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Leveraging social circles and algorithmic processes in digital mental health tools for college students' stress management

Farhanuddin Fazaluddin Kazi and Jomara Sandbulte

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Abstract

Introduction. College students frequently face stress from academic pressures, social demands, and the challenges of daily life. Digital mental health (DMH) interventions have shown promise in helping manage these stressors. However, many students quickly abandon DMH tools, which limits their effectiveness. Previous research has identified social interaction as a key factor in improving user engagement with DMH tools. Still, most existing DMH tools have not been designed with these sharing practices in mind. Moreover, research on recommender systems (RSs) has mainly focused on single-user interactions, leaving a gap in the development of RSs for group settings, particularly in the health domain.

Method. To address this gap, we developed a technological probe that integrates social features with algorithmic processes to provide recommendations for both individuals and groups, aimed at supporting students' stress management efforts. We conducted a user study with 15 college students and their social circles, who interacted with the probe over the course of a day.

Results. Our findings revealed that students appreciated the opportunity to share daily activities with friends and felt motivated to engage in well-being-enhancing behaviours. Participants also gave valuable feedback on the stress management recommendations. We discuss and provide recommendations for future research.

Introduction

College students face stress from various sources, including academic demands, social pressures, and time management challenges (Choi, 2020, Rodgers et al., 2016). Digital mental health (DMH) tools hold significant potential to help students manage stress by incorporating personalization techniques (Cheung et al., 2019; Xu et al., 2021) through recommender system (RS) algorithms, which suggest relevant items to support users' health and well-being (Kelley et al., 2017; Rodgers et al., 2016). However, many users quickly abandon DMH tools, which limits their effectiveness to promote long-term health benefits (Wang et al., 2022). Thus, one of the primary design challenges for DMH tools remains increasing sustained user engagement (Lattie et al., 2020; Meyerhoff et al., 2022).

Research has shown that social interaction is a crucial factor in enhancing college students' engagement with DMH tools (Burgess et al., 2019; Meyerhoff et al., 2022; Park, 2018). College students are known to frequently share self-tracked data, such as exercise routines, mood logs, and study habits, with their peers (Gulliver et al., 2010, Lattie et al., 2020). Yet, DMH technology designs frequently overlook the social roles that support networks play in students' lives (Lattie et al., 2020; Park, 2018). Furthermore, most RS research has focused on single-user interactions, particularly in entertainment domains like movie recommendations (Delic et al., 2018, Tran et al., 2019). Research on health recommender systems (HRS) remains limited, especially in contexts where recommendations must direct multiple users working toward a shared goal (Alvarado et al., 2022; Coppens et al., 2023). There is a valuable opportunity to explore systems that not only address individual student's needs but also incorporate their social networks, aligning with their daily experiences and supporting their stress management efforts.

To address this research gap, we propose a DMH technology probe called '*FreeMind: Groups*', a social application designed for students to interact with peers and receive support in coping with stress. Our goal is to explore how a DMH design probe that incorporates college students' social circles and algorithmic processes could offer support for stress management, as well as to understand the benefits, challenges, and implications of such designs. To achieve this goal, we have examined the following research questions:

1. How can a design solution increase awareness of behaviours among students and their social circles?
2. How can health recommendation systems (HRS) be leveraged to promote collaboration in supporting students' self-care?
3. What concerns do people have regarding a) sharing experiences and b) algorithmic processes?

To answer our research questions, we conducted a user study with 15 college students and their social circle to understand individual's needs in a real-world setting and to inspire people to imagine the use of a new technology (Hulkko et al., 2004; Hutchinson et al., 2003). Participants interacted with our proposed system with a group of friends for a day. Our findings indicate that college students valued the opportunity to share their daily activities with friends and receive updates in return. Participants also reported feeling motivated to engage in positive activities for their personal well-being. Additionally, we present feedback from students on receiving recommendations for stress management and social support. Finally, we discuss the implications of these findings and offer recommendations for future research.

Related work

College students' stressor and social support

College students often experience significant transitions that can increase their stress levels (Nepal et al., 2022; Rodgers et al., 2016), potentially impacting their overall well-being (McLean et al., 2022; Rodgers et al., 2016). While daily stressors are inevitable, certain factors can influence how stress affects students' well-being (Keyes, 1998). Social support plays a crucial role in helping individuals better manage daily stress by offering opportunities to adjust both individual and collective behaviours to promote mental health wellness (Lattie et al., 2020; Park, 2018). For instance, a friend can become a valuable partner for a student struggling with social pressure, providing unconditional support and guidance (Meyerhoff et al., 2022; Park, 2018). However, past conflicts and poor relationships can limit students' willingness to seek help and share information with their peers (Eisenberg et al., 2009; Park, 2018). Despite these challenges, leveraging social support can still offer significant benefits, such as reassurance and practical guidance in managing daily stressors (Feinberg et al., 2022; Park, 2018). Although previous studies have proposed strategies for incorporating social support into technology design (Burgess et al., 2019; Lattie et al., 2020), the social roles of individuals in college students' lives have often been overlooked (Lattie et al., 2020; Park, 2018). To bridge this research-to-practice gap, it is crucial to implement these strategies and evaluate their effectiveness under realistic conditions.

Inspired by prior works (Burgess et al., 2019; Burgess et al., 2020; Epstein et al., 2015; Hollis et al., 2017; Lattie et al., 2020; Morshed et al., 2019; Murnane et al., 2018), we developed a technology probe that integrates college students' social networks and algorithmic processes to support stress management. Our research makes two key contributions: a) providing insights into how the proposed system could aid college students in managing stress, and b) offering valuable guidance for designing interventions that encourage self-care practices.

