D6.1: Reporting of Technology Testing - Bewell–Vestel Wearable Physiological Monitoring Device and Data Integration Component

1. General information

Name of technical system/component: Bewell–Vestel Wearable Physiological Monitoring Device and Data Integration Component

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Additional partners:

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- BEWELL TEKNOLOJİ SANAYİ VE TİC. A.Ş. (Taşkın Kızıl)
- ARD GRUP BİLİŞİM TEKNOLOJİLERİ ANONİM ŞİRKETİ (Berk Cengiz)
- ETİYA BİLGİ TEKNOLOJİLERİ YAZILIM SANAYİ VE TİCARET ANONİM ŞİRKETİ (Taner Orta)

Aim of the validation: The aim of this validation was to technically evaluate the functionality, usability, data quality, and system integration of the Bewell–Vestel wearable device within the DAIsy platform. Specifically, the validation targeted the assessment of hardware ergonomics (new curved design), battery optimization, and the reliability of the BLE-to-Gateway data transmission chain during a pre-clinical pilot involving 25 participants over an average of 8 days.

If follow-up, name of the previous validation: [Information not available in source document]

2. Validation

The validation process was structured to ensure that the hardware and software components of the DAIsy ecosystem met the rigorous requirements of clinical monitoring. This chapter outlines the background, the specific technical components involved, the design of the validation study, and the implementation procedures.

2.1 Motivation / Background

The primary motivation for this validation phase was to verify the readiness of the wearable sensor technologies and their integration into the broader DAIsy ecosystem before deploying them in clinical trials with patients diagnosed with Major Depressive Disorders. Wearable sensor technologies play a central role in the DAIsy project by enabling continuous monitoring of physiological parameters.

Prior to the main clinical trials, it was essential to verify the device's updated hardware design. The consortium identified specific needs for improved ergonomics and charging reliability based on earlier feedback. Consequently, a new design featuring a thinner, curved shell and a magnetic pin-based charging system was developed. Validating these hardware updates was crucial to ensure user comfort and device durability during prolonged use.

Furthermore, the reliability of data transmission in real-world scenarios, particularly where connectivity might be intermittent, was a critical technical concern. The validation aimed to assess the "offline buffering" and reconnection logic between the wearable device and the gateway. This feature is vital for ensuring zero data loss in hospital and home settings where continuous Bluetooth connectivity cannot always be guaranteed. The integration with the "Meditis" mobile application and the backend systems also required rigorous testing to ensure seamless data flow and security compliance.

2.2 Technical Component

The validated system is a comprehensive physiological data collection platform consisting of specialized hardware, a gateway software layer, and a secure backend infrastructure.

Hardware

The core hardware component is a wearable device developed by Vestel and Bewell. In the 2025/1 period, the device underwent significant design updates to meet clinical and user requirements.

- **Design and Ergonomics:** The device features a new, thinner, and curved shell design optimized for wrist ergonomics. This design update was driven by the need for better skin contact and user comfort during long-term wear.
- **Sensors:** The device is equipped with sensors for monitoring Heart Rate (HR), SpO2, and acceleration (motion). An electrode-based temperature sensor was also integrated as an alternative to IR sensors to meet IP67 standards.
- **Power Management:** A new electronic board was prepared to support the updated design. The charging mechanism was transitioned from a socket-based system to a magnetic pin-based connection to facilitate easier use and maintain the device's slim profile. Additionally, the battery monitoring system was upgraded from voltage-based measurement to a current-based percentage calculation for more accurate power management.
- **Components:** The accelerometer was replaced with a low-power model to extend battery life. Two different integrated circuits were used for memory to separate update packages from signal data, optimizing cost and performance.

Software/Gateway

The software architecture facilitates secure and reliable data transmission from the hardware to the cloud.

- **Communication Protocol:** The device communicates via Bluetooth Low Energy (BLE) with a gateway (mobile application or dedicated gateway device).
- **Gateway Functionality:** The gateway software manages the connection with the wearable device. It is responsible for receiving sensor reports, timestamping them, checking format integrity, and buffering data in case of connection loss. The gateway utilizes MQTT protocols to transmit telemetry data to the backend servers.
- **Mobile Application:** The "Meditis" mobile application serves as a user interface and data relay point. It includes features for device pairing via QR code, notification management, and visualization of daily health metrics (sleep, steps, HR).
- **Backend Infrastructure:** The backend is built on a microservices architecture using technologies such as Spring Boot, Node.js, and FastAPI. It employs InfluxDB for storing time-series sensor data and uses Grafana for visualization. The architecture supports standard data exchange formats like JSON and is designed to be FHIR-compliant for interoperability.

Data Security

Security and privacy were paramount in the design of the technical components.

- **Authentication and Access:** The system implements token-based authentication and Role-Based Access Control (RBAC) to restrict data access based on user authorization levels.
- **Encryption:** All data transmission is secured using TLS encryption.
- **Compliance:** The system adheres to GDPR and KVKK (Turkish Personal Data Protection Law) standards. This includes mechanisms for data anonymization, logging of access and data transfer events, and secure storage policies as verified by NP Istanbul's requirements.

2.3 Validation Design

The validation design was multifaceted, aiming to cover usability, technical performance, and data integrity.

Validation objectives

The specific objectives of this validation phase were:

- **Ergonomics:** Verify the ergonomic comfort of the new curved device design during daily wear to ensure it causes no irritation and is acceptable to users.
- **Connectivity Stability:** Test the stability of the BLE connection and the efficacy of the "offline buffering" mechanism when the gateway is out of range.
- **Battery Performance:** Assess the accuracy of the new current-based battery level estimation and ensure the device meets the required duration for continuous monitoring.
- **Data Integrity:** Validate the end-to-end data flow from the sensor to the "Meditis Pro" web dashboard, ensuring that data packets are complete, correctly timestamped, and free from corruption.

Outcome measures

The success of the validation was measured using the following specific metrics and scales:

- **Usability:** System Usability Scale (SUS) and NASA-TLX (Task Load Index) scores were used to quantify user satisfaction and the perceived workload of using the device.
- **Performance Metrics:**
  - **Packet loss percentage:** The ratio of data packets lost during transmission.
  - **Median latency:** The time delay between data collection and availability on the dashboard.
  - **Reconnection success rate:** The percentage of successful automatic reconnections after signal loss.
  - **Battery duration:** The operational time of the device on a single charge.
- **Safety/Comfort:** Documentation of any incidence of skin irritation and qualitative observations regarding physical ergonomics.
- **Data Quality:** Evaluation of the valid session rate, video quality scores (for parallel protocols), and synchronization error rates.

Description of datasets used

The validation utilized data collected from a controlled pre-clinical pilot study.

- **Pre-clinical Pilot Data:** The dataset includes physiological and system performance data collected from 25 voluntary participants.
- **Duration:** The data collection covered a period of approximately 8 days per user.
- **Data Types:** The dataset comprises raw and processed signals including PPG signals, Heart Rate (HR), SpO2, actigraphy (step counts), sleep duration, and system logs (connection events, battery levels).

2.4 Validation Implementation

The validation was executed through a structured procedure involving distinct stages of testing and verification.

Procedure

The validation was conducted in two primary stages to ensure incremental verification of the system's capabilities.

