Harnessing Home IoT for Self-tracking Emotional Wellbeing: Behavioral Patterns, Self-reflection, and Privacy Concerns

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The home environment plays a critical role in shaping daily routines that influence emotional wellbeing. While previous research has leveraged mobile and wearable devices to track emotional wellbeing indicators, these approaches often suffer from limited adherence and data gaps when users are not actively engaged. To address this, we further explore home IoT sensing as a passive and unobtrusive modality for monitoring emotional wellbeing. We conducted a four-week user study (N=20), collecting data from mobile devices, wearables, and home IoT sensors. Our quantitative analysis showed that incorporating home IoT data better captured associations between domestic routines and emotional wellbeing than mobile and wearable data alone. However, domestic activity patterns varied significantly across participants, highlighting the personalized nature of domestic routines. To further investigate these differences, we developed an informatics tool for participants to visualize and reflect on their behavioral data. Semi-structured interviews revealed that participants found home IoT data intuitive and insightful in understanding their emotional wellbeing, leading to a positive shift in privacy concerns. Our findings highlight home IoT sensing as a promising tool for tracking emotional wellbeing and provide design implications for future sensor-enabled home healthcare services.

CCS Concepts: • **Human-centered computing → Empirical studies in ubiquitous and mobile computing**; • **Applied computing → Health informatics**.

Additional Key Words and Phrases: Smart home; Internet of Things; Self-tracking; Personal informatics; Self-reflection; Privacy

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1 INTRODUCTION

The domestic environment has long been recognized as an important setting for observing daily behaviors that influence health and wellbeing [46]. In this context, home healthcare services, such as telehealth and remote monitoring, have been continuously developed [51]. This is particularly important for individuals experiencing depression or anxiety, as they often exhibit reduced physical activity and social engagement, leading to extended

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time spent at home [57, 59]. At the same time, the global increase in single-person households has further amplified concerns about mental health and social isolation [112]. As more people live alone, the home has become not only a private space but also a primary setting in which emotional wellbeing is shaped and experienced. These trends underscore the growing need for mental wellbeing care that is embedded within the home.

To enable effective care in this setting, it is essential to continuously monitor users' health and lifestyle in situ. The home, where people naturally form routines and engage in daily activities [100], provides an ideal context for capturing naturalistic behaviors to understand and improve user health status. Advances in ubiquitous sensing technology have made it possible to monitor domestic behaviors through Internet of Things (IoT) sensors [20, 34, 50]. For example, motion sensors or appliance-embedded IoT devices can be used to track activities of daily living (ADLs) [23], facilitating support for both physical health (e.g., fall detection [114]) and cognitive health (e.g., dementia [6]). Data collected in such sensor-enabled home environments, commonly categorized as patient-generated health data (PGHD), offers rich behavioral insights that can inform personalized care and timely interventions [19].

While sensor-enabled home environments have been explored as potential healthcare settings, most existing efforts have primarily focused on cognitive and functional health in older adults [21]. These approaches often remain centered on the diagnosis and treatment of diseases, rather than addressing the broader spectrum of psychological and emotional wellbeing [68]. As awareness of mental health increases, there is a growing need to move beyond reactive, illness-focused models and instead adopt proactive strategies that promote emotional wellbeing in everyday life [71]. Emotional wellbeing, defined as presence of positive emotions and absence of negative ones [25, 27], requires active management of common negative states such as depressed mood, anxiety, and stress, which remain prevalent globally [42, 69]. Importantly, supporting emotional wellbeing should not be limited to individuals with clinically diagnosed mental health conditions. Those with subclinical symptoms, who may not meet formal diagnostic criteria but still face emotional difficulties [31, 83], also require meaningful support. This shift highlights the importance of embedding emotional support into everyday routines, marking a transition from *medicalized* interventions to more *mundane* self-care practices integrated into daily life [67].

