Self-tracking for Mental Wellness: Understanding Expert Perspectives and Student Experiences

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Self-tracking for Mental Wellness: Understanding Expert Perspectives and Student Experiences

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ABSTRACT
Previous research suggests an important role for self-tracking in promoting mental wellness. Recent studies with college student populations have examined the feasibility of collecting everyday mood, activity, and social data. However, these studies do not account for students' experiences and challenges adopting self-tracking technologies to support mental wellness goals. We present two studies conducted to better understand self-tracking for stress management and mental wellness in student populations. First, focus groups and card sorting activities with 14 student health professionals reveal expert perspectives on the usefulness of tracking for three scenarios. Second, an online survey of 297 students examines personal experiences with self-tracking and attitudes toward sharing self-tracked data with others. We draw on findings from these studies to characterize students' motivations, challenges, and preferences in collecting and viewing self-tracked data related to mental wellness, and we compare findings between students with diagnosed mental illnesses and those without. We conclude with a discussion of challenges and opportunities in leveraging self-tracking for mental wellness, highlighting several design considerations.

Author Keywords
Self-monitoring; self-tracking; personal informatics; Quantified Self; mental health; mental wellness; health communication; patient–clinician communication.

ACM Classification Keywords
H.5.2. Information interfaces and presentation (e.g., HCI): User-centered design; J.3. Life and medical sciences: Health.

INTRODUCTION
Mental health and wellness concerns are a major public health issue, with an economic cost in the US of over $2.5 trillion per year [44]. Although people of all ages are affected by stress and poor mental health, these concerns are particularly rampant in undergraduate and graduate student populations. Student emotional health is at an all-time low as students face increasing stress and academic pressures [12]. In a recent national survey of college students, 85% of students reported that they felt overwhelmed by demands over the last year and 47.8% reported feeling that things were hopeless [1]. A widely-recognized college mental health crisis [5,13,34] has led to overwhelming demand on counseling services at campuses across the country [40].

A variety of efforts aim to make the identification and treatment of mental health concerns more readily accessible. Companies like Ginger.io [19] use mobile sensing to provide app-based mental health coaching at opportune moments, while Computerized Cognitive Behavioral Therapy (CCBT) allows patients to undergo remote treatment for anxiety [37], and insomnia [39]. Meanwhile, the StudentLife study at Dartmouth College [44] has demonstrated that it is possible to use automatic smartphone sensing to gather passive data corresponding to certain behaviors (e.g., attending a class or a party). By combining this passive sensing with ecological momentary assessment (EMA) responses, researchers have begun to draw correlations between tracked behaviors and self-reported indicators of mental well-being.

Understanding user preferences is crucial to the adoption of any health monitoring system [3], yet no prior studies, of which we are aware, bring to light the experiences and challenges of those who actually self-track to achieve mental wellness goals. We aim in this work to better understand both the general and mental wellness-focused practices of student self-trackers and the expert perspectives of student health professionals. Together, these viewpoints contribute to a foundational understanding of the role that self-tracking can play for the student population, and its potential to help—or hinder—stress management and mental wellness.

We focus our scope of mental wellness on the issues—both clinical and non-clinical—of stress, anxiety, and depression, as they are the three mental health concerns most prominent for students [6]. We further define stress in the context of this work as negative stress which, while sometimes adaptive, can lead to negative psychological and physical effects over time [2,28]. This definition guided our work but, importantly, we also aimed to better understand how student stress is perceived by students and clinicians; specifically, how they approach subjective evaluations of students' ability

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to cope with the demands posed by student life, and affective responses to that evaluation.

This paper makes the following contributions:

(1) An investigation of student health professionals' experiences with and perspectives on the role of self-tracking for student mental health and wellness, through which we identify ways that self-tracking can be particularly beneficial or harmful, and distill expert perspectives on leveraging active and passive sensing to support students' mental wellness goals.
(2) Results of a survey with 297 college and graduate students, probing their self-tracking practices, their attitudes toward the value of self-tracking for mental wellness, and their data-sharing preferences.
(3) Further investigation into how student self-trackers with and without diagnosed mental illness use self-tracked personal data to support individual mental health and wellness management.

Findings from our studies allow us to examine how student self-tracking practices compare to clinicians' recommendations. We conclude with a discussion of the challenges and opportunities we see in leveraging self-tracking for student mental wellness, highlighting several considerations for the design of self-tracking technologies.

RELATED WORK

Personal Informatics and Self-tracking

Personal informatics is a growing field based on *collecting* one's own personal information and *reflecting* on it [13,26]. Personal informatics systems often utilize *self-tracking* technologies, many of which include goal-setting and data review capabilities to report status and progress toward goals over time. Such self-tracking applications have been effective in promoting physical activity [27], weight loss [4], and medication adherence [25], improving use of sleep diaries [7] and productivity [24], and influencing what people attend to online [29].

Self-tracking in Mental Health Contexts

Just as it is important to manage health behaviors such as sleep and exercise, the HCI community has long recognized the importance of tracking psychological elements of health. Work in this space has shown the potential of sensing technology to identify, track, and improve stress and mental wellness: stress has been detected through typing analysis [45] and computer mouse pressure [21], while wearable sensors such as AutoSense [16] and SPIRE [41] show potential to detect stress using physiological signals.

