Food, Mood, Context: Examining College Students' Eating Context and Mental Well-being

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Deviant eating behavior such as skipping meals and consuming unhealthy meals has a significant association with mental well-being in college students. However, there is more to what an individual eats. While eating patterns form a critical component of their mental well-being, insights and assessments related to the interplay of eating patterns and mental well-being remain under-explored in theory and practice. To bridge this gap, we use an existing real-time eating detection system that captures context during meals to examine how college students' eating context associates with their mental well-being, particularly their affect, anxiety, depression, and stress. Our findings suggest that students' irregularity or skipping meals negatively correlates with their mental well-being, whereas eating with family and friends positively correlates with improved mental well-being. We discuss the implications of our study in designing dietary intervention technologies and guiding student-centric well-being technologies.

CCS Concepts: • **Human-centered computing** → **Ubiquitous and mobile computing design and evaluation methods**; **Empirical studies in ubiquitous and mobile computing**; • **Applied computing** → *Psychology;*

Additional Key Words and Phrases: Eating behavior, eating detection, eating context, mental health, stress, depression, anxiety, college students, wearable, affective computing

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1 INTRODUCTION

The experience of a college education not only opens a gateway to new possibilities but also challenges students in a variety of ways, such as adjusting to a new environment, living apart from family—many for the first time—and adapting to more extensive academic workload [32]. Such challenges often lead to college students adopting unhealthy eating behaviors, such as irregular eating patterns and junk food consumption [82, 91]. Unhealthy eating behavior is often associated with a variety of mental well-being concerns such as depression [62], anxiety [113], stress [54], and mood [22]. For example, irregular meal patterns, such as skipping breakfast, have been shown to negatively correlate with mental well-being [11, 95, 112]. 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. This further underscores the importance of supporting existing intervention programs or undertaking new initiatives toward encouraging healthy eating practices (e.g., not skipping major meals) within college student communities.

However, measuring eating behavior on a daily basis is rarely done consistently, because it is very challenging [5, 110, 121]. Most dietary pattern assessment methodologies rely on self-reports by individuals to reflect on their meals [53, 57]. It is generally known that self-reported food consumption quantities are under-reported or over-reported, even when logged within a period of as little as 24 hours [42, 65, 121]. This issue poses a challenge for daily dietary assessment. Moreover, gold standard dietary assessment surveys (e.g., food frequency questionnaire [131]) do not capture the social context of an individual's food consumption.

Human activity recognition using passive sensors available on pervasive devices (e.g., smartphones, wearables) can address some of the challenges of dietary assessment methods. For example, just knowing when individuals are eating can be used to infer whether individuals are consuming food at a regular or irregular time. Researchers in the computing community have formed a subcommunity around eating detection, primarily demonstrating various ways to infer when an individual is eating. However, the dietary patterns of an individual are not simply exclusively related to when an individual is consuming food.

Several contextual factors are related to eating and, indirectly, mental well-being, including with whom a person is eating [124, 134], where they are eating [122], what other activities are being performed while eating [58], or their mood around the time of eating [22].For example, regular family meals are associated with positive mental well-being. Hence, it is valuable to understand in what context people eat to assess their mental well-being.

A minimally intrusive and widely adopted way of collecting subjective contextual data is by using **Ecological Momentary Assessments (EMAs)** [13, 69]. EMAs are short questionnaires that can capture, through self-report, relevant contextual information from individuals [109]. Self-reports about life experiences are, however, often prone to recall bias if the subject is asked to recall the experience too long after the actual event [42, 57]. Hence, EMAs are most effective when asked near real time about the actual event of interest [108, 109]. As such, a real-time eating episode detector is required to harness the strength of an EMA tool to gather insights about an individual's dietary patterns and use said insights to gauge the mental well-being of individuals.

Based on the promise of gathering contextual data near an event of interest with EMAs, we used a smartwatch-based eating detection technology that triggers EMA questions when it detects that individuals are having meal-scale eating episodes [80]. Using such a system, we conducted a three-week-long study in a public US institution with 28 college students from diverse backgrounds to capture their eating behavior through computational means at a meal-level granularity. The eating detection system allowed us to study the eating behaviors of college students in naturalistic settings, which was not the case for any prior studies, which primarily relied on retrospective self-reports about eating behaviors.

In particular, by primarily focusing on the context of eating, we address the following two research questions:

> **RQ1:** How can we assess the relationship between meal frequency and mental well-being? How can we find temporal patterns in meal consumption among a college student population?
> **RQ1:** What is the relationship between instantaneous stress, anxiety, depression, mood, and eating context (e.g., eating location, meal companions, etc.) of college students?

For our first research question, we investigate meal consumption patterns of college students at both the individual level and at the group level. We found that skipping meals was strongly associated with higher levels of stress, depression, and anxiety and lower levels of energy and happiness. Such observations are aligned with insights from previous eating behavior research and helped us establish construct validity [85] of our research. For the latter, we investigated temporal patterns of meal consumption behavior and its relationship with mental well-being in a student population. We demonstrate how student meal consumption follows a seasonal pattern over a week, where students tend to miss more meals on weekdays compared to weekends.