The domestic environment offers a valuable opportunity to support the management of everyday emotional wellbeing. According to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) [8], emotional wellbeing risks, such as depression, anxiety, and stress, are closely associated with behavioral factors, including sleep and eating patterns [89]. Since these routines naturally unfold within the home, the domestic setting provides an ideal context for the continuous and passive monitoring of behaviors that are tightly linked to emotional states. Moreover, self-awareness of one's emotional state is essential for effective emotional wellbeing management [82]. By leveraging home IoT sensing to monitor subconscious and repetitive domestic routines [10, 113], home-based monitoring systems can provide objective, data-driven insights into how everyday behaviors relate to emotional states. These insights can foster self-reflection, enabling individuals to identify behavioral patterns, make informed lifestlye adjustments, and take proactive steps toward emotional wellbeing management [54]. These capabilities underscore the potential of passive, IoT-enabled sensing technologies to facilitate personalized and preventive mental healthcare in everyday contexts.

Despite its potential, existing studies on emotional wellbeing have primarily relied on mobile devices and wearable technologies to track indicators such as step counts, heart rate, and GPS data [11, 43, 106]. However, such data collection becomes limited when users are at home and not actively carrying or wearing these devices [24, 39]. In contrast, home IoT data serves as a complementary modality by enabling continuous monitoring of users' naturalistic behaviors in the home environment without requiring device attachment or active user engagement. This unobtrusive and seamless sensing approach minimizes user burden while providing a valuable opportunity to analyze multifaceted lifestyle factors associated with everyday emotional wellbeing. Although home IoT data has significant potential to understand emotional wellbeing, there is limited research investigating how such data can be systematically leveraged to infer emotional states. Furthermore, user perceptions and privacy concerns around using home IoT data for emotional self-tracking and wellbeing management have yet to be thoroughly examined.

With this background, we set the following research questions (RQs):

- RQ1: How is home IoT data associated with everyday emotional wellbeing?
- RQ2: What are users' perceptions of behavioral patterns identified via home IoT data that are related to everyday emotional wellbeing?
- RQ3: What are users' privacy concerns regarding the collection and use of home IoT data for everyday emotional wellbeing?

To address these questions, we conducted a four-week field study with 20 participants, collecting sensor data from mobile devices, wearables, and home IoT sensors, along with self-reported measures of emotional wellbeing. We first performed a quantitative analysis to examine the relationship between home IoT data and emotional wellbeing. Our results indicated that incorporating home IoT data improved the ability to capture associations with emotional wellbeing, compared to relying solely on mobile and wearable data. However, we also observed substantial variability in domestic activity patterns across participants, highlighting the individualized nature of home routines and their connection to emotional wellbeing.

To further investigate these individual differences, we examined how participants reflected on their home IoT data in relation to emotional wellbeing. To support this reflection, we developed a personal informatics tool that enabled users to explore the connections between their sensor data and emotional states. Through semi-structured interviews, we found that most participants perceived home IoT data as intuitive and easy to interpret and gained insights into their emotional wellbeing. Specifically, participants contextualized the sensor data within their daily lives and integrated multiple data streams to better understand how their behavioral routines related to emotional states. Moreover, participants reported a positive shift in their privacy concerns, indicating increased comfort with the collection and use of home IoT data after interacting with the tool.

Taken together, the key contributions of this study are as follows.

- Our study broadens mental healthcare research by demonstrating the feasibility and challenges of using home IoT data, complementing mobile and wearable sensing, to track emotional well-being, based on a four-week in-the-wild study with 20 single-person households.
- Our findings reveal how users reflect on their emotional wellbeing through visualizations of domestic activity data collected via home IoT sensors, and uncover nuanced privacy concerns emerging from in-home emotional wellbeing tracking.
- This study offers insights derived from empirical analysis and design implications for sensor-enabled home healthcare systems that support everyday emotional self-tracking.

2 RELATED WORK

2.1 Tracking Home IoT Data for Emotional Wellbeing

Mental health is shaped by various behavioral and environmental factors that influence daily life [89, 104]. Studies in lifestyle medicine and psychiatry have identified several key lifestyle factors such as *sleep patterns*, *eating habits*, *physical activity*, *social interaction*, and *environmental conditions* as critical determinants of mental wellbeing [73]. Since these factors play a critical role in mental health, continuously tracking these factors can facilitate early intervention and improve emotional wellbeing.

