Mobile Data Collection for Depression Analysis: An App Framework for Monitoring Mood and Depression Using Smartphone and Wearable Data

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Abstract: Depression is a leading cause of disability worldwide, affecting around 5% of the global adult population. To address this problem, researchers are exploring methods for early detection of relapses, mood swings and their relation with health data and external influences. The aim of the present study was to evaluate the usability and feasibility of a mobile application designed for active and passive data collection, with potential future applications for improving mental healthcare through a virtual therapy assistant. The application allows users to self-report their mood, complete PHQ-9 questionnaires, and track measures such as sleep, physical activity, location, smartphone usage, and social media engagement.

A six-week pilot study was conducted with 22 healthy participants (68% male, 32% female). Participants recorded their mood three times a day and completed weekly mental health assessments. Results showed that the application effectively collected relevant data and was user friendly. However, limitations included reliance on self-reported data, short study duration, and occasional technical issues with data collection. Despite these limitations, the study showed that it is possible to use smartphones and wearable technologies to monitor mental health, laying the foundation for future developments in digital therapeutic interventions and personalized healthcare through app-based virtual therapy assistants.

1 INTRODUCTION

According to the World Health Organization, depression affects approximately 5% of the global adult population, making it one of the most prevalent mental health disorders worldwide (WHO, 2023).

Depression can affect anyone. Risk factors include, for instance, traumatic experiences, genetic predisposition, age, pre-existing illness, stress or social isolation (WHO, 2023). The core symptoms include persistent depressed mood, loss of interest and lack of motivation (Nationale Versorgungsleitlinien, 2024). Depression is typically diagnosed when symptoms persist for at least two weeks. The severity of the disorder is determined by the number and intensity of these main symptoms as well as secondary symptoms such as fatigue and sleep disturbances (Nationale Versorgungsleitlinien, 2024). In severe or chronic cases, depression can lead to significant health risks, including inability to work, and, in extreme cases, suicide (WHO, 2023).

Treatment for depression commonly includes cognitive behavioral therapy (CBT) (Kazantzis et al., 2018), which is often supplemented with medication in severe cases (WHO, 2023). Despite increasing awareness, significant challenges remain, such as limited access to treatment (Deutscher Bundestag, 2022), misdiagnosis, and reluctance to seek treatment (Kessler et al., 2002). In addition, current healthcare systems often lack the capacity to provide continuous monitoring, although the relapse rate for depression ranges between 40% to 60% (Nationale Versorgungsleitlinien, 2024). Continuous monitoring of mood, sleep patterns, physical activity, and social interactions could enable more personalized and timely interventions, thus improving long-term outcomes (Mohr et al., 2017). Integrating innovative digital tools such as mobile applications and wearable technology offers a scalable and accessible approach to complement current treatment methods. Thanks to unobtrusive sensors, these devices can be used to

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monitor mental health, detect mood swings, and support early interventions (Torous et al., 2018).

Research has linked several factors to mood swings in depression, including demographic variables (e.g., gender, age, relationship status) (WHO, 2023; Grundström et al., 2021), physical activity (Kvam et al., 2016; Stanton and Reaburn, 2014), vital signs, sleep quality (Irwin, 2015; Short and Louca, 2015; Rykov et al., 2021), weather conditions (Denissen et al., 2008; Klimstra et al., 2011; Taniguchi et al., 2022), and location (Masud et al., 2020). Moreover, research showed that individuals with depression often have increased phone use, and excessive screen time was shown to be associated with poorer mental health outcomes (Razavi et al., 2020; Asare et al., 2021; Javaid et al., 2022). At the same time excessive social media use, particularly among young women, is correlated with greater depressive symptoms as well (Fardouly et al., 2015; Thorisdottir et al., 2019; Bengtsson and Johansson, 2022; Cunningham et al., 2021; Drouin and Abbasi, 2019). Moreover, Hong et al. applied machine learning based to Global Positioning Service (GPS) and phone usage to detect depressive symptoms (Hong et al., 2022), while Ghosh et al.'s achieved 78% accuracy in emotion recognition from typing patterns (Ghosh et al., 2019). Similarly, Masud et al. integrated several smartphone metrics such as physical activity and time spent at home to predict depression severity using PHQ-9 scores (Masud et al., 2020).