In our second research question, we model contextual factors during meals with instantaneous stress, depression, anxiety, and mood, due to their prevalence in the student population. In particular, we use regression models, where the dependent variables are a collection of mental well-being parameters and the independent variables are a collection of contextual factors that we measured in our study. Our findings align with the propositions put forth by prior work that family meals are associated with better well-being outcomes [123, 124]. Furthermore, we show how irregularity of meal timing, especially for breakfast and lunch, can affect stress, affect, valence, and arousal of our study population, which was not observed in prior literature.

Finally, based on our findings, we 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. Our research contributes to the growing computing literature that leverages the automated analysis of human activities through computational means to understand their relationship with mental well-being in student populations [29, 30, 106].

While answering these RQs, we make the following contributions with our work:

(1) We present the results of a three-week naturalistic, uncontrolled data collection study with 28 college students to investigate how an eating detection system can be used used to understand the relationship between different contextual factors of eating and instantaneous stress, depression, anxiety, and affect.
(2) We show that our findings support previously observed relationships between eating behavior and mental well-being gathered through other forms of eating behavior data collection systems (e.g., surveys). In addition, we find newer evidence such as irregularity of meal timing is associated with poorer mental well-being outcomes.
(3) Based on our findings, we discuss the theoretical, practical, and design implications that surround this new observation on the relationship between eating behavior and the mental health of college students.

2 BACKGROUND

In this section, we first discuss literature from non-computing and computing disciplines that highlight the importance of eating behavior concerning mental well-being. We discuss our contribution to the growing body of work on the mental well-being and eating behavior of college students.

2.1 Eating Behavior and Well-being

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 [56, 111, 113]. 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, there exists a complement of individuals who do not adhere to this meal pattern. Irregular meal patterns, such as those that skip breakfast, have shown to be negatively correlated with mental well-being [95, 113]. However, several studies found that regular breakfast consumers are less stressed, less anxious, and less depressed than those who skip breakfast [112, 113]. Similar findings have been made for lunch consumption [56, 111].

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 [91], 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 [81, 124, 134]. For these reasons, Maurer and Sobal noted "food and nutrition as social problems." In addition to the company during meal-time, activities are also associated with mental well-being. An aspect of healthy eating behavior is mindful eating [55], which translates to eating without any distraction, such as watching TV [55], and eating without any judgment of the food (e.g., good, bad, etc.) [79]. Distracted eating, the opposite of mindfulness, often leads to overeating and, eventually, weight gain [14]. In addition, mindful eating has a significant correlation with a variety of mental well-being measures [2, 59]. Khan and Zadeh found that individuals who had mindful eating behaviors showed significant positive mental well-being outcomes. However, irregular eating patterns are known to be related to the brain's reward mechanisms in regulating stress [115]. It is well known that problematic eating behavior is accompanied by difficulty in regulating emotional states [125]. Several studies have also reported that people with obesity 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 [129]. Since physiological reactions to negative emotions or stress mimic the internal sensations associated with feeding-induced satiety, loss of appetite and decrease in food intake have been considered natural physiological responses to negative emotions [104].

A population particularly susceptible to negative eating habits is the young adult age group (18–25 years old). During this period of transition from adolescence to adulthood, young adults often start living independently, studying at university, or working, often resulting in irregular or inconsistent lifestyles [91]. Such lifestyles lend themselves to dietary pattern changes such as skipping breakfast and increased fast food consumption [28, 82]. Individual health behavioral patterns developed during this transition persist throughout the lifetime of an individual, influencing the health of the individual and those around them [88].

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, we focus our work on the young adult population and various contextual factors around eating to understand their mental well-being.

2.2 Eating Behavior and Well-being in Computing

Research on analyzing eating behavior through automated means has been focusing on three main aspects: (1) understanding eating behavior [26, 87, 89], (2) designing technologies to facilitate healthy eating behaviors [45, 47, 105], and (3) designing eating moment detection technologies [8, 119]. Such research, thus, covers investigating eating behavior in a continuum of disordered eating behavior to healthy eating behavior. Since we are not investigating problematic eating behavior, we will not reflect on this literature. Instead, we focus on computing literature on healthy eating behavior.

To promote healthy eating habits, Grimes et al. designed a game that aimed at educating people about healthy food choices [47]. However, human behaviors have social underpinnings, and when considered via the lens of the Social-Ecological Model [23]. 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 [23]. As such, eating behavior also comprises of 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 [45]. Chung et al. studied how peer support on social media can be used to promote healthy eating behavior [26]. More recently, Gligorić et al. investigated how social ties affect food choices in student population through a longitudinal study [44]. 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 10 low-**socioeconomic status (SES)** families [105]. They found that the use of the application improved the healthy snacking behavior of 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 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 because they are in a social situation, some eat when they are hungry, and some eat as a response to emotions such as stress [7]. HCI researchers have investigated how computing technologies can be used to mitigate stressed 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. All participants in the study were emotional eaters [22].

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 [60]. Epstein et al. developed a mobile application, Food4Thought, to promote mindful eating behavior.

