition intake of individuals in their daily life. Although I did not conduct a nutrition-based study, my meal detection system can prompt users in-the-moment to log their dietary intake using appropriate methodology. Since my eating detection system uses commercial off-the-shelf smartwatches, it is easily deployable to large populations, either by recruiting participants that already use smartwatches or by prescribing such a device to anyone.

CHAPTER 4

USING A REAL-TIME MEAL DETECTION SYSTEM TO STUDY THE RELATIONSHIP BETWEEN EATING BEHAVIOR AND MENTAL WELL-BEING OF COLLEGE STUDENTS

Despite the progress of the eating detection community in developing eating detection systems, the applications of such systems are limited. In this chapter, I show an application of the real-time meal detection system developed in the last chapter to gather meal-time context. Furthermore, I investigate how such behavior is associated with mental well-being outcomes for college students. The experience of a college education not only opens a gateway to new possibilities but also challenges students in various ways, such as adjusting to a new environment, living apart from family—many for the first time— and adapting to more extensive academic workload [42]. Such challenges often lead to college students adopting unhealthy eating behaviors, such as irregular eating patterns and junk food consumption [172, 159].

Furthermore, unhealthy eating behavior is often associated with a variety of mental well-being concerns such as depression [102], anxiety [212], stress [90], and mood [31]. For example, irregular meal patterns, such as skipping breakfast, have been shown to negatively correlate with mental well-being [14, 178, 211]. While the eating patterns of college students form a critical component of their mental well-being, insights and assessments related to the interplay between eating patterns and mental well-being remain under-explored in both theory and practice.

Based on these motivations, I address this research question in this chapter: *Does meal-time context have a relationship with mental well-being?* To capture meal-time context, I use the smartwatch-based eating detection technology (Chapter 3) that triggers EMA questions when it detects that individuals are having meals [150]. Using this system, I conduct a three-week-long naturalistic study in a public US institution with 28 college students from diverse backgrounds to capture their eating behavior at a meal level granularity. I will achieve the following two aims in this chapter as part of addressing address this research question.

Aim 1: Assessing the relationship between meal frequency and mental well-being among a college student population

Aim 2: Establishing the relationship between instantaneous stress, anxiety, depression, mood, and eating context (e.g., eating location, meal companions, etc.) of college students.

For the first aim, I investigate meal consumption patterns of college students at both the individual level and at the group level. I will demonstrate that skipping meals is strongly associated with higher levels of stress, depression, and anxiety and lower levels of energy and happiness. Furthermore, I investigate temporal patterns of meal consumption behavior and its relationship with mental well-being in a student population. I demonstrate that student meal consumption follows a seasonal pattern over a week, where students tend to miss more meals on weekdays compared to weekends.

For my second aim, I model contextual factors during meals with instantaneous stress, depression, anxiety, and mood, due to their prevalence in the student population. I show how irregularity of meal timing, especially for breakfast and lunch, can affect stress, affect, valence, and arousal of my study population, which was not observed in prior literature. Based on my findings, I discuss the theoretical, practical, and design implications that surround this new observation between the relation of context during meals and college students' mental well-being.

4.1 Data and Study

In this section, I describe the study design that comprises of my choices of mental health questionnaires, system-level details of an eating detection system that was used in the study,

Table 4.1: Academic Year of Participants

Student Category	# Students
Undergraduate Students	
Freshmen	3
Sophmores	6
Juniors	4
Seniors	2
Graduate Students	
Master's student	9
Ph.D. student	4
Total	28

and finally, the demographics of the participants that were recruited in the study. In addition, I mention the system performance of the eating detection system.

4.1.1 Study Design

My study concerns examining students' eating behaviors, along with their context of eating and their mental well-being states. For this purpose, I collected data from students in a large public university in the southeast of the U.S. The study was approved by the Institutional Review Board (IRB) at the same university, and I enrolled participants on a rolling basis from July 2019 to September 2019. Participants were requested to remain in the study for three weeks. I enrolled a total of 30 participants. 2 participants could not continue with the study because of complications with the eating detection system running on their phones. Hence, I enrolled 28 participants, among whom 15 self-identified as females and 13 self-identified as males; 16 participants belonged in the age group of 18-24, and 12 participants belonged in the age group of 25-34. The participant pool belonged to diverse ethnic and academic backgrounds (see Table 4.1 for academic years and Table 4.2 for ethnicity).

At the entry of the study, the participants answered self-reported survey questionnaires on demographics and intrinsic traits (personality). I collected students' eating behavior patterns by administering an eating-detection system implemented on a smartwatch. This device also obtained in-the-moment survey questions (or EMAs) to capture the participants'

Table 4.2: Ethnic Identity of Participants

Ethnic Identity	# Students
Non-Hispanic White/Euro-American	5
Black/Afro-Caribbean/African American	2
Latino/Hispanic American	1
East Asian	7
South Asian	13
Total	28

contexts during eating episodes.

Compensation. The typical timeline of the data collection was three weeks. I adopted a (commonly used) time-differential compensation approach [204, 34]: If a participant stayed in the study for more than two weeks, they received an AmazeFit Bip watch valued at $80. For participants who stayed in the study less than two weeks, they received a $25 Amazon gift card if they stayed for more than a week, and received no compensation otherwise.

Entry Surveys. During enrollment, participants answered a demographic survey reporting their age, gender, student status, and ethnicity, and a big-five personality traits survey (BFI [58]).

Eating Detection System with a Smartwatch. Participants were provided with a Pebble smartwatch that they were supposed to wear on their dominant hand during their participation period. I installed a real-time meal detection system that can identify when someone is eating. This system extends and improves upon prior work [228] and uses passive sensors on a smartwatch to detect eating episodes with an F1-score of 88% [150]. It is essentially a machine learning-driven activity recognition system that first "passively" detects eating episodes, then prompts smartphone-based EMAs to validate the detection. If participants validated the detection with a "Yes", they were prompted with follow-up multiple-choice questions on 1) the type of meal (breakfast, lunch, dinner); 2) people around them during meals (alone, partner, family, friends, others); 3) location of meals (home, dorm/apartment, workplace, restaurant, classroom, others); 4) simultaneous activities during meals (watching TV, using smartphone or laptop, in class, etc.). In order to obtain the ground truth total number of eating episodes, at the end of each day, participants were asked which meals (e.g., breakfast, lunch, and dinner) they had during that day. If the eating detection system did not passively detect that meal, I considered that meal a false negative. Since the participants could validate the prediction with "Yes" and "No", false positives did not affect the system's meal detection performance.

I followed a systematic theory-driven approach to design the survey questionnaires in collaboration with psychology researchers and nutrition experts — *the details of which, along with the eating detection system, in discussed in Chapter 3*.

Among the total consumed meals, 90% of breakfast, 99% of lunch, and 98% of dinner episodes were detected by my novel meal detection system (Table 4.3). The system showed a high accuracy by capturing 96.4% of the meals (1,259) out of 1,305 meals consumed by the participants. The meal detection classifier shows a precision of 96%, recall of 80%, and F1 of 88%. Only true positive meals were used for analysis in my study.

I found that over 99% of the meals were consumed with distractions, which means that the students were performing some other activities (e.g., studying, working, etc.) while eating. The majority of portions (62.39%) of meals were consumed alone in dorm rooms (54.09%) or in apartment housing (31.19%). The remaining meals (37.61%) were taken with a company either at home (56.29%), in dining halls (30.21%), in restaurants (5.22%), or other places. The other places included churches, grocery stores, etc.

While there are various ways of identifying whether a food is healthy or not based on its nutritional composition, computing research on barriers to food journaling unpacked that food journalers often did not journal their food if they perceived the food to be unhealthy. I drew upon this consideration and did not ask the participants to list nutritional components of the food or take any pictures of the food that they were eating [40]. Rather I asked them to report whether the food that they were eating was healthy or unhealthy. Participants reported 63% of their meals as healthy.

Table 4.3: Percentage of meals detected by the eating detection system

Meal Type	# Episodes	% of Detected Episodes	# Detected Episodes
Breakfast	294	90%	264
Lunch	410	99%	406
Dinner	601	98%	589
			Total: 1,259

EMA-based Mental Well-being Assessments. Throughout the course of the study, I administered EMAs assessing participants' mental well-being states thrice a day (one between 6-9 AM, 11 AM-3 PM, and 5-8 PM). I designed the system to prompt these EMA assessments independent of individual eating episodes of participants. My design decision is based on the rationale of minimizing confounds of individual meals and immediate mental health changes, as observed in prior literature [21, 123]. This helps us to better estimate a participant's general well-being over the course of a day. In particular, each EMA survey administered the following assessments, all of which are considered critical components of one's mental well-being state [242, 204].

Affect. The Russel's circumplex model of affect [188] translates affect into a two-dimensional representation: 1) the valence dimension measures how happy/unhappy one individual feels, and 2) the arousal dimension measures the intensity of the feeling. To obtain affect, I used a two-item questionnaire motivated by prior work [137]. Participants were asked *How do you feel right now?* which could be answered with one option among *negative, somewhat negative, somewhat positive, and positive*, and one option among, *relaxed, somewhat relaxed, somewhat pumped, and pumped*.

Stress. To measure instantaneous stress, I used a validated single-item questionnaire [55] that asked *"Stress means a situation in which a person feels tense, restless, nervous, or anxious or is unable to sleep at night because his/her mind is troubled all the time. Do you feel this kind of stress in the past few hours?"*, which could be answered on a Likert scale with 5 options from 1 (not at all) to 5 (very much).

Depression. To measure instantaneous depression, I draw upon the PHQ-2 instrument [104]

Table 4.4: Descriptive statistics of mental health EMA questions answered by the participants.

EMA	Min.	Max.	Mean	Standard Deviation	Compliance Rate (%)	# Number of Responses
Depression	1.0	4.0	2.2	0.51	75.3	1,331
Anxiety	1.0	4.0	2.43	0.78	79.4	1,402
Stress	1.0	5.0	2.38	1.07	81.3	1,428
Valence	1.0	4.0	2.73	1.19	73.8	1,304
Arousal	1.0	4.0	2.16	0.87	73.8	1,304

to design the EMA questionnaire. These questions asked the participants: 1) *"Over the past few hours, how often have you been bothered by little interest or pleasure in doing things?"*; and 2) *"Over the past few hours, how often have you been bothered by feeling down, depressed, or hopeless?"*, which could be answered with one option for both questions from *not at all, several times, more than half the times, and nearly every hour.*

Anxiety. For measuring instantaneous anxiety, I draw upon the GAD-2 instrument [171] to ask the participants: 1) *"Over the last few hours, how often have you been bothered by feeling nervous, anxious, or on edge?"*; 2) *"Over the last few hours, how often have you been bothered by not being able to stop or control worrying?"*, which could be answered with one option for both questions from *not at all, several times, more than half the times, and nearly every hour.*

Table 4.4 represents the descriptive statistics of the EMAs gathered as part of the mental well-being assessment.

4.1.2 Ethical Considerations

The study was conducted after getting approval from the institutional review board (IRB). Due to ethical considerations, participants who had an eating disorder or had food insecurity were excluded from the study since the study did not have scope for providing them with sustainable resources to responsibly engage with them in research. Food insecurity and eating disorders were diagnosed using validated surveys [120, 231]. However, each participant, irrespective of their eligibility criteria, was provided a list of campus resources that they could reach out to for a variety of needs (e.g., food and housing problems, academic problems, harassment-related concerns, physical safety issues, etc.).

4.2 Methods

In this section, I describe the methods for addressing the research questions. Recall the first research question was to investigate how meal consumption is associated with mental well-being in a student population. The motivation for addressing this question was to establish the construct validity of my study since the relationship between meal frequency, and mental well-being is a well-studied phenomenon. Hence, I adopt features that are used in studies that investigate the relationship between meal frequency and mental well-being. Once I established the construct validity of my study, I show how students' meal consumption patterns change over the week at a group level and how this change corresponds to various mental well-being attributes.

Second, I investigate how contextual factors during meals are associated with the mental well-being of participants. I develop linear regression models, where the independent variables are various mental well-being measures, and dependent variables are meal contexts. In particular, I provide details on how I extracted features for each variable.

4.2.1 Aim 1: Meal Frequencies and Mental Well-being

To achieve my first aim, I look into meal frequencies with respect to various well-being measures. I break the analysis down into two aspects: group level and individual level. In the group level analysis, I show how the meal consumption patterns change in a student population over the week and how it correlates with various mental well-being measures. To the best of my knowledge, there has been no quantitative research that investigates how students' overall meal consumption varies over a week and its relationship with mental well-being, and hence, I conducted this analysis.

For the individual-level analysis, I investigate how various mental well-being measures correlate with meal frequencies. This examines the construct validity of the data based on what literature suggests about the evidence in the relationship between meal frequencies and mental well-being [211].

Feature Extraction for Individual Behavior Analysis

Average Meal Counts Per Individual Taking average meals consumed over a period of a study, gathered through surveys, is a common approach for understanding the relationship between meal consumption and well-being [232, 234, 233]. Hence, I adopted the same approach in this analysis. To investigate the relationship between meal frequency and mental well-being, I analyzed the average number of breakfasts, lunches, dinners and the total number of meals each student had during their enrollment period.

Average Mental Well-Being State Per Individual Based on the same rationale as above, I took the average of stress, depression, anxiety, valence, and arousal, per individual over the period of the study.

Once I calculated the features above, I performed a Pearson correlation analysis and reported the results. I discuss these results in the following section.

Feature Extraction for Group Behavior Analysis

Recall that the participants were recruited on a rolling basis from July to September 2019 for the Summer and Fall semesters. Since I am looking at a group-level meal consumption pattern, I took overlapping days for both Summer and Fall participants. Overlapping days correspond to the days that are common during which all participants were in the study. For both Summer and Fall participants, I got 17 days of overlapping days, and I used data for those days for further group-based analysis.

For overlapping days, I aggregated the total meal counts per individual. Then, I aggregated meal counts for the total number of participants on a particular day. I took a similar approach for aggregating instantaneous stress, anxiety, depression, valence, and arousal responses.

Once the aggregation was complete for both meals and mental health measures, I scaled meal counts, stress, anxiety, valence, arousal, and depression values via min-max normalization to [0, 1]. Once the features were extracted, I conducted a Pearson correlation analysis with the normalized total meal count and normalized mental health states of participants on that day.

4.2.2 Aim 2: Meal Context and Mental well-being

Modeling Methodology

For every well-being measure—*MH*—I built linear regression models with *MH* as the dependent variable and various eating contexts as independent variables. I control for age, gender, education level, and personality types per individual (see Equation Equation 4.1). My inclusion of the covariates is influenced by prior literature [232, 53, 183]. I further included interaction terms (degree 2) in the regression model.

$$\mathcal{MH} \sim age + gender + education + personality + M_{\text{healthy}} + M_{\text{num.}} + M_{\text{dev.}} + M_{\text{com.}} + M_{\text{loc.}} \tag{4.1}$$

For each day –

$\mathcal{MH}$: Mental Health State (valence, arousal, depression, anxiety, stress);

M_{healthy} : Number of healthy meals;

$M_{\text{num.}}$: Number of meals;

$M_{\text{dev.}}$: Deviation time of meal;

$M_{\text{com.}}$: Company during meal;

$M_{\text{loc.}}$: Location of meal

Calculating Independent Variables

Number of Meals Regular consumption of meals, or lack thereof, is used as a proxy for mental well-being. Hence, I use the total number of meals individuals had each day as one of the independent variables. When the eating detection system detected a meal episode, individuals reported whether the prediction was accurate and also identified which meals they were having. I further broke down the meal counts as breakfast, lunch, and dinner to have a holistic picture of which meal event was a better predictor for the independent variables – stress, mood, anxiety, and depression.

