Designing Dashboard for Campus Stakeholders to Support College Student Mental Health

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ABSTRACT

Stakeholders, such as college campus administrators and clinicians, are committed to alleviating students' mental health concerns and the campus' mental health climate, but they suffer from a lack of timely and actionable information. Research has revealed that student personal data, such as self-tracking and social media data, can provide in-situ insights about students' mental health states. However, *how* they can support stakeholders' goals remains unexplored. We examine the potential of user-centered technology in addressing this challenge. We interview campus administrators and clinicians to understand their needs and current practices. Then through a paper prototype, we gather design suggestions for stakeholder-facing dashboards. We discuss three design implications revealed through our studies: that social media can be a potentially useful resource for understanding student mental health despite concerns of data reliability and interpretability; that the dashboards need to assuage stakeholders' concerns around bias and intelligibility of the visual presentations, which can become barriers to future adoption; and that ethical considerations, particularly securing privacy of student data, need to be salient in the design.

CCS CONCEPTS

• **Human-centered computing** → **Visualization application domains**.

KEYWORDS

College student mental health; social media; self-tracking; campus administrators; clinicians; user-centered design

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1 INTRODUCTION

A college campus encompasses a socially and geographically cohesive, situated community, where poor mental health of an individual student can have spillover effects on others, for instance, exacerbating the risk of copycat suicides [55]. Maintaining a healthy mental health climate on campus, alongside connecting students in need with timely clinical care and counseling is, therefore, of paramount importance from a public health perspective [29]. In a recent nationwide survey, 32.9% of college students reported having been diagnosed with or treated by a professional for mental health, such as anxiety and depression [1]. 57% of students experienced higher stress than non-student peers. Mental health concerns can negatively impact academic success, and hamper social and vocational foundations. In response, there is a growing need for campus-wide strategies to improve student mental health [40].

Since mental illness is rarely a solitary experience, rather often characterized by social and ecological underpinnings, one proposed solution suggests involving multiple stakeholders within a college campus [6]. These stakeholders could include the students' family members, peers and friends, instructors, on-campus clinicians, and campus administrators. Despite acknowledging this need, currently, a lack of sufficient information about student well-being and behaviors in situ inhibits the efficacy, timeliness, and appropriateness of the actions of many campus stakeholders. Consider the case of campus administrators like student affairs officers. These individuals assist students with achieving their educational and professional goals, however because mental health concerns frequently impede students' performances, administrators intend to employ campus-wide intervention measures, often targeting vulnerable students. However, they suffer from a lack of timely, actionable data about students that can support evidence-based adjustment or deployment of adequate mental health resources and policies [26]. Another stakeholder is on-campus clinicians, including counselors, psychiatrists, and case managers. These clinicians seek to help students navigate negative feelings, combat stress, handle crisis situations, and treat mental illnesses. However, clinician interaction with students often use self-reported information about retrospective experiences from weeks or months past. Therefore, proactive approaches to reduce adverse effects of mental health in students, or to prevent risky episodes altogether, such as suicide, remain challenging to implement.

In recent years, college students have been recognized to be wide adopters of *self-tracking technologies* (smartphones, wearables) and *social media*[12]. These technologies allow students to share and record their daily lives in digital forms, and can assess physical activities, location, or physical proximity [24]. This content has been appropriated to serve as a "lens" to what students do, how they engage socially, and what they are feeling [3, 47, 48]. Although not specific to the college context, leveraging the potential of these data, especially self-tracking data, many tools and applications have been proposed and developed [8, 11, 28, 31]. These tools enable self-reflection, promote self-awareness and change behaviors.

However, the extent to which tools built upon self-tracking and social media data can support the goals of various campus stakeholders, like the ones above, remains unexplored. Although studies have

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proposed student self-tracking data to be beneficial to stakeholders [25], diverse campus stakeholders' perspectives have not been explored—what value they see in these data and how it can influence stakeholders' workflows. Moreover, self-tracking and social media data complement each other in terms of both the types of data they capture and the rate and granularity at which they are generated and acquired; however this has not been examined in mental health technology design targeted at (campus) stakeholders.

Our Contributions. Motivated by these observations, this paper offers formative research toward designing stakeholder-facing tools to tackle the challenges of college student mental health. Adopting a participatory approach and focusing on two stakeholders—campus administrators and on-campus clinicians in a large U.S. public university, we seek to accomplish two research goals:

(1) *Understanding the current practices and needs of campus administrators and clinicians concerning the use of students' (voluntarily shared) personal data in their work.*

(2) *Identifying design guidelines and implications for tools that present students' personal data to fulfill stakeholder goals.*

Focusing on self-tracking and social media as the two major sources of students' personal data, we conducted two connected studies towards the research goals. The first comprised semi structured interviews with campus stakeholders, that found stakeholders expressing a strong need for in-situ data about and from students. However, due to its limited availability, such data was rarely a part of their existing practices and workflows. Accordingly, we developed paper prototypes for each group of stakeholders in the second study. We conducted follow-up interviews to help stakeholders reflect on and envision new tools that can address current gaps in understanding student mental health. Our studies revealed enthusiasm and interest in both stakeholder groups. Despite initial skepticism, both administrators and clinicians recognized student social media as an underexplored opportunity in the design of mental health tools. Nevertheless, we learned that the future tool's visual presentation needs to be cognizant of the time constraints of on-campus clinicians, while, also, providing a bias-free representative picture of the student population for campus administrators. Most importantly, the stakeholders emphasized the need to address privacy and ethical concerns in the design. We conclude with a discussion of the challenges and opportunities we see in leveraging students' personal data to support the needs of mental health stakeholders on college campuses.