Building on these findings, we developed a mobile application (app) that collects both active data such as mood ratings and questionnaire responses, as well as passive data from smartphones and wearable devices. This approach aimed to complement existing mental health apps by incorporating a wider range of behavioral and lifestyle factors. Although existing apps have been shown to be effective (Bakker and Rickard, 2017), they often have limitations. For instance, MindDoc (MindDoc, 2023) tracks mood symptom management, but does not integrate social media data. Woebot (Fitzpatrick et al., 2017) provides AI-driven CBT and personalized mood feedback, but does not collect passive behavioral data from wearable devices. In addition, many mental health apps lack formal regulations and rely heavily on user input, often overlooking individual differences.

Our goal was to embed established processes into an app and evaluate that app, which was iteratively adapted to meet the specific needs of the target group while adding factors such as social media consumption and smartphone usage. By linking mood data with passively and actively recorded data, the app allows for monitoring a comprehensive range of factors influencing depression. Developed within the DAIsy project (*Developing AI ecosystems improving diagnosis and care of mental diseases*), the DAIsy data collector (DC) app will be integrated into a larger ecosystem that aims to address limited mental health resources, support continuous monitoring of conditions with high relapse risk, and personalizing treatment. Wearables integrated into the ecosystem capture health and behavioral data, like heart rate and physical activity, to improve mood monitoring (Klein et al., 2023). To assess the functionality and usability of the DAIsy DC app, we conducted a six-week pilot study with 22 healthy individuals, focusing on qualitative assessment of user experience and app performance.

2 DAIsy DATA COLLECTOR (DC) APP

DAIsy DC was developed for Android and collects data both actively (user input required) and passively (no user input required). The overall architecture of the app is shown in Figure 1.

2.1 Passive Data Acquisition

Table 1 summarizes the passive data collected via smartphones and wearable devices. Wearable devices such as smartwatches can be integrated via the Google Health Connect interface. Currently, the app focuses on three key categories of passive wearable data: activity, sleep, and vital signs are included, as these metrics provide more accurate and reliable measurements compared to manual user input. If wearables are unavailable, apps like Google Fit can track physical activity. Heart rate and heart rate variability are primarily collected through smartwatches or compatible apps such as Google Fit. Similarly, sleep duration is measured using these sources.

Weather and bio-weather data are obtained from OpenWeather and the German Weather Service (Deutscher Wetterdienst, 2024) and capture parameters such as minimum and maximum temperatures, perceived temperature, air pressure, humidity, and the corresponding date and time. For bio-weather, the date is logged along with its potential impact on well-being, pain sensitivity, headaches, sleep quality, concentration, irritability, and depression. The location is also stored in the database in encrypted form.

Phone usage, including screen time and time spent on specific apps, is passively recorded using Android's internal functionality through the Android Usage Stats Manager.

Using GPS technology, the user's location is recorded and categorized into predefined categories such as home, work, or leisure areas. Users must specify these locations once in the app. Any location not specified is classified as 'location' without further