1. **Preliminary Technical Pilot:** This stage involved volunteer university students using the device for one week. The primary focus was to stress-test the device ergonomics, verify the battery life predictions, and ensure the stability of the mobile application under standard usage conditions.
2. **Pre-Clinical Verification:** This stage was executed in collaboration with NP Istanbul Brain Hospital. Participants, including healthy controls, wore the device during their daily activities. The study followed strict protocols defined in the consortium meetings, including the February 2025 meeting at NP Istanbul.
   - **Onboarding:** Devices were paired with the mobile application using a QR code-based system to ensure secure and easy setup.
   - **Monitoring:** Data synchronization and device status were actively monitored via the "Meditis Pro" dashboard by the technical team to identify gaps or anomalies in real-time.

Gateway Testing

Specific testing was conducted to validate the performance of the gateway and Bluetooth modules within a clinical environment.

- **Environment:** Tests were performed at NP Istanbul Brain Hospital to replicate the actual RF environment of the future clinical trials.
- **Methodology:** Bewell and Vestel engineers mapped the RF signal strength and identified potential interference zones. The testing focused on the device's ability to maintain a connection with the gateway and the gateway's ability to transmit data to the server via MQTT.
- **Reconnection Logic:** The "offline buffering" and automatic reconnection features were rigorously tested by simulating range limitations and network interruptions to ensure that the system could recover and backfill missing data without corruption.

3. Testing Results

The testing phase yielded comprehensive data regarding the hardware reliability, data transmission capabilities, and overall system integration. The results indicated that the system has achieved a high level of technical maturity.

Hardware Reliability

The hardware updates implemented in the 2025/1 period demonstrated significant improvements in user experience and device stability.

- **Ergonomics:** The new curved shell design received positive feedback regarding comfort. The physical form factor was found to be suitable for continuous wear, with no significant reports of discomfort or skin irritation.
- **Charging and Power:** The magnetic pin-based charging system proved to be user-friendly and reliable, addressing previous concerns about socket-based charging. The current-based battery measurement system provided accurate and linear discharge profiles, allowing for reliable estimation of remaining battery life.
- **Sensor Performance:** The integration of the low-power accelerometer and the optimization of the electrode-based temperature sensor functioned as expected, providing stable readings while adhering to the IP67 protection standards.

Data Transmission

The robustness of the data transmission pipeline was a key focus of the testing results.

- **Offline Buffering:** The "offline buffering" feature was validated successfully. During periods where the Bluetooth connection was intentionally severed or lost due to range, the device correctly stored sensor data. Upon reconnection, this data was transmitted to the gateway and backend, ensuring data completeness.
- **Reconnection:** The automatic reconnection logic demonstrated a high success rate. The system was able to re-establish connections without user intervention in the vast majority of test cases.
- **Latency and Loss:** While the system achieved the target data integrity, minor

synchronization delays were noted in isolated cases. These were addressed through optimizations in the gateway software. Packet loss percentages remained within acceptable limits for clinical monitoring purposes.

System Integration

The integration of the various system components—device, mobile app, backend, and dashboard—was verified to be functional and cohesive.

- **End-to-End Flow:** The validation confirmed the successful end-to-end flow of data from the wearable sensor, through the BLE link to the gateway, over MQTT to the backend, and finally to the "Meditis Pro" visualization dashboard.
- **Visualization:** The "Meditis Pro" dashboard successfully visualized vital signs such as Heart Rate (HR) and SpO2 in time-series graphs. The system was capable of flagging anomalies and presenting scale scores alongside physiological data.
- **Data Management:** The backend successfully managed the ingestion of data, including timestamp alignment and format verification. The separation of device telemetry from patient clinical data was maintained in the database architecture, supporting data privacy and management requirements.

Connectivity

Field tests conducted within the hospital environment provided assurance regarding connectivity in the target deployment setting.

- **RF Performance:** The mapping of RF signal strength in the hospital confirmed that the chosen Bluetooth modules and gateway configurations could maintain adequate coverage.
- **Interference:** The system demonstrated resilience to the typical RF interference found in a hospital setting. The MQTT-based telemetry transmission from the gateway to the server proved stable, utilizing the available hospital network infrastructure effectively.

4. Discussion

The validation activities conducted during the 2025 periods have provided a solid foundation for the subsequent phases of the DAIsy project. The results confirm that the Bewell–Vestel wearable system has reached a technical maturity suitable for the upcoming clinical pilot with Major Depressive Disorder patients.

Key takeaways

- **Operational Stability:** The system is capable of supporting continuous monitoring for periods averaging 8 days, with reliable battery performance and user comfort.
- **Data Integrity:** The implemented mechanisms for data integrity, including offline buffering, checksum verification, and automatic reconnection, are functional and effective in preventing data loss during typical usage scenarios.
- **Integration Readiness:** The seamless integration of the wearable device with the "Meditis" app and the "Meditis Pro" backend platform proves that the technical architecture is robust and ready for scaling. The microservices-based backend successfully handles the data load and provides necessary visualization for clinicians.

- **User Acceptance:** The positive feedback on the new ergonomic design suggests that patient compliance in the upcoming clinical trials will not be hindered by device discomfort.

Future Work

Building on the successful technical validation, the project will proceed with the following steps:

- **Clinical Pilot Deployment:** The validation will extend to the full clinical phase involving patients diagnosed with Major Depressive Disorder. This phase will utilize the validated hardware and software to collect longitudinal data.
- **Multimodal Analysis:** The physiological data collected by the wearable device will be cross-referenced with the "Valence-Arousal" video protocols and other clinical assessments to develop comprehensive AI models.
- **Advanced AI Services:** Further optimization of the AI-based services, such as the "Micro-habit insight service" and the "General Health Score," will be integrated. These services will leverage the stable data flow established during this validation to provide actionable insights for clinicians and patients.
- **Academic Output:** The technical findings and datasets generated from these pilot studies will be used to produce academic publications and contribute to the dissemination goals of the DAIsy project.

D6.1: Reporting of Technology Testing - DAIsy Data Collector (DAIsy DC) for monitoring movement and behavioral patterns

1. General information

This section captures the essential details of the evaluation and provides an overview of its scope, management, and personnel.

Country and name of use case (take from list below): German: Virtual Therapy Assistant

Name of technical system/component: DAIsy Data Collector (DAIsy DC) App

Study director/manager: OFFIS - Institut für Informatik - Prof. Dr.-Ing. Andreas Hein, Patrick Elfert, M.Sc.

Contact (e-mail): patrick.elfert@offis.de

Additional partners: University Hospital Bonn (UKB)

Aim of the validation: The aim of the component is to develop a mobile application that automatically and ambiently records parameters related to depression, such as behavioral and movement patterns. The aim of the validation was to conduct a field test to verify that the app can successfully collect these relevant factors in the context of depression and mental well-being, providing a basis for future research on the correlation between the collected data and the severity of depression.

If follow-up, name of the previous validation: -

2. Validation

This chapter introduces the validation process, beginning with the motivation for the technical component. It then describes the component's architecture and functionalities. Finally, it details the design and implementation of the validation study that was conducted to test the component.

2.1 Motivation / Background

Mental health, and depression in particular, is a significant and growing global health issue. The World Health Organization (WHO) estimates that 5% of adults worldwide are affected by depression, which is a leading cause of disability. In Germany, it is estimated that one in five employees suffers from depression. The challenge is compounded by several factors: physicians without psychiatric training often diagnose depression inaccurately, patients may avoid lengthy inpatient treatments, and there is a nationwide shortage of psychotherapy places in Germany.