2 RELATED WORK

2.1 Student Mental Health Assessment

Extensive prior literature has focused on college student mental health [18, 22, 43]. Prior research indicates that campus stakeholders use approaches to understand and gauge many mental health concerns, and use these insights to frame campus policies, support provisions, and stage formal and informal interventions [21].

Campus administrators, an important stakeholder of college student mental health, serve various aspects of student life, from admissions, dining, and disability services to wellness and recreation units. One of the main resources currently used by campus administrators includes surveys on student health, such as the National College Health Assessment II administered by the American College Health Association (ACHA-NCHA II) [1]. It covers diverse health topics such as alcohol, tobacco, other drug use, sexual health, weight, nutrition, exercise, mental health, and personal safety and violence. From time to time, many colleges also conduct research or service oriented surveys to gather context-specific information about students' mental health, e.g., the Healthy Minds Study [32].

However, one major drawback of such surveys is that they rely on self-reporting from students who may not be accurate in their responses that require retrospective recollection of past events. Further, students' self-reports about their mental health can be misleading or inaccurate since it concerns sensitive and stigmatizing experiences. Additionally, because of their annual or biannual nature, these surveys lack temporal granularity and do not effectively depict trends over time—information that can be key to improving mental health policies on campuses [19].

On-campus clinicians, a second important campus stakeholder, include counselors, therapists, psychiatrists, case managers, and dietitians, affiliated with counseling centers and/or student health services. Their main purpose is to administer counseling and treatment, via interviews during face to face sessions and clinical questionnaires [13]. Verbal assessment during these sessions includes open-ended questions to help a patient present their problems, closed-ended questions to examine the degree of the presented problems, and physical examinations. Clinical questionnaires (e.g., the Counseling Center Assessment of Psychological Symptoms Scale [51]) can be taken by patients during their sessions for initial assessment, symptom tracking, and after-treatment assessment [30]. However, the approaches only capture their status at the precise time of face-to-face sessions, furthermore, information captured about any changes may not be accurate due to recall bias.

There are needs for and interest in bridging these gaps using new technologies targeting the needs of the two stakeholders [21], currently, however, they are lacking. Our work provides design implications for dashboards for campus administrators and clinicians, that present students' personal data relating to supporting a better understanding of students' mental health.

2.2 Personal Data and Mental Health

Past work has explored opportunities for *self-tracking* technologies for mental health. These works have utilized different digital devices which can track users' physical activities, such as smartphones, computers, and smartwatches [39]. One line of work uses personal data from smartphones for mental health diagnosis and intervention in bipolar disorder [34, 35, 37], depression, [5, 46] and stress [33]. *How* these personal data can be used in a clinical setting or in technologies to support college campus stakeholders remains unaddressed. One exception is the work of Kim et al., who conducted exploratory design research to develop a clinician interface of patient self-tracking data for physical health [27]. However, we do not yet know the usefulness of such data for mental health.

Specific to the college student population, there is also growing research assessing mental health status via data gathered from smartphones. The StudentLife project used students' smartphone data to find associations of mental health with academic performance [52] (also see Chow et al. [9]). Kelley et al. conducted focus groups and card sorting activities with student health professionals, identifying their perspectives on students' self-tracking data and how these perspectives could help manage students' stress, anxiety, and depression [25]. Our studies contribute to this expanding body of work by developing and testing low fidelity prototypes that seek to meet campus stakeholders' needs for student mental health.

Finally, *social media* data has been used to infer and predict mental health ranging from postpartum depression [14] and depression [16] to eating disorders [7]. In fact, work has begun examining attributes of college student mental health using student-generated social media data. In a first study, Bagroy et al. analyzed Reddit posts to generate a mental well-being index for students in 100 US universities [3]. Other research has observed that students' stress can be affected by incidents of crisis on campus, visible in the linguistic attributes of content shared on Reddit [48]. The CampusLife project—a multi-institution extension of the StudentLife project, collected social media data from college students alongside other behavioral data to infer mood instability [47]. Our research draws on these studies to examine how mental health insights from social media could be incorporated in tools to help campus stakeholders.

2.3 Mental Health Technologies for Stakeholders

Because of the tremendous amount of personal data that people amass in their daily lives, meaningful presentations are important in utilizing personal data. Some previous studies have explored how we can visualize personal data for people who collect their own data (see [17, 38] for a review). Many individuals want not only to collect and reflect on their own data but also to share the data with others including their healthcare team [10]. Additionally, given the social ecological dimensions of mental health, sharing relevant information with stakeholders within family and friend networks is a way to control one's health identity, enable shared motivation, gain help and support, and share experiences with peers [25]. When stakeholders, like an individual's mental health clinician, get access to volunteered personal data of individuals, it can also facilitate evidence-based recommendations and treatment strategies [38].

Mental health technologies targeting the needs of diverse stakeholders, beyond the individuals themselves, however, are limited. Prior work includes the research of Schueller et al., who investigated mental health providers' current use of technology in their practices, their interest in adopting new technology, and barriers in the desired adoption, though not specific to the college campus context [49]. Studies have also explored developing visualizations of personal data to support stakeholders [27, 45]. Ryokai et al. [45], for instance, found that interactive visualization tools enabled health coaches to spend more time making personalized recommendations to their clients. Our work complements and extends this limited body of work in two ways. First, we provide one of the first studies examining how personal data of students could support the workflows and needs of stakeholders of college student mental health, other than the students themselves. Second, we examine the potential of two very distinct but complementary data streams in our paper prototypes, coming from technologies that students are reported to widely use—self-tracking and social media data.