2.3 Automated Eating Detection Technologies

Due to the popularity and availability of wearable sensors, researchers have investigated various approaches for detecting when an individual is eating. 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 [25, 133], (ii) camera-based sensing [68, 83], and (iii) inertial sensing [6, 120].

Yatani et al. presented BodyScope, which used a wearable acoustic sensor attached to the user's neck [133] and was able to classify four activities: eating, drinking, speaking, and laughing. Cheng et al. also used a similar design for nutrition monitoring [25]. Liu et al. used a combination of camera and head-mounted microphone to predict, in real time, whether an individual is chewing. Upon an affirmative chewing prediction, a wearable camera would take a picture of the food [68]. However, the use of wearable cameras poses challenges concerning privacy and real-time image analysis. Furthermore, Alharbi et al. investigated how natural behavior is affected by the usage of a camera for data collection [3]. To address the real-time analysis limitation, Noroha et al. proposed Platemate, which is a crowd-sourcing platform for deriving nutritional information from food photographs [83]. In recent work, Reference [4] investigated how privacy concerns can be mitigated with obfuscation strategies with wearable cameras [4]. However, privacy concerns remain an issue.

Hence, the choice of wearable inertial sensors is more practical in addressing privacy concerns compared to camera-based sensing. Most work leveraging inertial sensing for eating detection has been based on custom-made wearable devices [6, 9, 136]. The motivation for such work is to explore different areas of the body that can be used as proxies for recognizing eating episodes.

Amft et al. placed five inertial sensors on the body (wrists, upper arms, torso) for eating gesture detection [6]. Dong et al. [31] instrumented their participants' hands with a smartphone and developed a wrist-motion-based heuristic that could detect eating in real-world settings. Thomaz et al. designed an offline eating detection system using the IMU in a commercial smartwatch [120]. A number of research projects use commercial devices to detect whether an individual is eating. A recent systematic review of publications up to March 2019 reported that at least 26 studies have investigated how commercial devices can be used for detecting eating episodes [51]. More recently, Zhang et al. investigated how multimodal sensing (e.g., motion sensor, proximity sensor, ambient light sensor) can be used to detect eating episodes in-the-wild [136].

Despite the relationship between the context surrounding an eating event (e.g., meal companions, activities while eating, meal location, etc.) and mental well-being [38, 124, 134], none of the eating detection research has used the eating event to trigger EMA questions to gauge the mental well-being of individuals. A natural connection between real-time eating detection systems and EMA questions will be to 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 eating context and situate such context with individual mental well-being, which we address in our article.

2.4 Mental Well-being, College Students, and Computing

Due to the growing concerns about mental well-being in college students, CSCW and other HCI researchers, in recent years, have focused on both online (e.g., social media [103]) and offline (e.g., physical activity) [127] 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 [127]. The research team gathered passive data from a variety of sensors available on the students' smartphones and well-being data through EMA (ecological momentary assessment) [109] questions. Such an approach has been widely adopted by other researchers as well 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 [106]. Bin Morshed et al. investigated how passively sensed data from smartphones can be used to infer mood instability [13] and self-esteem [12]. Egilmez et al. investigated how a wristwatch can be used to detect stress levels of college students through a lab-based study [34].

While most of these research approaches focus on client-centric information, several research efforts investigated how infrastructure sensed data could be used to measure well-being in student population [116, 128, 135]. For example, Zakaria et al. used WiFi association logs collected by university administrations to detect stress in student population [135]. Ware et al. use similar information to detect depression in a student population based on their mobility pattern inferred from the WiFi association logs [128]. WiFi association logs have also been used to develop contact tracing tools to curb the spread of COVID-19 [49]. Apart from these sensing modalities, social media has been adopted for assessing the mental well-being of college students [100, 101].

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. We bridge this gap by studying eating behavior with a real-time meal detection system in a college student population with respect to mental well-being.

3 DATA AND STUDY

In this section, we describe the study design that comprises of our choices of mental health questionnaires, system-level details of an eating detection system that was used in the study, and, finally, the demographics of the participants that were recruited in the study. In addition, we mention the system performance of the eating detection system.

3.1 Study Design

Our study concerns examining students' eating behaviors, along with their context of eating and their mental well-being states. For this purpose, we collected data from students in a large public university in the southeast of the U.S. Our study was approved by the **Institutional Review Board (IRB)** at the same university, and we enrolled participants on a rolling basis from July 2019 to September 2019. Participants were requested to remain in the study for three weeks. Our study enrolled a total of 30 participants. Two participants could not continue with the study because of complications with the eating detection system running on their phones. Hence, we 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. Our participant pool belonged to diverse ethnic and academic backgrounds (see Table 3 for ethnicity and Table 4 for student status).

At the entry of the study, the participants answered self-report validated survey questionnaires on demographics and intrinsic traits (personality). We 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' contexts during eating episodes.

Compensation. The typical timeline of the data collection was three weeks. We adopted a (commonly used) time-differential compensation approach [24, 106]: If a participant stayed in the study for more than two weeks, then 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 [41].