Number of Healthy Meals Regular consumption of healthy meals, or lack thereof, is used as a proxy for mental well-being. Hence, I use the total number of self-identified healthy meals individuals had each day as one of the independent variables. When the eating detection system detected a meal episode, individuals reported whether the meal they were having was healthy or not.

Meal Deviation Time One less observed phenomenon in the eating and well-being literature is meal timing. Since most research studies investigate meal consumption in a retrospective manner and gold-standard surveys can ask participants to reflect on this information from a period of 24 hours [60] to even months [46], it is difficult—if not impossible—to gauge how much individuals are varying from their regular meal time [229]. Some evidence suggests that delayed meal consumption is associated with more food intake than usual. However, there is no clear evidence of how deviance from individual regular mealtime can be associated with individual mental well-being. Hence, I investigated this relationship.

The eating detection system recorded true positive events (after getting confirmation from participants) with a time of eating events. Hence, based on these logs, I knew when individuals were having specific meals. Once I extracted this information per meal per individual, I standardized the meal timing—per individual—with respect to their average meal timing. Adopting such a technique allowed us to understand the meal deviation for each meal since all the meal timings are standardized, per individual, with respect to their mean meal consumption time. This standardization was done separately for breakfast, lunch, and dinner for each individual.

Meal Company Several contextual factors are related to eating and, indirectly, to mental well-being, including with whom a person is eating [256, 234]. For example, Utter *et al.* found a strong negative correlation between family meals and depression among adolescents. Based on such insights, I used this phenomenon as one of the features [234, 233].

When the eating detection system correctly identified a meal and the participants validated the prediction, they were asked follow-up questions to record with whom they were having meals. I used this to identify the company during meals per day.

Meal Location On-campus students operate on a busy schedule where they have to move from place to place for academic reasons. Hence, their locations for taking various kinds of meals are most likely to vary. For example, one can assume that students would take most of their lunch on-campus and always take their dinners at dorm/apartment/home. I have provided multiple pieces of evidence in the literature that family meals are associated with mental well-being. Such meals are most likely to occur at home, where most family members reside. Hence, based on this motivation, I investigated where students are taking their meals. When the eating detection system correctly identified a meal and the participants validated the prediction, they were asked follow-up questions to record where they were having meals. This information was used to calculate the location of meals per day.

Calculating Dependent Variables

For dependent variables, I considered all mental well-being measures described in section 4.1. I calculated the average level of stress, depression, anxiety, valence, and arousal, per day per participant.

4.3 Results

In this section, I highlight my findings for both research questions. With my first aim, I situate my findings with theoretically grounded observations in eating and mental well-being literature. In particular, I show how skipping meals are correlated with poorer mental well-being outcomes. As an extension of my first aim, I show how group-level behavior can be used to understand how students follow a seasonal pattern every week in meal consumption and how it is associated with their mental well-being. No literature on eating behavior has investigated this phenomenon since most of them are not able to capture the meal-specific information I capture through my study.

With my second aim, I establish the relationship between meal context and mental well-being. Some of these observations are theoretically grounded in the literature. For example, family meals are significantly associated with positive mental well-being outcomes, and I also found that evidence in my research. However, some observations, such as regularity in meal timing and its association with mental well-being, are unique to this study. I highlight these results in the next two subsections.

4.3.1 Aim 1: Meal Frequency and Mental Well-being

Individual-Level Meal Frequencies

To obtain quantitative insights into how meal frequencies and mental well-being were correlated on an individual level, I calculated the Pearson correlation between (variants of) meal frequencies and average EMA measures of mental well-being for all participating days of each individual. Table 4.5 shows the results of this correlation analysis.

Table 4.5: Relationship between meal frequency and mental well-being. The (*) indicate statistically significant ($p < 0.05$) differences in correlations.

	Stress	Anxiety	Depression	Valence	Arousal
Avg. Breakfast Frequency	-0.51*	-0.46*	-0.32*	0.21*	0.33*
Avg. Lunch Frequency	-0.32*	-0.29*	-0.22 *	0.10*	0.07
Avg. Dinner Frequency	-0.08	-0.03	0.01	0.04	0.07
Avg. Meal Frequency	-0.43 *	-0.56*	-0.47 *	0.37*	0.15*

As expected from eating and well-being theories, average meals consumed per individual were strongly correlated with stress, depression, anxiety, and affect. In particular, meal frequencies were positively correlated with valence and arousal. Several studies report that students who had regular meals reported high activation, better mood, and less depressive symptoms [131, 177] compared to their cohort who skipped meals.

Then, I focused my analysis on specific meals such as breakfast, lunch, and dinner and investigated how their frequency is correlated with an individual's mental well-being. I observed that for some meals, such as breakfast and lunch, their frequencies were significantly negatively correlated with stress, anxiety, and depression. My results confirm the findings of previous non-automated studies that relied on longitudinal surveys to capture meal frequencies and investigate their relationship with mental well-being. For example, Tajik *et al.* found that skipping major meals such as lunch significantly contributed to poorer mental health outcomes [222]. Smith found that adolescents who had regular breakfasts were less depressed, less anxious, and less stressed compared to adolescents who skipped breakfast [211]. I did not see any significant correlation between dinner frequency and mental well-being. This is because the participants did not generally skip dinners throughout the study [150].

In addition to stress, depression, and anxiety, I investigated how affect is associated with meal frequencies. I found that breakfast frequency was positively correlated with both valence ($r = 0.21, p < 0.05$) and arousal ($r = 0.33, p < 0.05$) of individuals, which

Table 4.6: Relationship between Meal Frequency and Mental well-being. The $*$ indicate statistically significant (p<0.05) differences in correlations.

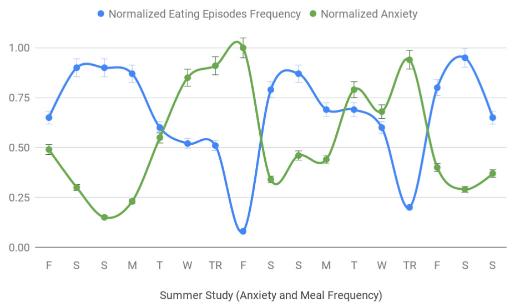
	Stress	Anxiety	Depression
Meal Frequency	-0.68*	-0.47*	-0.52*

was not the case for both lunch and dinner. This observation means that if individuals had regular breakfasts, they reported higher activation and positive emotion throughout the study. This has been a well-established phenomenon in adolescents [22, 250]. Next, I investigate whether I can see any temporal pattern in students' meal consumption and well-being.

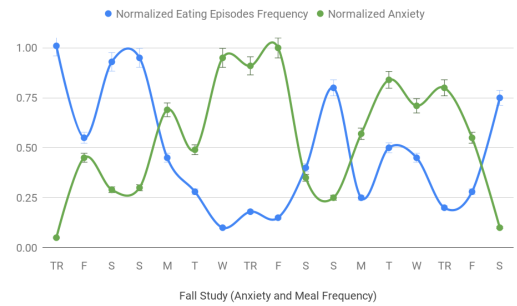
Group-Level Meal Frequencies

Figure 4.1 captures the relationship between meal frequencies and various mental well-being measures. It can be seen that for stress, depression, and anxiety concerning the meal frequencies, there is an inverse trend with total meals. However, this trend has a seasonality. In particular, during weekends, students generally tend to be less stressed, anxious, and depressed and miss fewer meals compared to weekdays (see Figure 4.1). Previous studies also reported that students were doing better during weekdays compared to weekends with respect to their mental well-being [174, 163]. This particular observation could be explained by factoring in the busy schedule of students as they tend to have more commitments (e.g., deadlines, classes, presentations, etc.) during the week and tend to miss meals.

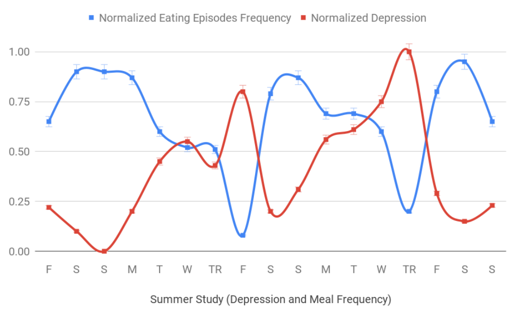
To quantify this observation, I did a correlation study between meal frequencies and mental well-being measures for all the overlapping days. Table 4.6 shows the correlation coefficient between meal frequencies and mental well-being. Skipping meals is strongly associated with various mental well-being measures in several studies [110, 112]. Hence, my observation is supported by previous studies investigating the relationship between meal frequencies and mental well-being. In addition, I also extended insights into how various kinds of contextual information can be used to assess students' mental well-being. I will



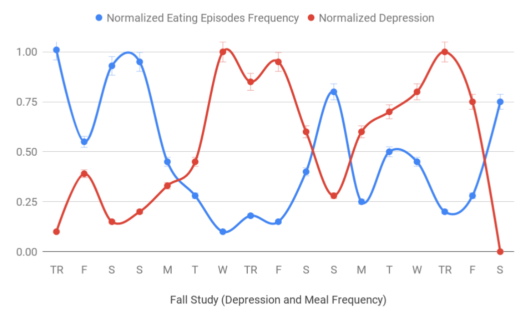
(a) Anxiety and Meal-Frequency (Summer)



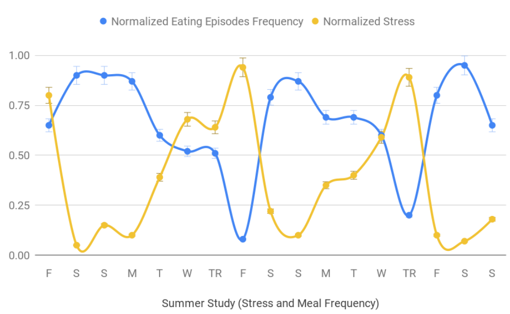
(b) Anxiety and Meal-Frequency (Fall)



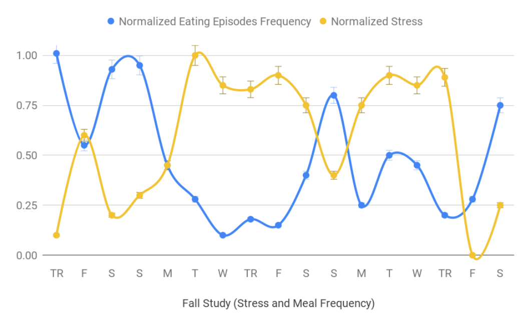
(c) Depression and Meal-Frequency (Summer)



(d) Depression and Meal-Frequency (Fall)



(e) Stress and Meal-Frequency (Summer)



(f) Stress and Meal-Frequency (Fall)

Figure 4.1: Meal frequencies and mental well-being. x-axes represent days of the week, and y-axes represent normalized meal frequency, depression, anxiety, and stress values. For investigating group behavior, I arranged overlapping days of participants during the study and scaled meal counts, stress, anxiety, and depression values via min-max normalization to [0, 1]. For both Summer (left) and Fall semesters (right), an inverse trend between the frequency of meals and self-reported stress, depression, and anxiety can be seen.

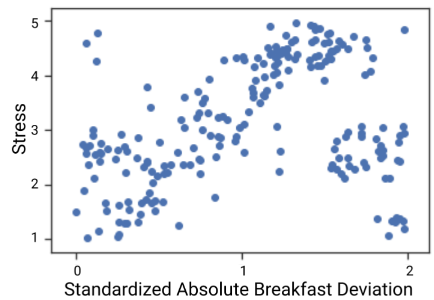
Table 4.7: Standardized coefficients of linear regression models with contextual features as independent variables and mental well-being attributes as dependent variables. Only statistically significant relationships are shown in the Table. (Stat. significance: * p<0.05, ** p<0.01, *** p<0.001). Each column represents results for independent models.

Dependent Variables →	Affect		Mental Health		
Independent Variables ↓	Valence	Arousal	Depression	Anxiety	Stress
Age	0.11	-0.14	0.03	0.15	0.07
Gender	-0.07	0.20	0.14	0.25	0.20
Personality: Openness	-0.13	-0.11	0.07	0.09	0.03
Personality: Conscientiousness	0.07	0.08	-0.04	-0.21	-0.16
Personality: Extraversion	0.16	0.04	0.14	0.04	0.07
Personality: Agreeableness	0.07	0.04	-0.17	-0.07	-0.10
Personality: Neuroticism	-0.05	-0.02	0.15	0.11	0.23
Meal Quality: Healthy	0.11	0.07	0.06	0.03	0.21
Meal Context: with Family	**0.21****	0.08	**-0.29*****	-0.23	**-0.37*****
Meal Context: with Friends	0.04	**0.13***	-0.19	-0.27	**-0.22*****
Meal Context: Alone	0.08	-0.05	**0.19*****	**0.14*****	**0.34*****
Meal Location: at Home	**0.17****	0.12	**-0.45****	**-0.23***	**-0.32****
Meal Time Deviation: Breakfast	**-0.16***	**-0.23****	**0.20****	0.17	**0.36****
Meal Time Deviation: Lunch	-0.11	**-0.17***	0.12	0.07	0.13
Meal Frequency	**0.36***	**0.27***	**-0.22****	**-0.25****	**-0.45*****
R^2	**0.21***	**0.17***	**0.19*****	**0.39*****	**0.23***

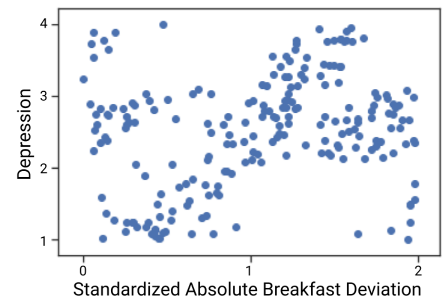
explain my findings in the next subsection.

4.3.2 Aim 2: Relationship between context and mental well-being

In this section, I present the results of my regression analysis. Note that I considered a variety of independent variables for regression analysis. Among them, I only present results that turned out to be significant in the regression analysis. Though I considered age, personality, gender, and education level as independent variables, they were not statistically significant ($p > 0.05$) in the regression analysis. Further, I included interaction terms (degree 2) in the regression, which did not reveal any statistical significance either.



(a) Breakfast Deviation Time vs Stress



(b) Breakfast Deviation Time vs Depression

Figure 4.2: The figure on the left shows the relationship between meal deviation time and self-reported stress level. The figure on the right shows the relationship between meal deviation time and self-reported depression level. Breakfast deviation time is absolute, meaning the breakfast deviation could be early or late. The standardized absolute difference is calculated based on the mean time of an individual's recorded breakfast episodes.