3 STUDY 1: INTERVIEWS

3.1 Participants

Leveraging a word of mouth strategy, we recruited an executive level administrator in the health division (including campus health services, recreation services, and health initiative) in a large public research university in the southeast U.S. as the first participant of our study. This participant recommended subsequent potential subjects after the interview. By using snowball sampling, we recruited five other campus administrators and five on-campus clinicians (ref. Table 1). Of the six total *campus administrators*, five were affiliated with the health division, and one was in the information technology division. Their average career tenure as campus administrators was 13.2 years and they reported having served at this institute for 6.3 years on average. Two of them had some formal (educational or service) background in health. Of the five *on-campus clinicians*, there were three psychiatrists, one dietitian, and one licensed psychologist who worked across the university's counseling center and student health services. On average, they had 13.3 years of career tenure and reported to have served at the university for about 3.8 years. Hereafter, we refer to the campus administrator participants as “A" (e.g., “S1A1" is a campus administrator in Study 1) and the on-campus clinician participants as “C" (e.g., “S1C1" is a clinician in Study 1). Studies were approved by our institutional review board.

	Group	*N*	Specialty
Study 1: Interview	Campus Admins	6	Health related (5), Non-health related (1)
	Clinicians	5	Psychiatrist (3), Licensed psychologist (1), Dietitian (1)
Study 2: Paper prototype	Campus Admins	6	Health related (5), Non-health related (1)
	Clinicians	4	Psychiatrist (1), Licensed psychologist (1), Dietitian (2)

Table 1: Recruited participants in Study 1 and 2.

3.2 Procedures and Data Analysis

We conducted 11 individual semi-structured interviews from Sep to Nov 2017. One author visited the participants' offices and explained the purpose of this study along with what types of student self-tracking and social media data were under consideration. We defined self-tracking data as any piece of data students generate electronically, ranging from smartphone applications to wearable devices. We also defined social media data as traces on social media, such as Facebook, Twitter, Instagram, and Reddit.

After this brief explanation, the researcher asked questions about each stakeholders' experiences and perspectives on student self-tracking and social media data. They also asked questions regarding their current work environments, for example, what devices they use at their workplace, directed at student mental health issues. The sessions took 40 to 70 minutes to complete and were audio-recorded with permission; one participant chose not to be recorded. The recordings were transcribed for analysis; the transcripts were anonymized and the recordings deleted after transcription. Based on the transcripts and notes taken during the sessions, we conducted thematic analysis to understand our participants perspectivs surrounding students' personal data [41].

3.3 Findings of Study 1

3.3.1 Current Practices. Five out of six **campus administrators**, whose main roles were closely related to student health, mentioned that mental health was one of their focal interests. The main methods of gathering student mental health status were campus-wide surveys, such as the ACHA-NCHA. However, administration of the survey had been suspended in recent years. Instead of surveys, they conducted focus groups with students. However, the focus groups were somewhat limited because they often recruited participants from the pool of students who had already participated in one of the programs they offer. Hence they did not consider the results to be reflective of the average students' opinions. Our participants also reported working closely with student organizations; the representatives of various student groups provided aggregated opinions which were collected informally and sporadically. Aligning directly with the purposes of this study, the administrators were highly open to utilizing technology to have more student information; at the time of our study, they were already considering the adoption of personal health tracking smartphone apps at the institute level.

Licensed psychologists and psychiatrists reported to have 5-10 one-on-one sessions with student patients on a typical day. The sessions spanned from 30-90 minutes, with new patient sessions at the upper end of this range. The counseling and psychiatry centers both provided group sessions led by these clinicians. Students who visited the psychiatry center were required to fill out a depression screening survey when they self-checked-in using desktops at the center. At the counseling center, they provided tablet computers and had their patients fill out Counseling Center Assessment of Psychological Symptoms (CCAPS) surveys. Clinicians reviewed the results of these surveys at the beginning of each session.

Our clinician participants also noted both centers utilizing technology to collect and manage their patients' self-reporting; however information was managed differently (via different electronic health record (EHR) systems) at the two sites, leading to a variety of barriers in collaboration. Given that the clinicians often referred students to one another, they wanted future technology to assuage this disconnect between campus stakeholders in gathering and managing student personal data.

The dietitian participant also stated meeting students but less regularly than other mental health clinicians. They used customized surveys for new students, but they did not report utilizing technologies in administering them. They also described working closely with both the health centers, but dietitians manually referred students and shared information with other clinician stakeholders.

3.3.2 Needs and Concerns – Self-tracking Data.

We found that both campus administrators and on-campus clinicians were interested in using student volunteered self-tracking data. **Campus administrators** were less familiar with their possibilities and potential, but they expressed a strong interest in student related information in general. They mentioned that they needed student health data to plan and assess their campaigns and policies, and were trying to find a source better than surveys and focus groups.