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. We installed a real-time meal detection system that can identify when someone is eating. This system extends and improves upon prior work [120] and uses passive sensors on a smartwatch to detect eating episodes with an F1-score of 88% [80]. 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," then 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), and (4) simultaneous activities during meals (watching TV, using smartphone or laptop, in class, etc.). 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, then we 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.

We followed a systematic theory-driven approach to design our survey questionnaires in collaboration with psychology researchers and nutrition experts—*the details of which, along with the eating detection system, form a part of a separate research paper* [80].

Among the total consumed meals, 90% of breakfast, 99% of lunch, and 98% of dinner episodes were detected by our novel meal detection system (Table 1). The system showed a high accuracy by capturing 96.4% of the meals (1,259) 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 our study.

We 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

Table 1. Percentage of Meals That Was Detected by Our 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

(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, and so on.

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. We drew upon this consideration and did not ask our participants to list nutritional components of the food or take any pictures of the food that they were eating [27]. Rather, we asked them to report whether the food that they were eating was healthy or unhealthy. Participants reported 63% of their meals as healthy.

EMA-based Mental Well-being Assessments. Throughout the course of the study, we administered EMAs assessing participants' mental well-being states thrice a day (one between 6 and 9 AM, 11 AM and 3 PM, and 5 and 8 PM). We designed our system to prompt these EMA assessments independent of individual eating episodes of participants. Our design decision is based on the rationale of minimizing confounds of individual meals and immediate mental health changes, as observed in prior literature [16, 71]. 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 [106, 127].

Affect. The Russel's circumplex model of affect [98] 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, we used a two-item questionnaire motivated by prior work [75]. 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, we used a validated single-item questionnaire [39] 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, we draw upon the PHQ-2 instrument [63] to design our 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, we draw upon the GAD-2 instrument [90] to ask the participants: (1) *"Over the last few hours, how often have you been bothered by feeling nervous, anxious, or on edge?"* and

Table 2. Descriptive Statistics of the Mental Health EMA Questions Answered by the Participants

EMA	Minimum	Maximum	Mean	Standard Deviation	Compliance Rate(%)	Total 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

Table 3. Ethnic Identity of Participants in the Online Survey

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

Table 4. Student Distribution According to Current Academic Year

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

(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 2 represents the descriptive statistics of the EMAs gathered as part of the mental well-being assessment.

3.2 Ethical Considerations

The study was conducted after getting approval from the authors' IRB. Due to ethical considerations, participants who had an eating disorder or had food insecurity were excluded from the study, since our 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 [1, 70]. 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 METHODS

In this section, we describe our methods for addressing the research questions. Recall our 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 our study, since the relationship between meal frequency and mental well-being is a well-studied phenomenon. Hence, we adopt features that are used in studies that investigate the relationship between meal frequency and mental well-being. Once we establish the construct validity of our study, we 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, we investigate how contextual factors during meals are associated with the mental well-being of our participants. We develop linear regression models, where the independent variables are various mental well-being measures, and dependent variables are meal contexts. In particular, we provide details on how we extracted features for each variable.

4.1 RQ1: Meal Frequencies and Mental Well-being

To address our first research question (*How can we assess the relationship between meal frequency and mental well-being? How can we find temporal patterns in meal consumption among a college student population?*), we look into meal frequencies with respect to various well-being measures. We break our analysis down into two aspects: group level and individual level. In the group-level analysis, we 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 our 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, we conducted this analysis.

For the individual-level analysis, we 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 [112].

4.1.1 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 [122–124]. Hence, we adopted the same approach in this analysis. To investigate the relationship between meal frequency and mental well-being, we analyzed the average number of breakfasts, lunches, and 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, we took the average of stress, depression, anxiety, valence, and arousal per individual over the period of the study.

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

4.1.2 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 we are looking at a group-level meal consumption pattern, we 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, we got 17 days of overlapping days, and we used data for those days for further group-based analysis.

For overlapping days, we aggregated the total meal counts per individual. Then we aggregated meal counts for the total number of participants on a particular day. We 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, we scaled meal counts, stress, anxiety, valence, arousal, and depression values via min-max normalization to [0, 1]. Once the features were extracted, we conducted a Pearson correlation analysis with the normalized total meal count and normalized mental health states of participants on that day.

4.2 RQ2: Meal Context and Mental Well-being

4.2.1 Modeling Methodology. For every well-being measure (*MH*) we build linear regression models with *MH* as the dependent variable and various eating contexts as independent variables. We control for age, gender, education level, and personality types per individual (see Equation (1)). Our inclusion of the covariates is influenced by prior literature [37, 96, 122]. We further included interaction terms (degree 2) in the regression model.

$$\mathcal{MH} \sim age + gender + education + personality + M_{\text{healthy}} + M_{\text{num.}} + M_{\text{dev.}} + M_{\text{com.}} + M_{\text{loc.}} \quad (1)$$

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

4.2.2 *Calculating Independent Variables.*

Number of Meals. Regular consumption of meals, or lack thereof, is used as a proxy for mental well-being. Hence, we use the total number of meals individuals had each day as one of our 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. We 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, we use the total number of self-identified healthy meals individuals had each day as one of our 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 [42] to even months [33], it is difficult—if not impossible—to gauge how much individuals are varying from their regular meal time [121]. 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, we 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, we knew when individuals were having specific meals. Once we extracted this information per meal per individual, we 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 [124, 134]. For example, Utter et al. found a strong negative correlation between family meals and depression among adolescents. Based on such insights, we used this phenomenon as one of our features [123, 124].