Mobile applications (apps) offer a promising, low-threshold solution to some of these challenges. Given that a vast majority of the population owns a smartphone equipped with a wide array of sensors (e.g., accelerometer, GPS, light sensor), these devices are well-suited for collecting health data and behavioral patterns. An app that records a user's movement and behavior patterns can serve as a therapeutic tool to support patients waiting for a therapy spot and can also assist clinicians in the diagnostic process.

The primary goal of this work was to develop such an application, the DAIsy DC (Data Collector), which automates the ambient recording of parameters relevant to depression. The selection of these parameters was based on a literature review of medical background information and the state of the art in similar research projects. A field test was then conducted with non-depressed participants to validate that the developed app can effectively record these factors related to mental well-being. The overarching objective is to use this system in future studies to investigate whether the collected data correlates with the severity of depression in diagnosed patients.

2.2 Technical Component

The technical component developed and validated is the DAIsy DC (Data Collector) app, created as part of the DAIsy project. The app is designed for the Android platform and its primary function is the automated and ambient recording of a wide range of factors that have been identified in the literature as being correlated with depression and mental well-being. Unlike some existing research platforms, the DAIsy DC app was developed to integrate with existing OFFIS systems and to improve upon previous studies by incorporating data from smartwatches, thereby potentially increasing data quality compared to smartphone-only data collection.

The system architecture relies on communication between the DAIsy DC app, various third-party applications, external APIs, and a central database server. A key element of the architecture is the integration of Google Health Connect (GHC), an Android API that allows the aggregation of health and fitness data from different apps and devices into a standardized format. This enables the DAIsy DC app to read data from sources like Google Fit, Withings, MyFitnessPal, and others, giving users flexibility in their choice of devices.

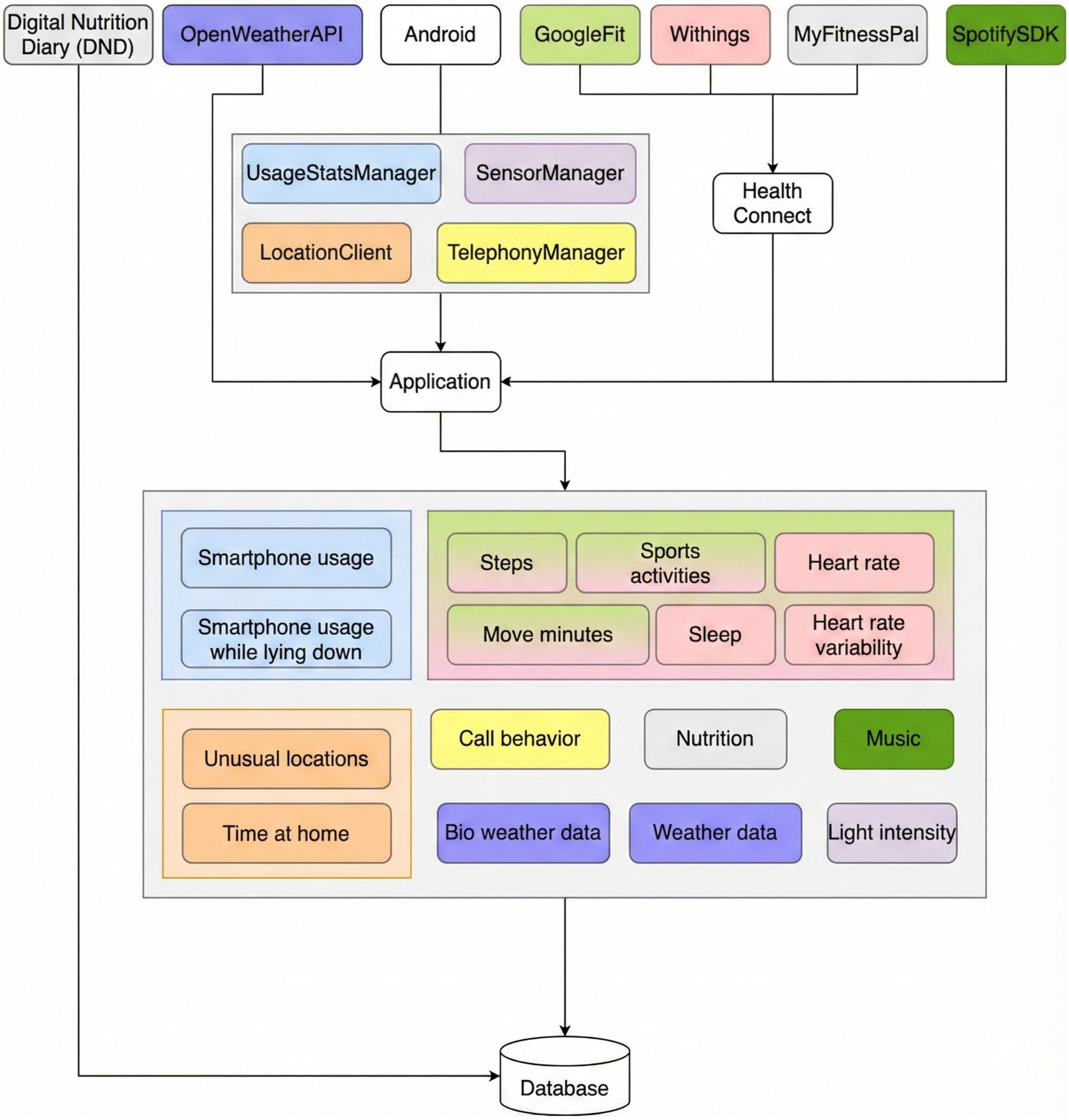


Image 1: Overview of the general architecture
[See Figure 6 on page 26 of the source document]

The app itself uses native Android APIs like the SensorManager, LocationClient, UsageStatsManager, and TelephonyManager to collect data directly from the smartphone's sensors and logs. For external data, it connects to the OpenWeather API for weather data and the Spotify SDK for music history. All collected data is associated with a user ID and stored in a database. To ensure data integrity, a client-server model with an offline-first approach was implemented. Data is first stored in a local SQLite database on the device. A sync_status flag tracks whether the data has been successfully sent to the main SQL server. If the device is offline, the data is queued and synchronized once an internet connection becomes available.