> *S1A1: My biggest concern right now is I don't have data, so I'm challenging all of my team to let's figure out what data we need and how to find it and how to build it.*

On the other hand, **on-campus clinicians** expressed a higher level of experience in gaining insights from self-tracking data, either with or without technology. They reported already asking their patients to track aspects of their daily lives: sleep, nutrition, feelings, etc. They mentioned that self-tracking can be useful in treatment because it can prevent recall bias and increase self-awareness. However, they expressed caution in requiring their patients to track their daily lives because the patients could become obsessed with recording every detail. Based on experience, clinicians noted that these practices may have detrimental results on mental health states:

> *S1C2: I think, for some people, being more self-aware might not be helpful. Sometimes I want them to not think about it so much. That might cause them to be obsessing over monitoring themselves constantly. Sometimes it's easy to get bogged down in the details.*

At the same time, the clinicians noted some obstacles in their current use of self-tracking data, such as Fitbit and MyFitnessPal for treatment. They felt that these tools do not show trends over time, and time constraints prevent them from reviewing lengthy and detailed reports during sessions:

> *S1C1: If they noticed something about a variation in their sleep or activity levels, I will write that in my note and track it, but I don't have any official way to follow it or track it. So it's only useful for me in going back and looking at my last note, but there's no built in thing in [record keeping system] that follows any of this sort it shows trends.*

3.3.3 Needs and Concerns – Social Media.

Both participant groups reported they seldom had experience with student social media data—one campus administrator participants mentioned that she occasionally visits the university's subreddit page to check what students are saying about mental health related issues. Two clinician participants said they had a few patients who wanted to talk about what they have seen on their Facebook. However, our participants felt they did not have enough time to look over extensive amounts of social media data and they expressed privacy concerns about accessing students' private social media, as it might contain the personally identifiable information of others.

Most **campus administrators** mentioned that they had not yet seen the benefits of using social media data, compared to self-tracking data, and were concerned if social media reflected the actual life of students:

> *S1A1: I don't know. And the reason is because people tend to share their best and hide their worst. And it's such a small moment in time.*

While acknowledging that algorithmically processed social media data can overcome these hurdles, they felt unfamiliar with the potential of algorithmic inferences derived from social media data of students. In fact, none of them had seen the results of linguistic analysis or prediction of mental status from social media, when prompted that these opportunities exist in the research field.

The **clinicians** said that they did not encourage their patients to share identifiable social media activities with them. This contrasts self-tracking data because most clinicians encouraged the tracking of patient daily lives either with or without technology. A lack of time was noted to be a significant hindrance:

> *S1C2: Any [social media] data points can be interesting but we may not have enough time to discuss them.*

Despite these obstacles, they pointed out a scenario where social media information could be useful. They thought people's social media activities may reveal certain insights that otherwise could not be accessed, e.g., detailed information about their daily activities and social lives, which may not be shared during an appointment:

> *S1C4: It could be helpful in that it might even sort of shed light on something that they might not otherwise share. So I think it could be helpful that they're sharing it with the public but they're not necessarily sharing it in an appointment. Or what they're doing on the days when I don't meet with them.*

From this study, we learned that the stakeholders have a need for student in-situ information and that there is potential for designing new technology which can be adopted in their current work practice.

To invite them to suggest their own detailed ideas, we decided to provide rough examples of a future technology: paper prototypes.

4 STUDY 2: PAPER PROTOTYPES

4.1 Paper Prototype

From Study 1, we learned that many participants were less familiar with utilizing student personal data, especially social media data. To help our participants envision a future stakeholder-facing technology powered by such data, we decided to use paper prototyping, widely used for brainstorming, designing, and evaluating user interfaces [50]. An obvious benefit of paper prototyping is that designers and researchers can receive feedback from potential users before they invest their resources in implementing functional systems. Further, they can iterate their designs quickly and easily [44]. Because of the exploratory nature of this study, we focused more on the brainstorming and designing aspects of paper prototyping, rather than assessing our potential interface.

4.1.1 Working Environment. We assumed a situation where students would voluntarily participate in data collection with informed consent, as demonstrated to be feasible in the StudentLife project [52, 53] and social media research involving college students [47]. Other research also suggested that college students are positive about sharing their self-tracking data with stakeholders [25].

Situated in these assumptions, we adopted a dashboard style presentation for our paper prototypes targeted to campus administrators and clinicians. A dashboard is a visual display which, at a glance, comprehensively shows the most important information on a single screen [20]. We believe a dashboard presentation to be helpful for our context because the amount of personal data from student devices/technologies is huge and our potential user groups do not have enough time to review all of the data, as noted in the interviews.

For on-campus clinicians, we designed a dashboard for a specific patient visiting a clinician or seeking treatment at the student health clinic. We supposed that it would be an independent application, which will be run outside of their electronic health record system for the sake of expediency. In our paper prototype, we assumed that they already had a specific patient whose data they wanted to look at. We selected the default time frame for the data to be one week, because most of our clinician participants reported seeing their patients regularly. They could also set a custom time frame by clicking a calendar icon.

The paper prototype for campus administrators was an online website or desktop application. Based on our initial interviews, we supposed that they would access student information "on demand", and would prefer an aggregated and abstracted view of the data because of their primary focus on comparing different student groups. This was also a means to alleviate the privacy issues they noted in the interviews. Accordingly, our design provided a query feature that would allow them to see the aggregated data for a certain student group (e.g., undergrads, CS majors, students enrolled in a course). The design also allowed them to compare data between groups by adding more custom groups as and when needed.

Figure 1 gives a visual of the paper prototypes for potential administrator and clinician use.

Finally, we envisioned that the working environment of both dashboards would protect contributing students' privacy by never making raw data accessible or visible to unauthorized users.

4.1.2 Data Types. Our initial interviews and literature informed the data types for our prototype. First, we prioritized data types mentioned during the interviews; among clinicians, mood, sleep and nutrition were most popular, while administrators were interested in all of these in addition to activity and academic attributes. We assumed that both dashboards would be able to leverage abstracted measures and algorithmic inferences of these relevant mental health related attributes derived from students' self-tracking (e.g., smartphone use) and social media (e.g., Facebook) data.

For the first attribute *mood*, our interface design adopted the Photographic Affect Meter (PAM) because it is designed to gather in-situ mood (valence and arousal) data from individuals in a less-intrusive way, and uses a pictographic (16 image) representation of mood for gathering the self-reports [42].