Recent studies have shown that mobile and wearable devices (e.g., smartwatches) facilitate self-tracking major lifestyle factors [106–108]. For example, sleep disturbances, commonly experienced by individuals with depression and anxiety, can be monitored using mobile and wearable devices that track sleep duration and patterns [72, 106]. Similarly, smartwatches can detect eating patterns by tracking wrist movements [64], although self-reports are often required to address gaps or inaccuracies in automated detection [36, 96]. For physical activity, mobile and wearable devices collect GPS data [87, 113] and accelerometer data [3], offering insights into a user's mental state. Since reduced physical activity is a common symptom of depression, tracking movement patterns through these devices can help identify changes in mental wellbeing [3, 87].

While sensor-based mental health research has primarily focused on outdoor and mobile contexts, many key lifestyle factors influencing emotional wellbeing are rooted in habitual, everyday behaviors at home. Therefore, it is important to consider domestic settings, where much of daily life and mental health-related activity occurs. For individuals with health issues, tracking behaviors at home is particularly important as they tend to spend more time indoors, reducing outdoor activities [59]. Naturally, other domestic behaviors (e.g., sleep, eating, and indoor activities) accompanied by the increased time spent within the domestic environment can also serve as an important indicator in assessing one's emotional wellbeing. Additionally, exploring domestic settings offers the opportunity to complement mobile and wearable data. For example, tracking domestic behaviors such as sleep or eating solely with mobile or wearable devices can compromise data quality due to missing or inaccurate data, as users do not always carry or wear mobile or wearable devices to track their states [24, 39]. Furthermore, environmental factors such as light, temperature, and humidity, which can influence mental health [77, 91], are not easily captured by mobile or wearable devices. While mobile and wearable devices can capture general physical activities like walking or running, they often fail to detect these finer-grained, context-specific domestic behaviors. In contrast, sensing within domestic settings can reveal home-specific activity patterns and environmental conditions, providing complementary insights into emotional wellbeing.

Therefore, home IoT data, which captures various behavioral and environmental factors in a domestic setting, presents a promising opportunity to provide a more comprehensive view of emotional wellbeing. Existing studies have widely used home IoT sensors to track various aspects of daily life, such as sleep, eating, and household activities as summarized in Table 1. Although prior studies have demonstrated the utility of home IoT sensors for monitoring daily activities, most research on sensor-driven health monitoring in domestic environments has focused on clinical or aging populations, particularly for monitoring functional and cognitive decline [105]. This is largely driven by the increasing demand for aging-in-place technologies, where IoT sensors (e.g., motion or door contact sensors) have been deployed in assisted living facilities to monitor the activities of daily living (ADLs) of older adults with dementia or mild cognitive impairment [5, 29]. For example, the Dem@Home project implemented a GUI system that tracked cooking activities, sleep patterns, and indoor locations using ambient home sensors to assist both clinicians and patients with mild cognitive impairment (e.g., Alzheimer's disease) [6]. Similarly, sensor-augmented devices attached to everyday household objects (e.g., phones, coffee machines, pillboxes) were developed to track ADLs such as pill-taking tasks and phone use in older adults [53], with the collected data presented graphically to help physicians monitor cognitive health.

Despite advances in home IoT sensing, its potential to support emotional wellbeing in everyday life remains underexplored. This gap is particularly important given that subclinical mental health symptoms, such as low mood, fatigue, or mild anxiety, affect a large proportion of the population and can significantly impair daily functioning [26, 31]. Although these individuals do not meet diagnostic thresholds, they often report reduced quality of life [83], and early interventions have been shown to reduce emotional distress and prevent symptom escalation into clinical disorders [22]. Given the high prevalence and impact of subclinical symptoms, developing supportive technologies tailored for this group is critical for promoting emotional wellbeing and addressing unmet needs. Our work addresses this gap by focusing on how home IoT sensing can support emotional wellbeing among subclinical populations.