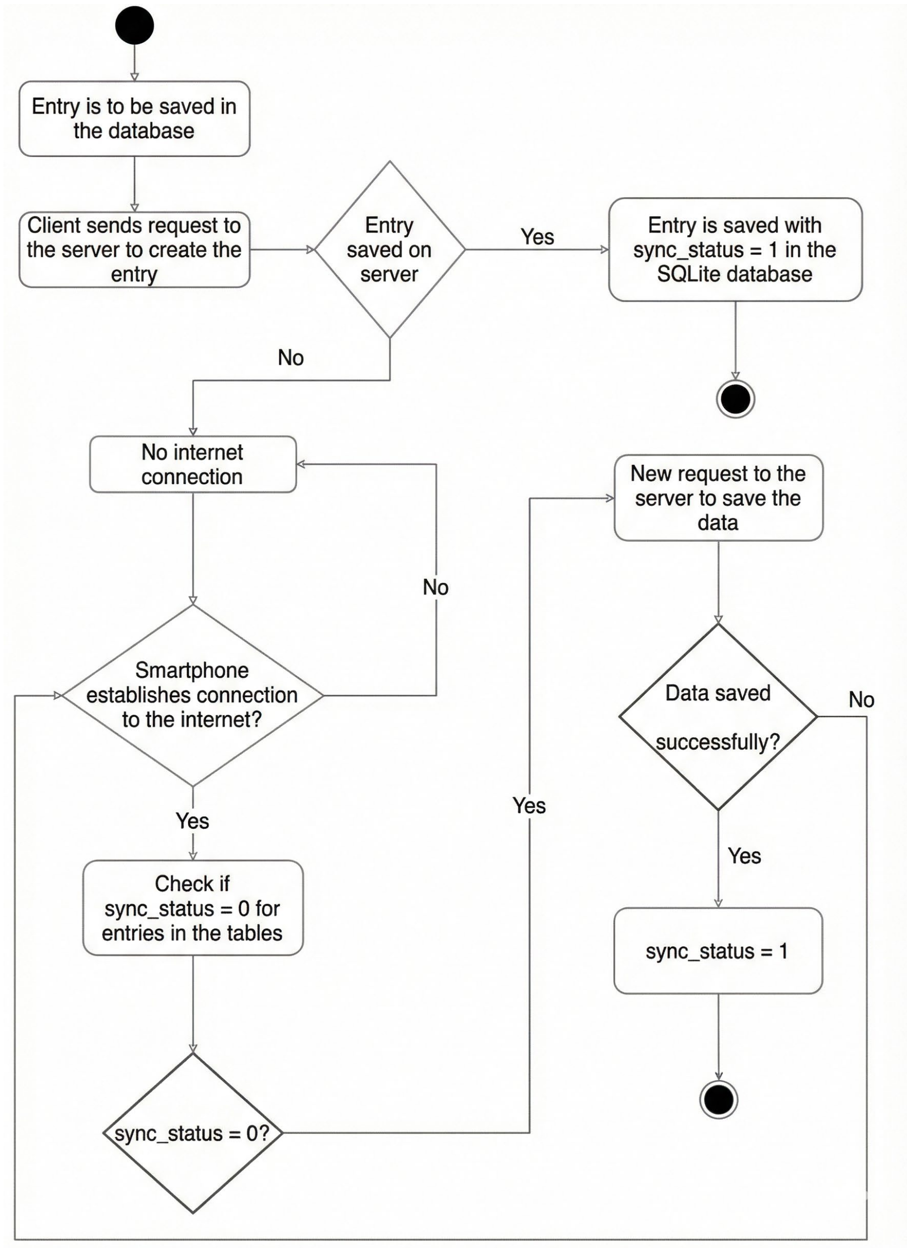


Image 2: Activity chart of data synchronisation with DAIsy DC server
[See Figure 7 on page 28 of the source document]

The DAIsy DC app is designed to collect and record the following 13 factors:

- **Call Behavior:** Duration of incoming and outgoing calls.
- **Movement Minutes:** Total time the user was physically active.

- **Nutrition:** Nutritional values of consumed food (energy, protein, carbohydrates, fat), recorded via the Digital Nutrition Diary (DND) or third-party apps like MyFitnessPal.
- **Heart Rate:** Daily average, maximum, and minimum heart rate.
- **Heart Rate Variability (HRV):** The root mean square of successive differences between normal heartbeats (RMSSD).
- **Steps:** Daily step count.
- **Sleep:** Duration of sleep.
- **Smartphone Usage:** Time each app was active in the foreground.
- **Smartphone Usage while Sitting, Standing or Lying:** Duration of phone usage while the user is stationary at home.
- **Physical Activity:** Type and duration of specific exercise sessions.
- **Location Information:** Hashed longitude, latitude, and address information, recorded every 15 minutes to identify recurring patterns without revealing exact locations.
- **Time at Home:** Duration of time spent at the user's pre-defined home location.
- **Weather and Bio-Weather Data:** Local weather conditions (temperature, humidity, pressure) and bio-meteorological data from the German Weather Service (DWD).
- **Music (Spotify):** Title and artist of tracks listened to on Spotify.

Users retain control over data collection through a detailed permissions screen within the app and through the native GHC interface.

2.3 Validation design

A field test was conducted to validate the DAIsy DC app. The study was designed to assess whether the app could effectively and reliably collect the identified factors in a real-world environment with a sample of mentally healthy participants.

Validation objectives/hypotheses

The primary objective of the validation was to test the hypothesis that the DAIsy DC app can successfully record data relevant to depression and mental well-being. To structure the analysis, a set of secondary hypotheses was derived from the literature and confirmed as relevant by psychological experts from the University Hospital Bonn (UKB):

- High physical activity has a positive effect on mental well-being.
- Low location entropy (visiting fewer different places) is associated with negative mental well-being.
- High smartphone usage has a negative effect on mental well-being.
- High usage of social media apps has a negative effect on mental well-being.
- An eating disorder (indicated by abnormal calorie intake) is associated with negative mental well-being.
- Weather has an influence on mental well-being.

- A sleep disorder is associated with negative mental well-being.
- Spending a lot of time at home is associated with negative mental well-being.
- A bright environment has a positive effect on mental well-being.
- High scores on the PHQ-9 and BDI questionnaires correlate with negative self-reported mental well-being.

Outcome measures

The primary outcome measures for the validation were:

1. **Self-Reported Mental Well-being:** Assessed frequently throughout the day using a 5-point Likert scale with smileys, accessible via a home screen widget.
2. **Depression Symptom Scores:** Measured weekly using the clinically validated Patient Health Questionnaire-9 (PHQ-9) and Beck Depression Inventory (BDI).
3. **Passively Collected Data:** The continuous data streams for the 13 factors listed in section 2.2.
4. **Demographic and Contextual Information:** Collected once via a questionnaire at the start of the study.

Type(s) of validation

The validation was conducted as a field test. This method was chosen to test the app's functionality, usability, and data collection capabilities in the participants' natural environment as they went about their daily lives. The analysis employed quantitative methods to identify patterns and correlations in the collected data.

Tools and instruments used

- **Data Collection Apps:** DAIsy DC App, Digital Nutrition Diary (DND), Google Health Connect, Google Fit, MyFitnessPal, Spotify.
- **Questionnaires:** An in-app demographic and medical history questionnaire, the Patient Health Questionnaire-9 (PHQ-9), and the Beck-Depressions-Inventar (BDI).
- **Analysis Software:** The data analysis was performed using Python (v. 3.10.11) within an Anaconda environment, utilizing libraries such as Jupyter Notebook, NumPy, pandas, Matplotlib, and Seaborn for data manipulation, analysis, and visualization.

Description of datasets used

The dataset was collected from a convenience sample of 18 participants (13 male, 5 female) aged between 18 and 56. The majority of participants (10) held an academic degree. Most participants (15) were non-smokers. One participant reported being in psychiatric treatment for depression and taking antidepressants; however, their data did not meet the minimum threshold for inclusion in the final analysis. The study was planned for a two-week period, but the actual data collection duration varied as some participants registered later. For the final analysis, only data from participants who provided at least eight days of data for a given factor were included.

2.4 Validation implementation

The validation was implemented as a two-week field study where participants used the DAIsy DC app and associated third-party apps on their personal Android smartphones.

Data collection schedule

The data collection was designed to be as ambient as possible, but required some active participation:

- **Mental Well-being (Likert Scale):** Participants were prompted via push notifications to report their current mental well-being via the home screen widget at least three times a day (mornings at 9:00, afternoons at 17:00, and evenings at 20:00).
- **PHQ-9 and BDI Questionnaires:** These were administered once per week through the app.
- **Passive Data Collection:** The collection schedule for passive data varied by factor:
  - *Location:* Every 15 minutes.
  - *App Usage & GHC Data (Steps, Sleep, etc.):* Collected daily, retrieving the data from the previous day to ensure completeness.
  - *Light Intensity:* Recorded whenever the screen was on and a change in ambient light was detected.
  - *Call Behavior, Stationary Phone Usage, Music:* Recorded in real-time based on system events (e.g., call started/ended, screen on/off).
- **Manual Data Entry:** Nutrition data had to be entered manually by the user into the DND or MyFitnessPal app. Data for sleep, heart rate, and certain activities also required manual entry if a smartwatch was not used.