We also included information from *social media* in our dashboard design, in order to allow end users to examine how students' social media data can augment the insights gathered from the above self-tracking sensed data. Drawing upon prior work that employed natural language analysis on the textual content of social media posts for mental health assessment [3], we included several time-varying social media attributes: expressions of mood, algorithmic assessments of stress and depression as inferred from social media data [15], and a list of frequently used words in social media feeds to understand topical proclivity and interest. We only included those social media assessments that have been shown to be feasible, reliable, and statistically and clinically valid in prior work [3, 7, 16]. We assumed that these words would enable end users to understand in what situations specific moods, stress, or symptoms of depression were expressed. Further, an understanding of recurring words in a student's social media feed can reveal, or at least point to, the underlying causes of changes in moods, depression, and stress level. We selected a river presentation technique as it highlights trends of changes in word use [23]. Wherever possible, we also included information on how all of the social media attributes were calculated, in order to provide more context to their review by the participants.

Next, for *sleep* data, we supposed the obtainment of data from patients' activity trackers or smartphones—these applications provide information on when an individual goes to bed, when they wake up, and sleep duration. We also chose to present physical activity data, gathered from smartphones and wearable devices, in a similar way: how long the patients walked, ran, and/or did exercise on a specific day. Adherence to diet goals was also noted by our participants as a valuable signal to monitor; we supposed this information to be volunteered by individuals through a variety of health applications on smartphones. Therefore, based on information such as a student's risk of failure to meet diet goals, our design provided easy to review non-numerical results, such as low, neutral, and high, to indicate this risk of non-compliance.

Additionally, our participants mentioned that they were interested in not only statistics of students' sleep but also their sleep hygiene (e.g., lights, sound, television and technology use). Daily patterns of social media usage, such as late night use, has been shown to be indicative of poor sleep hygiene and increased mental health concerns [16]. We therefore adopted measures that quantify circadian patterns of social media usage as a potentially useful data in our design: an approach that did not require implementing intrusive devices in students' personal spaces.

For campus administrators, the data types we picked for the design were similar to those for clinicians. However, based on our

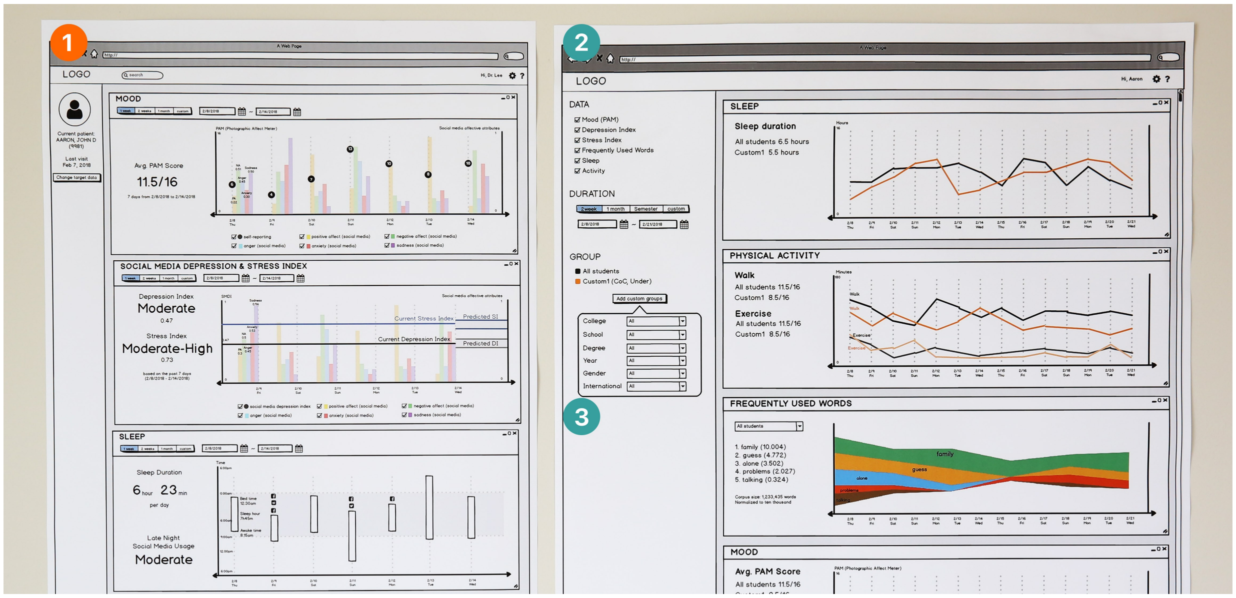

Figure 1: Paper prototypes. 1) A prototype for on-campus clinicians. As it shows only one student's personal data, it utilized several presentation techniques (bar graph, line graph, and icons) together to deliver different aspects of student mental status. 2) Prototype for campus administrators. It shows aggregated student data, such as the sleep durations of sophomores, in a simple presentation style. 3) Campus administrator users can select a certain group of students and visualize their data.

preliminary interviews, we eliminated nutrition information for campus administrators: we believe that the aggregated average calories from students would not be meaningful; it also may not be feasible to expect groups of students to record their nutrition because it is a difficult behavior to track.

4.2 Participants

We recruited participants for a think-aloud study with the above paper prototypes through two means: by reaching out to Study 1 participants, or via snowball sampling. Among the six campus administrators and four on-campus clinicians recruited for Study 2, three clinicians did not participate in Study 1. Among the four on-campus clinicians, we had two dietitians, one licensed psychologist, and a psychiatrist. Table 1 includes details of these participants.