2.2 Supporting Emotional Wellbeing Reflection with Personal Informatics

Managing users' emotional wellbeing requires systems that not only track everyday behaviors but also help users make sense of such data and reflect on their emotional states. Personal informatics (PI) systems provide a

Table 1. Types of sensors for lifestyle monitoring in domestic environments, summarized from prior literature

Observation	**Sensor Type**	**Data type**	**Reference**
Sleep	Pressure-based sleep sensor Motion sensor	Sleep duration	[6] [14]
Cooking/Eating	Door contact sensor Plug sensors	Kitchen appliances usages Refrigerator usages	[29, 50, 53, 94, 111] [6, 88]
Taking Medicine	Door contact sensor	Medicine repository	[53, 81, 94]
Indoor Location Tracking	Motion sensor Door contact sensor Light sensor	Indoor motion Room door open/close Light changes of the room	[6, 14, 20, 29, 32, 81, 94] [32] [50]
House Chores	Plug sensors Door contact sensor	Vacuum cleaner usages Washing machine usages	[88] [111]
Entering and Leaving	Door contact sensor	Main door open/close	[20, 94, 111]
Environmental Conditions	Temperature Humidity sensor Light sensor Noise sensor	Temperature Humidity Light Noise	[20, 50, 88, 94] [50, 88] [20, 50, 88] [29]

framework by enabling both behavior tracking and informative feedback to support self-reflection [54]. With the proliferation of ubiquitous sensing, a large volume of HCI studies on PI systems powered by mobile and wearable sensing technologies have emerged [85]. As interest in mental health issues grows [75], PI system designs for mental health increasingly focus on delivering collected data to users through data visualizations [60, 96]. For example, LifelogExplorer [45] supports self-reflection by visualizing the relationship between stress and various life aspects using wearable sensor data, such as skin conductance and accelerometer measurements, alongside personal calendar data. Similarly, Health Mashups [11] and DreamCatcher [72] collect sensor data from mobile and wearable devices to visualize user moods and daily activities, such as sleep and food intake, facilitating user reflection. In addition, MindScope [43] and Emotical [36] utilize prediction models to assist users in reflecting on their mental health. MindScope predicts users' stress levels using behavioral data from smartphones, providing intuitive explanations and prediction results. Emotical builds a mood prediction model using self-reported sleep and social activity data, visualizing future moods to encourage behavior changes that regulate negative moods.

While current research highlights the potential of sensor-driven PI systems for emotional wellbeing, these systems largely rely on data from mobile or wearable devices, which often fall short in capturing certain domestic behaviors and environmental factors. As discussed earlier, many everyday activities that are closely tied to emotional wellbeing such as sleep, eating primarily take place within the home, and environmental factors (e.g., light, temperature) are also challenging to monitor using mobile and wearable sensors alone. These limitations highlight an opportunity to augment existing PI systems, and our work explores how incorporating home IoT data can support emotional wellbeing reflection in domestic contexts, offering complementary perspectives beyond mobile and wearable approaches.

2.3 Privacy Concerns in Home IoT Data Collection

Privacy concerns are critical in sensor-enabled environments or services that extensively leverage personal data. Prior studies have emphasized the importance of understanding users' privacy perceptions and concerns related to sensor-based personal data collection [52, 84]. With the advancement of IoT technologies, researchers have

Table 2. Overview of study phases and activities

Preliminary Study	Main Study (N=20)	
Preliminary Exploration	*Data Collection Setup & Execution*	*After Data Collection*
- Preliminary Survey (N=30)	- Participant Recruitment	- Visualization Tool Usage
- Literature Review	- Sensor Setup & Data Collection	- Interview & Post-Survey

increasingly studied user perception of privacy in domestic settings [17, 61]. For example, Choe et al. [17] found that users are less willing to record and share private in-home activities such as cooking/eating and intimacy behaviors, while Zheng et al. [115] revealed that users often overlook privacy risks from seemingly less sensitive data collected by non-audio/visual devices. Similarly, Tabassum et al. [97] found that users tend to underestimate privacy risks associated with smart home devices.