Measured variables

The study measured a comprehensive set of variables:

- **Primary Dependent Variable:** Mental Well-being (rated on a -2 to +2 scale).
- **Independent Variables (Passively Collected):** The 13 factors detailed in section 2.2, including location entropy, steps, movement minutes, smartphone and social media usage time, sleep duration, time at home, light intensity, and weather parameters.

- **Contextual Variables:** Demographic information (age, gender, education, etc.) and medical history collected at baseline. Scores from the PHQ-9 and BDI questionnaires.

Pilot measurements

No pilot measurements have been published

Data monitoring

Data quality and integrity were managed through the system's technical design. The client-server architecture with its offline-first approach, using a local SQLite database and a sync_status flag, was designed to prevent data loss due to intermittent internet connectivity. The app periodically checked for unsynchronized data and attempted to upload it to the central server. All data on the server was linked to a user via a pseudonymized user ID to maintain participant anonymity in the dataset.

3. Testing Results

This section presents the results of the field test. Due to the limited number of participants and the short duration of the study, a descriptive analysis was chosen over a full statistical evaluation. The analysis focused on generating scatterplots and calculating Pearson correlation coefficients to identify initial trends and test the feasibility of the data collection for each hypothesis.

Overall results & visual representations

The study successfully demonstrated that the DAIsy DC app is capable of collecting data across the targeted domains. The collected data allowed for a preliminary analysis of the relationships between various behavioral factors and self-reported mental well-being.

The central finding of the analysis is summarized in a boxplot of the Fisher-transformed correlation coefficients for each factor, calculated across all participants who provided sufficient data. This visualization provides an at-a-glance overview of the direction and variance of the correlations.

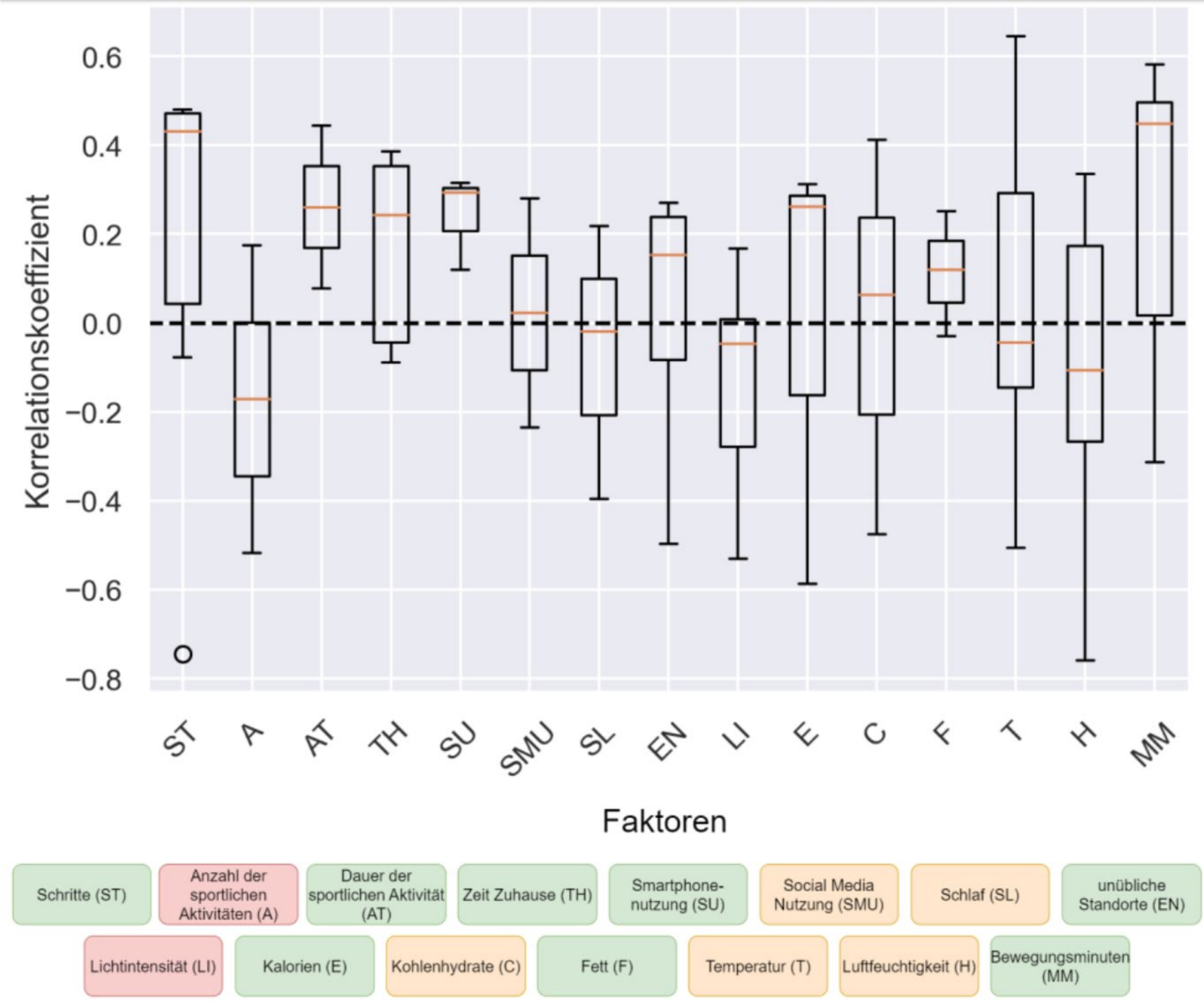
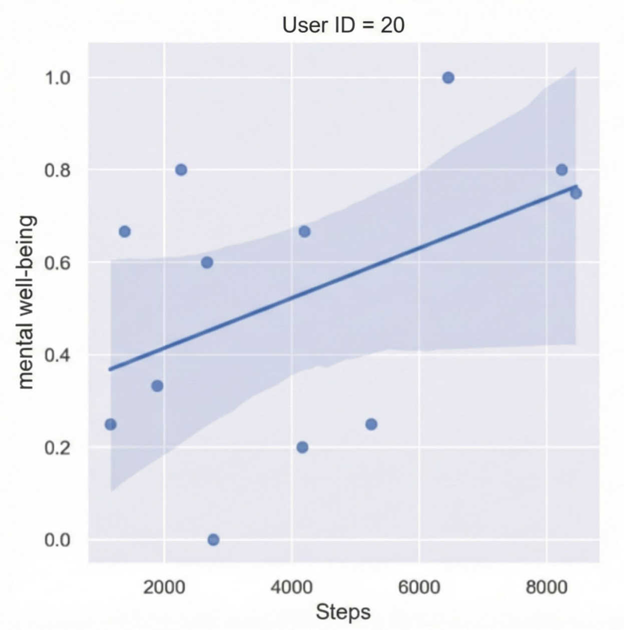


Image 3: Box plot of the correlation coefficients for the evaluated factors, including the effect of the factor on mental well-being
(green box = positive, yellow = neutral and red = negative)
[See Figure 33 on page 58 of the source document]

Key findings from the analysis of specific hypotheses are detailed below:

- **Physical Activity and Well-being:** The data supported the hypothesis that higher physical activity is associated with better mental well-being. For factors like total steps and movement minutes, a majority of participants showed a positive correlation. For instance, one user showed a clear positive trend between movement minutes and mood. However, individual differences were notable; for example, one participant showed a statistically significant *negative* correlation between steps and well-being, possibly due to overexertion.