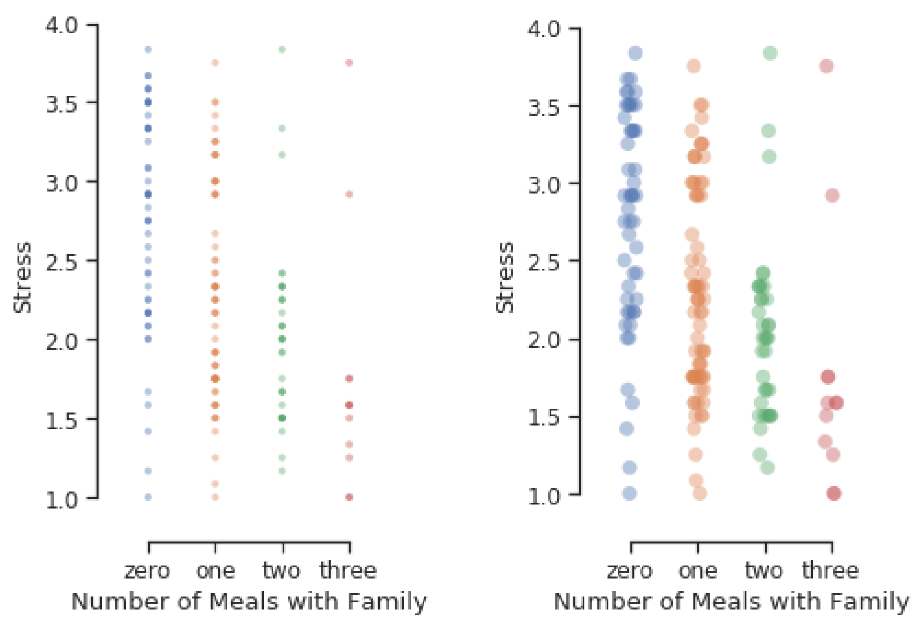


Figure 4.3: Relationship of stress concerning the total number of meals consumed with family in a day. The right plot is the same representation of the plot on the left. However, I have introduced jitter in the right plot to expose data points that might overlap on the left plot.

Meal Company and Mental Well-Being

The company with whom an individual is taking their meals is a very important aspect of an individual's well-being, and it has been studied in health disciplines [51, 234]. I found similar evidence in my results. More specifically, I found that family meals were negatively associated with stress, depression, and anxiety (see Table 4.7). Such meals were positively associated with the valence of individuals. These observations mean that family meals were associated with lower stress, depression, anxiety, and a happier mood. Figure 4.3 shows the relationship between stress and the number of meals taken with families.

My observations are theoretically grounded. For example, Utter *et al.* found that family meals were significantly correlated with lower levels of depression and other well-being scores such as low risk-taking behaviors, better family relationships, etc. [234]. Eisenberg *et al.* found that adolescents who had regular family meals were less depressed and argued that family meals were a proxy measure for understanding family connectedness [51]. My findings confirm the importance of family meals and mental well-being. In particular, I found that family meals are a strong indicator of stress, depression, and the valence of college students.

Another important finding is that meals taken in isolation were a significant predictor of depression, anxiety, and stress. Depressive symptoms generally follow several behavioral patterns, such as social isolation [28]. Meals are not necessarily meant to address hunger and nutritional needs, and they are means for interaction and socialization as well [70, 7]. Family meals or social meals serve as an opportunity to interact with people. Such interaction has positive implications on well-being [233]. Hence, those interactions might be why I found meal companies to be an important predictor of mental well-being.

Deviation from Regular Meal Time and Mental well-being

I found that deviation in breakfast and lunch was strongly associated with a lower activation level. This means that if individuals were not having meals at their regular mealtime, they felt less energetic. Deviation from breakfast time was strongly associated with high stress (Figure 4.2a) and depression (Figure 4.2b) of individuals. The x-axis on both figures indicates the absolute standardized (by individual mean meal starting time) breakfast deviation time, and the y-axis indicates average self-reported stress levels for respective days. In both figures, the breakfast deviation time is absolute.

Meal deviation time is an understudied area in eating behavior. Since most eating behavior assessment strategies rely on recall-based methods, it is hard for participants to reflect on when they had each meal. Most research studies investigate meal consumption retrospectively, and gold-standard surveys can ask participants to reflect on this information from 24 hours [60] to even months [208]. It is difficult—if not impossible—to gauge how much individuals vary from their regular meal time [208]. There is evidence that suggests that delayed meal consumption is associated with high caloric food intake [13]. However, to the best of my knowledge, no prior study investigates the relationship between meal timing and mental well-being, which I established through my study.

Meal Location and Mental Well-being

I found that, among other locations, meals at home were strongly associated with positive mental well-being. In particular, meals at home were indicators of valence, depression, anxiety, and stress. Transitioning from home to a dorm is a significant stressor for college students [186]. Hence, such a transition, added with various other academic and professional commitments, might have negative implications for students. Students who had more meals at home might have had access to better well-being support compared to students who did not have access to family. Though I did not see any evidence of negative well-being for eating at dorms, I can imply the benefit of having access to families during meals, and I show that with my results.

4.4 Discussion

In this chapter, I addressed the second research question of my thesis: *Does meal-time context correlate with the mental well-being of college students?* I demonstrated the significance of the eating context in relation to student mental well-being. In particular, I showed that skipping meals—breakfast and lunch—were strongly correlated with higher levels of stress, anxiety, and depression. In addition, I showed that several contextual information related to when and where and with whom the meal was taking place was also correlated with mental well-being. For example, taking meals with family members and meals in the home were negatively correlated with higher levels of stress, anxiety, and depression. Crucially, I have used a novel eating context gathering system to capture meal-related contextual information. Prior studies relied on entirely survey-based methods to capture eating behaviors. Based on the relevance of context, gathered through a meal detection system in understanding the mental well-being of students, I now formulate theoretical, practical, design, and policy implications for computing researchers and campus stakeholders.

4.4.1 Theoretical Implications

Implications for Mental Well-being Assessment Research

My work provides newer empirical insights into the broad area of mental well-being assessment research. This body of research has hitherto considered several causes and correlates of mental health in the form of many human behaviors. Contributing to this body of work, my research shows how eating behavior and the context of eating gathered through novel means (i.e., real-time meal detection system, EMA, etc.) correlates with college students' mental well-being. My study is situated in the theory that human behaviors have social underpinnings, and when considered via the lens of the Social-Ecological Model [32], these behaviors and well-being attributes are deeply embedded in the complex interplay between an individual, their relationships, the communities they belong to, and societal factors [32].

Existing psychology and nutrition research has noted that the dining table provides an opportunity for conversation, storytelling, and reconnection [238]. When people bond with others and experience a sense of connection, endogenous opioids and oxytocin are released that stimulate pleasant feelings[1]. The neurochemical changes lead to improved well-being and contentedness[1]. Consequently, it is perhaps not surprising that my findings suggest how contextual eating (eating with family members or friends) within situated communities as college campuses plays a role in students' mental health. The social context is thought to be an important determinant of human behavior in general [73]. Field and laboratory studies have demonstrated that the presence of other people can alter many different forms of behavior [20]. This phenomenon is termed social facilitation [79]. As is rightly said: "never eat alone"[1] – for centuries, people have noted that breaking bread with others makes a meal more than just a meal. My findings reveal how such social facilitation is key in eating behaviors and people's experiences of mental well-being – an aspect that needs to be considered in the emerging body of research on mental health assessment.

I showed various eating contexts and their significant relationship with various mental well-being measures. Most of their correlation coefficients are not high, though they are significant. In the context of low correlations, the results need to be interpreted in context [134]. In particular, in addition to the correlation values, R^2 indicates the percentage of the variance of the dependent variable that can be explained with the collection of independent variables. For stress as a dependent variable in Table 4.7, the R^2 value is 0.23, which means that only 23 percent of the stress score can be explained through the independent variables that I investigated. In fact, the instantaneous stress detection problem is a well-studied problem by means of other sensing modalities (e.g., facial expression [62], heart rate [29], electrodermal activity [205], etc). I am only looking at certain demographics and eating-related contextual factors in the context of stress, which explains the low correlation and low R^2 values. The goal of my research was to establish the evidence that different

[1] https://brainworldmagazine.com/never-eat-alone-the-benefits-of-eating-with-others/

contextual information related to eating is correlated with a variety of instantaneous mental well-being measures with statistical significance. The low values of coefficient along with low R^2 values potentially highlight that there are more latent variables (e.g., caloric intake, nutritional components of foods, students' daily routine, etc.) that can help model different target variables (affect, depression, anxiety, and stress) that I have studied in my research.

Furthermore, a plethora of computing literature argues in favor of multi-modal passive sensing for gauging mental well-being [242, 204, 153, 198, 84]. Multi-modal sensing data can provide a holistic picture of an individual's daily activities compared to single modalities. Hence, multi-modal data tend to perform better for predicting mental well-being compared to single modalities [153, 224]. Eating and context around eating have been missing from the list of modalities, perhaps due to the difficulty of gathering continuous longitudinal eating-related data. More recently, Meegahapola *et al.* investigated how different aspects of eating, such as food consumption level (e.g., overeating) and social context during meals (e.g., eating alone, eating with someone, etc.) company can be predicted with passively sensed data [142, 141]. However, the relevance of such an eating context remains unexplored in mental well-being assessment problems. I bridge that gap by using a real-time meal detection system that can capture eating-related contextual data from a student population and show the relevance and significance of such contextual information in the case of mental well-being research. I hope that future mental well-being assessment-centric problems incorporate eating-related contextual data for modeling mental well-being.

Implication for Leveraging Context in Eating Behavior Assessment Research

Understanding how individuals perceive the relationship between food and well-being can contribute to a better understanding of food choices, as well as to the development of efficient strategies for modifying eating patterns. For these person-specific interventions, dietary assessment is essential. However, dietary assessment is challenging since most dietary assessment methods are based on subjective recall [27, 85, 95]. Such recall can vary from a day to a few months [208]. Delays as little as 24 hours in answering questions related to dietary portions can generate significant recall errors [60, 95]. In addition, the current dietary assessment strategies do not incorporate specific times individuals are having their meals and with whom they are taking their meals [208]. I showed the importance of these two aspects, among other things, concerning students' mental well-being. For example, I found that deviation at breakfast time was associated with a high stress level, and deviation at lunchtime was associated with low activation. Besides, I found that meals with family were strongly associated with low stress levels, depression, and anxiety. Hence, my research has implications for the further development of eating behavior assessment instruments that incorporate the social context and temporal context of individual meals.

4.4.2 Practical and Design Implications

It has long been recognized that health and well-being are closely linked to various socio-cultural, political, and physical-environmental conditions within communities [25]. Various pathways exist by which changes in communities' physical and social conditions enable individuals to increase control over and improve their health [101]. Health promotion research has, therefore, delineated a social-ecological paradigm for understanding the complex community and environmental origins of public health problems, including eating and nutrition, and for organizing intervention and wellness programs that can effectively ameliorate those problems [138].

Accordingly, I discuss the practical and design implications of my work by borrowing the lens of the social-ecological model [32]. According to the social-ecological model, human behaviors and attributes can be considered to be deeply embedded in the complex interplay between an individual, their relationships, and the communities to which they belong to [190]. I use the social-ecological model to situate the discussion on how technology design can leverage my findings.

Implications for Dietary Intervention Technologies

I have shown at an individual level how eating behavior can be used to unpack temporal patterns of meal consumption among a student population and how meal consumption, or lack thereof, is significantly correlated with mental well-being (subsubsection 4.3.1). In addition, I showed that deviations in meal timing, especially for breakfast and lunch, are associated with various mental well-being measures (subsubsection 4.3.1). Hence, a natural intervention approach would be to remind students to take their meals on time if they miss out on meals. Using the same eating detection technology I used in my study, it can be inferred when students are not taking their meals. Then the system can remind students to take their meals. Furthermore, if the meal detection system notices deviation from of timing of when a meal is taken, it can remind individuals to take meals at regular times since I have uncovered that, especially for breakfast and lunch, the deviation is significantly correlated with poorer mental well-being measures.

My motivation behind suggesting this intervention stems from studies that emphasize the importance of regular mealtimes, which can provide a sense of rhythm and regularity in lives [254]. They offer a sense of containment and familiarity and can evoke deep feelings of contentment and security. Interventions to structure or remind meals can offer people the opportunity to stop, stand still psychologically, reflect on their day and days ahead, and listen to and interact with others. Such interventions can also serve as a grounding opportunity, a time when anxieties can be expressed and people can be listened to. Such intervention strategies could be adopted at an individual level, and this intervention sits at an individual level according to the social-ecological model [32]. However, adopting such an intervention approach requires significant scrutiny of privacy and ethical concerns, which I have described in detail in the following section. The meal detection system used in my research brings us much closer to designing such personalized interventions.

Implications for Leveraging Social Support in Promoting Healthy Eating Behavior

Any academic experience opens up possibilities for academic, personal, and professional connections. Some of these connections mature into friendships that have a significant amount of online interaction through various kinds of social networking sites. HCI researchers have found evidence that an individual's social circles on online platforms—Instagram—influence them to develop healthy eating behavior [36]. I provided evidence that can inform this existing practice to further support specific healthy eating behavior. In particular, I showed that irregular mealtimes are associated with high levels of stress and, and skipping meals is associated with higher levels of stress, depression, anxiety (subsubsection 4.3.2). Hence, peers through existing connections can help track each other to have regular and timely meals, thus building healthy eating habits. One technology-mediated solution could look into how such eating detection systems can leverage the social network of individuals to build and track healthy eating goals such as not skipping major meals and eating meals on time. My research leverages a real-time meal detection technology that can facilitate such design choices and shows the promise of delivering such interventions in real-time, addressing a major limitation of survey-based approaches.

I have shown with whom an individual is having a meal is a significant indicator of mental well-being for college students. Specifically, I found evidence that family meals were correlated with lower levels of stress, depression, and anxiety. In addition, meals with friends were correlated with lower levels of stress (subsubsection 4.3.2). However, I acknowledge that I did not investigate the existing family relationships of the participants. Hence, my research has implications for technology design for social meals. However, having a meal-time companion might not be possible given the possible geographical distance between individuals and their social circles. Hence, remote technologies that can support social meals can be explored to address this issue. Grevet *et al.* explored the usefulness of a remote social eating experience probe and found that participants appreciated the value of being connected with their peers and colleagues [69]. This line of work should be further explored since the technology landscape has changed significantly. Both of these intervention strategies that leverage peer support and support social meals sit at the social level since it is leveraging the social relationships of college students.

Implications for Data-Driven Community-Centric Interventions

In my results, I found evidence that students skip more meals during weekdays as opposed to weekends (subsubsection 4.3.1), and these observations have implications for technology and intervention design on a community level. Since college students spend a significant amount of time on college campuses, spaces on campus have the potential to serve as a potential intervention location. Sogari *et al.* argued that according to the social-ecological model, the college stakeholder could act as enablers to facilitate healthy eating habits [213]. For example, campus stakeholders can incentivize regular meal consumption behavior for students in dining halls, and technology-mediated solutions can help track the regularity of meal consumption at an aggregated level. Incentives can include giving credits to get meals for free in the campus dining hall if students in a dorm are irregularly consuming their meals during weekdays. The eating detection system used in this chapter provides an opportunity to investigate eating behavior data as an aggregate (e.g., on a dorm level or campus level). Technology-mediated intervention approaches can include reminding students in certain dorms to consume meals regularly based on the daily meal consumption pattern detection by relevant eating detection technologies.