While these studies provide valuable insights into privacy concerns in smart home contexts, none have specifically addressed users' perceptions regarding the utilization of home IoT sensor data for self-tracking emotional wellbeing. Given that mental health-related data is often perceived as one of the most sensitive types of personal health information [33], it is important to understand how people perceive the collection and use of home IoT data for emotional wellbeing tracking. This understanding is essential for informing the design of systems that are not only effective in tracking emotional wellbeing but also aligned with users' privacy expectations. Our work contributes to this growing body of research by offering firsthand insights into users' experiences of living with a variety of IoT devices in their homes, specifically in the context of self-tracking emotional wellbeing.

3 METHODS

Our study consisted of three stages: (1) an initial phase combining a preliminary survey with 30 participants and a literature review to define data selection criteria; (2) four weeks in-the-wild data collection with 20 participants, distinct from those in the survey; and (3) a post-hoc reflection phase involving the design of a visualization tool based on the collected data, followed by user study using the tool. Table 2 presents the overall study phases.

3.1 Data Selection Criteria

By reviewing prior studies, we identified five behavioral and environmental factors related to emotional wellbeing: sleep, eating, physical activity, social interaction, and environmental conditions [73, 89, 104]. To investigate how these factors could be tracked in domestic settings, we examined sensing modalities from the literature and summarized them in Table 1. Drawing from this prior work, we selected a subset of sensors that are particularly suitable for capturing lifestyle factors likely to be associated with emotional wellbeing in everyday domestic settings. This literature-based overview served as a reference point in designing our sensing setup, from which we selected sensors that could feasibly be deployed to monitor the most relevant behavioral and environmental factors. To further ground our sensor selection in real-world conditions, we conducted a pre-study survey with 30 individuals living in single-person households. Participants were recruited through an online university community board, and all lived in private residences, explicitly excluding on-campus dormitories or shared housing. This survey was approved by the institutional review board (IRB). Among the respondents, 29 were in their 20s and 1 in their 30s; 9 were male and 21 female. The goal of the survey was to identify commonly owned appliances that could serve as proxies for lifestyle factors related to emotional wellbeing (Appendix A, Table 6).

Sleep plays a crucial role in mental health, with sleep duration being a key diagnostic factor in the DSM-5 [8]. Mobile and wearable devices have been widely used to estimate sleep duration [72, 106, 107]. While smartphone-based sleep detection has recently become feasible through sensor-based modeling [63], smartphones are not originally designed for sleep tracking and thus infer sleep status indirectly from a combination of data such as accelerometer and screen usage, which may affect reliability. Wearables, though equipped with sleep tracking features, require consistent user compliance [39]. Considering these limitations, we leverage a bed-mounted pressure sensor that enables unobtrusive, passive, and continuous sleep monitoring.

Eating is another lifestyle factor directly associated with emotional wellbeing, and changes in appetite (either increase or decrease) are part of the DSM-5 diagnostic criteria for depression [8]. However, monitoring eating behavior remains a challenge due to the difficulty of automatically detecting food intake. Most studies rely on self-reported meal frequency [64] or manual food intake logs [11]. In domestic settings, interactions with kitchen appliances (e.g., fridge, microwave, coffee maker) have been used as a proxy for food-related routines [50, 53, 111]. In our study, rather than attempting to detect precise intake events, we focused on identifying food-related routines, such as the frequency of appliance use, which may indirectly reflect changes in eating patterns relevant to emotional wellbeing. To support this approach, we first surveyed 30 single-person households to identify commonly used kitchen appliances. Over 90% of the participants reported owning microwaves and refrigerators. Accordingly, we monitored their usage frequency as an approximation of food-related behavior patterns. While appliance ownership alone does not confirm eating behavior, prior work suggests that usage patterns can serve as reliable behavioral proxies in domestic settings [50].