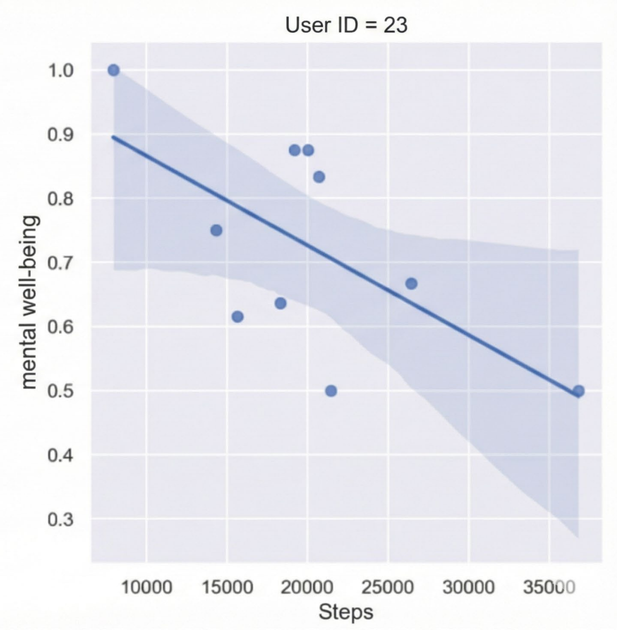


Image 4 (left): Scatter plot showing the steps taken per day and mental well-being (u_id = 20) over the study period. Positiv correlation
[See Figure 20 on page 48 of the source document]
Image 5 (right): Scatter plot showing the steps taken per day and mental well-being (u_id = 20) over the study period. Negative correlation
[See Figure 21 on page 48 of the source document]

- **Location Entropy and Well-being:** The results were consistent with the hypothesis that lower entropy (visiting fewer unique locations) is linked to lower mental well-being. A majority of participants (5 out of 8) exhibited a positive correlation, where visiting more varied locations corresponded to a better mood.

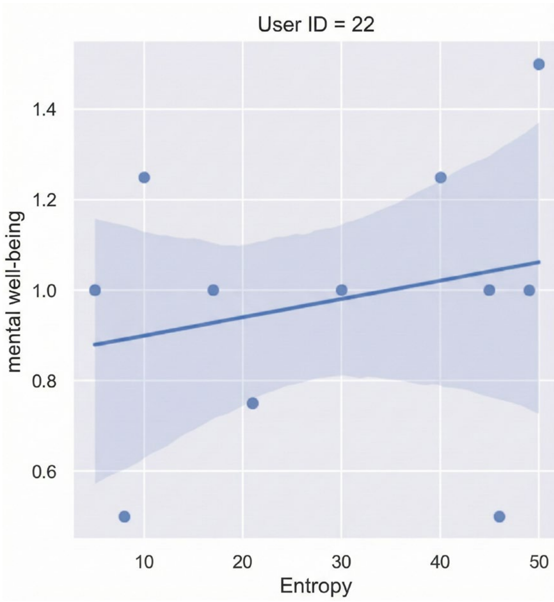


Image 6: Scatter plot showing the locations visited during the day and mental well-being (u_id = 22) over the period of the study
[See Figure 24 on page 50 of the source document]

- **Smartphone/Social Media Usage and Well-being:** Contrary to the initial hypothesis, the analysis did not find a clear negative relationship. For general smartphone usage, all three participants with sufficient data showed a *positive* correlation between usage time and well-being. For social media usage, the results were split, with one participant showing a positive correlation and the other a negative one.

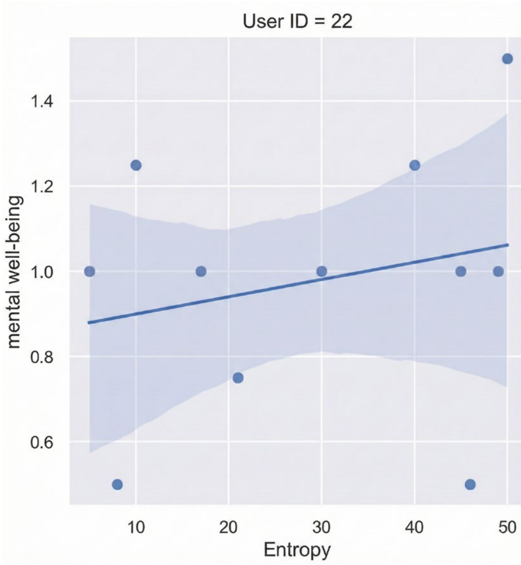


Image 7: Scatter plot showing smartphone use and mental well-being (u_id = 23) over the period of the study
[See Figure 25 on page 51 of the source document]

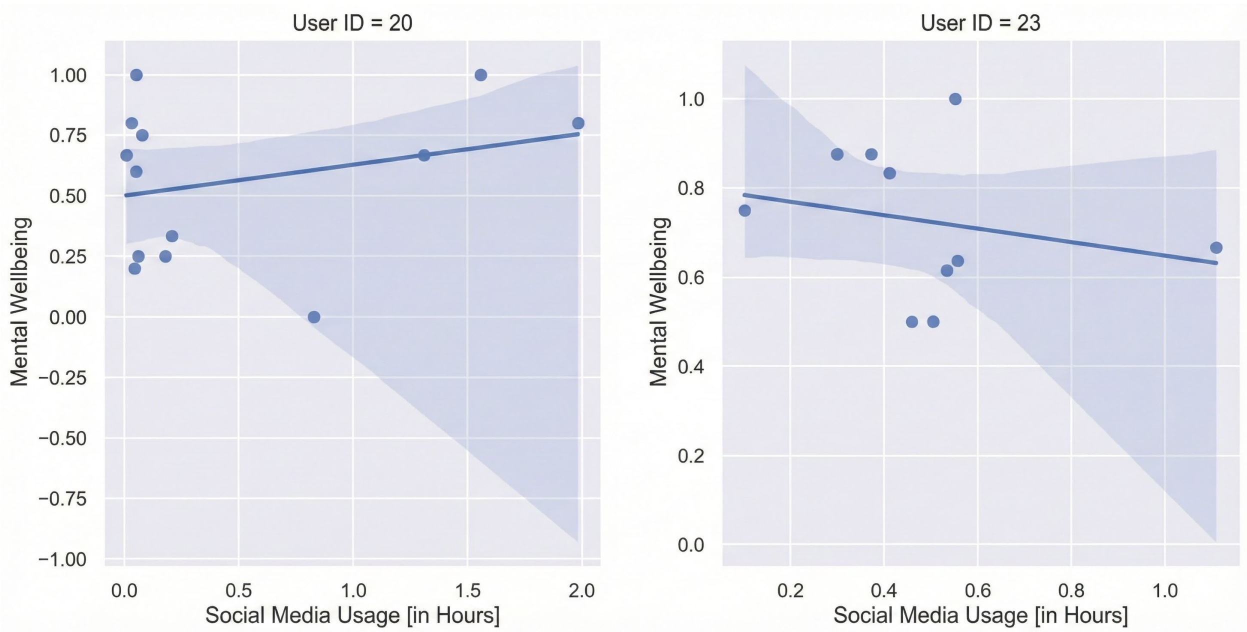


Image 8: Scatter plot showing social media use and mental well-being (u_id = 20&23) over the period of the study Positiv and negative correlation.
[See Figure 26/27 on page 52 of the source document]

- **Nutrition and Well-being:** The app was able to capture nutritional data, making it possible to identify patterns like low caloric intake which could indicate appetite loss, a symptom of depression. The data from one participant suggested a positive correlation between calorie intake and well-being.