Intelligent computing in health informatics

With advances in intelligent computing, systems enhanced by algorithm processes have shown great potential in supporting users' mental well-being (Hollis et al., 2017; Kazi & Sandbulte, 2023; Kim et al., 2022). For example, systems like Emotical (Hollis et al., 2017) predicts future moods and recommend healthy activities, while MindScope (Kim et al., 2022) predicts stress levels and provides explanations to aid user reflection. Building on prior works (Hollis et al., 2017; Kazi & Sandbulte, 2023; Kim et al., 2022), our study probe employed existing algorithms to provide both individual and group recommendations, while also incorporating explanations informed by prior literature (Afzal et al., 2018; Ehsan et al., 2021; Kim et al., 2022; Tran et al., 2019).

Group recommendations

Among various technologies, RSs are important in helping users efficiently navigate the overwhelming number of available options and information (Delic et al., 2018; Herzog & Wőrndl, 2019). However, these systems typically focus on serving individual users, often overlooking the potential to help groups. To address this gap, researchers have been increasingly implementing RSs in cooperative and social computing domains (Alvarado et al., 2022; Delic et al., 2018; Herzog & Wőrndl, 2019). In this context, group recommendation systems (GRS) offer valuable functionalities, such as selecting music that suits a group of people (Crossen et al., 2002). GRSs are most widely researched in entertainment, leisure, and event planning, where activities are often group-oriented and the system considers the preferences of the group (Alvarado et al., 2022; Herzog & Wőrndl, 2019; Pujahari & Padmanabhan, 2015). However, research in other areas, such as health, remains limited.

This study addresses this gap by using existing algorithmic processes to generate recommendations to support students' collaborative interactions around stress management. Those algorithms informed our design to a) better understand the user's inputs and b) enhance the quality of the recommendations based on the user's preferences (Alvarado et al., 2022; Pujahari & Padmanabhan, 2015).

Explanations in recommender systems

Prior studies have shown that explanations may influence user's behaviour, as they help users understand why certain items are recommended, thereby increasing the likelihood of user engagement (Sharma & Cosley, 2013; Tran et al., 2019). In GRS, explanations serve additional purposes compared to those in single-user systems. GRS must consider not only individual preferences but also the collective preferences of all group members to address fairness and resolve potential conflicts (Stettinger, 2014; Tran et al., 2019). An example of this is the Choicla group decision application, which supports various decision-making scenarios in a domain-independent manner (Stettinger, 2014). Building on these findings (Stettinger, 2014; Tran et al., 2019), we incorporated explanations within our recommendations. The explanations provided suggestions for coping with stress (G. Mitchell et al., 2021; Hollis et al., 2017; Kim et al., 2022) and utilized different explanation styles based on prior literature (Kouki et al., 2017; Liao et al., 2022; Sharma & Cosley, 2013).

Technology probe: design

We developed a technology probe called '*FreeMind: Groups*', a social application designed for students to interact with peers and receive support in coping with stress. *FreeMind: Groups* was built using Flutter (https://flutter.dev/) and the Django framework (https://www.djangoproject.com/).

Drawing on prior research (G. Mitchell et al., 2021, Kazi & Sandbulte, 2023, Kim et al., 2022, Lattie et al., 2020), the *FreeMind: Groups* system includes social features such as the ability to share photos, and the option to comment on and like posts, all designed to enhance users' social interactions (see Figure 1 - Left). Users receive automated recommendations in their feed from our RS named 'Zoha' (see Figure 1 - Right).

In addition, our probe includes a grouping function to reflect college students' social environments and roles (Burgess et al., 2019; Burgess et al., 2020; Kazi & Sandbulte, 2023; Park, 2018). Each group has a dedicated space to interact, addressing privacy concerns (Newman et al., 2011; Sandbulte et al., 2021). Users can view or join groups through a menu option that displays all their affiliated groups. Finally, users can select which group to post in, and each post within a group includes the group name and image to indicate its association (see Figure 1).

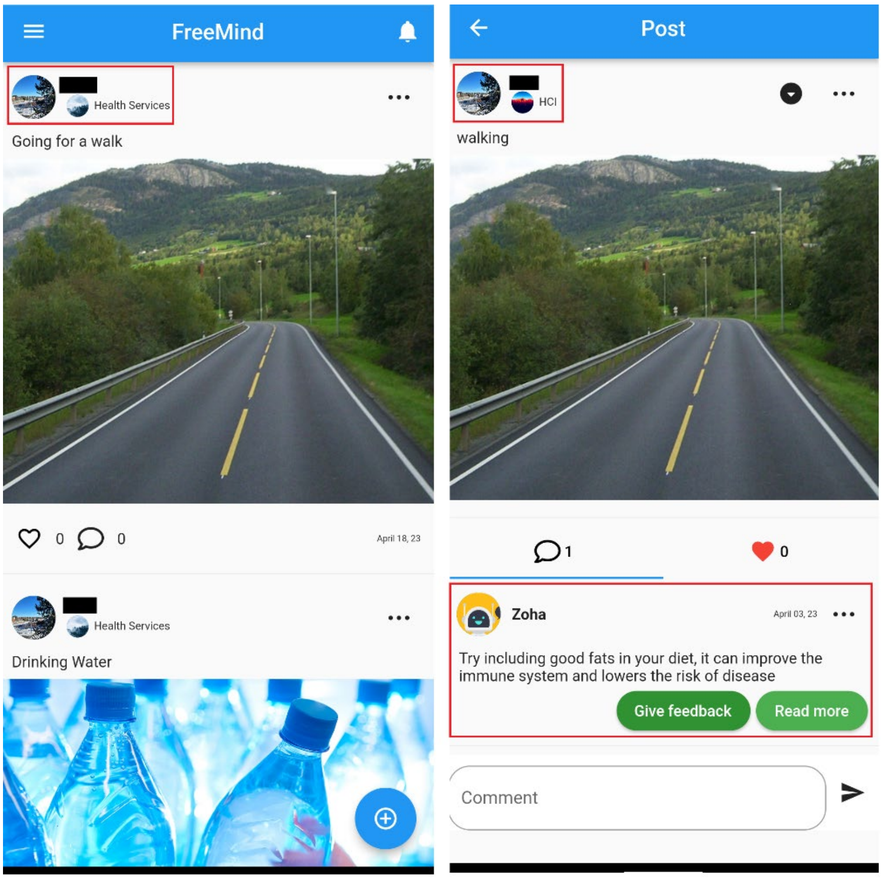

Figure 1. The *FreeMind: groups* probe. User feed with posts of daily activities (Left) and single-user recommendation sample based on survey data (Right).