4.4.3 Ethical and Policy Implications

In the study design section, I discussed the exclusion of students with food insecurity and students with eating disorders due to ethical and clinical obligations (subsection 4.1.2). Because it is hard to propose any guaranteed sustainable solutions for students with food insecurities, it would not have been an ethical decision for us to recruit these students. Additionally, students with an eating disorder were excluded because food journaling might make students self-aware of their eating episodes and may trigger an emotional episode, which is a common phenomenon for people with eating disorders [50]. If any eating detection or intervention approach is used in student populations to understand or change their eating behavior, they should be carefully studied before to understand whether they belong to, at least, any of these categories.

Finally, my research has implications for policy design as well. I have demonstrated that missing out on major meals is a significant indicator of an individual's well-being (Section 4.3.1). Besides, I have also shown that having companions during meals has a positive impact on students' mental well-being (Section 4.3.2). Several other studies have shown similar insights for student populations [234, 233], however, through retrospective surveys. Such insights have policy implications for stakeholders. For example, policymakers across university campuses can design cafeterias or relevant food consumption places to be more social than isolating. A recent focus of computing literature has been around how to have more social experiences with collocated people in a shared space such as home or workplaces [161]. Such technologies augmented with automated eating detection technology can be used to inform the benefits of social eating in a sustainable manner. However, relevant privacy and ethical measures need to be in place before executing such policy-level changes. My work has policy implications in spreading awareness and education regarding healthy eating on college campuses. Drawing on the insights from my analyses, colleges can conduct awareness drives and public service announcements to promote and encourage healthier eating practices.

CHAPTER 5

DEVELOPING AND EVALUATING A SNACKING DETECTION SYSTEM USING EARBUDS

While the previous two chapters showed the development and application of a real-time meal detection system, the system cannot detect short and sporadic chewing episodes during snacking. Snacking has significant implications on an individual's mental and physical well-being [144, 152]. This chapter aims to overcome the limitation of detecting snacking episodes with passive sensing. Unhealthy snacking habits are associated with multiple negative outcomes [181, 63]. For example, irregular snacking can affect the regularity of meal consumption [199, 181], leading to lower intake of nutrition [135] while stressed snacking can often lead to weight gain [63]. Hence, understanding snacking habits alongside meals are very important to gauge an individual's dietary habits.

Despite its influence on the daily eating patterns of an individual, the term "snacking" does not have a static definition [81]. Various methodologies have been proposed in the nutrition literature to define snacking without consensus [91]. Such methodologies include nutrient profiling [68], time of the day (e.g., between lunch and dinner etc.) [158], food clusters based on caloric intake [15], duration of the episode (e.g., less than 10 minutes) [243], and self-identification by individuals [89]. Each approach is informed by the nutrition domain and presents its advantages and limitations. For example, food classification based on nutrients might not overlap with what an individual identifies as a snack. I borrow motivation from each of these definitions and define snacking in the context of this chapter as: *"Snacking is a self-identified sporadic eating episode that contains short bursts of chewing episodes (i.e., often a few seconds), and often done in conjunction with other activities and/or with disruptions."*

In the definition of snacking, I consider semi-naturalistic settings in order to simulate

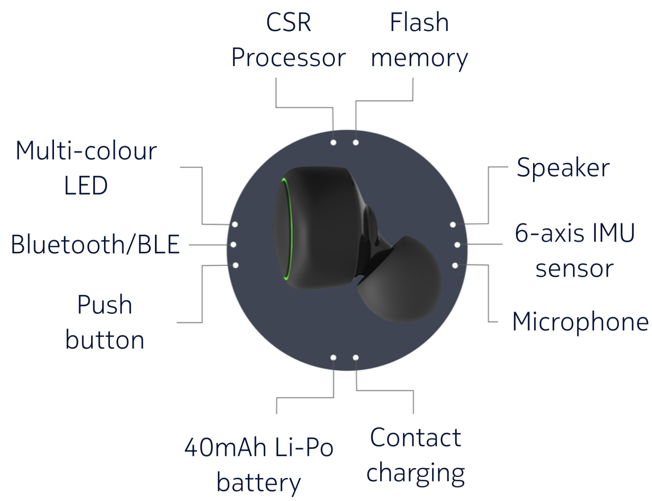


Figure 5.1: eSense Device

in-the-wild conditions (i.e., self-identification of snack foods, short chewing episodes). I use IMU-instrumented Nokia eSense earbuds [96, 145] (refer to Figure 5.1) to collect data from 18 participants who snacked on their preferred items over the course of around one hour. I investigated the efficacy of earbuds for snacking detection by evaluating a variety of classifiers (incl. Random Forest, Support Vector Machine, and Multi-Layer Perceptron) in both Leave-One-Participant-Out and Leave-One-Session-Out settings. In this chapter, I address the following question: *How can we passively detect short and sporadic eating episodes such as snacking?*

I will demonstrate that gyroscopes are more effective for detecting snacking episodes relative to accelerometers, while utilizing both sensors leads to improved performance. Furthermore, I will demonstrate that the semi-naturalistic data collection led to poor performance on unseen users (n=18), yet performing personalization (n=14) with approximately 2 minutes of chewing samples results in significantly better performance for detecting snacking episodes. This clearly showcases the suitability of earables for snacking (and eating) detection systems.

5.1 Study Design and Data Collection

My study aims to investigate the efficacy of detecting short burst of chewing episodes that are present in snacking using Nokia eSense earbuds [145, 96]. Hence, I designed a protocol that simulates participants' naturalistic snacking behavior (i.e., self-identification of food, short duration of chewing). Chewing episodes in snacking are generally short and non-periodic, often co-occurring with other activities (as per the nutrition literature [91, 243]). I used these insights while designing the study and did not impose any constraints on snacking items and duration during data collection.

I obtained IRB approval for conducting the user study and recruited participants via word of mouth and email announcements sent to different mailing lists of the authors' institute. I requested participants to select two food items they generally snack on, such that the total price of these items did not exceed $15. I relied on the participants' definition of snacking due to the relevance of subjective interpretation in categorizing foods as snacks [91, 243, 257], unlike prior works towards eating detection, which resulted in 19 snacking items in my study (refer to Table 5.1). The mixed fruit bowl (MFB) contained a combination of six fruits (e.g., watermelon, cantaloupe, honeydew, strawberries, grapes, and pineapple). The fruit and nut contained six items (e.g., peanuts, raisins, dried pineapple, banana chips, cashews, dried cranberries, and dried papaya).

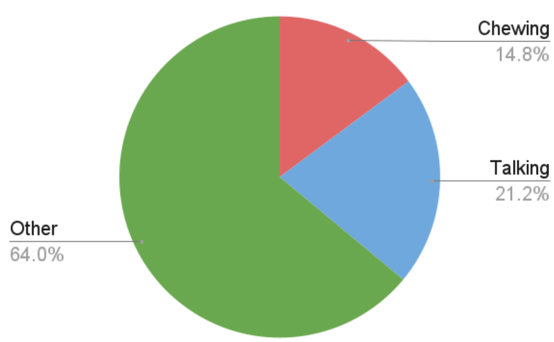


Figure 5.2: Distribution of Chewing, Talking, and other Classes

Once participants signed the consent form, they wore a chest-mounted camera that

Table 5.1: Statistical Description of the Dataset. In the second and third columns, BC stands for banana chips, MFB stands for a mixed fruit bowl, CN TM stands for chocolate and nut trail mix, FN TM stands for fruit and nut trail mix, PC stands for Potato Chips, PF stands for panini finger, GB stands for gummy bear, YB stands for yogurt with berries, CCS stands for cheetos cheese snack.

ID	First Item	Second Item	Median Cont. Chewing Time (s)	Total Chewing Time (mm:ss)	Total Talking Time (mm:ss)	Other Activities Time (mm:ss)
P01	BC	NA	14	5:17	12:3	30:22
P02	MFB	CN TM	19	6:34	11:10	20:5
P03	BC	MFB	15	4:10	17:2	46:12
P04	BC	FN TM	12	6:40	9:23	27:9
P05	MFB	BC	17	10:39	7:11	45:45
P06	BC	PC	21	6:54	10:17	25:33
P07	MFB	PF	27	13:21	20:17	30:20
P08	TB	MFB	9	6:34	9:11	23:23
P09	BC	PC	19	4:3	7:47	32:28
P10	MFB	FN TM	14	8:39	6:14	40:41
P11	MFB	GB	19	10:14	6:15	27:51
P12	PC	FN TM	18	7:27	12:20	21:49
P13	MFB	YB	27	5:34	8:11	48:27
P14	MFB	CCS	16	7:16	10:13	24:12
			Total:	103:12	147:34	444:17

Figure 5.3: View from the Chest-mounted Camera Worn by Participants

would record their faces (refer to Figure 5.3). Participants were in a room where they could maintain social distancing from the researchers present during the data collection. Participants wore the left Nokia e-Sense earbud to collect accelerometer and gyroscope data, recorded at 25Hz and transmitted in real-time to a Google Pixel 5 smartphone. I used the camera's video data for annotation.

A total of 20 participants participated in three sessions of approximately 20 minutes duration, where they could snack on their pre-selected snacking item. At the beginning and end of each session, participants performed synchronization gestures by saying "one, two, three, four" out loud while moving their heads sideways such that I could annotate the IMU data while using the video data as ground truth. The participants did not re-attach the devices between sessions. Since the goal of the study was to simulate naturalistic snacking episodes, which are often short and sporadic, I distracted the participants in order to prevent long, continuous chewing episodes. The distractions comprised asking participants to write down in a document the quality of the food they were having, how frequently they would snack on a given day, etc. In addition, I would also converse with the participants about different responses they wrote in order to keep them distracted. The first-, second-, and third-quartile ranges of continuous chewing windows were 7, 15, and 34 seconds respectively. The median distance between two chewing segments was 47 seconds. Such strategy allowed for naturalistic snacking behaviors since a plethora of research highlights that snacking episodes are often interrupted (e.g., watching TV, talking, reading, etc.) [81].

5.2 Methodology

The activity of snacking entails chewing food and swallowing it, resulting in muscle movements in the ear-canal. The rationale for using a 6-axis IMU was that the acceleorometer/gyroscope placed inside the earbud can detect the chewing based on the jaw movement that causes a change in muscle movement in the ear-canal. However, chewing is not the only activity that can trigger such change. For example, talking might be confused with chewing. Though in-ear microphones have also been investigated for detecting chewing, I decided not to use them because IMUs pose fewer challenges with respect to privacy compared to an always-on microphone.

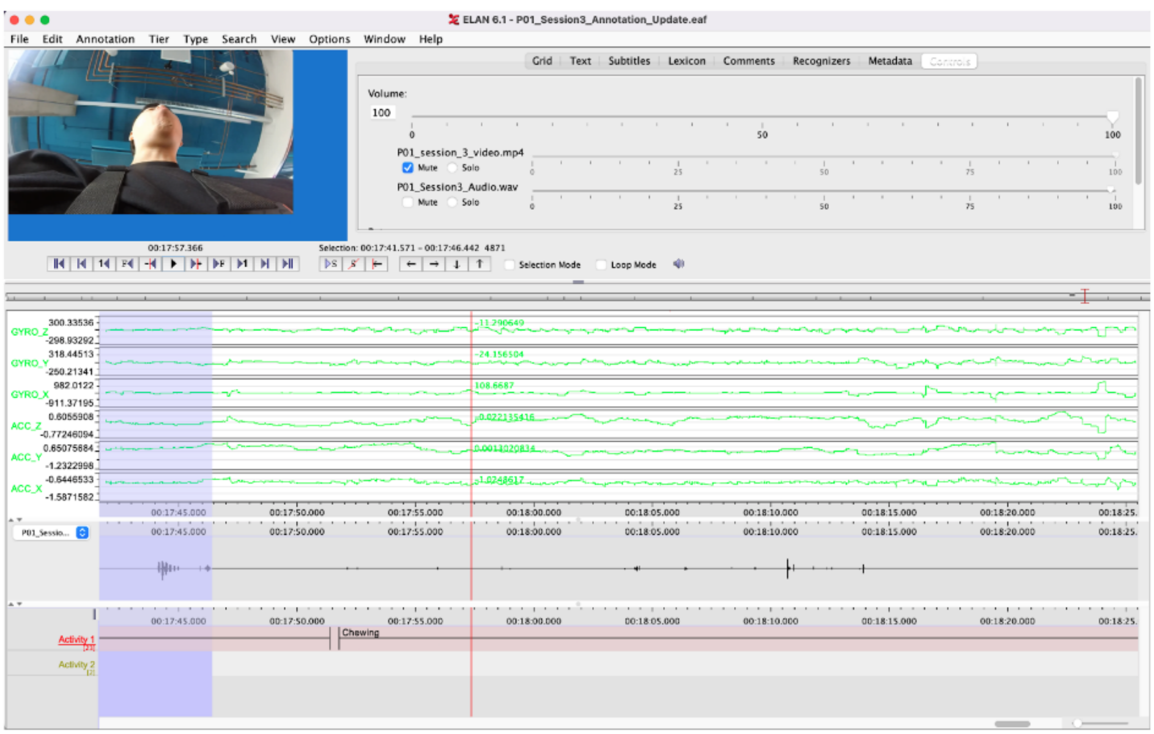


Figure 5.4: Snapshot of Elan Annotation Tool

After data collection, I annotated the sensor data using Elan [252]. Refer to Figure 5.4

for a snapshot of the annotation tool. Anything apart from chewing and talking was labeled as “Other” (sitting, watching videos, attending a remote meeting, working on a computer, etc.). Upon inspecting the data quality, I discovered gaps in the IMU data caused by lost packages during transfer from the earbuds to the phone, which is expected for the device. In order to account for the loss of data, I downsampled it from 25 Hz to 10 Hz before segmentation and feature extraction. After downsampling, I got rid of any 1-second windows that did not have at least 10 samples, resulting in a loss of 5 minutes and 35 seconds of data. Further losses in the video and sensor data resulted in a collective total of 18 participants. In particular, after data collection, I found that some video files could not be imported to ELAN due to compatibility issues. In addition, for the videos that could be imported to ELAN, in some cases, the video and the IMU data lengths did not match, making it impossible to use such sessions. Hence, I had to discard these sessions. As a result, for user-independent evaluation, I could use data for 14 participants who had more than one usable session and for user-dependent evaluation, I used 18 participants’ data. I adopted a sliding window approach [26] with the window size of 1 second and 50 percent overlap, which is an established choice for modeling IMU data [76]. I computed five ECDF components per axis [75], leading to 36-dimensional features.

Developing user-independent models: I modeled snacking detection as a three-class problem: Chewing, Talking, and Other. To evaluate the efficacy of detecting snacking episodes automatically and to investigate if the models were generalizable to unseen participants, I applied a leave-one-participant-out (LOPO) protocol. In particular, I studied the performance of Random Forest (RF), Support Vector Machine with RBF Kernel (SVM), and Multi-Layer Perceptron (MLP) classifiers. Apart from these models, I developed a random prediction model that would predict a random class out of the three target classes. My choice of classifiers is informed by prior work on eating detection [227, 10] and I report the test set mean F1-score, as it is robust to class imbalance [170].