Physical activity is typically monitored using step counts, GPS tracking, and accelerometer data [3, 55]. While mobile and wearable devices effectively track outdoor activities, they are less suited for monitoring movement within the home. Additionally, these devices rely on users consistently carrying or wearing them, which may not always be the case at home, leading to gaps in domestic activity tracking. To capture physical activity in domestic settings, prior studies have considered indoor movements, household chores, and entry/exit events as indicators of activity levels [20, 111]. In our study, we leveraged home IoT sensors and wearable devices to monitor both indoor and outdoor activities. Indoor activities were assessed through household chores and movement within the home, while outdoor activities were inferred from entry/exit patterns and step counts. For tracking household chores, we focused on the usage of vacuum cleaners and washing machines, as these were the most commonly owned appliances based on our survey. By integrating home IoT data with traditional mobile and wearable activity tracking, we aimed to provide a more comprehensive view of users' daily movement patterns.

Social interaction has been assessed primarily through phone call logs, messaging frequency, and social media activity using mobile devices [55, 113]. Similarly, we relied on smartphone data to monitor call duration and the number of sent/received messages as indicators of social interaction patterns.

Environmental conditions such as light exposure, temperature, and humidity also significantly influence mental health [77, 91]. To capture these conditions, we employed sensors that track indoor light levels, temperature, and humidity. This data allows us to explore potential links between environmental factors and emotional wellbeing.

For the collection of *mental health states* data, we used the Patient Health Questionnaire-2 (PHQ-2) [58] and Generalized Anxiety Disorder-2 (GAD-2) [49], which are abbreviated versions of the PHQ-9 [47] and GAD-7 [95], to assess depression and anxiety, respectively. Additionally, we incorporated a questionnaire used in a prior study [41] to collect self-report data on stress, valence, and arousal (Appendix A Table 3).

3.2 In-the-Wild Data Collection

In this section, we elaborate on the data collection methods and the overall design process of the personal informatics tool which supports users in understanding their data. This study was approved by the university's institutional review board (IRB).

3.2.1 Participant Recruitment. We recruited 20 single-person households through online promotions at universities and local community websites. The average age of the participants was 24.79 (SD: 2.86), with 13 males and 7 females. Our recruitment criteria included individuals living in single-person households who owned essential household appliances, including a bed, chair, microwave, refrigerator, washing machine, and vacuum cleaner.

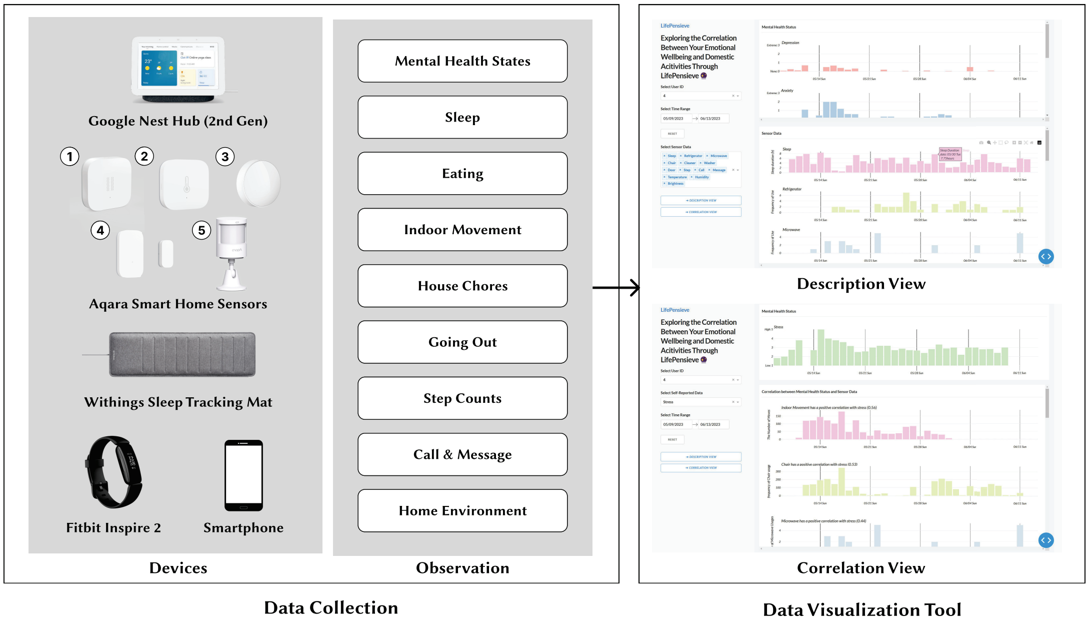


Fig. 1. System overview. Aqara sensors include 1) vibration sensor, 2) temperature & humidity sensor, 3) light sensor, 4) door contact sensor, and 5) motion sensor.