However, stress and mental wellness bring unique challenges to the design and evaluation of self-tracking technologies. Prior systems have largely focused on the development of psychometric sensing and self-regulation of behaviors, and there is limited understanding of how people have appropriated such systems to meet their wellness goals. We expect that those who track for mental wellness will have different experiences and encounter different challenges than those who track other types of personal information, as there are many social and environmental factors that can affect mental well-being [20,37] and make it more challenging to monitor.

Moreover, as in other health contexts, self-reflection is crucial to the tracking process for stress management and mental well-being—but holds additional challenges in this domain. People can be overwhelmed by their data [46] and ashamed of what the data reflects [20,42]. Additionally, it is non-trivial to choose when and how to display feedback. Biofeedback displays in the form of games have been found to help reduce stress levels more quickly [10], but representations matter: displaying someone's stress data does make them more aware of their stress levels, but can also exacerbate their stress [33].

Communication, Sharing, and Privacy

Many self-trackers want not only to collect and reflect on their own data but also to share the data with others including their healthcare team, though their sharing preferences may differ based on what is shared and with whom. Sharing health information with family and friend networks is a way to control one's health identity [22], keep loved ones up-to-date [34], gain social support [32], and share experiences with others in similar situations [22]. Sharing self-tracking data can also enable shared motivation, accountability, and recommendations [15].

Sharing self-tracking data with one's healthcare team can be more challenging. Healthcare providers in primary care settings already face information overload and difficult time constraints. They may also have concerns about the quality, completeness, or relevance of patient-generated data, as well as potential legal issues [48]. Moreover, though providers may disagree, patients often believe that what they have to share is uninteresting, or that sharing certain information may not help [22]. These perceived barriers to sharing relevant data can hinder the assessment of—and discussion around—mental wellness in clinical contexts and understanding how to overcome them remains an open challenge.

INFORMING RESEARCH DIRECTIONS

Our research began with a more general attempt to understand health-related use of self-tracking technology in student populations. To gather informal perspectives of experts, we conducted four focus groups over 11 months in 2015, with a total of 10 student health professionals (3-5 in each focus group, with some overlap between groups) at our home institution (Study 0 in Table 1). These focus groups served as a preliminary investigation into how experts perceive the role of self-tracking in improving student health. Experts emphasized students' struggles to recognize symptoms and triggers of their stress, their likelihood of engaging in negative behaviors to relieve stress, and their challenges in developing self-care skills that could mitigate chronic stress and other conditions. Student health professionals also commented on their own challenges in identifying potential mental health and wellness needs with limited information. Informed by

Study	Methods	Analysis	Participants	Specialty
Study 0: Informing research directions	Focus groups	Thematic analysis	Student health professionals ($n = 10$)	Primary care (4), psychiatry (2) women's health (2), health promotion (1), nutrition (1)
Study 1: Understanding clinician perspectives on self-tracking data for mental wellness in clinical contexts	Card sorting sessions	Think-aloud, inductive iterative thematic analysis, descriptive statistics	Student health professionals ($n = 14$)	Psychiatry (9), primary care (2) women's health (2), health promotion (1)
Study 2: Understanding student perspectives on self-tracking for mental wellness	Online Qualtrics survey	Closed-format questions: descriptive statistics and non-parametric comparison tests; Open-format questions: inductive thematic analysis	Undergraduate and graduate students ($n = 297$) Undergraduate ($n = 211$), Graduate ($n = 86$) Male ($n = 185$, 62.29%), Female ($n = 108$, 36.36%) Declined to specify ($n = 4$, 1.35%)	

Table 1. Study design for the focus groups, subsequent card sorting study, and student survey.

these focus groups, we narrowed our research questions and generated student personas for our subsequent study based on recurring examples and scenarios mentioned by student health experts. The focus groups, subsequent card sorting study, and student survey were each approved by our institution's IRB; informed consent was obtained for each participant in each study.

STUDY 1: UNDERSTANDING EXPERT PERSPECTIVES

Our first study focused on elucidating expert perspectives on the role of active (e.g., EMA) and passive sensing for mental wellness applications (Study 1 in Table 1). Human communication and expert review are still important in therapeutic contexts, so we aimed to understand how self-tracking currently alters these conversations and how this might manifest differently in the future.

We conducted study sessions with 14 student health professionals from two universities, over February–March 2016, to understand the current and future role of students' personal, self-tracking data in the context of stress management. All study participants were employed by on-campus health services and worked directly with students; seven had participated in the initial focus groups. Nine participants worked in psychiatry, two in primary care, two in women's health, and one in health promotion.

Study Material and Procedure

Our study combined individual card sorting (Fig. 1) with note-taking and retrospective think-aloud, to structure feedback on specific data types while permitting flexibility in grouping, sorting, and noting additional information. These methods allowed us to probe what specifically experts found useful and in which scenarios, and whether considerations or concerns arose surrounding specific types of data.

Card sorting materials consisted of 26 data types from Dartmouth College's StudentLife study [43] so as to include a combination of actively- and passively-sensed data types that are geared towards student experiences. Data types included passively-sensed proxies for routines and behaviors (e.g., bed time, minutes of vigorous exercise), EMA-based health measures (e.g., Patient Health Questionnaire (PHQ-9) depression scale), and data unique to student life such as class attendance (inferred through GPS data and student schedule), dining hall visits, and workload.[1] These data are feasible to collect now, and were found to be potentially useful to clinicians during our initial focus groups.