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. We 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. We have provided multiple pieces of evidence in the literature that

Table 5. Relationship between Meal Frequency and Mental Well-being

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

The (*) indicate statistically significant ($p < 0.05$) differences in correlations.

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, we 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.

4.2.3 Calculating Dependent Variables. For dependent variables, we looked into all mental well-being measures described in Section 3. We calculated the average level of stress, depression, anxiety, valence, and arousal per day per participant.

5 RESULTS

In this section, we highlight our findings for both research questions. With our first question that looks into meal frequency and mental well-being, we situate our findings with theoretically grounded observations in eating and mental well-being literature. In particular, we show how skipping meals are correlated with poorer mental well-being outcomes. As an extension of our first research question, we show how group-level behavior can be used to understand how students follow a seasonal pattern every week in meal consumption and how this pattern 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 we capture through our study.

With our second research question, we 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 we found that evidence in our research as well. However, some observations such as regularity in meal timing and its association with mental well-being are unique to this study. We highlight these results in the next two subsections.

5.1 RQ 1: Meal Frequency and Mental Well-being

5.1.1 Individual-level Meal Frequencies. For obtaining quantitative insights into how meal frequencies and mental well-being were correlated on an individual level, we 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 5 shows the results of this correlation analysis.

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 [72, 94] compared to their cohort who skipped meals.

Then, we focused our analysis on specific meals such as breakfast, lunch, and dinner and investigated how their frequency is correlated with an individual's mental well-being. We observed that for some meals, such as breakfast and lunch, their frequencies were significantly negatively correlated with stress, anxiety, and depression. Our 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

Table 6. Relationship between Meal Frequency and Mental Well-being

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

The (*) indicate statistically significant ($p < 0.05$) differences in correlations.

et al. found that skipping major meals such as lunch was a significant contributor to poorer mental health outcomes [117]. Smith found that adolescents who had regular breakfasts were less depressed, less anxious, and less stressed compared to adolescents who skipped breakfast [112]. We did not see any significant correlation between dinner frequency and mental well-being. This is due to the fact that our participants did not generally skip dinners throughout the study [80].

In addition to stress, depression, and anxiety, we also investigated how affect is associated with meal frequencies. We 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 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 over the course of the study. This has been a well-established phenomenon in adolescents [17, 130]. Next, we move on to investigating whether we can see any temporal pattern in students' meal consumption and well-being.

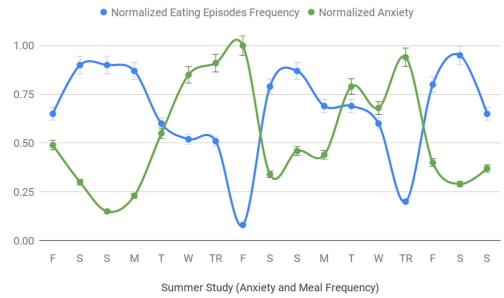
5.1.2 Group-level Meal Frequencies. Figure 1 captures the relationship between meal frequencies and various mental well-being measures. It can be seen that for stress, depression, and anxiety with respect to the meal frequencies, there is an inverse trend with total meals. However, this trend has a seasonality. In particular, during weekends, students generally tend to be less stressed, anxious, and depressed and miss fewer meals compared to weekdays (see Figure 1). Previous studies also reported that students were doing better during weekdays compared to weekends with respect to their mental well-being [86, 93]. 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.

For quantifying this observation, we did a correlation study between meal frequencies and mental well-being measures for all the overlapping days. Table 6 shows the correlation coefficient between meal frequencies and mental well-being. Skipping meals is strongly associated with a variety of mental well-being measures in several studies [66, 67]. Hence, our observation is supported by previous studies that investigated the relationship between meal frequencies and mental well-being. In addition, we also extended the insights into how various kinds of contextual information can be used to assess students' mental well-being. We explain our findings in the next subsection.

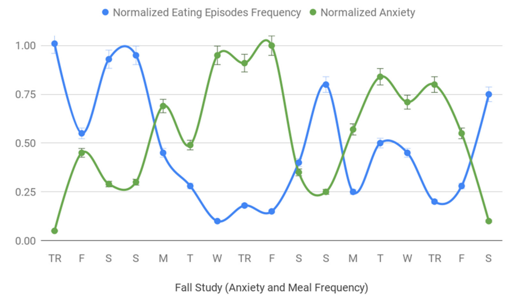
5.2 RQ2: Relationship between Context and Mental Well-being