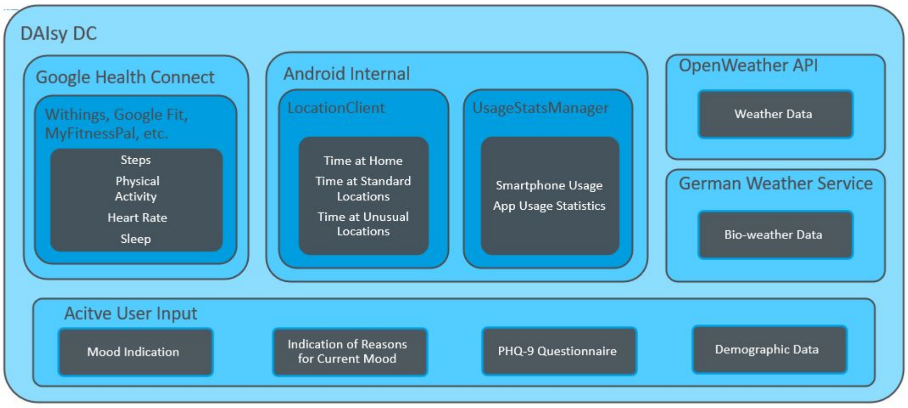

Figure 1: Illustration of the app architecture and data sources.

Table 1: Summary of passively collected data.

Data Type	Sampling Rate	Source
Physical Activity	once per day	Smartwatches, Withings App, Google Fit
Sleep	once per day	Withings Sleep Analyzer, Google Fit
Weather	every eight hours	German Weather Service, Open Weather API
Location	every 15 minutes	GPS
Smartphone Usage	once per day	Android Usage Stats Manager
Social Media Consumption	once per day	Android Usage Stats Manager

categorization. To protect privacy, all location data are encrypted.

Compared to existing apps like mindDoc (MindDoc, 2023), DAIsy DC differs in that it captures a broader range of passively collected data, including social media consumption, smartphone usage, and bio-weather influences. These factors have previously been underrepresented in other platforms focusing on mood and well-being, making DAIsy DC a more comprehensive mental health monitoring tool.

2.2 Active Data Acquisition

Active data acquisition includes user-initiated interactions with the app, including submitting current moods, providing reasons for that specific mood and completing surveys.

2.2.1 Questionnaires

Demographic data is collected via a short questionnaire. The questionnaire includes six questions covering age, gender, marital status, educational background, number of children, and smoking habits. In addition, the app integrates the PHQ-9 questionnaire, a widely used screening tool for assessing the severity of depression (Kroenke et al., 2001). It assesses key indicators of depression such as sleep quality, physical condition, mood, eating behavior, and suicidal ideation. Results are presented graphically, along with explanations of the scores and links to resources for further support if needed.

2.2.2 Mood Tracking

The mood tracking feature requires active user input as it cannot be passively captured. The app uses a simplified version of the Circumplex Model of Affect (Posner et al., 2005), which organizes emotions along two dimensions: valence (positive vs. negative) and activation (energizing vs. deactivating). Users choose from a range of emotions (e.g., ”happy,” ”sad,” ”angry,” and ”nervous”) using sliders to adjust the intensity of their mood. Each emotion is visually represented by a smiley and ranges from unexpressed to very expressed. The values are stored in the database with values from 0 (unexpressed) to 3 (very expressed) (cf. Figure 2a). In addition users can adjust sliders for energy levels, lethargy, and general discomfort. As shown in Figure 2b, mood changes are visualized on a separate screen, allowing users to track their emotional states.

2.2.3 Mood Reasons

After submitting their mood, users are asked to indicate the factors that influence their emotional state (cf. Figure 2c). Users can choose from a variety of predefined categories such as news, weather, stress, family, and more. For more flexibility, an open text field is available for additional input if none of the listed reasons apply. These reasons were selected based on aforementioned known influences on mental well-being, such as physical health, environmental conditions, and social relationships (Umberson and Montez, 2010). This feature allows users to track both

(a) (b) (c)

Figure 2: Image of the selectable moods and according sliders (a), according overview of chosen moods and energy level (b) and the list of selectable influences on the current mood (c).

general and personal mood influences that may not be captured through passive data collection. Users can also indicate whether the selected reason had a positive (green highlighted) or negative impact (red highlighted) on their mood (cf. Figure 2c).

2.3 Exemplary Data Collection

2.3.1 Participants

Table 2: Overview of participants' demographics.