Developing user-dependent models: I also developed personalized models, where I

Table 5.2: LOPO performance with mean F1-score using Random Forest (RF), Multi-Layer Perceptron (MLP), Support Vector Machine with RBF Kernel (SVM), and Random Class Predictor (RCP).

Models	Accelerometer Only	Gyroscope Only	Acc. and Gyro.
RF	0.48	0.53	0.58
MLP	0.45	0.50	0.53
SVM	0.35	0.38	0.39
RCP	0.27	0.27	0.27

trained models using a leave-one-session-out protocol (LOSO). Finally, to quantify how much data is required for personalization, I incrementally varied the total number of randomly selected windows per test participant the machine learning model could learn from, in addition to the remaining participants. Subsequently, I computed the mean F1-score across all participants for each count of test user windows added to the train set (see Figure 5.7). The randomly added windows to the train set were excluded from the test set.

5.3 Results

My work aims to answer whether IMU-instrumented earbuds can reliably detect short and sporadic eating episodes during snacking, along with studying the role of personalization in developing such systems. I present my findings regarding these questions below.

5.3.1 Generalized Models are not Effective at Detecting Snacking Episodes

I find that generalized models (LOPO) are not effective for modeling short chewing episodes during snacking (see Table Table 5.2). Using an accelerometer only, the RF, MLP, and SVM classifiers achieve a performance of 48%, 45%, and 35% mean F1-score. I can see slightly better performance using gyroscope data where the classifiers obtain an F1-score of 53%, 50%, and 38%. Combining both modalities results in improvements over using them individually, resulting in an increase of 5%, 3%, and 1% over utilizing only the gyroscope.

I hypothesize that the individual differences in chewing styles during snacking explain the low performance in detecting chewing episodes. RF, the best-performing model, performs better than a random class predictor (27%, randomly chooses one of the three classes) yet has limited generalizability for unseen participants. Therefore, I investigate whether personalization can positively impact the detection of short chewing episodes during snacking.

5.3.2 Personalization in Snacking Detection

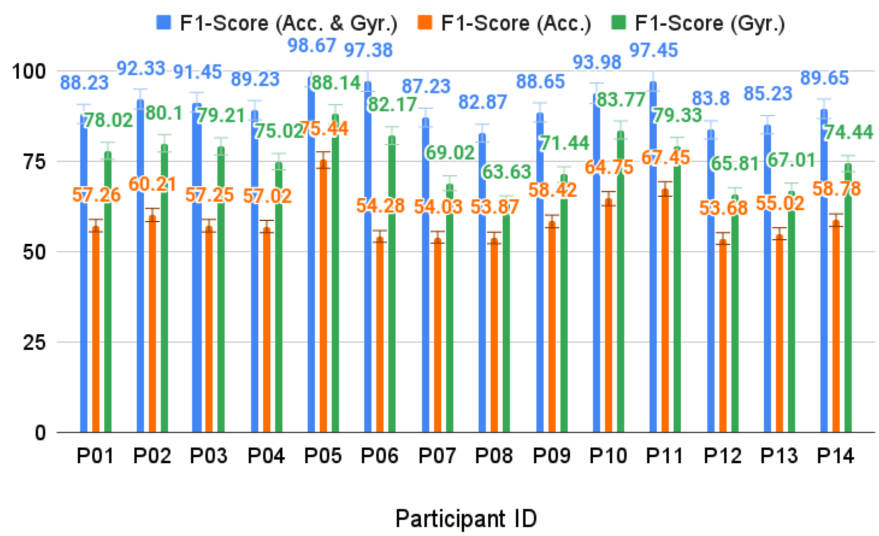


Figure 5.5: F1-scores for detecting snacking episodes using both accelerometer and gyroscope (blue bar), only accelerometer (red bar), and only gyroscope (green bar). The F1-scores are based on a leave-one-session-out protocol.

To investigate if personalization helps improve snacking detection performance, I adopt a leave-one-session-out (LOSO) protocol. I only include participants who have more than one session. I found that adding other sessions from the test user, i.e., the LOSO protocol leads to substantially improved performance for detecting snacking episodes (Figure 5.5). As each individual can chew differently and at different rates, the LOPO models do not generalize across participants. Like my previous finding, the gyroscope is better at detecting snacking episodes than the accelerometer. Furthermore, combining both modalities results in higher performance over utilizing individual sensors.

I also investigated how much data is necessary to detect snacking episodes effectively. As mentioned in section 5.2, I vary the total number of windows the RF classifier can learn

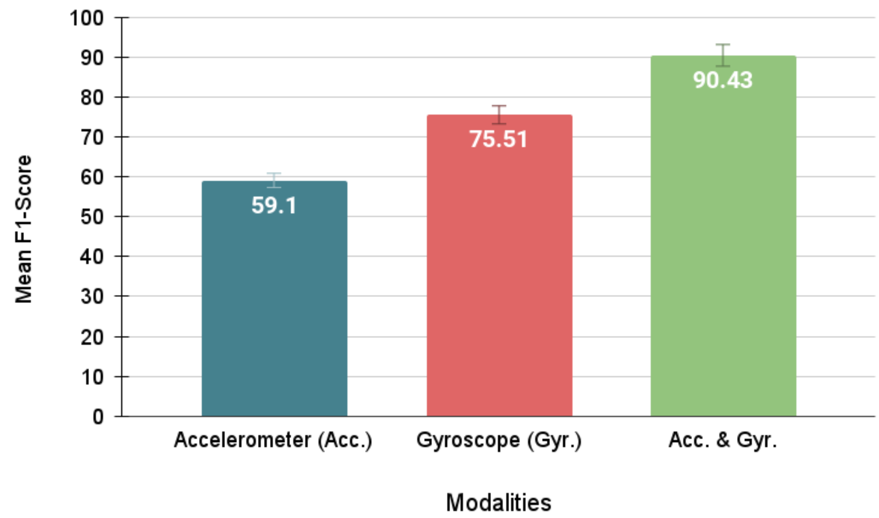


Figure 5.6: Mean F1-scores for detecting snacking episodes using both accelerometer and gyroscope (blue bar), only accelerometer (red bar), and only gyroscope (green bar). The mean F1-scores are based on a leave-one-session-out protocol.

from a participant, which was excluded from the test split. I incrementally add randomly selected windows from the test participant to the training set and evaluate the participant's remaining data. In Figure 5.7, the X-axis represents the number of windows added to the training set, whereas the Y-axis represents the corresponding mean F1-score across all participants. Therefore, the '0' on the X-axis represents the LOPO model as it does not contain any data from any user. The model reaches peak performance when around 130 windows from the test user are available for personalization, obtaining around 90% F1-score. As each window is 1 second long, approximately two minutes of data is needed from a user to develop effective snacking detection models.

5.4 Discussion

In this chapter, I addressed the third research question of my thesis: *How can we detect short and sporadic eating episodes such as snacking?* In particular, I presented my findings from a semi-naturalistic user study on 18 participants invited to snack on their preferred food at their own pace. IMU-instrumented earbuds are feasible and practical for detecting short

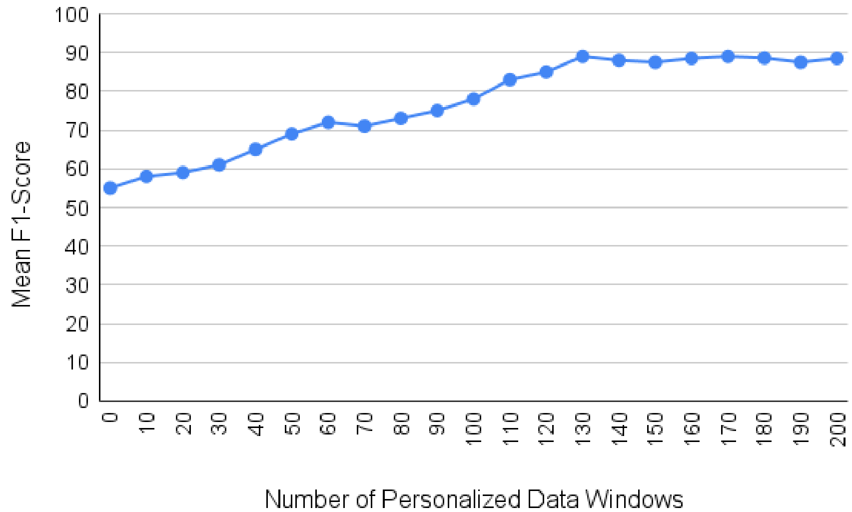


Figure 5.7: Effect of personalized data while detecting short and sporadic chewing episodes. The X-axis represents the number of randomly selected windows added to the training set. Y-axis represents the mean of the F1-score across participants.

and sporadic chewing episodes during snacking. The earbuds perform poorly at recognizing chewing episodes in unseen users; however, around two minutes of chewing data from a user is sufficient to produce highly effective personalized models. The gyroscope data can more accurately detect chewing episodes among the available sensors, but utilizing both sensors results in the best performance. Based on these results, I share the implications for study design to develop systems that require personalization.

5.4.1 Implications for Study Design

My study places a strong emphasis on collecting semi-naturalistic data in the lab without imposing scripted eating activities. The choice of snacks during data collection was also left to the participants. In addition, as part of the research protocol, I interrupted/disrupted the participants such that they could not snack continuously for prolonged periods, as I have defined based on nutrition literature in the context of my thesis. The semi-naturalistic nature of the study simulates real-world conditions and results in substantial variations in the sensor data, hindering generalizability in detecting snacking episodes of unseen users.

However, I found that approximately two minutes of training data per user is sufficient to increase the snacking detection effectiveness. My proposed methodology shows its promise for real-world deployment as two minutes of data can be reliably gathered from users after deployment without significant impact on user experience.

CHAPTER 6

WORKPLACE STRESS AND MEALTIME DEVIATION

In the last three chapters, I demonstrated how passive sensing technologies could help us detect eating events (e.g., meals, snacks), eating context, and how such context can inform us about the well-being of individuals. In particular, in Chapter 4, I showed evidence that mealtime deviation is significantly associated with higher stress levels. The results from the study were observational. As a result, I could not make any causal claims on whether a high-stress episode causes a deviation in one's mealtime. Furthermore, students' context can vary significantly, making it difficult to conduct a causal study to understand the relationship between stress and mealtime deviation. To inform a causal relationship between stress levels and mealtime deviation, I need to be able to account for as many covariates that can get affected by stress. Hence, conducting a causal study with the student population is difficult due to their highly dynamic routine and the lack of sensing infrastructure that can be easily integrated with one's technology ecosystem.

One of the major sources of daily stress is workplace stress which can be defined as the reaction that people may experience when they are subject to high demands and pressures at work that do not correspond to their experience and/or coping capabilities [29]. Some of the main contributing factors include, but are not limited to, juggling between professional and personal life, a perceived lack of job security, interpersonal issues with colleagues, and high workload [253]. When experienced over long periods, workplace stress has been shown to impair decision making, negatively affect productivity, and decrease job dissatisfaction [253] as well as lead to significant business costs (around $300 billion per year in the U.S. alone [143, 17]).

Hence, an interesting population to study the relationship between stress and mealtime deviation is information workers. However, passive sensing technologies can only gather some work-related information if these workers work at physical offices. For example, a worker might have multiple offline meetings in a day, and without intrusive sensing infrastructure, gathering information about the workers' workday routine and activities will be difficult.

After the COVID-19 pandemic, the traditional idea of the workplace has changed. A place of relaxation, home, has become the new workplace for many information workers. This change in the workplace provides us with a unique opportunity to conduct a causal study between stress levels and mealtime deviation since almost all of the work-related activities conducted by remote information workers are on their work machines. It provides me with the unique opportunity of accounting for a wide array of covariates gathered from a work machine to make causal claims between stress and mealtime deviation.

To explore the relationship between momentary stress and mealtime deviation, as part of this chapter, I investigate the following question: *For working adults working remotely from home, what is the causal relationship between their stress level changes and deviation in lunchtime?*

Furthermore, I investigated the end-user considerations when deploying stress sensing systems to understand user preferences of different sensing modalities that I used for gathering stress-related information. To address this question, I conducted a one-month-long observational study with 49 remote information workers across the U.S.

6.1 Study Design and Rationale

My study aims to understand the effect of stress levels on the deviation of meal timing. Ideally, such a problem would be best examined in an experimental or randomized control trial (RCT) [247, 33, 139]. However, these methods pose ethical and practical challenges for the study population. Hence, I draw on quasi-experimental approaches to observational data to investigate the effect of stress on mealtime deviation of remote information workers [187].

In particular, I adopt a causal framework based on matching, which simulates an experimental setting by controlling for as many covariates as possible [88]. This approach builds on the potential outcomes framework, examining if an outcome is caused by a treatment T by comparing two potential outcomes: (1) Y_i when exposed to T (T = 1), and (2) Y_i if there was no T (T = 0). Because it is impossible to obtain both kinds of outcomes in the same instance, this framework overcomes this challenge by estimating the missing counterfactual based on the outcomes of a matched instance — an instance with a similar distribution of covariates but differing treatment status. I employ propensity score analysis [162, 194, 197] to match instances and examine meal deviation outcomes in the Treated and Control groups.

This section describes the methodological considerations and approach in detail. The Ethics Review Board approved these methods of the respective technology company. As part of this study, I aimed to recruit around 50 information workers who were working remotely. The study entailed installing sensing software for the duration of the evaluation period, as well as answering multiple survey-based questions on stress as well as other well-being-related survey questions.