4.3 Procedures and Data Analysis

We conducted the user study sessions in-person in the respective offices of the participants. All sessions were individual except for one session with two dietitians. We kept these sessions primarily individual because the participants' main roles and interests could be substantially different from each other, and therefore they could have been hesitant to express their opinions in group sessions. At the beginning of the sessions, we explained the purpose of this research project and the paper prototype. After that, we provided them with a paper prototype (printed on 12" x 22" paper). We required them to explore the paper prototype using a think-aloud protocol. They were allowed to ask questions when they wanted to do so while engaging with the prototype. After their initial exploration, we asked questions surrounding general feedback on the prototype, other data types they wanted to have visualized on the dashboard, apparent challenges, and areas of improvement.

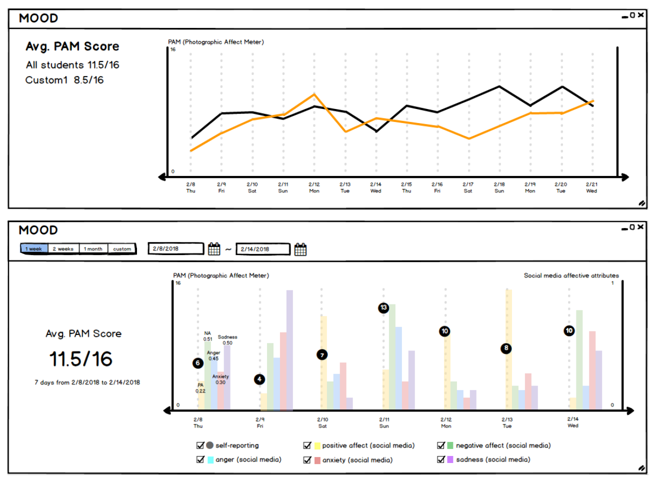

Figure 2: Mood category from two paper prototypes. The top visual is for campus administrators; it shows an aggregated PAM score at a certain time of the day for a specific student group. The visual below is for clinicians which provides two different mood related data; the first one is a PAM score in the black circle; the other information is social media affective attributes based on social media analysis. Each bar graph represents different types of affect such as anger, anxiety, positive affect, negative affect, etc.

We analyzed the transcripts and notes taken during the sessions using thematic analysis [41]. We discuss the findings that emerged out of this data analysis in the following section.

4.4 Findings

In general, our participants from both groups thought it would be beneficial for them to use our dashboards in their work process. They mentioned that the data types are what they wanted to have and the dashboards would help them to better understand the actual circumstances surrounding student mental health status.

In addition to the positive feedback for our paper prototype, we discovered their needs and opinions concerning students' personal data. Because our participants actually saw what our dashboards could be, they provided more specific information about their data preferences and suggestions for presentation techniques. We discuss some recurrent themes.

4.4.1 Data Order by Stakeholder Preference. Both participant groups were pleased with the data types provided in our paper prototype: mood, social media depression/stress indices/levels, sleep, activity, nutrition (only for clinicians), and frequently used words in social media feeds. To have a deeper understanding of their needs for data types, we asked them to rearrange the order of data types according to what would benefit them most.

All of the **clinician participants** wanted to place the mood and depression/stress index on the top of the paper prototype and the other behavioral data (sleep, activity, and nutrition) afterwards (ref Figure 2). S2C3 explained,

> *These two things, the mood and the social media depression and stress index, those two would be the things that I imagine would be what we would discuss the most in terms of our meeting, or our session. So that likely would be near the top.*

For the data on frequently used social media words, all clinicians mentioned that the data, by itself, would not be very meaningful:

> *S2C4: I just don't know that the words are necessarily going to tell you a whole lot about how they are feeling, it could just tell you more about what's going on in their life at that time. Like if they are getting ready to plan a wedding, then the word family might come up a lot, simply because they're planning a wedding, their family's planning a wedding, but it may have nothing to do with really how they're feeling.*

Unlike clinicians, the **campus administrators** preferred behavioral data, such as activity and sleep, because they are more objective and quantifiable than mood data. The difference in preference between behavioral and emotional data could be caused by the difference in the scopes of interest in the two stakeholder groups. Clinicians were likely to compare longitudinal changes of one specific student, but campus administrators intended to compare data between student groups.

The campus administrators appreciated a way to examine student groups' frequently used words on social media. One of the possible reasons for this would be that data presentations such as word clouds are popular in the marketing field and our participants found it meaningful for marketing and evaluation purposes:

> *S2A1: Cause that can help us create programming, either new, or tailor our existing programming like that. Like if we know we're not reaching people, what are the buzzwords that they're looking for? What are the buzzwords you're looking for, to help us fulfill that for you? I mean, that's very insightful for us, because most students aren't gonna come tell us that information, you know? So this would be very helpful and useful, I think this would be a great tool.*

4.4.2 Potential Merits and Concerns Regarding Adoption of the Dashboard. **Campus administrators** wanted to use our tool for planning purposes. First of all, they felt they can use it to plan health-related campaigns on campus. By segmenting and targeting the audiences of their campaigns, the dashboard could facilitate understanding what kind of campaigns will be beneficial to students based on the data. Importantly, they stated that the data presented in the dashboard can be valuable in making financial decisions.

> *S2A4: Well, I could see it being used for two things. One is certainly for more intervenient planning purposes, that'd be more of a semester type basis. And then annually, certainly around when we're looking at where we invest resources for technology solutions, I would want to use this as a source of data to base recommendations on. So that would be annually.*

A big concern for our campus administrator participants was the feasibility of reaching out to a sizable student audience who would voluntarily contribute their data. Because they were used to running focus groups and surveys, they were well-informed about how difficult it is to collect students' information. They felt that, unlike a clinical setting where mental health gains are more obvious, the students might be less incentivized to share their data with campus administrators.