Recommendation system

Using the recommendation model from (Kazi & Sandbulte, 2023), we generate single-user automated recommendations and deliver them as comments on the user's posts (see Figure 1, Right). The single-user recommendation is generated based on two data entries: a) the user's survey data and b) the user's caption from posts. Additionally, we have expanded the model in (Kazi & Sandbulte, 2023) by selecting the recommendation with the highest predicted rating, rather than randomly choosing from the top 10 highest-scoring options to enhance the quality of the suggestions.

Group-based recommendation system

We extend the work in (Kazi & Sandbulte, 2023) by developing group recommendations. Our system generates recommendations for group activities based on the preferences of all group members (Alvarado et al., 2022; Pujahari & Padmanabhan, 2015). These group recommendations are sent at specific times throughout the day, as determined by our research team.

To generate a group-based recommendation, the system uses collaborative filtering (Pujahari & Padmanabhan, 2015) to calculate the estimated rating of each activity with respect to each user in the group. For example, a group may have the following rating of an activity:

- User 1, Activity 1 = 5
- User 2, Activity 1 = 5
- User 1, Activity 2 = 3

Then, we combine the estimated ratings of activity given by each user (example: User 1, Activity 1 + User 2, Activity 1) resulting in a combined estimated rating of the activity for the whole group. Next, we select the activity with the higher rating. When the system recommends an activity, we included constraints to not allow to recommend the same activity repeatedly. The group recommendation is presented as a post without an image in the group feed to differentiate from the single-user recommendation (see Figure 2).

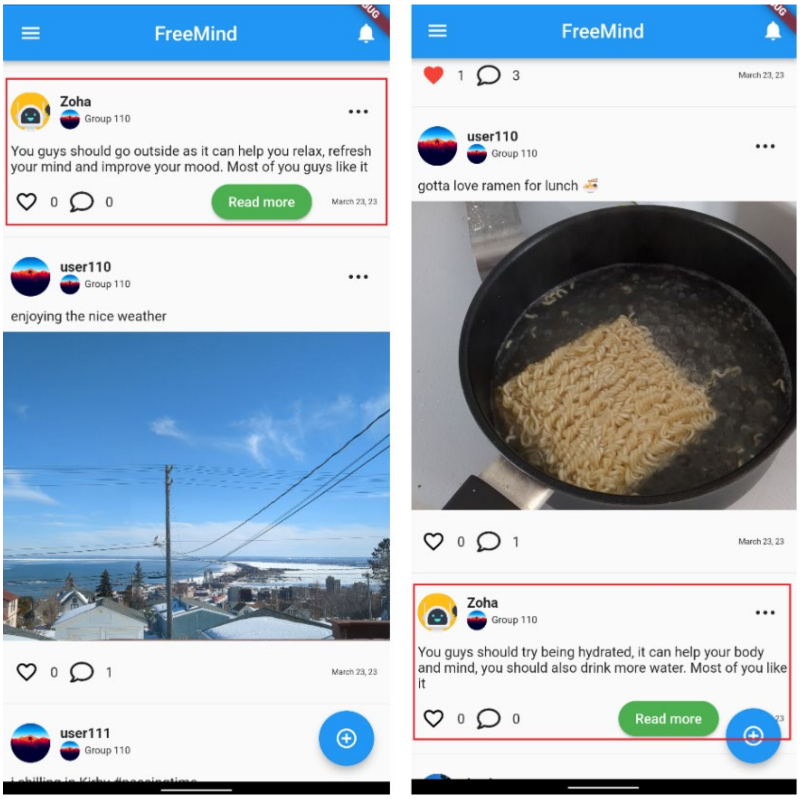

Figure 2. An example of a group recommendation suggesting physical activity (Left) and an example of a group recommendation suggesting a healthy behaviour (Right).

Recommendation explanations

We extend the recommendation explanation model presented in (Kazi & Sandbulte, 2023) by implementing three automated recommendations: a) knowledge-based (Liao et al., 2022), b) social-based (Sharma & Cosley, 2013), and c) hybrid-based (Kouki et al., 2017). The knowledge-based recommendation considers the post's caption and single-user survey preferences. Similarly, social and hybrid recommendations utilize the post's caption. Additionally, the social and hybrid recommendations incorporate the preferences of all group members to reflect the social context in the recommendation process.

We defined the following explanation templates for each recommendation based on prior literature to ensure they felt personalized and not '*robotic*.' Each recommendation includes an external link that directs students to our institution's website, where they can learn more about the benefits of the activity and explore available resources. Figure 3 illustrates how recommendation explanations are displayed within the application.

- **Knowledge-based**: this style presents a recommendation based on the benefits of the activity/strategy according to medical reports. For example: '*try going for a walk, since it strengthens muscles and bones, and improves physical energy and mood. Read more: [link]*'.

- **Social-based**: this style presents a recommendation based on social similarities within set of users (i.e., whether other group members like the activity too). For example: '*Try going for a walk, it is something your friends also like. Read more: [link]*'.
- **Hybrid-based**: this recommendation combines both knowledge and social styles. For example: '*Try going for a walk, since it improves physical energy and mood, and your friends like it. Read more: [link]*'.