We also recruited only individuals who, at the time of screening, reported spending at least five hours daily at home, excluding sleep. This threshold was aligned with prior work using smart speaker–based ESM in domestic settings [56], which adopted the same criterion to ensure meaningful in-home interaction opportunities with the system. Participants were required to install a research-developed data logger application on their smartphones (Android version 8.0 or higher).

Participants individually participated for 30 consecutive days within the period from May 8, 2023, to June 13, 2023. The start and end dates varied across participants. The main study participants were entirely independent from those who participated in the earlier survey. Since our study focused on supporting emotional wellbeing in everyday life rather than detecting severe mental health conditions, we did not pre-screen participants based on clinically diagnosed depression. Instead, we aimed to capture a broad spectrum of emotional wellbeing states and behavioral patterns, allowing us to examine variations in daily routines and their relationship to emotional wellbeing in the general population, including individuals experiencing subclinical symptoms. Participants covered a range of emotional wellbeing states, as indicated by varying PHQ-9 scores. Targeting this population is important because subclinical symptoms such as low mood, fatigue, and mild anxiety are common and can meaningfully impair daily functioning [26, 31]. By focusing on a subclinical population, we sought to investigate how home IoT sensing could support emotional wellbeing in naturalistic, everyday contexts.

We chose to focus on single-person households for two reasons. First, their relevance to mental health issues is increasingly recognized. Recent studies have shown a significant global rise in single-person households; according to the United Nations, the proportion of single-person households worldwide increased from 23% in 1985 to 28% in 2018, with projections reaching 35% by 2050 [102]. Furthermore, a recent meta-review found that individuals living alone faced a higher risk of depression [112]. The second reason is related to the internal validity of self-tracking at home. In single-person households, tracking behaviors is straightforward, as there

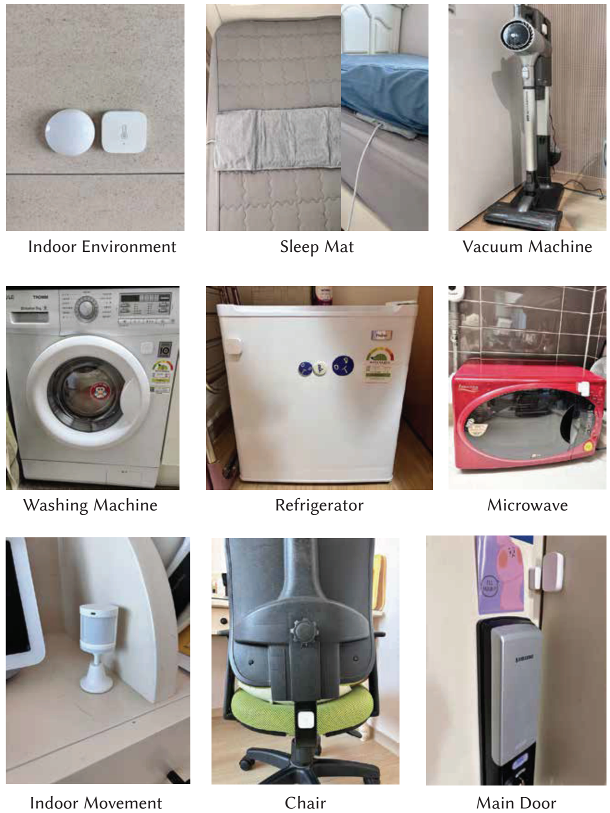


Fig. 2. Sensor installation for monitoring domestic activities

is no need for disambiguation between multiple occupants, ensuring cleaner and more reliable data collection. Most participants lived in studio apartments, with three participants residing in one-bedroom apartments. While living space could potentially influence daily behaviors, the majority of sensing devices used in our study were attached to specific appliances or furniture rather than installed by room, which may have reduced the impact of living space on data collection.