We also created representative hypothetical situations that could be discussed in the context of stress management. Each situation was made up of a persona and a clinical scenario, based on the findings from our prior focus groups:

Persona 1: Lack of sleep

- *Assessment:* you are looking over this data in advance of a consultation with a student who is having trouble sleeping.
- *Communication:* you are discussing this data in consultation with the student.
- *Self-care planning:* you are helping the student think about strategies for managing his/her stress and sleep issues going forward.

Persona 2: Poor diet

- *Assessment:* you are looking over this data in advance of a consultation with a student who is not eating well.
- *Communication:* you are discussing this data in consultation with the student.
- *Self-care planning:* you are helping the student think about strategies for managing his/her stress and improve their nutrition going forward.

For each of the six card sorting rounds, we gave participants 26 cards—each containing the name of one StudentLife data type—and introduced a hypothetical situation (described above). In round one, for example, we told participants that

[1] The full StudentLife dataset is available at `http://student-life.cs.dartmouth.edu/dataset.html`

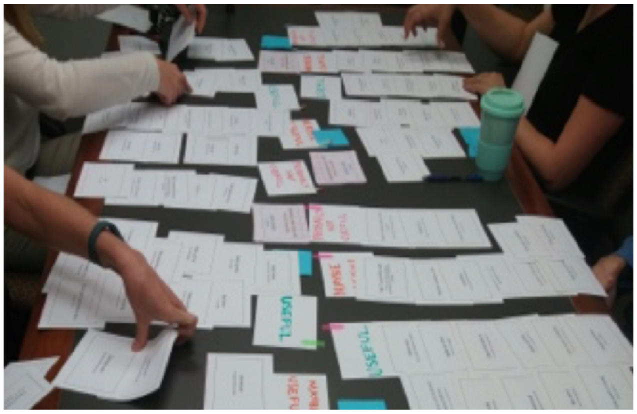

Figure 1. A card sorting session in progress.

they were reviewing data in advance of a consultation (assessment) with a student who had high-normal levels of stress but whose primary concern was lack of sleep. We asked participants to sort their 26 data type cards into *useful*, *maybe useful*, and *probably not useful* categories based on perceived relevance of the data type to the persona and scenario. We also encouraged participants to group data types that would be important to review together, and provided many blank cards to accommodate any additional data types that were not included. After each round, participants conducted a retrospective think-aloud about the results of their sorting, as we took notes and photographed the results. Each session lasted around 60 minutes, and all sessions were audio- and video-recorded and transcribed verbatim.

Data Analysis and Findings

Our goal was to use the card sorting to elicit structured feedback through a think-aloud protocol. We analyzed data with descriptive statistics (illustrating usefulness of each data type across and between participants, personas, and scenarios), but the bulk of our data analysis was qualitative. Using the card sorting results as a guide, we examined session transcriptions for trends, outliers, and representative quotations. We found some trends in data usefulness overall, with a few data types considered commonly useful across all personas and scenarios. The six data types reported most frequently useful (*vigorous exercise, sleep quantity, class attendance, academic workload, bed time,* and *depression scale)* were incorporated into the design of our student survey.

Most importantly, our results showed clear differences in perceived usefulness of other data types across different personas and scenarios. In the sections below, we illuminate these differences as well as other relevant findings and expert commentary. Throughout our findings, we refer to student health professionals as "HP" (e.g., HP1).

Persona 1: Lack of Sleep

Not surprisingly, the most useful data types for understanding student stress across all scenarios for Persona 1 were related to sleep habits: *sleep quantity*, *sleep quality*, *bed time*, and *wake up time*. Despite the common high-level ranking of these data types, however, a deeper analysis revealed considerations unique to student life. Participants were especially interested in *bed time* and *wake up time* data due to a concern that sleep is happening at unusual hours, with HP4 explaining that *"for a lot of people, a lot of students… their sleep isn't always just going to be sleep at the end of the day, so that's really important."*

Most participants were also eager to assess whether Persona 1's actual behavior supported their account of it, and whether this had changed over time. They clarified the importance of elaborating on any sleep-related data to understand the context behind the numbers, noting the role that environmental factors and sleep hygiene [31] can play. Participants were interested in augmenting sleep data with *time spent on phone apps*, worrying that *"they're staring at an app instead of sleeping… [or] they're constantly checking a particular app in the middle of night… [so] they're activating their brain in a way that won't engender a rest time for the brain"* (HP8).

Most participants found *class attendance* and *academic workload* to be useful data types for Persona 1 as well. HP5 noted the importance of understanding the relationship between sleep and academic data, explaining that *"this is kind of [a] which came first, the chicken or the egg… are these [academics] being impacted because of lack of sleep or [is] this impacting sleep habits? That's important to assess."*

Persona 2: Poor Diet

The most useful data for understanding stress across scenarios for Persona 2 included *dining rate* (useful to all participants in all scenarios) and all but one participant felt similarly about *meal timing*. Dietary habits and nutritional content of consumed foods, such as calories, were missing from the dataset, and five participants commented on the importance of these data. Participants also wrote in additional data types that they found important, including *weight*, *BMI, substance use,* and *body image*.