Finally, an example of the group recommendation explanation template: '*You guys should go for a walk, since it improves physical energy and mood, and most of you like it. Read more: [link]*'.

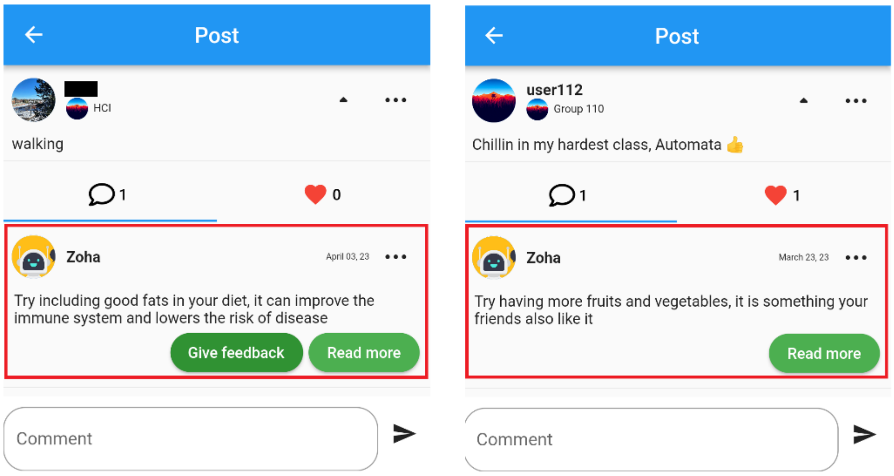

Figure 3. An example of a knowledge-based explanation style (Left) and an example of a social-based explanation style (Right).

Methods

This study aimed to explore how a DMH design probe that incorporates college students' social circles and algorithmic processes could offer support for stress management, as well as to understand the benefits, challenges, and implications of such designs. To achieve this, we conducted a user study involving 15 college students and their social circles in which they interacted with a technology probe for a day (approximately 8 hrs).

Participants recruitment

This research was approved by the Institutional Review Board (IRB) before any research activity. We recruited participants from various campus events and colleges, including the Computer Science (CS) graduate student's colloquium, distributed fliers around campus, and sent emails to student mailing lists.

Participants had to be 18+ years, currently enrolled in our institution, and were required to register in groups of at least three people. Interested individuals received an email detailing the study procedure, which involved using the app for a full day and providing feedback. Each participant was compensated with $30 for their contribution.

Study procedure

After receiving confirmation emails from all group members, we scheduled a study day for each group to participate. The study day was divided into two segments: a) an initial morning meeting and b) a final evening meeting. On the designated study day, we asked the entire group to meet in person with our research team during each session.

Initial morning meeting: We began by providing the participants with an overview of the application, and demonstrating basic tasks such as logging in and navigating the app. We also explained the survey questions within the app and introduced the multi-group function. After the presentation, participants were asked to log into the app using pre-created usernames and passwords to simplify the process. We set up the accounts and added them to a group, enabling participants to communicate with each other within the app.

Once the application setup was complete, we discussed the participants' availability to determine a suitable time for the final meeting at the end of the day. Throughout the day, participants received at least four recommendations (i.e., one knowledge-based, one social-based, one hybrid-based, and one group based). After scheduling the final meeting, participants completed a pre-study survey including Perceived Stress Scale (Cohen et al., 1994), participants' social circle awareness level (Sandbulte et al., 2021), and demographics.

Final evening meeting: In the evening session of the study, we requested participants consent to record the interview session, and upon receiving verbal consent, we began the group interview. During the interview, we asked participants about their experiences using the application throughout the day. Some of the questions included: '*in your opinion, how can this app help you focus more on your self-care*?' and '*give an example of something new you learn about your friend during the study, if any*.'

Following the interview, participants completed a post-study survey including usability questions (Koester et al., 1998), health chatbot feedback, and participants' social circle awareness level (Sandbulte et al., 2021). At the end of the session, we provided each participant with compensation as an award for their contribution.

Data collection and data analysis

We employed a mixed-method approach for data analysis, integrating qualitative insights to explore quantitative findings more deeply (Wisdom & Creswell, 2013). The quantitative data was gathered using two methods: 1) Surveys were administered to collect information on individual perceived stress level and social circle awareness both before and after using the application; 2) Participant engagement was assessed through user activities like photos shared, comments, and likes, as well as social interactions within groups, including exchanged comments and likes.

For qualitative data, we conducted semi-structured interviews (Braun & Clarke, 2013). An inductive, qualitative analysis approach was used, where the research team open-coded the transcribed interview recordings to identify emergent themes. These themes were then discussed and refined to develop key, high-level insights. We focused on themes related to application use and interactions between students and their friends during the intervention.

Participant overview

A total of 15 students participated in the study (see Appendix A–Table 1). Among them, 8 participants identified as male and 7 as female. In terms of racial identity, 46% of the participants identified as White, 13% as Black or African American, and 40% as Asian. The age range was 20 - 32 years old (M = 22.8, SD = 3.46).

46% of the participants reported occasional feelings of being upset by unexpected events and 33% reported experiencing a lack of control over important aspects of their lives. Additionally, 40% of participants experienced nervousness and stress, highlighting the prevalence of stress-related issues (see Appendix A–Table 2).

On a more positive note, 53% of the participants felt confident in their ability to handle personal problems. However, challenges, such as feeling overwhelmed by difficulties, were also reported by 53% of the participants (see Appendix A–Table 2). These data underscore the complexity of well-being, revealing both resilience and vulnerability among participants.

Results

In this section, we summarize the key themes that emerged from our data analysis, which focused on participants' experiences with the application and aimed to address the study's research questions.