User	m	f	18-23	24-30	31-40	51-60
22	15	7	4	10	2	6

A total of 22 individuals (15 male, 7 female) participated in the study to assess the functionality and usability of the DAIsy DC app. Participants ranged in age from 18 to 60 years, with a mean age of 34 ± 12 years. The demographic data of the participants are listed in Table 2. The study was approved by the OFFIS Ethics Board and participants gave their written informed consent.

To participate, individuals were required to own an Android-compatible smartphone with an operating system version of at least Android 10. Individuals diagnosed with depression were excluded, as the study focused on evaluating the app in a healthy population to enable a comprehensive assessment of the app's usability and functionality prior to its use among users with specific mental health needs.

During the six-week pilot study period, participants were provided with a smartwatch (Withings Steel HR) and/or a Withings sleep analyzer. Of the 22 participants, ten used the Withings sleep analyzer, six received a watch and four preferred to use their own smartwatch (Fitbit Charge 4, Fitbit Versa 4, Withings Scan Watch). In six participants, there was an overlap between the sleep analyzer and the smartwatch.

2.3.2 Data Collection

Active Data. At the start of the study, participants completed a profile to collect demographic information, including their place of residence and, if applicable, other frequently visited locations.

The participants' primary task was to record their current mood via the app at least three times a day. In addition, individuals were asked to provide context or reasons that influenced their mood for each entry. Reminders to report their mood were sent twice a day. In cases where devices, such as a smartwatch or Sleep Analyzer, were not available, participants manually logged their sleep duration and activity in Google Fit. Additionally, participants were asked to complete the PHQ-9 questionnaire weekly.

Passive Data. Data were continuously collected, with most data passively gathered in the background, requiring no active input from participants (cf. Table 1).

Questionnaires. At the end of the study, participants were asked to provide feedback on the app's usability and their own technological readiness. Two questionnaires were used for this purpose: the System Usability Scale (SUS) (Brooke, 1995) measured the app's usability, while the Technology Commitment (TC) short scale (Neyer et al., 2016) assessed the participants' willingness to use technology.

3 DATA EXPLORATION

3.1 Active Data

3.1.1 PHQ-9

The PHQ-9 questionnaire was completed an average of 4.45 ± 1.68 times. The minimum number of completed questionnaires was 1, the maximum 6. The average score was 5.9 for women and 7.3 for men, both of which were in the non-depressive ranges (healthy to inconspicuous 0 - 9). Most participants scored within a range indicating a generally healthy mental state. However, three participants recorded scores indicating mild or moderate depression (mild depression: 10 - 14, moderate depression: 15-19).

3.1.2 Mood Tracking and Subjective Mood Reasons

Table 3: Submission of the moods for each participant and across all participants per day, week and the entire study period.

User	Day	Week	Study Period
1	3.88±1.64	26.57±8.9	186
2	1.88±0.78	10.33±5.75	62
3	2.35±1.58	10±6.48	40
4	2.4±1.2	16.43±6.72	115
5	1.93±0.88	11.86±3.48	83
6	1.38±0.5	4.71±2.63	33
7	1.22±0.74	3.5±2	28
8	2.71±0.97	18.57±2.99	130
9	2±0.8	12.86±2.91	90
10	2.93±0.65	19.29±6.42	135
11	3.55±1.1	13.5±7.18	156
12	2.57±1.33	12±8.1	108
13	1.95±0.43	18.71±4.47	84
14	3.12±1.25	14.14±8.9	131
15	2.36±1.05	5.6±6.44	99
16	1.27±0.55	11±2.4	28
17	2±0.79	22.29±2.97	66
18	2.03±0.82	10.83±4.92	65
19	2.59±0.76	13.71±8.26	96
All	2.32±0.72	13.47±5.89	91.34±44.36
Total	34.7±7.86	216.88±91.52	1735

Table 3 displays mood data across daily, weekly and entire study period. The total number of submissions was 1735 across all participants. Participants reported their mood averagely 2.32 ± 0.72 times a day. Although six participants completed the study earlier than planned, three of them provided continuous data over a period of at least three weeks. After each mood submission, participants were asked to indicate factors that positively and negatively influenced their emotional state. Figure 3 illustrates the frequency of each factor. Although optional, participants provided reasons for 97% of the mood entries. Stress and sleep