We found that the use of passively-sensed proxies is much more challenging in the context of diet than sleep, and this led to more variety in data usefulness among participants and an interest in data types like *location*, which could support assumptions about eating habits (e.g., by restaurant) when nutritional data is lacking. HP4 noted, beyond asking students to keep a time-consuming food log, *"there is not much we can do objectively… so, [you] have to communicate and assess at the same time."* Many participants raised issues related to use and interpretation of data proxies in mental wellness applications. For example, HP6 worried that data on *time spent studying* might be incorrect, pointing out that *"[what seems to be] time in the library could be drinking coffee at Starbucks, which is not helping them [sleep]."*

To augment nutrition information and diet habits, *vigorous exercise* and *light exercise* were also found to be useful for Persona 2. Many participants were interested in some measure of physical activity: not as concerned with specific measures as much as a "picture" of general movement levels and exercise-related habits. Participants were also interested in understanding potential underlying psychological issues that might be contributing to poor diet. *Depression scale* was considered commonly useful here, as well as *heart rate* for identifying *"if they're having an eating disorder [or] affecting their metabolic processes"* (HP2).

Scenario 1: Assessment

Looking across student personas, we also found interesting trends in data usefulness based on scenario. For *assessment*, many participants mentioned the difficulty of drawing lines for what is "typical" or "healthy" for an individual. This difficulty complicates the design of systems that rely on specific behavioral targets—even personalized ones, and that report health status or progress toward goals based on limited behaviors. HP5 explained this disconnect in the context of social data, saying that *"we [could] have someone that spends three or four hours a day with friends and says, 'I'm lonely all the time,' [while] others would say, 'I spent three or four [hours] with friends, I wish they'd find something else to do so I can get my work done.'"*

Across personas, *depression scale* was another data type considered more useful in a diagnostic context, to help clarify or rule out the possibility of serious mental illness. Participants found the assessment phase as generally useful for understanding *"what else we'd want to screen [someone] for, depression, current well-being"* (HP7). Some participants also expressed an interest in seeing *anxiety scale* data in parallel with depression.

Scenario 2: Communication

Some participants believed that the same data would be useful for the communication scenario as the assessment scenario; still other participants focused on data that they already go over with students, explaining that it would be helpful to have concrete data to augment communication about stress, mental health, and behavior during a consultation. HP7 explained *"I do ask very specific questions about [sleep issues], so having information historically would be really useful rather than having to rely on their subjective report of their sleep."* Some participants worried about time constraints in a consultation, and wanted to focus more closely on only those data that pertain to specific consultation topics.

Scenario 3: Self-care Planning

Many participants articulated that self-care planning should be focused on directly-measured data that students have more control over to improve their stress levels and problematic behaviors. HP4 explained, for instance, that a depression scale *"gets [at] the diagnostic assessment of where they're coming [from]… but since this is self-care… this stuff, it's not going to be as useful for planning for them [though] it might… be useful for me thinking about it."*

HP10 added that *"if you are planning a conversation with a patient, you've got to focus on the things that are really concrete and practical, things that they can control themselves."* HP13 thought that physical activity and social measures would be useful for self-care as well, elaborating that *"these are things that on a day-to-day [basis] would be helpful for them to know where their time is going… now you know I'm going to class tomorrow and spending less time on phone [apps]… self-monitoring like this can be helpful to notice."*

STUDY 2: UNDERSTANDING STUDENT PERSPECTIVES

Our second study aimed to expand on expert perspectives by gathering data on students' current self-tracking practices (Study 2 in Table 1). We included questions about general self-tracking practices and preferences to provide important context, while incorporating focused questions on self-tracking as it relates to mental health and wellness.

Methods

Using Qualtrics [36], we conducted an online survey of current students (n = 297), probing self-tracking experiences and preferences, and perceived mental well-being. Both college and graduate students were eligible to participate as long as they were currently degree-seeking or matriculating into a degree program in the fall. Recruitment occurred for six weeks from July to August 2016, via postings to social media and online forums as well as through snowball sampling. Recruitment postings featured a link to a pre-survey in which respondents provided their email address and, if eligible (i.e., a ".edu" address was given), we emailed them a link to the consent form, which then linked to the full survey if consent was given. Participants who completed the survey received a $10 Amazon gift card as a gratuity.

All survey participants answered questions on demographics, history of chronic and mental illness, and the 10-question Perceived Stress Scale [9]. Respondents who have been self-tracking for at least three months also answered a series of questions about their motivations, preferences, and sharing habits for the data type they find most important for self-tracking. Finally, all participants (both self-trackers and non-trackers) were asked about their willingness to track and share the six data types that experts in Study 1 had found most useful across both students and all scenarios: *vigorous exercise, sleep quantity, class attendance, academic workload, bedtime, and depression scale*.

Data Analysis and Findings

We analyzed survey questions with single-selection and multiple-selection responses using descriptive statistics, and compared responses between the group of students with mental health conditions and those without using non-parametric comparison tests. We examined responses to open-format survey questions through inductive thematic analysis (by all authors). We analyzed 13 open-ended questions for themes. For the four primary open-ended questions (see Table 2, at the end of the paper, for details), three researchers independently coded the responses using constant comparison to iteratively arrive at themes, in a bottom-up fashion, until consensus was reached [17]. Nine remaining open-ended questions were simpler elaborations, which were coded independently by one researcher.

Students from 58 institutions of higher education participated in the survey. Respondents consisted of undergraduate ($n = 211$), master's ($n = 32$), PhD ($n = 52$), and professional degree ($n = 2$) students. 185 (62.29%) respondents were male, 108 (36.36%) were female, and four (1.35%) declined to specify. Most respondents were between 18 and 24 years old. Since the survey was initially advertised to students at our home institution, most respondents were students there ($n = 190$). All respondents had Internet access in their homes, while 97.98% also had an internet-accessible mobile device. Only 5.95% of respondents reported being part of a "Quantified Self" community.