Clinicians mentioned that the dashboard could provide a kind of starting point for their interactions with student patients. For instance, at the beginning of an appointment, clinicians may seek to understand a student's mood status or other behavioral markers, such as questions regarding activity and sleep. With a functional dashboard, they would be able to review such information quickly and gather more contextual and detailed information.

> *S2C3: So let's say I have a meeting with them on Wednesday every week. So I can go back and say, "Well it looks like on Saturday and Sunday that ... Sunday I guess, that you were feel kind of sad. What was going on?" So that would give me something to talk to them about, like what was happening over the weekend, or on Friday they were really sad, or that they seemed really happy on Saturday. What was happening on Saturday that made them have some much positive affect. Yeah I can see how that would be really useful.*

Clinicians' major concerns came from the limited time in their schedules to review the dashboard. A participant mentioned that the future dashboard should have less than three types of data (mood, sleep, and activity) otherwise it might not be feasible for them to review this. Three clinician participants further suggested that if the dashboard can highlight the part/specific data and trends that they need to look at, it would be helpful. Also, they brought up that the usefulness of the dashboard would differ across patients and in cases where patients' personal data is not insightful, they would proceed with their work without support from the dashboard.

5 DISCUSSION

The two studies presented in this paper have provided many valuable insights. Both participant groups confirmed that the potential interface, which would be powered by students' personal data, can improve their existing work practices around mental health monitoring and assessment. With the dashboard, campus administrators felt they could objectively compare behavioral data between student groups to support their decision and policy-making processes. Clinicians, on the other hand, expressed an interest in reviewing mood and stress related data, to support their treatment strategies and gather naturalistic and unprompted information about students' psychological states and behaviors.

At the same time, both groups of stakeholders also mentioned concerns regarding the dashboards. Campus administrators were concerned about the availability and willingness of sufficient student data needed to provide reliable aggregative assessments of the campus' mental health on the dashboard. On-campus clinicians were worried about the limited availability of time needed to review the dashboard. Drawing upon these observations, we discuss three design implications in the following subsections.

5.1 Social Media in Stakeholder Technology Design: Opportunities and Concerns

The possibilities of self-tracking data in mental health have been revealed by previous research[4, 54], however, our studies highlight the opportunities where self-tracking and social media data can complement each other to fulfill various unmet needs of campus stakeholders that surface in their everyday roles. Although there was some initial skepticism concerning the utilization of social media data, throughout this research, our participants in both groups came to the conclusion that this, in conjunction with self-tracked data, has the potential to augment the manner in which they currently understand and assess students' mental health.

Our participants appreciated the fact that our paper prototype showed a combined view of self-tracking data and social media based analysis, and importantly provided a summary of both data types. Due to the subjective and complex nature of mental health, it seems that these two forms of data, given their naturalistic nature, would provide non-overlapping perspectives and a fuller picture of student mental health status. We believe this to be an important step in designing tools that comprehensively represent the social, behavioral, cognitive, and affective dimensions of college student mental health, elucidated in the Social Ecological Model [6].

Nevertheless, stakeholders' enthusiasm for social media data was also punctuated with concerns regarding a possible lack of reliability and interpretability surrounding this data source. Campus administrator participants questioned the extent to which the visualized data on the dashboards is reliable, given students' presumable diverse impression management goals online. We note here that prior work has shown that social media activities reflect actual selves, not idealized versions [2], and a growing body of work has demonstrated the validity of inferences and predictions of mental health attributes assessed from social media data (e.g. [3]). Hence the skepticism of the campus administrators indicates that there is work to be done to change perceived barriers to the potential utility of social media in mental health technology design.

Similarly, on-campus clinicians felt that some of the social media assessments and inferences on the dashboard lacked clarity regarding their clinical meaning, context, and purpose, and the specific aspect of a student's mental health they presented. We conjecture this gap in interpretability could be attributed to the fact that interpreting and utilizing social media data—an otherwise non-clinical source of information—is currently not a part of mainstream psychiatric training or treatment paradigms, and clinicians are less familiar with how social media analyses could be incorporated in their workflows. Supplementary work needs to be done to bridge this algorithmic interpretability gap. Summarily, future iterations of the dashboard will need to be able to address these concerns to promote adoption among the diverse stakeholders.

5.2 Assuaging Concerns of Intelligibility and Bias in the Visual Presentations

Our studies revealed a desire of the stakeholders for a comprehensively detailed dashboard that is also streamlined to better suit the needs and constraints of their role and work environment. This indicates an *apparent tension* in the design of the dashboards. That is, they would need to provide a succinct amount of highly accurate, relevant, and trustworthy information that can be consumed easily, as well as pose reduced information load and burden to the stakeholders. At the same time, even though we included only the most desirable data types in our dashboards based on the interview findings, our on-campus clinicians mentioned their current work practices may not allow them enough time to review each data type. To this end, we do acknowledge that lessening the burden of users is one of the most prominent design goals in information visualization and visual analytic systems [56].

Essentially, we found that the need for glanceable, intelligible visual presentations is greater than we expected. One of the promising solutions to address this need and apparent tension is to provide a list of data attributes which users may be interested in, such as pairs of variables which show a strong theoretically/experientially grounded correlation [36]. This solution aligns with the above feedback from our participants. However, we do acknowledge that for this solution to be successful, future research will need to explore how we can identify relevant attributes for the stakeholders.