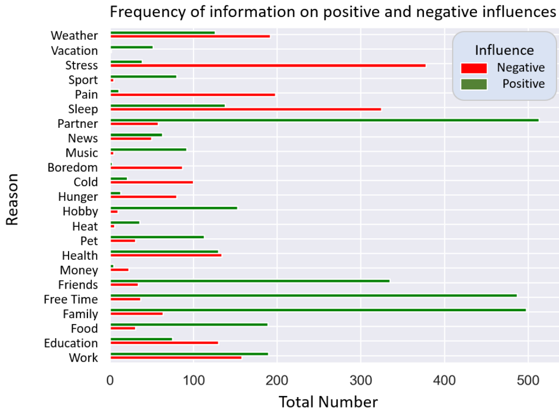

Figure 3: Presentation of the frequencies with which a specific reason was selected either positively or negatively.

were the most frequently cited negative influences. In contrast, family, friends, partners, and relaxation were the most commonly recorded positive influences.

3.2 Passive Data

The results of passive data collection can be summarized as follows:

- **Step Count:** The participants took an average of 4,450 ± 2,504 steps per day, with individual steps ranging from 2,009 to 11,938 daily steps. The impact of physical activity on mood was individual, with some participants reporting mood improvements on days with higher step counts. No participant showed a negative association between physical activity and mood.
- **Sleep Data:** Average sleep duration across all subjects was 7.6 ± 0.8 hours of sleep per day, which meets recommended guidelines for healthy adults (Irwin, 2015). Although sleep disturbances were rarely reported, some technical issues, such as loss of connection from the sleep analyzer or sleeping in another bed, resulted in missing data.
- **Number of Visited Unspecified Locations:** On average, participants spent 14.5 ± 2.9 hours at home daily, including sleeping time. During the study period, participants visited an averaged to 12 ± 6 different locations, apart from the time spent at home or at work.
- **Weather Conditions:** The weather's influence on varied individually. Most experienced mood improvements on clear and snowy days, while rainy or cloudy conditions tended to have negative effects. However, some participants reported better moods on rainy days. Additionally, weather was included in the list of selectable reasons for the current mood. Only three participants did not cite that weather had an impact on their mood. Due to their variability and the short study period, the biological weather data did not provide much infor-

mation and needs to be reevaluated after a longer time period.

- **Screen Time and Social Media Use:** Daily smartphone use averaged approximately 3 hours, with a range of 0.3 hours to 6.5 hours. Time spent on social media varied from 0.25 to 1.75 hours per day. The effects of social media use on mood were highly individual.

3.3 Usability and Technology Commitment Questionnaire

Following the study, participants provided feedback on the design and usability of the DAIsy DC app.

The evaluation of the SUS resulted in an average score of 89.4 ± 3.5 out of 100, which corresponds to a "very good" usability rating. The average technology commitment score was 46.4 ± 5.9 out of 60, indicating that the sample consisted of tech-savvy participants.

A common point of feedback was the desire to expand the list of selectable mood influences. Five participants suggested adding "Traffic" or "Public Transport" as these were common causes of frustration or anger. Participants also requested an "Outdoors" or "Walking" category. Additionally, some participants suggested adding "Myself" to reflect self-centered negative moods that often stem from personal dissatisfaction. Other desired additions included "Procrastination" or "Unproductivity", with one participant recommending "Sexuality" as an option. One participant recommended distinguishing specific work-related influences (colleagues, bureaucracy, home office).

Participants also suggested extending the list of predefined locations. Suggestions included adding frequently visited locations such as family or friends' homes, to the existing options.