The survey collected some demographic health data to better understand the physical and mental well-being of respondents. Twelve percent of those who took the survey had been diagnosed with a chronic illness and 16.50% had been diagnosed with a mental illness; 6.73% currently see a mental health professional, and an additional 19.87% have previously seen a mental health professional but do not see one currently. For respondents with chronic or mental illness, many reported that their tracking is related to the illness (41.67% of those with chronic illnesses; 43.48% of those with mental illnesses).

Taking a closer look at respondents who had been previously diagnosed with a mental illness (*Diag* group, $n = 49$), we found that these respondents were significantly more likely to have a co-morbid chronic illness ($\chi^2 = 7.09$, $p = .008$) and to be female ($\chi^2 = 16.34$, $p < .001$). Like other differences between *Diag* and *non-Diag* respondents, the prevalence of women in the *Diag* group does not necessarily mean that women are more likely than men to have mental health issues, but could be attributed to other factors. The most common mental illnesses in the *Diag* group were anxiety ($n = 34$; 69.39% of those with mental illness) and depression ($n = 22$; 44.90%). This is consistent with prior findings that anxiety and depression are the most common mental health conditions in student populations [6]. In the remainder of the paper, we will refer to students in the *Diag* group as "PD" (e.g., PD1) and student in the *non-Diag* group as "PN" (e.g., PN2).

The PSS, a validated measure of stress with a maximum score of 40, was incorporated into the survey to gather a baseline measure of self-reported student stress levels across and between groups. While past studies have shown student PSS averages around 18 [38], our respondents had an overall average score of 16.89; however, students in the *Diag* group scored significantly higher, with an average score of 20.8 compared to 16.11 for those without mental illness ($U = 8729.5$, $p < .001$).

Overall, ninety percent of respondents currently self-track one or more things; see Table 3 for a complete list of items. While the survey was open to non-trackers as well, due to the nature of the survey, students who self-track would have been more likely to participate. Workouts were selected as "most important" for tracking 17.84% of the time ($n = 48$), followed by steps (14.87%), weight (14.13%), eating habits (12.64%), and sleep (9.29%). Students were most likely to use mobile apps for self-tracking (46.27%), but 17.01% used wearable devices and 12.54% used a paper journal.

Data type	% who track	Data type (cont.)	% who track (cont.)
Steps	48.15	None	9.43
Workout (excluding walking)	47.14	Medication	7.41
Weight	44.44	Social interactions	7.41
Sleep	33.33	Caffeine	4.71
Eating habits, diet, or supplements	30.64	Allergies	4.04
Phone or internet usage	29.63	Psychometrics (e.g., mood)	3.70
Heart rate	21.21	Alcohol	3.03
Menstrual cycle	20.88	Blood pressure	3.03
Water intake	13.47	Other	3.03
Time spent working	12.12	Blood glucose	2.36
		Migraine	2.02

Table 3. Percentage of survey respondents who track various items, ranked by their frequency.

Encountering Negative Data

Thirty-six percent of respondents said that there has been a time when they felt that the data they collected reflected something negative about them. Students with mental illness were significantly more likely to report experiences with negative data (56.52%; $\chi^2 = 11.12$, $df = 2$, $p = .004$). Respondents who reported encountering negative data were then asked to explain in free text what it was that they felt reflected something negative. A main theme that emerged in our inductive qualitative analysis of these responses was the disconnect between the data itself and individual reactions to that data; students seemed to give more meaning to the data than it deserved, and often found that the representation of the data did not match their experiences. PN43 described this disconnect as *"[feeling] that the results were not to the best of my ability even though each workout was,"* while PN228 *"started questioning my physical health and wondering if there was anything wrong with my body"* since the data showed an inability to lose weight.

Thematic analysis also demonstrated that students commonly experienced personal guilt and disappointment in themselves, as well as the social pressures, stigma, and embarrassment they felt regarding their data. There was frequent description of failure to achieve goals or lack of progress towards a goal, as well as lack of self-control and, correspondingly, lack of control over the data. Some students were frustrated by inconsistency, and others feared that their data made them look lazy. As PN254 explained, *"I wasn't* *making progress as quickly as I would have liked… I am afraid that it shows that I am lazy (despite the fact that I know I'm not).”*

Finally, some students found that their self-tracking data revealed an *unhealthy behavior* or an *incorrect assumption*. PN102 found that the *data “shocked me at the beginning,”* and PN3 wrote that *“initially I was surprised by… how vastly I had underestimated my calorie intake… I also found my idea that [fewer] meals per day equal[s] less calorie input wasn't necessarily well-founded.”*

In closed-format questions about what they did when they encountered this data they perceived as negative, students were most likely to report feeling more motivated to achieve their goals (41.24%) or that the negative data was “just another hurdle” in achieving their goals (29.90%). However, students in the *Diag* group were more likely to report feeling very demotivated and frustrated by the data (19.23% vs. 8.45%).

Sharing Preferences

Many respondents who currently self-track reported that they share information about their tracking with others. When responding to closed-format questions probing why they share and with whom, respondents' most common reason for sharing with both family (37.17%) and friends (44.98%) was “I feel a greater sense of accomplishment when I share my success with others,” while the most common reason for sharing with peers (19.70%) was “I want to help others by sharing my experiences.”