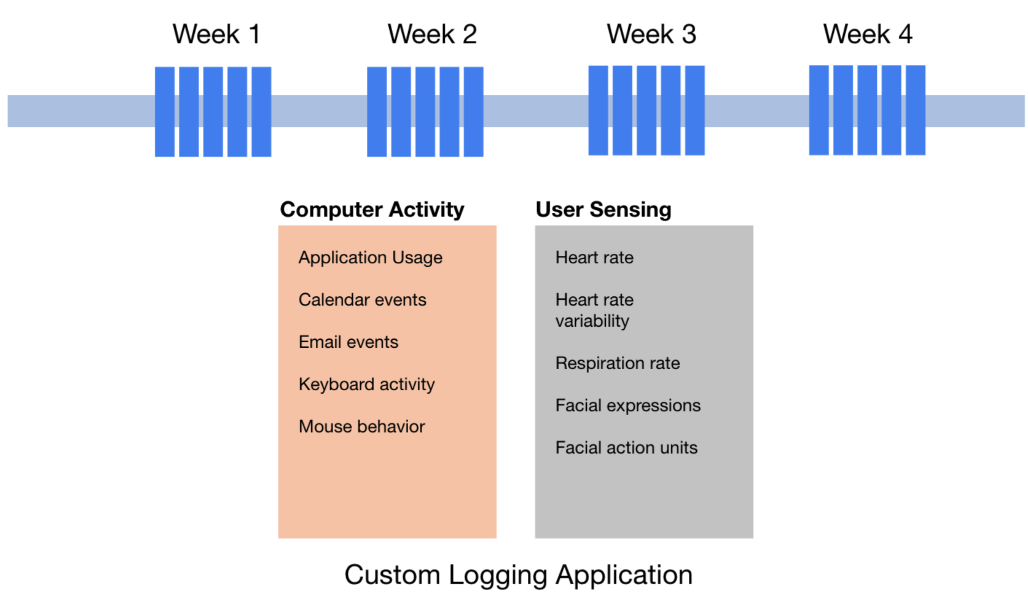


Figure 6.1: Study Design for Capturing Passively Sensed Data from Study Participants

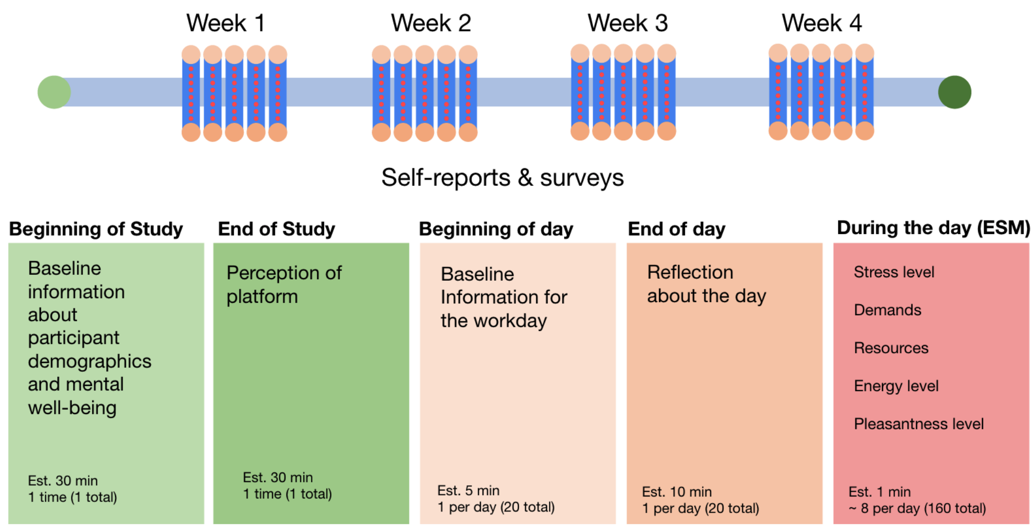


Figure 6.2: Study Design for Capturing Self-Reported Demographics and Well-being Data from Study Participants

6.1.1 Data Collection

The data collection comprised primarily of two data sources: a passive sensing stream from the sensing platform (Figure 6.1) and survey responses (Figure 6.2) gathered at various stages of the study. In the subsequent sections, I explain the data I collected using these two sources.

Passive Sensing

I used a custom multimodal logging software to capture the digital manifestations of stress that recorded information about the participants' activities, behaviors, and physiological states. The main components are as follows:

Email, Calendar, and Application Usage Information. The software ran on the participant's desktop computer and logged the number of emails received in their inbox, the number of calendar appointments, and applications used (including when they were opened and closed, in the foreground, etc.). It logged informative events about an individual's stress level based on prior work. For example, email is one of the most significant signals of work-related communications for information workers [129]. In addition, calendar information contains vital workday-related information for information workers. Especially during COVID-19, the frequency of remote meetings has increased significantly [12], and individuals spend significantly more time in meetings, often leading to stress and fatigue [12, 223]. Application usage, keyboard, and mouse activity are direct proxies of how much interaction an information worker has with their work environment. They are often investigated in the stress literature as meaningful signals for detecting the stress levels of participants [180, 80].

Facial Action Units. Based on the relevance of facial expressions in the context of emotional understanding, the software captured the facial action units of participants. The software had access to the participant's webcam, which enabled it to log a participant's facial position and facial action units [52]. The software used a pipeline to process the video frames in real-time (i.e., without storing video frames in the cloud for privacy) at one frame per second. Using a convolutional neural network (CNN) facial detector, it extracted the bounding box corresponding to the user's face[1] and then processed this region of interest using another CNN model to extract the probabilities of 12 facial action units (AU01, AU02, AU04, AU05, AU06, AU09, AU12, AU15, AU17, AU20, AU25, AU26) [61], based on a standard Facial Action Coding System (FACS) [52]. These FAUs were selected as they are generally the most frequently observed and most accurate at predicting projected emotional actions. These actions are associated with expressions of both positive (e.g., AU12/zygomatic major/smiling) and negative (e.g., AU04/corrugator/brow furrowing) effects. However, it is essential to note that no action unit maps uniquely to anyone's expression or emotional state, but they may still capture a rich array of users' behaviors.

Non-Contact Physiological Sensing. Physiological sensing technologies have been extensively studied for passively monitoring stress levels of individuals [29, 224]. Hence, a parallel computer vision pipeline analyzed the video frame to extract heart and breathing rates using a non-contact video-based approach [114].

[1]https://github.com/Linzaer/Ultra-Light-Fast-Generic-Face-Detector-1MB

Surveys Instruments

During the study, participants responded to various surveys, which can be grouped into five main categories based on their delivery time. The number of responses per survey category can be found in Table 6.1.

Study Intake. At the beginning of the study, I gathered baseline information from the participants about their demographics (e.g., age, gender, number of direct reports within the company, personality type [176], etc.) and baseline mental well-being. I used validated survey instruments for gathering the baseline information using DASS-21 [118] that capture stress, depression, and anxiety using a 21-item instrument, the Perceived Stress Scale [37] that captures stress levels using a 7-item instrument.

Experience Sampling (EMA). During each workday, participants, received multiple prompts (around every hour $\pm$ 15 min) containing 5-Likert scale questions to rate the amount of perceived work demands and resources [44], their valence and arousal levels [188, 24] and their stress levels.

Participants were instructed to answer these questions based on their previous 30 minutes of activity. The instructions contained the operational definitions for each of the measures based on prior work so that participants could review the definitions at any time. Participants were given the following options for demands and resources: *very low, low, moderate, high, and very high.* These definitions and options were consistent with the previous literature looking at workplace demands and resources [44]. For valence and arousal, participants were given the following options: *very unpleasant, unpleasant, neutral, pleasant, and very pleasant* and *very low, low, moderate, high, and very high* respectively. Participants were given the following options for stress: *not at all, slightly stressed, moderately stressed, very stressed, and extremely stressed*.

Daily Check-In and Check-Out. Poor sleep quality has been associated with higher levels of work stress [103, 93]. Hence, at the beginning of each workday, participants answered questions about their previous night's sleep and their readiness to start their workday. I

Table 6.1: Overview of survey compliance during the study

Question Type	Average # of Responses Per Participant	Standard Deviation	Total # of Responses
Study Intake	1	0	49
EMA	97.29	27.32	4767
Daily Check-In	18.35	2.88	899
Daily Check-Out	16.39	2.9	803
End of Study	1	0	49

incorporated these questions as part of the daily check-in, based on previous literature [30].

At the end of each workday, I asked participants to reflect on their daily stress, valence, arousal, demands, and resources with the same 5-Likert scale questions of the Experience Sampling. In addition, I asked participants about their food and caffeinated drink intake episodes during the workday. Eating and drinking have been associated with individuals' stress levels. Having a stressful workday might often lead to more snacking [214], irregular meal patterns[132], and drinking more caffeinated drinks [39], among other things.

Finally, participants were asked to indicate the presence and potential intensity of the following stressors: 1) a highly paced workday, 2) too many meetings, 3) too much email, 4) an overly packed day, 5) too many ongoing activities, 6) sitting for too long, 7) a lack of breaks, 8) missing exercise, 9) loss of sleep, and 10) a blurred boundary between professional and personal life. The answers ranged from 0 (did not apply today) to 5 (applied with a lot of impacts). Hence, the higher the intensity score, the more intense this stressor was during the workday for a participant. These stressors emerged as being some of the most relevant ones during an exploratory survey of 1200 employees at the same company.

End of Study. At the end of the study, I wanted to investigate the participants' comfort level with the sensing infrastructure that we have asked them to use. In particular, I posed several hypothetical questions to the participants: 1) what would be their level of preference for different sensing modalities (e.g., wearable device, computer usage, webcam, etc.), 2) where they would prefer their data to be stored (e.g., local vs cloud) for stress level analysis. Both questions were likert-based.

6.1.2 Participant Recruitment and Compensation

To select participants in the study, I followed three steps: 1) I sent recruitment emails with an intake form to randomly selected employees of a large technology company, 2) I requested eligible participants to install custom sensing software on their work machine and use it for at least 30 minutes, 3) if the test software worked without any issues (e.g., crashes, slowing down the machine), I recruited the participants. At the end of these steps, I recruited 50 participants to participate in a 4-week data collection (passive and active) study while performing their regular work. One participant dropped out during the second week of the study due to software problems.

As part of the eligibility criteria, I recruited participants who mostly used a single work computer. Their work computer was preferably always connected to the Internet, they did not use a virtual machine from their work machine, and they also had a webcam (external or built-in). In addition, their computer should be able to run a custom sensing software that runs on Windows Operating System and uses around 2 GB RAM and 20% CPU on average.

Each participant could receive up to $300 in the form of a gift card. To promote engagement, I followed a scalable monetary reward. In particular, each participant received $50 after the 1st week, $50 after the 2nd week, $100 after the 3rd week, and $100 after the 4th week.

6.1.3 Demographics

Table 6.2 presents the demographics of the participants in the study. I have an almost even split of participants who identify as females (N=21) and males (N=26). In addition, two of the participants identify as non-binary (N=2). Regarding age, most participants are in the 26-35 (N=18) and 36-45 (N=18) age groups. Regarding education, two have attended college, 23 have a bachelor's degree, 1 has a postgraduate degree, 22 have a master's degree, and 1 have a doctorate degree. Finally, the majority of the participants work in engineering/development (N=29) related occupations, followed by sales (N=7), technical support (N=5), marketing (N=3), strategy (N=3), and human resources (N=2).

Table 6.2: Demographics summary of the study participants. The table below lists the demographic summary of the participants broken down by their gender, education, occupation, and age group.

Category	Count
Gender	
Female	21
Male	26
Non-binary/gender diverse	2
Highest Level of Education	
College	2
Bachelor's degree	23
Postgraduate degree	1
Master's degree	22
Doctorate degree	1
Age Group	
18-25	3
26-35	18
36-45	18
46-55	10
Main Job Function	
Engineering/development	
Technical Support	5
Sales	7
Marketing	3
Strategy	3
Human resources	2

6.2 Methodology

6.2.1 Defining Treatment: Treated and Control

During the workday, study participants reported their instantaneous stress levels multiple times throughout the day. The interpretation of stress is subjective. Hence, people might report different stress levels for the same context [151]. To account for individual differences within each individual, I chose an adaptive baseline for splitting stress labels into two classes that would lead to the least difference in samples for high/low-stress classes [151]. When considering instantaneous stress, I considered stress scores that were reported by the participants between breakfast and lunchtime and computed the average stress level between that window. If the average stress level was higher than the adaptive baseline, the instance was classified as high-stress. Otherwise, it was classified as a low-stress instance. I considered high-stress instances where an individual has received treatment. I considered low-stress instances where an individual did not receive treatment.

6.2.2 Define Outcomes: Lunch Time Deviation

Since I am investigating the causal effect of high/low-stress levels on lunch times, the outcome, in the context of my study, is the deviation from the average lunchtime reported by the participants. The average lunchtime is calculated from the lunch times reported as part of the daily check-out surveys. Since most of the participants worked on a regular schedule, the breakfast and dinner episodes were before and after the workday, respectively. Hence, I did not investigate the causality between the stress levels and dinner and breakfast times for the participants.

If individuals did not report any single lunch and breakfast time throughout the study, I excluded them from the analysis since I could not impute their missing data. If participants did not report lunch times for some days, I considered these days where participants did not have lunch. For these days, I introduced a 4 hours delay for deviation in having lunch, which is the recommended difference between lunch and dinner [140].

6.2.3 Feature Extraction to Control for Covariates

To perform the causal analysis and matching for covariates, I extracted several features from the different sensing modalities (see Table 6.3). The features were extracted from the beginning of the workday through the time participants reported that they had lunch.

On some occasions, a particular feature could not be computed due to missing data (e.g., the camera not working), so I had to implement a strategy to impute the features. If a participant had at least seven days of data for a missing data stream, I imputed the missing data with the median values of the feature of the participant. If the participant did not have at least seven days of data, I imputed data missing features by taking the median of all participants.

6.2.4 Matching for Causal Inference

Matching Covariates

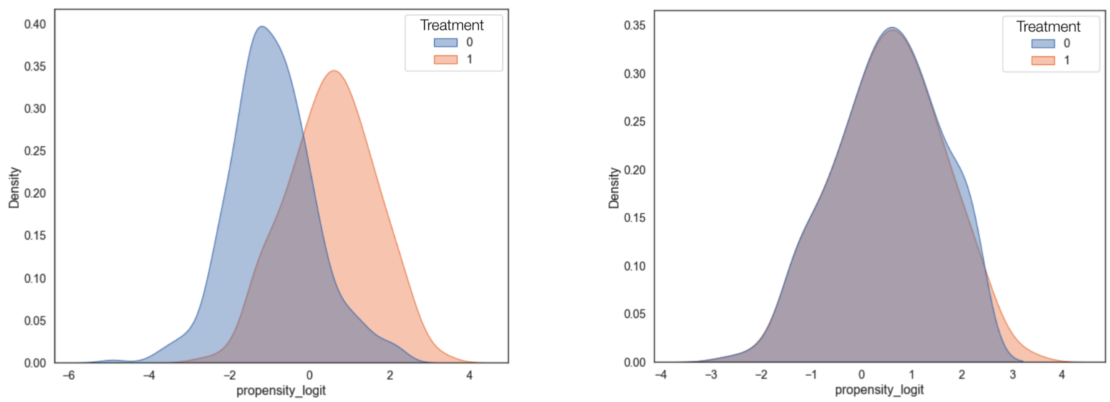
Matching aims to control for covariates so that the effects of treatment are examined between two comparable groups of instances [88]. We should note that mealtime deviation can be confounded by different factors (e.g., age, gender, work routine, etc.). To mitigate such confounds in my analyses, I adopt an approach called matching — when conditioned on high dimensional covariate data, matching can minimize biases compared to naive correlational analyses [88]. My approach controls for a variety of covariates so that the compared Treated and Control show similar baseline behaviors and demographics information for matched instances. Drawing on prior work [100, 162, 197, 195], I use 132 covariates (listed in Table 6.3).

The first set of covariates is based on demographic information such as age, gender, job function, level of education, and the number of direct reports. In addition, I also controlled for resilience, alexithymia, baseline depression, anxiety, and stress scores.

The second set of covariates was captured to control for the change in someone's workday and physiology due to a change in stress levels. For example, I controlled for application usage, email communication patterns, calendar activities, physiological changes, keyboard and mouse activities, etc. The complete list of these covariates can be found in Table 6.3.