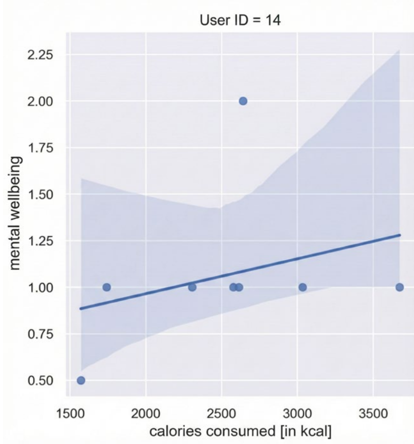


Image 9: Scatter plot showing calories consumed and mental well-being (u_id = 14) over the study period
[See Figure 28 on page 53 of the source document]

- **Weather and Well-being:** The app successfully collected weather data. The analysis revealed individual differences: for temperature, the effect on mood was positive for half the participants and negative for the other half. For humidity, a majority (5 of 8) showed a negative correlation, consistent with some literature.

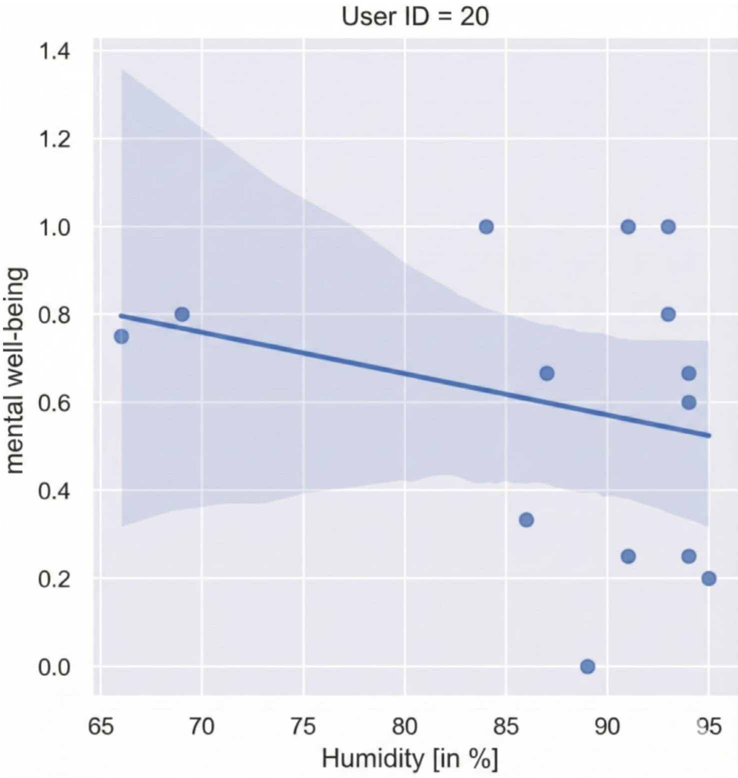


Image 10: Scatter plot showing humidity and mental well-being (u_id = 20) over the period of the study
[See Figure 29 on page 54 of the source document]

- **Sleep and Well-being:** The system was able to detect potential sleep disturbances, such as nights with very short sleep duration (e.g., 2 hours). The correlation with well-being was again varied among participants.

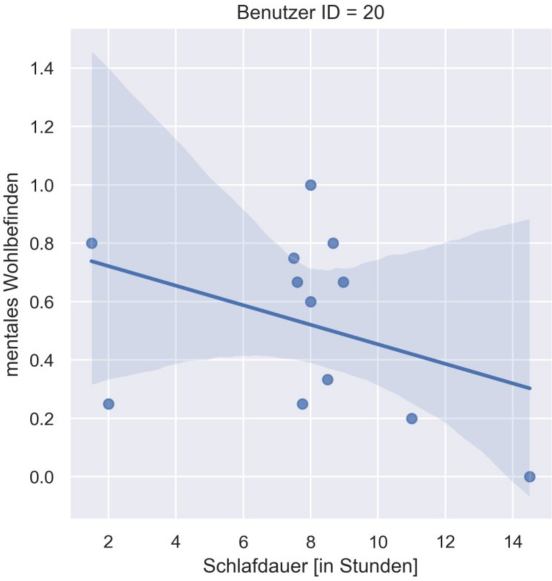


Image 11: Scatter plot showing sleep duration and mental well-being (u_id = 20) over the study period [See Figure 30 on page 54 of the source document]

- **Questionnaire Scores and Well-being:** A strong correlation was observed between the weekly PHQ-9/BDI scores and the daily average of self-reported mental well-being. Participants with higher scores on the depression questionnaires consistently reported lower mental well-being, and vice-versa, validating the use of the simple widget as a proxy for mood.