In closed-format questions about sharing data with healthcare providers, 36.43% of respondents said that their tracking has in some way changed their visits with healthcare providers. Most of the remaining 63.57% who did not experience a change explained that they either do not see doctors frequently or had not shared their tracked data with one. Only one respondent said that tracking made communicating with a provider more difficult, while 27.51% said it helped them better communicate with their health care team. Over 12 percent reported that it helped them follow their provider's instructions, while 6.69% said it helped their provider make a crucial decision about their healthcare.

For those who did share data with their doctors and found it useful, our thematic analysis offers some insight into why. Students frequently mentioned satisfaction with the higher levels of detail and accuracy they were able to share with their providers, and the increased confidence they felt regarding the information they shared because it was data-driven. For instance, PN82 was *“able to give accurate and consistent data,”* while PN47 expressed that *“I am able to speak more intelligently about my health.”* Other students found that the data was helpful for tailoring treatments to their individual needs or demonstrating abnormalities or irregularities in their health. PN78 noted that *“I was able to understand why [my doctor] wanted me to go on a diet.”*

Students also found self-tracking data useful in showing progress between appointments with their doctors, or as proof that they are doing what they say they are doing. PN97 discussed these benefits of self-tracking for anemia, explaining that *“some people can become perfectly healthy taking a supplement, and there is this undertone that I must not be taking my pills and not eating correctly if I am still having problems… having some records help me stand up for myself [to show] that I am doing all of the things that I need to be doing and still not seeing improvements.”*

To learn more about student sharing preferences and willingness, we asked all survey respondents (both current trackers and those who do not currently track) to tell us whether they would be *willing* to track and share information on the six data types that student health professionals found to be most useful (*vigorous exercise, sleep quantity, class attendance, academic workload, bedtime, and depression scale*) with student health clinicians. Due to its relationship to depression and our broader focus on mental well-being, we added a question about self-tracked mood.

On average, 69.41% of respondents do or would be willing to share these data types with clinicians. Students in the *Diag* group were *more* willing to share data with healthcare professionals than those without mental illness (81.92% vs 66.71%), and there was no single data type that *Diag* students were less willing to share than *non-Diag* students. Students in the *Diag* group were most willing to share depression scale data (87.76%) while others were most willing to share exercise data (77.42%). Overall, respondents were *least* willing to share class attendance (53.87%) and workload (62.63%).

It is useful to note that students express a willingness to share additional information beyond what they currently track and share with healthcare providers. Likewise, it is informative to see that many respondents had positive experiences sharing self-tracking data with providers, as previous research of individuals with cancer has shown that patients often believe their providers would not be interested in the data they collect [22]. Findings from Study 1 reinforced previous findings that providers are in fact interested in seeing health-related tracking data from their patients; therefore, it is useful to know that some sharing of this data happens already and that student patients have had generally positive experiences.

Goals and Motivations

In open-format responses, students described diverse motivations for their self-tracking (Table 2). Many of these themes reflect similar motivations found in previous work, namely Epstein et al.'s Lived Informatics Model [14] and Choe et al.'s report on tracking practices of Quantified Self (QS) community members [8]. Common motivating themes emerging from our inductive qualitative analysis align especially with Choe et al.'s overarching motivation category of *improving health*, as most of our study participants were tracking health-related data. Our thematic findings also matched two of the three classes of motivations defined by

Epstein and colleagues: *behavior change goals* and *instrumental tracking goals*.

Behavior change goals replicated by our results include testing a hypothesis, understanding patterns, and managing goals and expectations. For instance, PN18 described a goal of *"understanding patterns of what causes me to feel the way I do and further rooting out certainties or uncertainties that drive them."* Many other students focused on the sustainability of a behavior or goal, including managing expectations and setting the right goal, as well as understanding their own limits or ranges. PD52, who has anxiety and depression, explained *"my main intentions are to keep myself from becoming addicted or dependent."* Desires to improve general health, increase physical activity, and lose or maintain weight were also commonly cited as goals.

Other students reported being motivated by what Epstein et al. refer to as *instrumental tracking* goals, such as rewards or competition with others. Some respondents felt *"encourage[d] to want to work out every day even if I don't want to because I don't like to see where I skipped a day"* (PD212) or noted how *"reaching milestones makes me feel good"* (PN73). Students were also frequently motivated by *social and appearance-related goals*, noting *"a personal drive to look my best"* (PN21) and that *"I didn't like being the one scrawny guy who wasn't good at sports"* (PD15). Interestingly, these social and appearance-related goals were absent from the QS study—for us, students' specific developmental and life stage directly shaped their goals.

Our respondents also demonstrated other motivations not captured in either prior study. Rather than being driven by *curiosity*, identified as a motivational class by Epstein et al., our respondents were instead motivated by *awareness*. Respondents noted their interest in improved awareness such as *"understand[ing] my fitness level"* (PN151), becoming *"aware of the status of my heart"* (PN231), and *"be[ing] aware of what I am eating to make healthy choices."* While QS practitioners were motivated by a desire to be mindful in their daily lives, self-trackers in our study were motivated to be more mindful specifically of their own health.