Table 6.3: Extracted features from each signal modality to control for covariates

Signal Modality	Type	Features
Sleep	Survey	Self-reported sleep quality, time participants went to bed, time participants tried to fall asleep, number of awakenings during the sleep, time participants got out of bed, total sleep time, and difference of total sleep time compared to the mean sleep time for each participant.
Email	Passive	Total number of unique email threads, average number of CC'ed contacts, and total number of emails that an individual received until the time that they reported stress.
Calendar	Passive	Total number of various meetings, total allocated time (in minutes) for different meetings that an individual had on their calendar up to the time they provided the stress report, total count and total duration (in minutes) for accepted meetings, number of cancelled meetings, number of tentative meetings, number of self-meetings, and number of recurring meetings.
Application Usage, Keyboard, and Mouse	Passive	Total number of minutes, number of different computer applications were running in the foreground, total number of minutes different applications were being actively used by the participant, total number of key press events from the keyboard, total number of mouse clicks, and total number of mouse wheel rotations.
Physiological Sensing	Passive	Mean, median, and standard deviation of Root mean squared difference between successive inter-beat intervals (RMSSD), beats per minute, and breaths per minute.
Facial Action Units	Passive	Mean, max, median, and standard deviation of action units AU01, AU02, AU04, AU05, AU06, AU09, AU12, AU15, AU17, AU20, AU25, and AU26.
Day Specific Features	Passive	Day of the week.
Face Position Features	Passive	standard deviation of face rectangle's length, width, and standard deviation of top and left coordinates.
Alexithymia	Active	Total alexithymia score.
Direct Reports	Active	Total number of direct reports.
Personality Types	Active	Extroversion, agreeableness, openness, conscientiousness, and neuroticism scores on the assessment scale.
Age and Gender	Active	age and gender.
Resilience	Active	Total resilience score
Demand and Resource	Active	Average work demand and resource between breakfast and lunchtime.
Valence and Arousal	Active	Average valence and arousal between breakfast and lunchtime.
Caffeinated Drinks	Active	Total number of caffeinated drinks between breakfast and lunchtime.
Snacking Episodes	Active	Total number of snacking episodes between breakfast and lunchtime.



(a) Propensity Logit Distribution Before Matching

(b) Propensity Logit Distribution After Matching

Figure 6.3: Propensity Logit Distribution Before and After Matching

Propensity Score Analysis

I use one-on-one matching to find pairs (generalizable to groups) of Treated and Control instances whose covariates are statistically very similar. The propensity score model matches instances based on their likelihood of receiving the treatment or the propensity scores [185, 164]. My matching approach pairs instances with similar propensity scores. In particular, for each treatment instance, I match it with the closest control instance based on the propensity score. To account for large distances in matching, I adopt a maximum caliper width of 0.2 of the standard deviation based on the control group, which is the commonly used maximum distance for observational data [6, 164]. To compute the propensity scores, I build a logistic regression model that predicts a user's binarized treatment status (0 for Control and 1 for Treated) based on their covariates. This leads to a final matched dataset of 332 Treated and Controlled pairs.

Quality of Matching

To test that the matching yields statistically comparable Treated and Control instances, I evaluate the balance of covariates. In Figure 6.3a and Figure 6.3b, I plot the propensity logits before and after the matching. As can be seen in Figure 6.3b, the propensity logits for the Treatment and Control groups almost overlap, highlighting a good quality match [164].

Furthermore, I computed the standardized mean difference (SMD) of the covariates between the Target and Control groups to compare their similarity of them statistically. Two groups are considered to be balanced if all the covariates have an SMD lower than 0.2 [100, 217]. After matching, the SMD was 0.17 between the Treatment and the Control groups. Hence, I conclude that the Treatment and control groups are balanced based on the overlap of the propensity logits and the small difference in SMD.

6.3 Results

6.3.1 Causal relationship between stress level changes and deviation in lunchtime

To examine the effect of stress levels on lunchtimes, I compute the differences in the outcomes (lunchtimes) between the matched Treated and Control instances. I computed these differences in effect size (Cohen's d) and paired t-tests which also helped me evaluate the statistical significance of differences. I also conduct Kolmogorov-Smirnov (KS) test, which tests against the null hypothesis that the outcomes in the Treated and Control groups are drawn from the same underlying distribution. To quantify the effect of treatment, I measure the Relative Treatment Effect (RTE) between the Treated and Control groups. An outcome RTE greater than 1 would mean that the outcome (lunchtime deviation) is greater in the Treated (high Stress) instances, which is when users experience experienced higher levels of stress compared to their baselines.

Table 6.4: Summary of deviations in Treated and Control groups along with Relative Treatment Effect (RTE), Effect Size (d), paired t-test, KS-test, and Mann Whitney test (MW-test). Statistical significance reported after Bonferroni correction (*** $p<0.001$).

Outcome	Avg. Dev. Tr.	Avg. Dev. Ct.	RTE	d	t-test	KS-test	MW-Test
Dev.	58.05	29.62	1.96	0.26	3.36***	0.19***	46286.5***

Table 6.4 reports the differences in outcomes of the Treated and Control instances in terms of RTE, Cohen's d, paired t-test, KS test, and MW test. KS-test and MW-test are

non-parametric tests that are not dependent on the distribution of the data. The results and the tests indicate statistically significant outcome differences in the Treated and Control groups. The magnitude of Cohen's *d* value with a positive sign indicates that the Treated group shows a higher outcome than the control group. t-statistic for the t-test and KS-test, and U-statistic for the MW-test shows that the differences in the Treated and Control groups are significantly different. In addition, since the relative treatment effect (RTE) is 1.96, it implies that high stress leads to delayed lunchtime. The relative time deviation for high-stress days can be up to twice as much compared to low-stress days.

6.3.2 Key end-user considerations when deploying stress sensing systems

At the end of the study, participants provided their preferences in relation to having a stress sensing system at work. I summarize the main findings in this section.

What sensing modalities are preferred by the participants?

Participants were more comfortable sharing their keyboard and mouse activity, followed by computer usage, wearable device data, microphone, smartphone, and webcam. Keyboard and mouse activity were significantly higher than any other (Wilcoxon signed-rank test, $p<0.05$), and computer usage was significantly higher than the microphone, smartphone, and webcam modalities ($p<0.01$). However, it is important to note that all the ratings were above the average, indicating that the studied population could potentially accept all of them. Such insights provide a direct implication for keeping user preferences in mind while developing automated and multi-modal systems that can be deployed to detect employees' stress levels continuously.

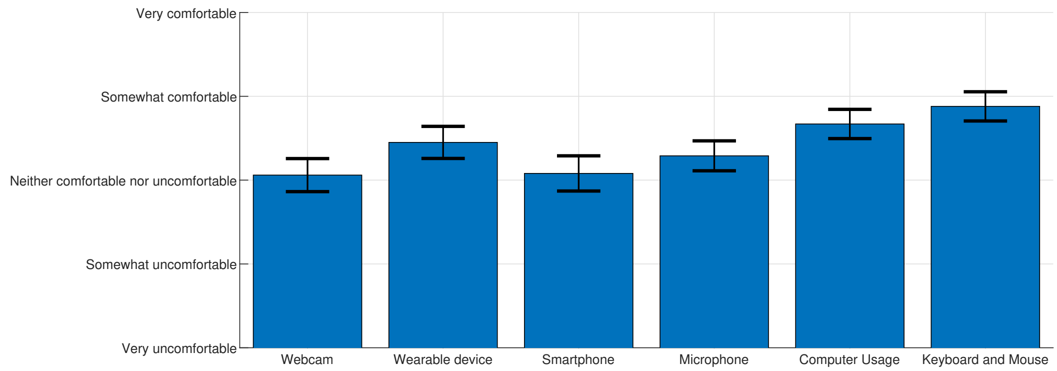


Figure 6.4: Preferred sensing modalities in the context of stress sensing

What kind of storage (e.g., local and cloud) do participants prefer for storing their stress-related data?

To investigate if participants have any preference for where the stress-related features and inferred stress scores should be stored, I asked participants to identify their comfort levels if their data were stored locally on their computers and/or in the cloud. For both options, participants could identify their preferences using a 5-point Likert scale, ranging from very comfortable (option 1) to very uncomfortable (option 5). The median response for local storage was "somewhat comfortable" (option 4), and the median response for cloud storage was "neither comfortable nor uncomfortable" (option 3), which were close to being significantly different (Wilcoxon signed-rank test, p: 0.0576). This indicates that participants felt more comfortable with the local option, probably due to privacy concerns and the ability to control the information more easily.

6.4 Discussion

In this chapter, I addressed the last research question of my dissertation: *For working adults working remotely from home, what is the causal relationship between their stress level changes and deviation in lunchtime?* In particular, I showed that remote information workers who experience high stress are more likely to deviate twice from their regular lunchtime.

Furthermore, any sensing modality introduces challenges concerning privacy. Therefore, I investigated the signal modality preferences. I found that individuals are least comfortable with camera-based sensing technology. In what follows, I discuss the implications of my results.

6.4.1 Directionality of Causal Relationship between Stress Level and Meal-Time Deviation

I demonstrated in my findings that if someone is experiencing higher stress compared to their baseline, they are more likely to deviate twice as much for their lunchtimes compared to the regular days while controlling for other confounds. In the scope of this chapter, the directionality for the causality is from stress to meal-time deviation. Hence, if someone experiences a higher meal-time deviation, it might not necessarily be tied to a higher stress level. I can answer this question by considering lunchtime deviation as the treatment variable and stress levels as the outcome variable. However, that analysis is beyond the scope of this chapter and this dissertation.

6.4.2 Implications of Context for Dietary Intervention Technologies

In Chapter 4, I showed that deviations in meal timing in the student population, especially for breakfast and lunch, are associated with various mental well-being measures (subsubsection 4.3.1). In this chapter, with causal methods, I showed how high-stress levels could cause remote information workers to deviate from their lunchtime twice as much compared to their deviation times during low-stress levels. This observation has implications for thinking carefully about interventions that target meal-time regularity. Unlike previous chapters, in this chapter, I have focused on a context of individuals that can regulate meal time instead of developing an eating detection technology to gather contextual data about an eating episode. All eating detection technologies, if deployed in the wild, have the potential to detect when an individual is eating, which can then be used for developing interesting applications. For example, knowing when individuals are eating can be a trigger to launch food journaling applications for individuals who are journaling food intake. Or, just access to this information can be used to understand if someone is consuming their major meal regularly. If not, relevant interventions can be delivered to nudge individuals to follow a healthy and regular eating routine. The most important question in that intervention delivery is if the intervention will work. If individuals are regularly experiencing high stress because of their workplace, interventions that target meal-time regularity might see little success unless the cause of stress is mitigated. Hence, meal-time-based intervention should carefully consider workplace stress for an effective outcome.

6.4.3 Ethical and Privacy Considerations

My work is the first in computing to investigate the causal relationship between changes in stress levels and lunchtime deviation of remote information workers. My work should not be used to track worker behavior to monitor their work performance. Before conducting my study, I had several iterations of discussions with the ethical review board to get approval for the study design. These discussions aimed to justify using sensing modalities and survey instruments and how they benefit the end-user by performing research studies. Any study or product that collects user information at a level such as this study should go through necessary data regulations to ensure responsible collection and usage of data.

Furthermore, users should be aware of the utility of the data and should be in control of the data as well. The communication of what kind of data will be gathered from the users and for what purposes is of surmounting importance in developing sensing applications that can detect human activities and, as a result, human behavior. Users should have the option of opting out at any time from data collection and should have the agency delete their data at any time. Langheinrich, in his seminal article: "Privacy by design—principles of privacy-aware ubiquitous systems [108]," discussed the idea of "Access and Recourse", which essentially bolsters the significance of user agency in managing their data.

CHAPTER 7
CONCLUSION

I began my dissertation to investigate the relevance of eating behavior for two different communities, students and remote information workers, in the context of mental well-being. I conducted four user observational user studies towards this goal. In that process, I highlighted findings from several in-the-wild user studies with college students and information workers, bolstering the relevance of eating behavior in mental well-being. In conclusion, in this section, I note the contributions of my thesis, some key limitations of my work, and future directions for the eating detection community.

7.1 Contributions

At the beginning of my dissertation, I shared my thesis statement: *"By combining the strengths of EMAs to capture contextual information with passive sensors to detect when people eat, we can gather rich contextual data about an eating episode, and such data can help us investigate the relationship between eating behavior and mental well-being."*

According to the social-ecological model [32], human behaviors and well-being are part of the complex interplay between multiple stakeholders (e.g., individuals, society, community, etc.). Hence, it is ideal to understand human behaviors in a situated context. *"Situated communities consist of geographically co-located, diverse, and close-knit communities of individuals, who share distinctive social ties"* [195, 153]. To model individual well-being and understand how eating behavior is associated with one's well-being, I developed a real-time meal detection system that can gather various contextually relevant information at the time of eating. During the development and evaluation of this system, I found that one of the limitations of a wrist-mounted eating system is that it is not precise enough to detect short and sporadic eating episodes that might be present during snacking. As a result, I moved away from the wrist-mounted solution and focused inside the area through an IMU-instrumented earbud to model snacking episodes. Finally, given that eating takes place in a highly dynamic environment, especially during work hours, it is crucial to account for confounds that can regulate the timing of meals. Most studies focusing on the relationship between mental well-being and meal timing rely on retrospective surveys that can pose challenges concerning recall bias. Hence, I conducted naturalistic user studies to collect relevant confounding factors that can regulate meal timing. The final user study of this dissertation showed a causal relationship between workplace stress and deviation in lunchtime while controlling for other confounds. While such results can be best confirmed by conducting a randomized control trial study, doing such a study is unethical for practical reasons.

7.2 Limitations

In Chapter 3 though I argued that a smartwatch is more practical for detecting when an individual is eating their meals, the chapter's contribution is limited in the sense that I asked the participants to wear the smartwatch on their dominant hand. Hence, I do not have insights into the system's robustness if the smartwatch is worn on a non-dominant hand. Thomaz *et al.* found in their study that wearing a smartwatch on the non-dominant hand produced similar results compared with wearing a smartwatch on the dominant hand [227]. I did not validate this observation in my study.

In addition, the system is not robust enough to capture short and sporadic chewing episodes that are present during snacking. Solely based on wrist movements, it is difficult, if not impossible, to detect if a hand movement close to the mouth is for eating or some other activity [228, 109]. Hence, as a follow-up of this work, I moved away from a wrist-mounted eating detection system to detect short and sporadic eating episodes. In particular, Chapter 5 focuses on appropriate eating detection technologies to capture snacking episodes [149].

For both Chapter 5 and Chapter 3, despite the promise of deep modeling techniques for detecting human activities, I could not leverage its potential due to the limited quantity of data. In Chapter 3, due to the technical limitations of the device, I could not sample the data at higher sampling rates, which often improves performance for detecting fine-grained activities [97, 109]. Despite my best effort to make the data collection naturalistic, I had to impose constraints on the data collection time, location of the study, etc. In addition, I had limited control over the variety of foods the participants chose to consume during the study time. As I showed in my results, such variability in food choices and personalized chewing patterns might have contributed to the need for personalization in developing a snacking detection system.

In Chapter 4, I looked into several aspects of eating behavior, which included kinds of meals, companions during meals, location of meals, mealtimes, etc. However, this is not an exhaustive list of eating behavior. For example, I did not look into the nutritional components of foods individuals were having and I did not factor in the celebratory aspect (e.g., fondness, pleasure, etc.) of food [70]. Adding these questions would have increased the response burden on participants since there are a lot of aspects that a participant can report about the particular kind of food they are having, which was beyond the scope of the meal context that I investigated in my research.