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

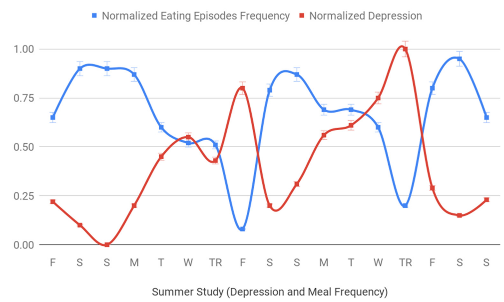
5.2.1 Meal Company and Mental Well-being. The company with whom an individual is taking their meals is a very important aspect of an individual's well-being, and it has been studied in health disciplines [36, 124]. We found similar evidence in our results. More specifically, we found that family meals were negatively associated with stress, depression, and anxiety (see Table 7). Such meals were positively associated with the valence of individuals. These observations essentially mean that family meals were associated with lower stress, depression,



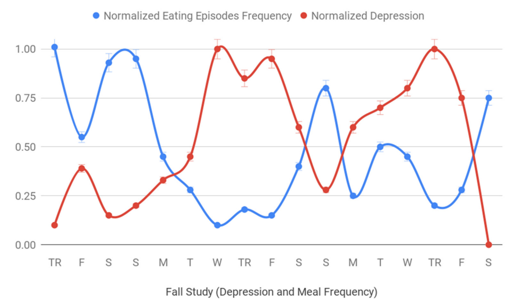
(a) Anxiety and Meal-Frequency (Summer)



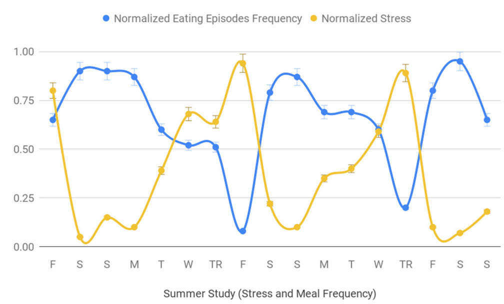
(b) Anxiety and Meal-Frequency (Fall)



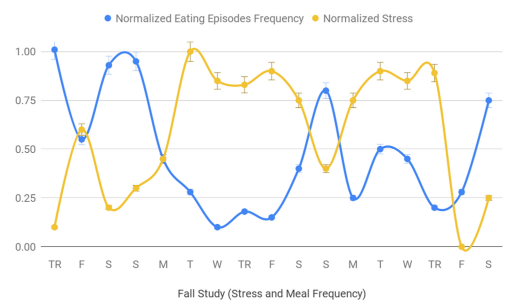
(c) Depression and Meal-Frequency (Summer)



(d) Depression and Meal-Frequency (Fall)



(e) Stress and Meal-Frequency (Summer)



(f) Stress and Meal-Frequency (Fall)

Fig. 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, we 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.

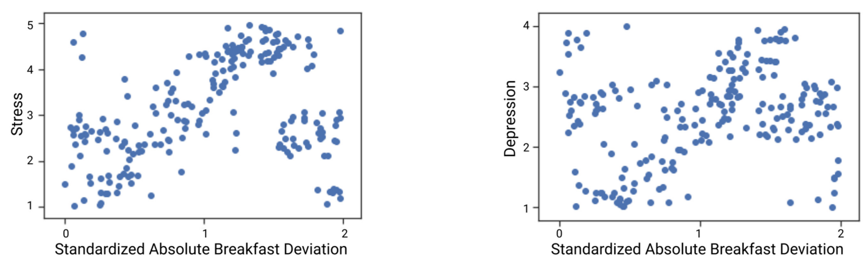
anxiety, and a happier mood. Figure 3 shows the relationship between stress and the number of meals taken with family.

Our 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, and so on [124]. 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 [36]. Our findings confirm the importance of family meals and mental well-being. In particular, we found that family meals are a strong indicator of stress, depression, and the valence of college students.

Table 7. Standardized Coefficients of Linear Regression Models with Contextual Features as Independent Variables and Mental Well-being Attributes as Dependent Variables

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***

Only statistically significant relationships are shown in the Table. (Stat. significance: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$). Each column represent results for independent models.



(a) Breakfast Deviation Time vs Stress
(b) Breakfast Deviation Time vs Depression

Fig. 2. The figure one the left shows the relationship between meal deviation time and self-reported stress level. The figure one the right shows the relationship between meal deviation time and self-reported depression level. Breakfast deviation time is absolute, which means that the breakfast deviation could be early or late breakfast. Standardized absolute difference is calculated based on the mean time of an individual's recorded breakfast episodes.

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 [20]. Meals are not necessarily meant to address hunger and nutritional needs, and they are means for interaction and socialization as well [7, 46]. Family meals or social meals serve as an opportunity to interact with people. Such interaction has positive implications on well-being [123]. Hence, those interactions might be the underlying factor of why we found meal companies to be an important predictor of mental well-being.