Many students in the *Diag* group were additionally motivated by a desire to improve their mental health. For some, the connection is direct, i.e., tracking is part of maintenance or treatment, e.g., PD157 noted *"tracking my food and caloric intake help[s] me manage my condition without immune suppressors/medication."* For others, tracking is related to illness in a broader sense; for mental illness especially, respondents described their tracking in ways that drew connections between their behaviors and their mental health and that focused on awareness of when something might be out of equilibrium. PD238 writes that *"tracking strength growth encourages me to continue working out, which in turn mitigates the anxiety/stress,"* while PD127, who also has anxiety, tracks *"exercise, sleep, and caffeine intake to minimize triggers."*

Some students in both the *Diag* and *non-Diag* groups also reported that their goals and motivations for tracking changed over time. For many, they started out with more specific goals which then grew more general over time. PN3 explained that, *"I'm more about keeping healthy now, getting fitter… it's less about staying below the calorie number and more about making sure I eat right."* Students found that as they grew up, their perspectives—and therefore their motivations—changed, with many gaining new knowledge or understanding through their tracking. For PN188, *"seeing qualitative progress motivates me to set more specific goals for larger achievements rather than just continued participation."* Additionally, some students moved from a *loss or gain stage* to a *maintenance stage*, or wanted to adjust their goals to challenge them more or less. As PN90 wrote, *"I have lowered my expectations a little and just want to be fit and feel healthy and active."*

DISCUSSION

The two studies discussed in this paper give us an important foundation for understanding current self-tracking practices in student populations and the role of self-tracking in managing stress and mental wellness. Mental health brings unique challenges to designing and evaluating self-tracking technology, and we sought to better understand current experiences and perspectives as a foundation for future research in this space. Here, we discuss challenges and opportunities that stem from our research, of the *what*, *when*, and *why* of self-tracking for mental wellness.

Proxies for Stress Management and Mental Wellness

While there is still much to learn regarding self-tracking for stress and mental wellness, some clear design considerations come out of this work. Understanding *what* to track to ultimately improve one's stress and mental well-being is important, but also incredibly challenging. There are fewer clear data correlates for mental than physical wellness, and understanding the interactions between behaviors and mental well-being can be its own challenge. We found in Study 2 that many students with mental illnesses made their own behavioral connections through their data collection; regardless of accuracy, drawing their own correlations between behaviors and mental health in a way that belies the difficulty of making such associations. PD235, for instance, described tracking sleep because *"I know that I feel more depressed and stressed when I am chronically tired,"* while PD279 tracks steps because *"walking and getting outside helps manage my depression."*

Interestingly, of those whose self-tracking is related to a mental illness, only one respondent reported tracking mood directly: all others tracked *behaviors* that relate to their mood or mental wellness. There are many readily-available tools for monitoring steps, weight, and other commonly-tracked physical health metrics than there are tools for tracking mental and emotional well-being, and it is therefore unsurprising that many students monitor behavioral proxies for mental wellness. Additionally, even clinical mental health treatment involves frequent use of behavioral proxies to detect, monitor, and treat mental illness; in this sense, the use of proxies by student trackers is a reasonable extension—and even a desired outcome—of clinical care for mental well-being.

The use of proxies is also a consideration not just for students with mental illnesses, but for anyone who is interested in tracking and managing their stress. Stress is difficult to track directly: more so for students who have trouble identifying when they are stressed or do not fully understand their stressors. The student health professionals in Study 1 echoed this understanding in how they defined data usefulness for stress-related self-care planning. Many encouraged the awareness of behavioral correlates of stress and mental wellness, noting that these data types are simply more "useful" in the day-to-day than many more direct measures of stress and mental health would be. Reflecting on the student who had trouble sleeping, HP6 said *"when you're actually giving treatment planning to somebody about what they're going to do, [some] things… are going to become much less useful. These things they can't control. [Those] things they may or may not be able to control. It's the stuff they can control that's useful [here], when they go to bed, when they wake up."*

While the use of behavioral proxies can be beneficial, students must be careful to draw well-founded hypotheses and conclusions, and systems should be designed to encourage and assist in these processes. Previous research has illustrated challenges with the sort of ad-hoc self-experimentation that can arise from health-related self-tracking: poor understanding of device accuracy, systematic error, and uncontrolled comparisons, for example, can lead to misguided trust in devices and misinterpretation of results [49]. As systems integrate multi-modal sensing and advancements in behavioral modeling to generate system recommendations, it will be vital to communicate not only sensed or self-tracked observations, but inferences drawn from them, while minimizing the potential for misinterpretation.

Helpful versus Harmful Tracking

Understanding self-tracking for mental health is made more challenging by the fact that **close monitoring is not always beneficial as a strategy of management**. In Study 1, student health professionals offered insights into situations in which self-tracking can be detrimental to students' physical and mental well-being, with many foretelling the dangers of self-tracking in disordered eating scenarios. HP14, for instance, noted that students with *"[eating] disorders have perfectionist sort of attitude[s]"* and careful tracking can veer into obsession and worsen the problem. HP3 explained that with disordered eating *"you're going to have to take care of that psychological part first…before [nutrition] is going to get any better."*

In Study 2, we found evidence that some students had engaged in elements of this *disordered tracking*—self-tracking that promotes negative health behaviors. PD129 explained, *"I used to track my calorie intake with the intention of losing weight and would set goals for myself that were extremely low and see if I could beat them… this was a function of my eating disorder."* Similarly, PN96 was *"somewhat obsessive in tracking while I was losing weight, and can't shake the habit for fear of gaining back the weight."* For students like these, with eating disorders or obsessive weight-loss habits, self-tracking can contribute to the problem; future research is crucial to understand the boundaries between helpful and disordered tracking in these and other mental health contexts.