To systematically identify all participants, we developed a coding system. Each group was represented by the letter 'G' followed by a number, while individual participants within those groups were represented by the letter 'P' and a corresponding number. For example, group 1, participant 1 was coded as G1P1, and group 4, participant 2 as G4P2.

Friends as partners on stress management

Social ecosystems' awareness on daily stressors

In our study, we aimed to observe whether students and their social circle would increase awareness of each other's behaviors (RQ.1) and how recommendations could foster collaboration towards self-care (RQ.2). Our data revealed three primary ways in which the intervention influenced interactions within college students' social ecosystems.

Firstly, participants reported learning new things about each other while using the application. Even though the group members felt they already knew each other well, the intervention provided an opportunity to discover more about each other's daily routines. For instance, within group 4, participant G4P3 mentioned that they were all close friends who hung out together at least every two days. Yet, participant G4P2 was surprised to learn that G4P3 makes his bed every morning. Despite their familiarity, G4P2 appreciated the chance to learn more about each other's everyday habits: '*I learned that he [G4P3] made his bed which I didn't realize. I learned he had a good nap. It's interesting to see what you're doing*' (G4P2).

Another example of discovering new insights occurred in group 2. Participant G2P3 shared that she learned something unexpected about G2P1: '*I don't know G2P1 goes to gym. I meet her every day when all of a sudden, I saw a picture from G2P1 working hard at the gym.*' (G2P3) In response, G2P1 explained that going to the gym was a recent habit:

> *actually, I just started, I just decided to start. After Spring Break, I didn't have time because of homework and stuff. But then I'm like, 'today I have to go'. So, I just went and decided to post it* (G2P1).

During the interview, G2P3 noted that, although she knew her friends well, the intervention allowed them to gain new insights into each other's daily practices: '*I know them personally a lot, [but] I learned more specifically about their habits, likes, or dislikes*, I guess. *So, I learned a lot*' (G2P3).

Second, we noticed that participants reinforced their existing knowledge of their friends' behaviours. For instance, in group 2, G2P3 mentioned that she was already aware of G2P2's dislike for her Chemistry course. However, during the intervention, this knowledge was further solidified: '*most of her posts are related to the Chem course [then] I realized 'okay, she literally hates it* (G2P3).' In this case, the intervention didn't introduce new information but reinforced what was already known.

Finally, we observed that participants used this experience to clear up some misconceptions. For instance, within Group 1, participant G1P3 mentioned, '*I saw someone's jacket was purple, and I saw another one who really liked Valorant.*' (G1P3) Based on this post, G1P3 assumed that G1P2 liked the game Valorant. However, G1P2 clarified, '*No, I didn't like I am trying to like it* (G1P2).' This highlights how group interactions can sometimes lead to misunderstandings. In another case, G1P2 initially thought that G1P3 disliked Android studio but later discovered otherwise. G1P2 noted, '*I thought he actually dislikes Android, but it turned out he didn't hate it but and actually likes it. Yeah, I learned that*' (G1P2). To which G1P3 responded: '*lot of people think I hate Android, but I don't hate it*'(G1P3).

Leveraging social support to manage stress

During the study, we also noted some participants provided support by encouraging each other on healthy behaviors. For instance, in group 3' s case, G3P3 mentioned to see participant G3P1's post on doing physical activity and that motivated them to provide encouragement: '*I guess one thing I did was he was like working out in one of his posts and encouraged him, you know, like go get it or whatever, like encouraging him, I guess*' (G3P3). Reflecting on the study experience, participant G3P3 appreciated the opportunity to share daily activities with friends and receive updates from them: '*...it was nice to have everyone posting on. You see how everybody else is doing. Kind of keeps you engaged, you feel, I guess, better too*' (G3P3).

In addition, participants reported feeling motivated to engage in positive activities for their personal well-being to share their experiences. Many viewed this as a beneficial aspect of the study intervention. For example, in group 5, participant G5P2 noted that she decided to go to the gym and share it with her friends to receive support despite her busy schedule:

> *So today I was like, 'I need one post, so I have to go to the gym.' So, I just made myself to go for that. And I think if I just put myself in a situation that I need to do that because of sharing it with my friends and then they can give me feedback, then it would be a great way to make me do something* (G5P2).

Privacy considerations while sharing experiences

We also examined people's concerns about sharing personal experiences (RQ.3a). Participants highlighted the advantages of having a dedicated group space within the application instead of a public one. One key benefit was the reduction in stress and anxiety over what to post. For instance, participant G2P2 appreciated that the private space allowed her to share only with close friends, which reduced her stress: '*I like you're not posting it to everyone. It's just nice that it's more private like it's only two people that you're close to me*' (G2P2).

Participant G2P3 shared that having a dedicated space gave her the confidence to be vulnerable when discussing daily stressors. She also reflected on the anxiety she might feel if her posts were public:

> *if you're [thinking], what should I say? It's just I can be as vulnerable as I can with my own friends. But like for the friends whom I see once in a month, I really would be feeling threatened* (G2P3).

Participant G2P4 echoed this sentiment, highlighting the importance of group design and privacy: '*Yeah, I would say it's also privacy because sometimes you post something you don't want like others to see like just some specific people.*' (G2P4) These insights offer practical examples of how user needs can guide design decisions.

Participants also provided suggestions for improvements. For instance, participant G1P2 proposed adding an anonymous mode for sharing posts:

> *so, I think it is good to have friends in the same group, but it might be helpful to have anonymous option. So, people would post things like 'I failed on this exam.' Anyone could comment with usual text but [the post has] no name or picture* (G1P2).

He further elaborated on why an anonymous mode could encourage sharing: '*so that might help me feel better in some cases when sometimes is hard to share* (G1P2).'