5.2.2 Deviation from Regular Meal Time and Mental Well-being. We found that deviation in breakfast and lunch had a strong association with a lower level of activation. This means that if individuals were not having

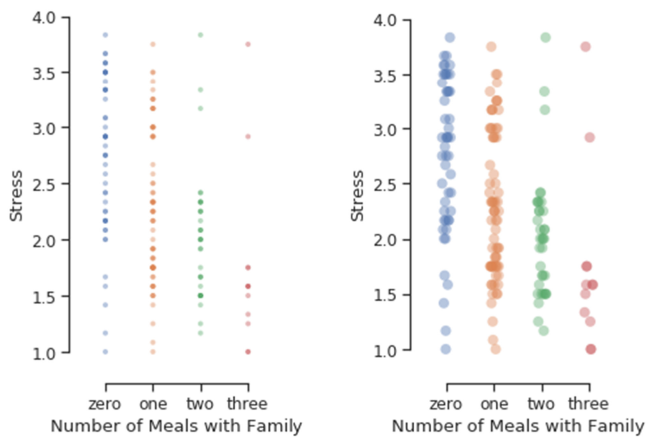


Fig. 3. Relationship of stress with respect to the total number of meals consumed with family in a day. The right plot is the same representation of the plot on the left; however, we have introduced jitter in the right plot so that it exposes data points that might be overlapping on each other on the left plot.

meals at their regular mealtime, then they felt less energetic. Deviation from the breakfast time was strongly associated with high stress (Figure 2(a)) and depression (Figure 2(b)) 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 to reflect for participants about when they had each meal. 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 [42] to even months [110]. It is difficult—if not impossible—to gauge how much individuals are varying from their regular meal time [110]. There is little evidence that suggests that delayed meal consumption is associated with high caloric food intake [10]. However, to the best of our knowledge, there is no prior study that investigates the relationship between meal timing and mental well-being, which we established through our study.

5.2.3 Meal Location and Mental Well-being. We 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. The transition from home to dorm is identified as a significant stressor for college students [97]. Hence, such transition, added with a variety of 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 we did not see any evidence of negative well-being for eating at dorms, we can imply the benefit of having access to families during meals, and we show that with our results.

6 DISCUSSION

Through our research, we highlighted the significance of the eating context in relation to student mental well-being. In particular, we showed that skipping meals—breakfast and lunch—were strongly correlated with higher levels of stress, anxiety, and depression. In addition, we 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, we 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, we now formulate theoretical, practical, design, and policy implications for computing researchers and campus stakeholders.

6.1 Theoretical Implications

6.1.1 Implications for Mental Well-being Assessment Research. Our 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, our 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. Our study is situated in the theory that human behaviors have social underpinnings, and when considered via the lens of the Social-Ecological Model [23], 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 [23].

Existing psychology and nutrition research has noted that the dining table provides an opportunity for conversation, storytelling, and reconnection [126]. 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 our 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 [48]. Field and laboratory studies have demonstrated that the presence of other people can alter many different forms of behavior [15]. This phenomenon is termed social facilitation [50]. 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. Our 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.

We 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 [74]. 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 7, the R^2 value is 0.23, which means that only 23% of the stress score can be explained through the independent variables that we investigated. In fact, the instantaneous stress detection problem is a well-studied problem by means of other sensing modalities (e.g., facial expression [43], heart rate [21], electrodermal activity [107], etc.). We are 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 our article was to establish the evidence that different 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 we have studied in our article.

Furthermore, a plethora of computing literature argues in favor of multi-modal passive sensing for gauging mental well-being [13, 52, 102, 106, 127]. 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 [13, 118]. Eating and context around eating have so far been

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

missing from the list of modalities, perhaps due to the difficulty of gathering continuous longitudinal eating-related data. More recently, Lakmal 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 [77, 78]. However, the relevance of such eating context remains unexplored in mental well-being assessment problems. We 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. We hope that future mental well-being assessment-centric problems with incorporate eating-related contextual data for modeling the mental well-being.

6.1.2 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 a challenging task, since most of the dietary assessment methods are based on subjective recall [19, 53, 57]. Such recall can vary from a day to a few months [110]. Delays as little as 24 hours in answering questions related to dietary portions can generate significant recall errors [42, 57]. 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 [110]. We showed the importance of these two aspects, among other things, concerning students' mental well-being. For example, we found that deviation at breakfast time was associated with a high level of stress, and deviation at lunchtime was associated with low activation. Besides, we found that meals with family were strongly associated with low levels of stress, depression, and anxiety. Hence, our research has implications for the further development of eating behavior assessment instruments that incorporate the social context and temporal context of individual meals.

6.2 Practical and Design Implications

It has long been recognized that health and well-being are closely linked to a variety of sociocultural, political, and physical-environmental conditions within communities [18]. Various pathways exist by which changes in the physical and social conditions of communities enable individuals to increase control over and improve their health [61]. 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 [76].

Accordingly, we discuss the practical and design implications of our work by borrowing the lens of the social-ecological model [23]. 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 [99]. We use the social-ecological model to situate our discussion on how technology design can leverage our findings.

6.2.1 Implications for Dietary Intervention Technologies. We have shown both 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 (Section 5.1.2). In addition, we showed that deviations in meal timing, especially for breakfast and lunch, are associated with various mental well-being measures (Section 5.1.2). Hence, a natural intervention approach would be to remind students to take their meals on time if they are missing out on meals. Using the same eating detection technology that we have used in our study, it can be inferred when students are not taking their meals, and 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, then it can remind individuals to take meals at regular times, since we have uncovered that, especially for breakfast and lunch, the deviation is significantly correlated with poorer mental well-being measures. Our 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 [132]. 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 [23]. However, adopting such an intervention approach requires significant scrutiny of privacy and ethical concerns, which we have described in detail in the following section. The meal detection system used in our research brings us much closer to designing such personalized interventions.