3.4 Discussion

We have developed a first version of a mental health monitoring app that could, in the future, help with both early detection of depression and monitoring relapses. We evaluated the app's usability and functionality in a six-week study with N = 22 healthy participants. The aim of the app is to collect active inputs such as mood and passive data that could later be used to identify connections between mood and external influences. The results showed that the app is suitable for a long-term study and users generally found it easy to navigate. However, user feedback also highlighted areas for improvement. Specifically, participants suggested adding more options for mood reasons and additional location options. Key areas for further improvement include:

- **Differentiation of Time Spent at Home:** The current GPS-based tracking system does not differentiate between work and leisure activities at home. Introducing a calendar or user input could be helpful, but may increase user effort.
- **Addition of Opposing Moods:** The mood tracking feature could be refined by allowing opposing mood categories (e.g., happy - sad, nervous - relaxed) to provide deeper insights. In addition, a stress level query should be incorporated.
- **Gamification Methods:** Taylor et al. found that incorporating gamification significantly improved participation in a study (Taylor et al., 2018). However, these features should be carefully tailored to the audience to ensure they increase engagement without overwhelming users or imposing additional requirements.
- **User Interface (UI) and User Experience (UX):** Further refining the UI and UX will likely improve navigation and create a more cohesive and visually appealing experience. Improving data visualization would provide clearer insights into mood trends over time. Additionally, all data entries, including mood reasons, could be organized and displayed in a calendar format.
- **Personalized Reminders:** The timing of the reminders to report on the current mood could be adjusted to suit users' individual routines (e.g., wake-up and sleep times) or triggered when their smartphone is in use (Nahum-Shani et al., 2016).
- **Additional Features:** Future app iterations could include additional features known to support mental health such as mood and depression detection through voice recognition (Schuller, 2018), journaling (Baikie and Wilhelm, 2005) and to-do lists to help establish routines. Personalized recommendations triggered by significant mood swings as well as AI-driven mood trend predictions could further tailor user support and intervention timing (Klein et al., 2023).

Limitations of the study include a relatively small sample size (N = 22), which limits the generalizability of the results, although it provided valuable insights at the individual-level. Future research with larger, more diverse samples, including participants diagnosed with depression, would allow for a more comprehensive assessment of the app's effectiveness. A broader dataset could also enable users segmentation based on behavioral patterns such as activity levels or weather sensitivity. Reliance on self-reported data for mood and behavior metrics may under- or over-report their experiences. Additionally, the six-week study duration limits the ability to observe long-term trends and effects that may develop over longer periods of time. It would also be useful to link the stated reasons for the current mood with the passively collected data. Furthermore, technical challenges associated with data collection by wearables and smartphones may have affected data reliability. Addressing these limitations in future studies will be critical to refining and improving the functionality and generalizability of the app.

The integration of DAIsy DC into the DAIsy project's virtual therapy assistant (VTA) offers the potential to significantly expand its capabilities in the future. As described in Klein et al. (Klein et al., 2023), DAIsy's framework will enable personalized, AI-driven therapeutic support with real-time recommendations. This integration would enhance the functionality of the VTA, by providing users with tailored therapeutic suggestions and feedback and enabling real-time interventions based on passive data (e.g., activity levels, location) and active inputs (e.g., mood reporting). Additionally, DAIsy VTA including DAIsy DC could facilitate tracking user progress, offer CBT exercises, and provide to support mental well-being, creating a more personalized, dynamic and responsive tool for treating depression.

4 CONCLUSION

In this study, we developed and tested DAIsy DC, a mental health monitoring app that collects both active and passive data to support early detection of depression in the future. Our evaluation with healthy individuals showed that the app is suitable for long-term use and that overall navigation is easy for users. However, the study identified key areas for improvement, such as expanding the selection of mood reasons, modifying the mood submission process, and potential for personalized reminders and gamification features to increase engagement.

Future iterations of the app should focus on UI and UX to improve data visualization and usability. Additionally, expanding functionality to include personalized interventions, voice recognition, and mood predictions could further support mental health management. Integration into the broader DAIsy project framework offers the potential for tailored, real-time therapeutic support, leveraging AI-driven recommendations and user insights to create a responsive and preventive mental health tool.

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