Our study indicates that special care must be paid to scaffolding students as they begin tracking for mental well-being. For instance, Study 2 results demonstrate that many students were more likely to track whatever the device they used recommended, which means that any device designed for tracking correlates of mental wellbeing must be deliberate in such recommendations. There must also be increased mechanisms in place for students who feel their data is reflecting something negative about them. This was more common in students with diagnosed mental illnesses, and it will be important that systems frame negative data in a way that does not further demotivate these students going forward.

Designing for Students' Life Stage

Undergraduates especially have motivations unique to college life, and certain constraints and lifestyle habits (e.g., finances, homework, parties) that shape their environment, daily routines, mental health concerns, and management styles. A common theme that emerged from our focus groups was the ubiquity of *"unhealthy means of self-care"* (HP1) by students (e.g., alcohol, drugs) and the importance of elucidating for students what self-care is, which practices are helpful or harmful, and how it can help improve well-being. It is also common for mental health conditions to emerge during young adulthood [30], and many students will be managing these concerns on their own and for the first time. Tailoring self-monitoring interventions to these needs and constraints will improve adoption and increase effectiveness of future systems. We note that since we focus our considerations on university students, the implications of our work may differ for students of other ages and situations.

CONCLUSION

Our work provides foundational insights through two studies examining student experiences of and expert perspectives on self-tracking for stress and mental wellness. These studies serve as an essential step towards advancing personal informatics systems and mobile health technology to promote mental wellness. By illuminating how students with and without mental illnesses track and share data, and comparing these experiences with the recommendations of student health experts, we can better inform the design of these technologies. Our future work will expand our focus to a wider audience, and will gather student perspectives via interviews to supplement our findings.

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Question	Themes	Examples
How is your tracking related to managing or treating your mental illness? (n = 19) [conditional question]	Correlation between behaviors and mental illness	"I track my yoga workouts, and I do yoga specifically to help manage my anxiety and stress." (P212)
	Indirect measurement of mental health	"trying to understand impact of sleep; exercise diet on mood." (P232)
	Treatment tracking (medication, schedule)	"...I do my best to track which medications I have taken when." (P52)
	Adjustments	"I track my period so that I know how to increase my medication doses. About a week before my period shout start, I take a higher dose of my anxiety medication." (P243)
	Triggers; finding signals that something is out of equilibrium	"Tracking exercise/sleep and caffeine intake to minimize triggers." (P127)
How is your tracking related to managing or treating your chronic illness? (n = 13) [conditional question]	Measuring a physical indicator (status, progress)	"Need to track blood glucose and [blood] pressure to ensure diabetes and hypertension are both controlled." (P139)
	Decision-making (lifestyle, medication)	"Have to make sure my blood pressure stays below a certain number while also making healthy life decisions." (P219)
	Managing schedules	"Blood tests and… regular medications." (P267)
	Symptom control	"Checking glucose levels to ensure they remain at a normal level." (P77)
	Hypothesizing about triggers	"I write down all occurrences of headaches in an attempt to figure out the cause." (P14)
What would you consider your main goal or motivation for tracking? (n = 269)	Understanding personal limits or ranges	"To know how strong I am so I don't hurt myself, but keep progressing at a maximum speed toward getting stronger." (P153)
	Sustainability of behaviors and goals (setting the right goal, expectations, predictions)	"Figuring out what I can do to decrease my weight (i.e. what works)." (P138)
	Hypothesis testing & understanding relationships	"I'd like to be able to prevent migraines by understanding my set of triggers as well as possible." (P135)
	Motivation through data (rewards, competition, fun)	"Keeps me going to the gym so that I can fill progress bars." (P49)
	Performance	"Keeping track of my running pace and mileage - to get faster and go longer." (P58)
	Social goals	"Competition with friends." (P68)
	Appearance-related goals	"A personal drive to look my very best." (P21)
	Being mindful about health	"To…be aware of my health." (P182)
	Improvements vs. maintenance	"Losing weight at first, then just generally staying healthy and eating right once I noted it made me feel better in general." (P3)
What was it [in the data] that you felt reflected something negative about you? (n = 97) [conditional question]	Disconnect between data and one's reaction to the data	"I felt that the results were not to the best of my ability even though each workout was... I was disappointed in the [amount of] activity I could achieve." (P43)
	Social pressures and stigma; embarrassment	"At times I felt embarrassed for having to be so dependent on my large amount of medicines." (P7)
	Guilt and disappointment	"I felt unhappy with how I slipped into unhealthy eating habits and how it reflected in my body." (P92)
	Laziness (physical activity related, not productivity)	"Sometimes my weight increases (if [I] skip [going to the] gym for a while or eat a lot), so it reflects laziness/lack of seriousness on my part." (P64)
	Lack or reversal of progress and gains, despite effort; failure to achieve a goal	"I felt the graph of my progress showed how I reversed on my progress." (P182)
	Lack of control over changes; lack of self-control	"Sometimes I splurged on high-calorie food." (P63)
	Inconsistency	"It showed that I wasn't as active as I should be, and that I wasn't consistent in the amount of steps I got each day." (P148)
	Revealing an unhealthy or unexpected habit or behavior	"[I]nitially, I was surprised by how bad my eating habits were and how vastly I had underestimated my calorie intake." (P3)

Table 2. Themes from four open-format survey questions.

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