6.2.2 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 [26]. We provided evidence that can inform this existing practice to further support specific healthy eating behavior. In particular, we showed that irregular mealtimes are associated with high levels of stress and, and skipping meals is associated with higher levels of stress, depression, anxiety (Section 5.2.2). 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. Our 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.

We have shown with whom an individual is having a meal is a significant indicator of mental well-being for college students. Specifically, we 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 (Section 5.2.1). However, we acknowledge that we did not investigate the existing family relationships of our participants. Hence, our 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 [45]. 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.

6.2.3 Implications for Data-driven Community-centric Interventions. In our results, we found evidence that students skip more meals during weekdays as opposed to weekends (Section 5.1.2), 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 [114]. 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 our article 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.

6.3 Ethical and Policy Implications

In the study design section, we discussed the exclusion of students with food insecurity and students with eating disorders due to ethical and clinical obligations (Section 3.2). 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 [35]. If any eating detection or intervention approach is used in student populations to understand or change their eating behavior, then they should be carefully studied before to understand whether they belong to, at least, any of these categories.

Finally, our research has implications for policy design as well. We have demonstrated that missing out on major meals is a significant indicator of an individual's well-being (Section 5.1.1). Besides, we have also shown that having companions during meals has a positive impact on students' mental well-being (Section 5.2.1). Several other studies have shown similar insights for student populations [123, 124], 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 [84]. 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. Our work has policy implications in spreading awareness and education regarding healthy eating on college campuses. Drawing on the insights from our analyses, colleges can conduct awareness drives and public service announcements to promote and encourage healthier eating practices.

6.4 Limitations and Future Work

In this study, we looked into several aspects of eating behavior, which included kinds of meals, companions during meals, location of meals, and so on. However, this is not an exhaustive list of eating behavior. For example, we did not look into the nutritional components of foods individuals were having and we did not factor in the celebratory aspect (e.g., fondness, pleasure, etc.) of food [46]. Adding these questions would have increased the response burden of our 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 we investigated in our research. Future research can investigate ways of capturing such granular information about the food characteristics, since such data might add a more holistic idea of an individual's eating behavior and how it can be used as a proxy for assessing the mental well-being of college students.

Furthermore, we did not investigate existing social ties (e.g., with family members, partners, spouses, etc.) and the SES of our participants. 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. We acknowledge that our observed results are not causal. In addition, belonging to a higher SES could support access to healthier and constant access to food. However, we did ask our participants if they were going through any financial hardships for getting access to food with a food insecurity questionnaire. Including SES questionnaires could make future research stronger for investigating the causality of our observed relationships.

Another limitation of the eating detection system is that it is not capable of detecting snacking-level events. There are several research efforts that have been undertaken in the last few years that can be potentially used for detecting snacking. However, such systems have limitations from a feasibility standpoint. For example, Laput and

Harrison developed a fine-grained activity detection system that uses a commercial smartwatch, which shows the potential for building snacking detector. However, the machine learning model runs on a laptop, and this has limitations to running on smartphones, since it uses a deep model [64]. More recently, Bedri et al. investigated how a smart glass can be used to automatically detect and log eating events [8]. However, using such systems is not practical for us, since we plan to collect data on a longitudinal basis and expect students to wear devices throughout their day. Hence, using commercial devices to passively understand snacking behavior in real time, to the best of our knowledge, is not yet feasible. We do acknowledge that having an understanding of snacking behavior along with meal consumption behavior would paint a clearer picture of an individual's eating habits and their correlation with mental well-being, and that is one of our future research goals.

We conducted our study by recruiting 28 participants—while our participant pool is diverse (see Section 3) and is comparable with sample sizes of similar student-centric well-being studies with passive technologies [92, 127], we do, however, acknowledge that our results may not generalize or be reproducible in the same way to make population-scale student estimates. Our work lays the foundation for conducting future studies that can adopt similar study methodologies to examine larger and longer participant datasets. We caution against making clinical claims on the basis of our results. We further acknowledge that our work does not study causality between eating behavior and mental well-being. Therefore, even though our study finds certain forms of eating behaviors to be correlated with certain kinds of mental well-being, their causal relationship remains to be explored in future research.

7 CONCLUSION

In this article, we have demonstrated the relevance of eating context concerning mental well-being based on a three-week-long study in a US-based college student population. In particular, we showed that skipping meals, especially breakfast and lunch, were strongly correlated with higher levels of stress, anxiety, and depression and lower level of activation and happiness. Besides, we showed that meals with family and friends were associated with lower levels of stress. Finally, we showed the relevance of regularity of meal timing, since irregular timing in meals, especially breakfast, was associated with higher levels of stress. We grounded our observations in theory and discussed the implications of our study in guiding student-centric well-being technologies.

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