Analysis of the recommendations' effectiveness to facilitate collaboration and promote well-being

In our study, we encouraged participants to reflect on their experiences with receiving recommendations for managing stress and facilitating social support (RQ.2). We also aimed to explore any concerns related to the algorithmic processes (RQ.3b).

Participants expressed overall satisfaction with the recommendations provided by the chatbot, finding them helpful for collectively improving lifestyles with friends (Appendix B-Table 5). For instance, participant G4P3 highlighted a benefit of receiving well-being reminders: '*…because it reminded me to do something that otherwise I wouldn't have* (G4P3).'

In group 3, all members reported receiving useful recommendations. Participant G3P1 shared: '*They [chatbot] told me to get water because I don't drink enough water during the day*' (G3P1) while G3P2 mentioned: '*It told me to eat my fruits and vegetables, which is good. I don't eat much of them. Get me on my toes.*' (G3P2). Additionally, G3P3 appreciated a specific recommendation, stating: '*I took a picture of me being in Stats class and It said, 'be open minded'. So, I thought that was pretty well.*' (G3P3)

However, participants felt that recommendations could be enhanced by making them more relevant to their posts rather than just their survey responses. For example, G5P2 observed: '*They're personalized now because it was relevant to what I chose in the surveys but not relevant to the post [image].*' (G5P2) Furthermore, participants suggested incorporating weather conditions based on location. For instance, G1P3 struggled with a recommendation due to poor weather: '*I mean, like It told you to go on a hike or go for a walk and it's like yesterday's weather, then you're probably gonna say I'm not going for a walk*' (G1P3).

Participants also showed a strong inclination to share health information with friends (Appendix B-Table 5). The system was reported to increase awareness of friends' lifestyles (Appendix B-Table 3) and facilitate health-related discussions among them (Appendix B-Table 3 and 5). For example, in group 5, participants mentioned they already had a WhatsApp group where they shared photos and chatted daily. However, the study intervention introduced a new topic of conversation — mental health. Previously, their discussions focused on parties and other activities, but the app prompted them to talk about health for the first time. Participant G5P1 shared:

> *now when I find something interesting, I send this for them and say, 'yeah, I found this really nice'. You can try that as well and they also give me some comments 'Oh yeah, let's try that together another time' we have the group to talk, manage anything, to ask question and talk about these specific things for our mental health, that is nice (G5P1).*

However, some participants felt that group recommendations could occasionally come across as rude, despite being based on observations. For example, G1P4 recounted a situation where a sarcastic comment he made led to an unintended personal recommendation from the bot:

> *I don't like how in one of the posts I made I said for the caption 'gotta enjoy Apple devices' and the bot said 'try being more kind' as it has been shown to boost mood and lengthen lifespan. I found that very personal to me (G1P4).*

Similarly, G4P2 commented on a group recommendation, noting that while they appreciated the suggestion to be optimistic, it might sometimes seem subjective or out of place:

> *I like the one about being optimistic, but it seems that one might be very subjective to put under someone's post because the bot might not really detect negativity, I guess. But as if it's just kind of a message for everyone in the group. I definitely like it as a recommendation* (G4P2).

These insights suggest that some recommendations may be better suited for general messages rather than comments on individual posts, as they could be perceived as targeting specific users, particularly when visible to the whole group.

Perceived benefits of recommendation explainability

Participants provided positive feedback on the recommendation system's ability to explain the reasoning behind its suggestions (see Appendix B – Table 4). For instance, participant G1P1 noted: '*I like the explanation because I just like to know why it is good to our health, although I don't want to do it right now. But it's good to know why it is good*' (G1P1).

Participants also preferred the hybrid approach used in the system, which combines both informational and social elements to enhance motivation for selfcare. Participant G4P1 said:

> *I like that there's kind of extra detail behind it that tells you how it can help you. And then I also do like knowing that my friends are doing this for wellness, well-being. So, it would make me want to do it too* (G4P1).

Participant G4P3 added that the '*read more*' option was beneficial for those who want additional information:

> *combination is definitely better I guess a lot for me, like you should do it because your friends are doing it and here's why and then you give like a short reason, and then you could extrapolate further if I decide to read* (G4P3).

However, some participants suggested improvements for the explanations, such as incorporating positive encouragement to support ongoing self-care. Participant G2P2 mentioned:

> *...even if it doesn't recommend based on what I was doing, but like if it just says, you're doing great, that comment is gonna make me smile more. I would say it doesn't particularly need to relate to something that I'm doing* (G2P2).

Similarly, participant G2P4 suggested that positivity could improve one's day, especially during stressful times:

> *so, I'm thinking maybe give positive notes like, oh, I have a great day. You're doing great ... I think you might like to make the person happy and like maybe the person is having a bad day, makes the person smile like* (G2P4).

Discussion

While our study involved a limited sample over a short period, the findings provide valuable insights into user experiences and perceptions of a social application designed to support stress management and well-being among college students. The following discussion highlights key themes that emerged from our data and explores their implications for design and future research.

Benefits of interventions leveraging social circles to support stress management

In this study, we identified three key findings: (1) increased awareness of everyday behaviours, (2) promotion of positive behaviours through social support, and (3) privacy considerations when sharing personal experiences.

First, the application significantly improved awareness within social groups about each other's daily stressors and habits. Increased awareness can encourage self-reflection, potentially leading individuals to modify their own behaviours (Sandbulte et al., 2021). Our findings revealed that even among close friends, the intervention facilitated the sharing of new insights into daily routines and personal challenges that might not have been discussed otherwise (e.g., G4P2, G2P3). This aligns with previous research focused on creating spaces that strengthen social bonds (Epstein et al., 2015; Murnane et al., 2018; Park, 2018). Moreover, our study expands on prior work by showing that sharing experiences can reinforce existing knowledge and provide opportunities to clarify misconceptions, as demonstrated in the cases of G2P3 and G1P2. This suggests that increased awareness among participants not only fosters connection but also helps refine social perceptions, potentially reducing misunderstandings within social groups.