Furthermore, I did not investigate existing social ties (e.g., with family members, partners, spouses, etc.) and the socio-economic status (SES) of the participants in Chapter 4. For the student population, it could be the case that having good ties with family members contributed to more meals with families and, as a result, better outcomes concerning mental well-being. I acknowledge that my observed results, in Chapter 4, are not causal. In addition, belonging to a higher SES could support access to healthier and constant access to food. However, I did ask the participants if they were going through any financial hardships to get access to food with a food insecurity questionnaire.

In Chapter 6, despite my best efforts to control for all confounds that can help us understand the relationship between stress levels and meal timing, I have limitations in terms of confounds in my study. For example, I did not ask for calorie estimation of foods individuals were consuming. I designed the questionnaires to have little to no chance of triggering any latent eating disorder episodes in the participants. It has been widely documented in the computing and nutrition literature that reflecting on the kind of food, such as food composition and caloric intake, might trigger eating disorder episodes [184, 111]. Hence, I made a design decision not to ask these questions. Instead, I only relied on the meal type and when people started to have that meal.

7.3 Future Work

In Chapter 3, I argued that eating detection technologies, in terms of development, has reached a point of diminishing returns, and we need to engage more in the space of application of such systems. It is vital to realize stakeholders' views outside the computing domain to understand how eating detection systems and eating-related insights can be leveraged to develop well-being assessment and intervention applications. I conclude my dissertation with a few future directions to pursue research on understanding eating behaviors at scale and how such behaviors can be leveraged in modeling one's well-being.

Moving Beyond On-Body Sensing to Detect Eating Behaviors. Most current work in this space has utilized on-body instrumentation to do the sensing. One area of work I have identified as potentially interesting and worth investigating is leveraging the infrastructure to answer the same questions. For example, students often eat at university dining halls or even pay for off-campus meals with a university ID. Meal payment data, collected in a consensual and ethical manner, can enable the inference of dietary patterns without burdening the individual. Recently, Gligorić *et al.* studied how food purchase data can be used to understand healthy and unhealthy food choices in the Ecole Polytechnique Federale de Lausanne (EPFL) university campus [65]. I suggest that the community explore these alternatives, potentially more scalable sensing techniques.

Leveraging Synthetic Data for Developing Eating Detection Systems. Data collection and annotation are among the biggest challenges in developing any human-activity recognition system. These two processes are very time-consuming, and, as a result, most activity recognition systems are not evaluated on large-scale populations. UbiComp researchers have recently explored an alternative to address this issue with limited data for HAR systems, namely IMUTube [107, 105]. However, IMUTube is currently limited to modeling data from external body surface areas such as the wrist, legs, etc. Based on my findings in Chapter 3, wrist-mounted IMUs have limitations in detecting short-eating episodes. On the contrary, IMU placed inside ear canals has better results in detecting short eating episodes (Chapter 5). Synthetic data generation pipelines such as IMUs can be extended to simulate IMU data inside the ear canal based on jaw movement.

Developing Just-In-Time Eating Interventions. Computing researchers have explored eating detection technologies to support just-in-time interventions to address deviant eating behavior, such as emotional eating [31, 175]. At the core of these technologies is the accuracy of detecting precise eating moments to deliver appropriate interventions at the right time. I am outlining two application areas that might interest the eating detection and nutrition community.

The first potential area is developing systems to support *some* aspects of mindful eating episodes. Mindful eating is *"nonjudgmental awareness of physical and emotional sensations while eating or in a food-related environment"* [147, 59]. Some characteristics of a mindful eating episode are paying attention to the food, eating without distractions, and eating at a constant rate, among other things. Eating at a constant rate can be facilitated by precise eating moment detection, perhaps in real-time, using eating detection technologies. In Chapter 4, I showed evidence that the student population takes a large portion of their meals while doing other activities. Smart spoons such as SWAN [99] have been explored to detect if someone is eating at a constant rate such that appropriate intervention can be delivered in case of distracted eating episodes.

The second application is to leverage eating detection technologies to address emotional or binge-eating episodes. Both episodes lead to overeating or consuming unhealthy food, leading to adverse well-being outcomes [219, 235]. Suppose an automated eating detection system can precisely detect the start of an eating episode. In that case, EMAs can be triggered at the moment to help users reflect on the motivation of the eating episode, such that the self-report can be factored in to deliver person-specific interventions.

From Individual Context to Social Context: Much of the computing literature focusing on using passive sensing technology for understanding well-being concentrates on an individual. This line of work could be due to the assumption that the passive sensors used for gathering well-being-centric data have a single owner. However, such an assumption will not work where individuals use shared digital devices. An example of such a situation might be a shared workplace, where multiple people use one work machine based on time-sharing. Another example might be the usage of shared iPads in a family setting. Such situations pose a unique opportunity for researchers to investigate how we can move beyond sensing individuals think leverage shared devices to understand the well-being of a unit of workers or family members.

Eating Context for Modeling Mental Well-being in Situated Communities. A plethora of computing literature argues in favor of multi-modal passive sending for gauging the mental well-being of individuals [242, 204, 153, 198, 84]. Multi-modal data promises to provide a holistic picture of an individual's daily activities that are often used to understand various well-being-centric outcomes. Hence, multi-modal data tend to perform better for predicting mental well-being compared to single modalities [153, 224]. Eating from this list of modalities has been mostly missing in the computing domain, perhaps due to the challenges of collecting real-time eating insights. I recently explored how eating-related insights and other behavioral data can model information on workers' stress levels [151]. However, the contextual data related to eating behavior gathered through computational means is limited to primarily times of eating times and some extent, what people are eating. I would argue in favor of exploring more eating-related insights that can be gathered through computational means such that we can leverage them for modeling and designing interventions to assess and improve individuals' well-being.

Balancing Harms/Benefits and Biases of Computational and Data-Driven Assessments. Throughout my dissertation, I have shown the various passive sensors for detecting different end-user activities. All these studies are conducted with non-clinical populations and in non-marginalized contexts. The student population I worked with was from a large US college campus, and the information workers were from a large technology company. It is imperative to understand where the data is being generated from and the demographics of the target population before using systems for deriving data-driven insights since such insights will most likely lead to a biased outcome due to the limited knowledge of the target population. Generalized models can be exclusionary, reinforcing stereotypes and existing societal biases.

Furthermore, if not carefully governed, sensing systems and infrastructure might lead to unforeseen negative use cases. Throughout several chapters of my dissertation, I have highlighted the need for data governance and clarity to end users about why certain data is collected from them and how they will benefit. I will reinforce this point in the conclusion highlighting the need for user agency in data collection and management while designing well-being-centric technologies.

Appendices

APPENDIX A

SURVEY INSTRUMENTS USED IN CHAPTER 4

A.1 EMA Questions for Gathering Eating Context Data

Entry Question

Please select the best option from below that defines your eating episode:

Breakfast

Brunch

Lunch

Dinner

Snack

Prefer not to answer

Other

What is motivating your eating episode?

Hunger

Emotion

Time/Scheduled eating time

Prefer not to answer

Other

Where were/are you eating?

Dining Hall

Dorm Room / Apartment

Family Home

Classroom

Restaurant

Workplace

Other

Who were/are you eating with?

Alone

Friends

Family

Partner

Colleague

Other

Do you identify the food that you are eating as healthy?

Yes

No

I do not know.

What other activities were/are you doing while you were/are eating?

Watching a presentation

Studying

Working

Doing homework

Using a laptop

Using a smartphone

Watching Television

Just eating

Chatting with someone

Other

A.2 EMA Questions for Gathering Instantaneous Mental Well-being Data

Default Question Block

How do you feel right now?

Negative	Somewhat Negative	Somewhat Positive	Positive
○	○	○	○
Relaxed	Somewhat Relaxed	Somewhat Pumped	Pumped
○	○	○	○

Over the last few hours, how often have you been bothered by feeling nervous, anxious, or on edge?

- ○ Not at all
- ○ Several times
- ○ More than half the time
- ○ Nearly every hour

Over the last few hours, how often have you been bothered by not being able to stop or control worrying?

- ○ Not at all
- ○ Several times
- ○ More than half the time
- ○ Nearly every hour

Stress means a situation in which a person feels tense, restless, nervous or anxious or is unable to sleep at night because his/her mind is troubled all the time. Did you feel this kind of stress in the last few hours?

- ○ To a great extent
- ○ Somewhat
- ○ Very little
- ○ Not at all

Over the past few hours, how often have you been bothered by little interest or pleasure in doing things?

- Not at all
- Several times
- More than half the time
- Nearly every hour

Over the past few hours, how often have you been bothered by feeling down, depressed, or hopeless?

- Not at all
- Several times
- More than half the time
- Nearly every hour

APPENDIX B

SURVEY INSTRUMENTS USED IN CHAPTER 6

B.1 Daily Check-In Survey

Stress Sensing Study: Beginning of Day

Start of Block: Relaxation

Q24
Finding your baseline

Please sit down in front of the camera and watch the following relaxing video for 3 minutes. If the video does not relax you, please close your eyes and try to relax.

Q28 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: Relaxation

Start of Block: Daily Sleep Diary

JS

Q36
Considering your sleep last night...

What time did you get into bed? This may not be the time that you began "trying" to fall asleep.

____

JS

Q37
What time did you begin "trying" to fall asleep?

____

Q6 How many times did you wake up between the time you first fell asleep and your final awakening?

	0	1	2	3	4	5	6	7	8	9	10
4 ()											

Display This Question:

If How many times did you wake up between the time you first fell asleep and your final awakening? [4] > 0

Q7 How many minutes did these awakenings last on average?

- ◯ 0-15 (4)
- ◯ 16-30 (7)
- ◯ 31-45 (8)
- ◯ 46-60 (9)
- ◯ 61-75 (10)
- ◯ 76-90 (11)
- ◯ More than 90 (12)

JS

Q38
What time did you get out of bed with no further attempt at sleeping?

____

Q10 How would you rate the quality of your sleep?

- ○ Terrible (6)
- ○ Poor (7)
- ○ Average (8)
- ○ Good (9)
- ○ Excellent (10)

Q25 Regardless of your sleep, how ready do you feel to face the challenges of the day?

- ○ Not ready at all (1)
- ○ Slightly ready (2)
- ○ Moderately ready (3)
- ○ Very ready (4)
- ○ Extremely Ready (5)

End of Block: Daily Sleep Diary

B.2 Daily EMA Questions

Stress Sensing Study: Experience Sampling

Start of Block: ESM

Considering the last 30 minutes...
... how would you rate the **demands** on you?

- very low (1)
- low (2)
- moderate (3)
- high (4)
- very high (5)

... how would you rate the **resources** you had available?

- very low (1)
- low (2)
- moderate (3)
- high (4)
- very high (5)

... how would you rate the level of **energy** you experienced?

- very low (1)
- low (2)
- moderate (3)
- high (4)
- very high (5)

... how would you rate the level of **pleasantness** you experienced?

- very unpleasant (1)
- unpleasant (2)
- neutral (3)
- pleasant (4)
- very pleasant (5)

... how would you rate your level of **stress**?

- not at all (1)
- slightly stressed (2)
- moderately (3)
- very stressed (4)
- extremely stressed (5)

... did you have any **eating episodes**?

- ◯ No (1)
- ◯ Yes (2)

... how many **social interactions** did you have?

- ◯ 0 (1)
- ◯ 1-2 (2)
- ◯ 3-4 (3)
- ◯ >4 (4)

End of Block: ESM

B.3 Daily Check-Out Questions

Stress Sensing Study: End of Day

Start of Block: Meals and Drinks

JS

Q46 **Meals and Drinks**

Please record the type (breakfast, lunch, snack, dinner) and start time of all the meals you had during the day of today before completing this form.

	Type Meal (1)	Start Time (2)
Eating episode 1 (1)		
Eating episode 2 (2)		
Eating episode 3 (3)		
Eating episode 4 (4)		
Eating episode 5 (5)		
Eating episode 6 (6)		
Eating episode 7 (7)		
Eating episode 8 (8)		
Eating episode 9 (9)		

Eating episode 10 (10)		

JS

Q44 Please record the type (coffee, tea, coke) and start time of all the caffeinated drinks you had during the day of today before completing this form.

	Type Drink (1)	Start Time (4)
Caffeinated drink 1 (9)		
Caffeinated drink 2 (10)		
Caffeinated drink 3 (11)		
Caffeinated drink 4 (12)		
Caffeinated drink 5 (15)		
Caffeinated drink 6 (16)		
Caffeinated drink 7 (17)		
Caffeinated drink 8 (18)		
Caffeinated drink 9 (19)		

Caffeinated drink 10 (20)		

End of Block: Meals and Drinks

Start of Block: Daily ESM

Q6
Considering the day of today...
... how would you rate the **demands** on you?

- very low (1)
- low (2)
- moderate (3)
- high (4)
- very high (5)

Q8 ... how would you rate the **resources** you had available?

- very low (1)
- low (2)
- moderate (3)
- high (4)
- very high (5)

Q10 ... how would you rate the level of **energy** you experienced?

- very low (1)
- low (2)
- moderate (3)
- high (4)
- very high (5)

Q12 ... how would you rate the level of **pleasantness** you experienced?

- very unpleasant (1)
- unpleasant (2)
- neutral (3)
- pleasant (4)
- very pleasant (5)

Q14 ... how would you rate your level of **stress**?

- not at all (1)
- slightly stressed (2)
- moderately stressed (3)
- very stressed (4)
- extremely stressed (5)

End of Block: Daily ESM

Start of Block: Short Stressors

Q30 **During the day of today**, how much the following factors contributed to your workplace stress?

	Did not apply today (1)	Applied with **no** impact (2)	Applied with **little** impact (3)	Applied with **some** impact (4)	Applied with **much** impact (5)	Applied with **lot** of impact (6)
Working at a high pace throughout the day (1)	○	○	○	○	○	○
Too many meetings (3)	○	○	○	○	○	○
Too many e-mails (4)	○	○	○	○	○	○
Overly packed day (6)	○	○	○	○	○	○
Too many ongoing activities or projects (12)	○	○	○	○	○	○
Sitting for too long (21)	○	○	○	○	○	○
Lack of breaks (24)	○	○	○	○	○	○
Missing exercise due to work/personal life demands (33)	○	○	○	○	○	○
Loss of sleep due to longer working hours or deadlines (34)	○	○	○	○	○	○
Unable to separate work and life demands (35)	○	○	○	○	○	○

Q31
Please add three additional factors that contributed to your workplace stress that were not captured above. Please do not enter any personally identifiable information.

	Little impact (2)	**Some** impact (3)	**Much** impact (4)	**Lot** of impact (5)
Stressor 1 (1)	○	○	○	○
Stressor 2 (2)	○	○	○	○
Stressor 3 (3)	○	○	○	○

Q29
During the day of today, how often have you...

	Never (2)	Almost Never (3)	Sometimes (4)	Fairly Often (6)	Very Often (7)
... felt that you were unable to control the important things in your life? (2)	○	○	○	○	○
... felt confident about your ability to handle your personal problems? (4)	○	○	○	○	○
... felt that things were going your way? (5)	○	○	○	○	○
... felt difficulties were piling up so high that you could not overcome them? (10)	○	○	○	○	○

Q48 **During the day of today**, where did you spend your workday?

○ Remote (e.g., home) (1)

○ Hybrid (e.g., some time in the office and some time at home) (2)

○ Onsite (e.g., Office) (3)

○ Other (4)

End of Block: Short Stressors

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