Next, it goes without saying, the dashboards will not be functional and feasible without student involvement in sharing their data with the stakeholders. Campus administrators felt that because they are interested in the data of the entire student population to be able to understand the collective mental health climate of the campus, the level of participation can directly impact the value of the dashboards. In fact, poor representation and involvement of voluntarily data-contributing students can lead to bias in the data presented in the dashboards, which can eventually have negative repercussions downstream, if employed for decision and policy making. To tackle such biases that can impact the visual presentations, various measures to incentivize student participation can be explored. While monetary compensation has been used in prior work [47, 52], other avenues, such as providing personalized recommendations and interventions for mental health can encourage student engagement. Additionally, providing the data back to the students can provide additional benefits to them, such as seeking mental-health related advice and an ability to engage with peers. Together, these strategies can support sustained engagement and data availability needed for bias-free visual presentations.

5.3 Assuaging Ethical Concerns

In our studies, we presumed that students would consent to have their data collected and shared with campus stakeholders toward the design and deployment of these dashboards. However, our interviews and evaluation of the paper prototypes revealed that there are ethical issues regarding privacy, confidentiality, and liability to consider. For instance, stakeholders felt that our proposed dashboards might be controversial: some people may feel uncomfortable due to possible surveillance issues, or have concerns that the tool can be too personally invasive. Moreover, students may decide not to share their personal data in the first place, due to privacy concerns; further, even if they agree to share their personal data, they may inadvertently provide certain information that they would not choose to intentionally share with the campus stakeholders otherwise. Importantly, since students' personal data is often not generated with the goal of inferring and measuring health status, any use of these datasets in the dashboards, even with consent, constitutes secondary use, and therefore needs to be handled and used responsibly.

To address issues surrounding **privacy**, we need to consider transparency features for the dashboards. These features can let students stay informed about what kinds of data will be shared with whom, when, and in what ways. During the informed consent process, as well as by adopting continued consent procedures, we can also provide an example screenshot of campus administrators' views and clinicians' views, which will enable them to know that only abstracted and aggregated data will be shared with campus administrators, and that individual level datawill be shared with their clinicians, but only in an abstracted form, such as the depression index based on their posts. Additionally, the designs could be augmented with complementary student views, which can provide a regular review of the sharing process. In the case of a potential mismatch of expectations, students would have the ability to opt out of the sharing process altogether, or just eliminate specific data that they desire not to be considered from the dashboards. In other words, regular reviews that show how their data will be processed and shared with others can assuage privacy related concerns.

Confidentiality concerns are related to situations wherein agreed upon personal data is exposed to people who do not have authorized access to that data. It can be caused by malicious attempts to access sensitive data or malfunctions in the security features of platforms. Both cases might be out of the scope of our work, however, the dashboard designs need to thoughtfully consider various aspects of data collection, storage, and presentation, in ways that prevent the need to access the raw data of students as much as possible.

Lastly, **liability** issues may occur if stakeholders are not able to take proper actions, even if they are notified of obvious trends in student mental health status that might need just-in-time interventions. As we discussed earlier, data related to suicidal risk or ideation would best illustrate these issues. Given the fact that student personal data would be leveraged in near real-time by the dashboards, the stakeholders may not be equipped to focus on such risk markers on the dashboard all the time and take proper actions toward preventing such tragic events. Further, there might be other situations where stakeholders are not able to deploy adequate resources, even if they are informed of adverse mental health crises, due to logistical or access limitations. To address this issue, there is a need to investigate the kinds of interventions that might actually be practical and possible via future iterations of the dashboards.

5.4 Limitations and Future Work

Although we distilled design implications for a novel student mental health technology for stakeholders, our research has some limitations. First, the sample sizes of the studies were small and recruitment happened at one university, so the results may not be generalizable. We envision that future research conducted at multiple sites and involving greater numbers of diverse stakeholders can address this issue. Second, we explored campus administrators and on-campus clinicians because we aimed to examine how indirect stakeholders, beyond the data creators/contributors (students) themselves, can leverage such data in meeting the campus' and students' broader mental health needs. We will include student perspectives, as well as broader stakeholder dynamics, in the future work. Finally, we chose to develop a low fidelity prototype in order to invite participants to freely provide their ideas, but it was not connected to actual student data and the low fidelity of the design prevented us from gathering more end user feedback regarding interaction design and usability issues. The future work can develop mid- and high-fidelity prototypes based on the design implications we presented, which can then be used for evaluations purposes in the wild. Nonetheless, the results of the low fidelity prototype in this paper can be a cornerstone to build future student mental health technologies, which end users can incorporate into their work practices to fulfill their goals.

6 CONCLUSION

This paper presented a first study demonstrating that student personal data, such as self-tracking and social media data, can have the potential to improve college student mental wellness if it is shared with stakeholders, such as campus administrators and on-campus clinicians. Assuming access to the data of consenting students, we presented the design of two dashboards, one for each group of stakeholders. To do so, we first conducted semi-structured interviews with campus administrators and on-campus clinicians to understand their current practices and needs. Based on those findings, we developed paper prototypes and tested them with the same stakeholders. We concluded with three design implications from the two studies: 1) that social media can potentially be a useful source for supporting the goals of the stakeholders, but with important caveats that need to be attended to and addressed; 2) that the future dashboard should adequately manage bias and intelligibility issues in the visual presentations of the dashboards; and 3) that there exist some ethical challenges around the design of these dashboards that require both refinement of the design itself as well as mechanisms to protect student privacy and data confidentiality, while simultaneously tackling liability issues on the part of the campus stakeholders.

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