Second, the study emphasized the potential of social support in promoting positive behaviours. Participants reported feeling motivated to engage in healthy activities, like exercising, because they wanted to share these experiences with friends and receive encouragement (e.g., G5P2, G3P3). While previous research has shown that relationship conflicts can sometimes hinder the willingness to share (Eisenberg et al., 2009; Park, 2018), our findings demonstrate that positive social influence and support can significantly impact individual health behaviours. Social support can strengthen resilience to stress, and the quality of relationships plays a crucial role in shaping students' coping mechanisms and mental health outcomes (Keyes, 1998; Thieme et al., 2015). Group recommendations in this context, such as those highlighted by participant G3P4, further emphasized the importance of fostering a sense of community and shared responsibility for well-being. Future research could explore ways to maintain these partnerships for managing daily stress. Also, there is opportunity to explore different group dynamics such as non-collocated friends. Finally, future research in GRS could explore alternative media to help maintain group motivation since most recommendation systems rely on text messages (Cheung et al., 2019).

Lastly, privacy emerged as an important concern for participants. The strong preference for private group settings over public spaces highlights the importance of creating safe environments where users feel comfortable sharing personal experiences. Several participants, such as G2P2 and G2P3, reported reduced stress and anxiety when communicating in private settings which indicates the important role of privacy in fostering honest and open conversations. This aligns with existing research, which suggests that users are more inclined to disclose sensitive information in trusted, private spaces (Newman et al., 2011; Sandbulte et al., 2021). The suggestion to implement an anonymous mode (e.g., G1P2) further emphasizes the need for flexible privacy options to cater to varying levels of user's comfort. Addressing this need in future developments is essential, as customizable privacy settings can enhance user trust and promote a safer, more supportive experience.

Design considerations for developing effective recommendations

While most participants found the recommendations useful, our data revealed opportunities for improving personalization. Participants, such as G5P2, expressed a desire for recommendations that were more closely tied to their posts rather than only based on survey responses. This finding suggests an expectation for a more dynamic and context-aware system (Afzal et al., 2018; Cheung et al., 2019; Kazi & Sandbulte, 2023). Additionally, incorporating external factors such as weather conditions (e.g., G1P3) could further enhance the relevance and practicality of the recommendations. Previous research has explored algorithmic processes that consider users' contexts, like weather and physical activity preferences, to improve personalization (Afzal et al., 2018). Future studies could extend this contextual knowledge to better align the recommendations with real-time user's activities and environmental factors, which may increase user engagement and satisfaction.

Our study also addressed the gap in leveraging RS for group settings. Mixed responses to group recommendations where some participants found them too critical or too generalized (e.g., G1P4, G4P2) highlight the need to balance offering helpful advice while respecting individual's self-image within a group. Similar challenges have been noted in other GRS domains, such as tourism (Delic et al., 2018; Herzog & Wőrndl, 2019). Future research could focus on exploring the optimal timing for delivering single-user versus group-based suggestions, to determine whether a recommendation is best suited for the whole group or not.

Finally, the positive reception of the recommendation system's explanations indicates that users value understanding the reasoning behind suggestions, even if they do not always act on them (e.g., G1P1). A hybrid approach combining informational and social elements was especially well-received, as it provided both context and motivation for the recommendations (e.g., G4P1, G4P3). However, feedback also suggests the explanations could incorporate positive reinforcement. For instance, simple motivational messages like '*you're doing great!*' could be integrated into the system's explanation to help sustain user's motivation.

Limitations

Our study introduces *FreeMind: Groups*, a social application designed to help students interact with peers and receive support in managing stress. We acknowledge the limitations of our brief user study and the preliminary nature of our findings, as the short duration may not fully capture the range of user behaviours. Future research should consider long-term interventions to address these limitations. Additionally, we acknowledge that our research is formative and informed by prior literature, and the limitation on relying on self-reported data. Moreover, similar to Newn et al., (2022), our study did not aim to evaluate different styles of explanation but rather the presence of explanations in general. We hope future studies can address these limitations.

Lastly, while we aimed to recruit a larger and diverse sample of students, we are aware that our sample size and participant group may not be representative of the general college student population. It is also possible that our sample may be affected by the Hawthorne effect, and social desirability bias. Still, our study's sample is consistent with the nature of this research (Braun & Clarke, 2013). Future studies should address these limitations, including a broader spectrum of stress levels and various types of friendship or group dynamics to gain deeper insights and propose innovative DMH interventions.

Conclusion

This study highlights the potential of a DMH tool that integrates social features and algorithmic processes to personalize the delivery of both individual and group recommendations aimed at supporting stress management for college students. Our findings indicate that college students valued the opportunity to share their daily activities with friends and receive updates in return. This interaction fostered a sense of connection and mutual support, which motivated participants to engage in positive activities for their personal well-being. Additionally, participants provided feedback on the recommendations they received for managing stress, highlighting the potential benefits of personalized, socially driven DMH tools. Finally, we offer recommendations for future research, emphasizing the need for further exploration into the design and implementation of socially integrated DMH tools that can effectively support college students' mental health.