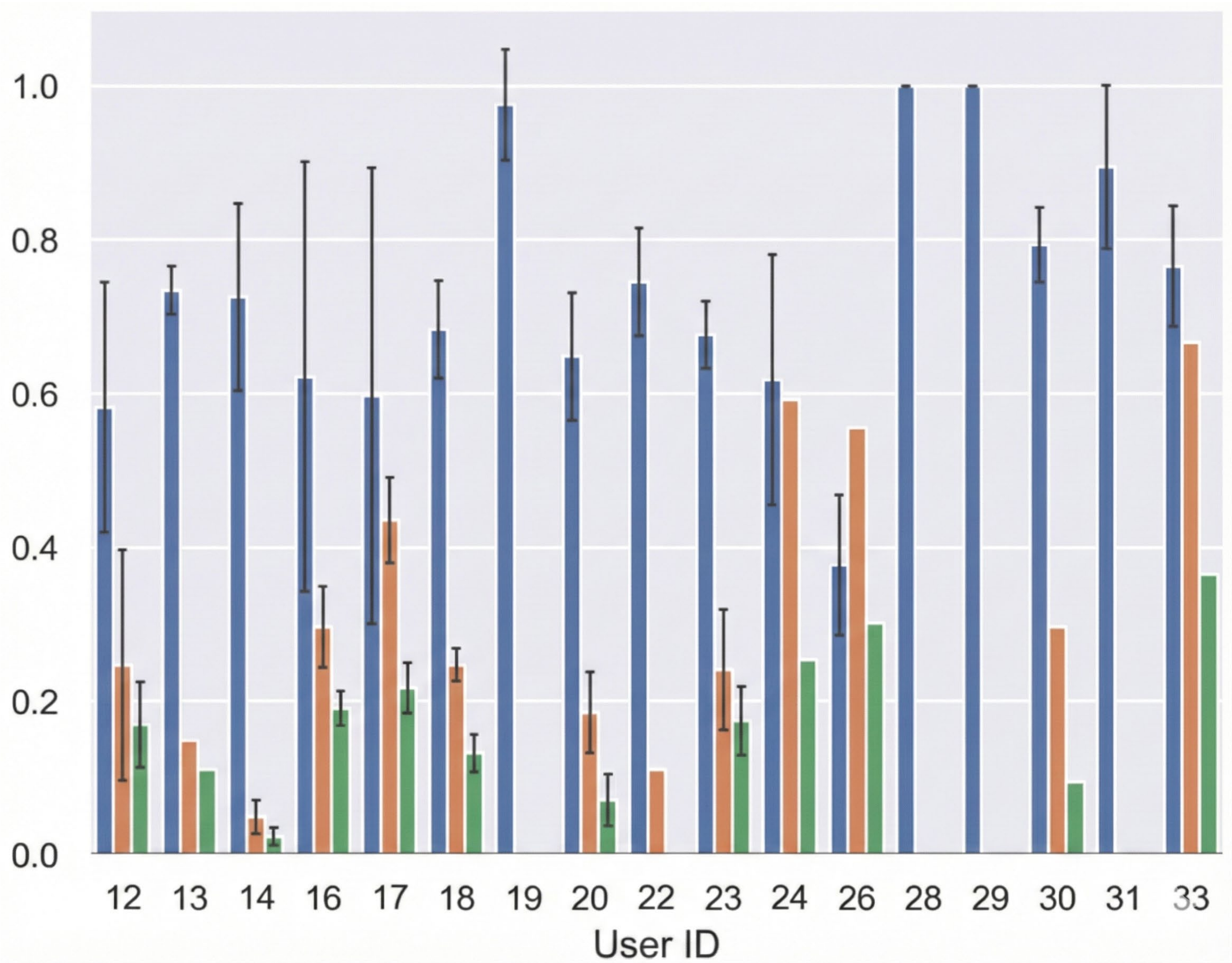


Image 12: Normalised sum scores of the PHQ-9 (orange) and BDI (green) questionnaires in relation to the normalised mental well-being (blue) of all participants over the study period.
[See Figure 32 on page 56 of the source document]

Possible side, unintended effects or remaining problems

The validation study also identified several problems and limitations with the current implementation of the DAIsy DC app:

- **Erroneous Data Collection:** The analysis revealed faulty data in several areas. The smartphone usage log sometimes produced impossible values (e.g., more than 24 hours of use in a day). The data for call behavior and Spotify music history also contained errors and duplicates, and were therefore excluded from the final analysis. The Spotify SDK was in beta, which may have contributed to its unreliability.
- **Incomplete Data Streams:** The app's data collection had gaps. Call behavior tracking was limited to the cellular network and did not capture calls made over internet services like WhatsApp. Similarly, media consumption could only be tracked on the smartphone, missing usage on other devices like PCs or tablets.
- **Hardware and Manual Entry Dependency:** The quality and completeness of data were highly dependent on the participant's hardware and willingness to perform manual entry. Very little data was collected for heart rate and HRV, as most participants did not seem to use a compatible smartwatch. Sleep data was also sparse for the same reason. Manually entering nutrition data proved to be a barrier for many participants.
- **Low Temporal Resolution:** The analysis was performed on a daily basis. It was noted that a higher temporal resolution—linking mental well-being reports directly to the data collected up to that specific point in the day—could provide more granular insights into the immediate effects of activities on mood.

4. Discussion

The following section interprets the results from the validation study, summarizes the main findings, discusses the strengths and limitations of the technical component, and proposes directions for future work.

Summary of main findings

The primary outcome of this work is the successful development and initial validation of the DAIsy DC app, a comprehensive data collection tool for research on mental health. The field test confirmed that the app is capable of collecting a wide array of behavioral and physiological data that is considered relevant in the context of depression.

The preliminary analysis of the collected data yielded several key findings. First, it confirmed strong correlations found in the literature for certain factors; for instance, increased physical activity was generally associated with improved mental well-being, while visiting fewer unique locations (low entropy) was linked to lower well-being. Second, for other factors like smartphone usage and ambient light intensity, the results were contrary to the initial hypotheses, suggesting that these relationships may be more complex or highly individualized. Third, the study highlighted significant individual differences in how almost every factor correlates with mental well-being, underscoring the need for personalized models in future work. Finally, the strong correlation between the simple, daily mental well-being rating and the comprehensive weekly depression questionnaires (PHQ-9, BDI) suggests that the high-frequency widget is a valid and useful tool for tracking mood fluctuations.

Interpretation & implications of the results

The results of this validation study have several important implications. The feasibility of collecting a rich, multimodal dataset related to mental well-being using a smartphone app has been clearly demonstrated. This opens the door for larger, longitudinal studies that can leverage this technology. The data collected by the DAIsy DC app can serve as the foundation for developing sophisticated machine learning models to analyze multidimensional data and identify complex cross-correlations.

The pronounced individual differences observed in the data strongly suggest that a one-size-fits-all approach to digital mental health is insufficient. Future models should aim for personalization, learning an individual's unique baseline and response patterns. For example, while high smartphone usage correlated positively with well-being in this small, non-depressed sample, this relationship might be different for individuals with depression. The system provides the means to investigate such nuanced questions.

However, the study also highlights practical challenges. The reliance on manual data entry for nutrition and the need for specific hardware like smartwatches for key physiological data (heart rate, HRV, automated sleep tracking) remain significant barriers to collecting a complete dataset. Future studies should consider providing participants with standardized hardware to improve data quality and completeness.

Strengths and limitations of component

Strengths:

- **Comprehensive Data Collection:** The app integrates 13 different data streams, providing a more holistic view of a user's behavior than many previous studies.
- **Improved Data Quality through Device Integration:** By using Google Health Connect, the system supports data collection from smartwatches and other wearables, which can provide more accurate physiological and activity data than a smartphone alone.

- **Robustness to Connectivity Issues:** The offline-first architecture with local data caching and a synchronization mechanism ensures that data is not lost when the user's device is not connected to the internet.
- **User Control and Transparency:** The app provides users with fine-grained control over which data types are collected, both through a dedicated permissions screen and the native GHC interface.

Limitations:

- **Data Collection Faults:** The initial validation revealed technical issues, with some data streams (smartphone usage, calls, music) being unreliable or erroneous. These require technical improvements.
- **Incomplete Behavioral Picture:** The system can only capture interactions with the smartphone. It cannot account for media consumption, social interaction, or work done on other devices like PCs or tablets, which could be significant confounding factors.
- **Causality Problem:** The collected data shows correlations, not causation. For example, it is unclear whether low physical activity leads to low mood, or if a low mood (perhaps caused by stress) leads to low physical activity. While collecting stress indicators like HRV could help, this remains a fundamental limitation.
- **Potential for Hawthorne Effect:** The act of monitoring can change behavior. Participants knew their activities were being recorded, which may have influenced their smartphone usage and other behaviors.

Future directions & Conclusions

Based on the findings of this validation study, several future directions are proposed. First, the identified technical issues with the app must be addressed to improve data reliability. An important feature to add would be an in-app dashboard where users can review their own data and correct any errors, which would improve data quality and user agency.

Second, the study should be extended in duration and scale. A longer study would provide the necessary amount of data for a rigorous statistical analysis and the development of robust machine learning models. It is also crucial to conduct a similar study with a clinical population of individuals diagnosed with depression to investigate how these factors correlate with the actual severity of the disorder.

Ultimately, the goal is to use the collected data to train a personalized AI. Such a system could learn each user's individual behavioral patterns and provide personalized feedback or even preventive tips to help them manage their mental well-being.

In conclusion, the DAIsy DC app is a successful proof-of-concept for a powerful research tool. It effectively collects a wide range of data relevant to mental health and, despite some limitations, provides a solid foundation for future research aimed at improving the diagnosis and care of mental diseases.

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5.1 Source Documents

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