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About the authors

Farhanuddin Fazaluddin Kazi was a graduate student at the Department of Computer Science, University of the Minnesota -Duluth, Duluth, USA. He holds a master's degree in Computer Science. He can be contacted at kazi0021@d.umn.edu

Jomara Sandbulte is an Assistant Professor at the Department of Computer Science, University of the Minnesota -Duluth, Duluth, USA. She holds a master's degree in Computer Engineering and Ph.D. in Informatics from Pennsylvania State University. Her main research interests are in Human-computer interaction with AI systems, recommendation systems, and health informatics. She can be contacted at jsandbul@d.umn.edu

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Appendix

Appendix A: pre-study survey results

Group ID	Participant ID	Age	Gender
G1	P1	20	Male
	P2	32	Male
	P3	28	Male
G2	P1	28	Female
	P2	24	Female
	P3	22	Female
G3	P1	22	Male
	P2	21	Male
	P3	21	Male
G4	P1	21	Female
	P2	21	Male
	P3	21	Male
G5	P1	21	Female
	P2	21	Female
	P3	20	Female

Table 1. Participants' groups, age, and gender

	Question	Never	Sometimes	About half the time	Most of the time	Always
1	In the last month, how often have you been upset because of something that happened unexpectedly?	13.34%	46.67%	13.34%	20%	6.67%
2	In the last month, how often have you felt that you were unable to control the important things in your life?	20%	33.34%	13.34%	20%	13.34%
3	In the last month, how often have you felt nervous and stressed?	13.34%	40%	6.67%	20%	20%
4	In the last month, how often have you felt confident about your ability to handle your personal problems?	6.67%	13.34%	13.34%	53.34 %	13.34%
5	In the last month, how often have you felt that things were going your way?	6.67%	40%	13.34%	40%	0.00%
6	In the last month, how often have you found that you could not cope with all the things that you had to do?	20%	53.34%	20%	6.67%	0.00%
7	In the last month, how often have you been able to control irritations in your life?	13.34%	13.34%	33.34%	33.34 %	6.67%
8	In the last month, how often have you felt that you were on top of things?	6.67%	40%	13.34%	33.34 %	6.67%
9	In the last month, how often have you been angered because of things that happened that were outside of your control?	6.67%	46.67%	13.34%	26.67%	6.67%
10	In the last month, how often have you felt difficulties were piling up so high that you could not overcome them?	26.67%	53.34%	0.00%	20%	0.00%

Table 2. Pre-study survey perceived stress scale (PCS) questions. Likert scale 0 to 5 (0= Never, 5=Always), n=15

Appendix B: post-study survey results

	Questions	Min.	Max	Mean	SD	Variance
1	I am more aware of my friend's healthy behaviors after participating in this study.	3.00	5.00	4.27	0.77	0.60
2	I feel happier about my friend's healthy lifestyle after participating in this study.	3.00	5.00	4.13	0.81	0.65
3	I feel closer to my friend after participating in this study.	1.00	5.00	4.13	1.09	1.18
4	I give more feedback to my friend about his/her healthy lifestyle after participating in this study.	0.00	5.00	3.67	1.30	1.69
5	I receive more emotional support from my friend after participating in this study. For example, I receive messages of encouragement to go exercise.	2.00	5.00	4.07	1.00	1.00
6	I receive more tangible support from my friend after participating in this study. For example, He/She goes exercising with me.	2.00	5.00	3.87	1.15	1.32
7	I receive more informational support from my friend after participating in this study. For example, He/She share articles about healthy living with me.	0.00	5.00	3.87	1.31	1.72
8	I feel I have a very healthy lifestyle.	1.00	5.00	3.87	1.20	1.45

Table 3. Survey awareness questions. Likert scale 0 to 5 (0= Strongly disagree, 5=Strongly agree), n=15

	Questions	Min.	Max.	Mean	SD	Variance
1	It was very easy to learn how to use the FreeMind: groups application	4.00	5.00	4.80	0.40	0.16
2	Using the FreeMind: groups application was a very pleasant experience.	4.00	5.00	4.60	0.49	0.24
3	I would like to use the FreeMind: groups application outside the study	3.00	5.00	4.20	0.75	0.56
4	I would really dislike to use the FreeMind: groups application daily	0.00	5.00	0.93	1.28	1.64
5	The recommendations were confusing	0.00	5.00	1.60	1.58	2.51
6	The recommendations were helpful	1.00	5.00	3.13	1.31	1.72
7	The recommendations were relevant	0.00	5.00	2.80	1.47	2.16
8	I read more about the recommendation activity by going to the link provided	0.00	5.00	3.07	1.53	2.33
9	I liked the way that the recommendation was presented	2.00	5.00	3.60	0.95	0.91
10	I disliked the way that the recommendation was presented	0.00	5.00	1.67	1.49	2.22
11	I was able to effectively interact with the FreeMind: Groups application	4.00	5.00	4.73	0.44	0.20

Table 4. Survey usability questions. Likert scale 0 to 5 (0= Strongly disagree, 5=Strongly agree), n=15

	Questions	Min.	Max.	Mean	SD	Variance
1	The health chatbot was providing good health information to me.	4.00	8.00	6.87	1.02	1.05
2	The health chatbot was useful for improving my lifestyle.	4.00	8.00	6.67	0.87	0.76
3	I like the health information recommended by the health chatbot.	4.00	8.00	6.80	1.11	1.23
4	I am convinced by health information recommended by the health chatbot.	4.00	8.00	7.07	1.06	1.13
5	The health chatbot explained why the health information was recommended to me.	4.00	8.00	6.73	1.06	1.13
6	I would share the health information recommended by the health chatbot with my friends.	4.00	8.00	7.07	1.06	1.13
7	The health chatbot helped me to improve my lifestyle with my friends.	4.00	8.00	6.80	1.11	1.23
8	The health chatbot made me more aware of my friend's lifestyle.	4.00	8.00	7.20	1.05	1.09
9	The health chatbot helped me to talk about health with my friends.	4.00	8.00	6.67	1.25	1.56

Table 5. Survey questions on health chat bot feedback. Likert scale 0 to 5 (0= Strongly disagree, 5=Strongly agree), n=15