3.2.2 Data Collection Procedure. The user study was conducted for four weeks to collect mobile, wearable, and home IoT sensor data. Before data collection, participants were informed of the study's purpose and details of data collection (e.g., sensors, devices, collected data types) at an online orientation. Following the orientation, researchers visited the participants' homes to install all necessary sensors and devices. Participants then completed a pre-survey including the PHQ-9 (Patient Health Questionnaire-9), GAD-7 (General Anxiety Disorder-7), and PSS (Perceived Stress Scale) to assess their baseline mental health status. Additionally, we administered a survey to measure participants' perceptions of privacy acceptability before the data collection period. They rated the perceived acceptability of each data type on a 7-point Likert scale (1 = highly negative, 7 = highly positive), using a questionnaire adapted from prior work [52].

IoT Data Collection: For home IoT data collection, we used commercially available sensors, including the Aqara sensor suite (i.e., vibration, door, motion, and environmental sensors) and the Withings sleep tracking mat.

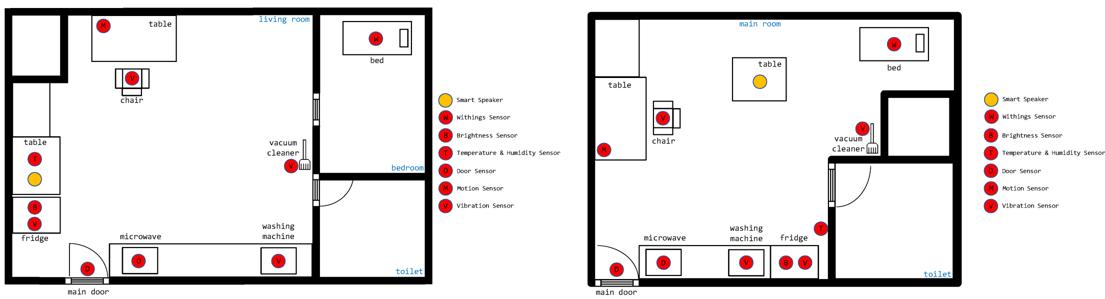


Fig. 3. Examples of floor plans for sensor placements. (Left: One-bedroom apartment layout, Right: Studio apartment layout)

Aqara vibration sensors detected vibration, tilt, and drop events, which were used to track the usage of a chair, refrigerator, vacuum cleaner, and washing machine. The door sensor recorded each instance of the front door and microwave usage. The motion sensor was placed on a frequently used desk to track activity levels, while the environmental sensor, mounted on the wall, monitored light, temperature, and humidity. Sleep duration was measured using the Withings sleep tracking mat installed on participants' beds. Every participant's home was equipped with a total of 10 sensors to comprehensively monitor their environment and behaviors, as shown in Figure 2, with example sensor placements for each home type illustrated in Figure 3.

Mobile and Wearable Data Collection: We also collected mobile and wearable data. A research team-developed smartphone application recorded call duration and the number of text messages sent and received. Participants were provided with a Fitbit Inspire 2, which tracked step counts.

Experience Sampling Method (ESM) Data Collection: To collect self-reported emotional wellbeing data, we implemented a context-aware ESM system, following approaches from prior studies [56, 109]. The system consisted of a mobile phone, an environmental sensor, and a smart speaker (Google Nest Hub 2nd Gen). It continuously monitored the home environment using the phone's built-in sensors (ambient light, ambient noise, camera-based human presence) and an external CO_2 sensor. ESM prompts were delivered multiple times per day through a multimodal interface supporting both touch and voice input. Prompts were triggered when an opportune context was detected (e.g., reduced ambient noise or user presence near the device) or after a maximum of 90 minutes since the previous prompt. To avoid excessive prompting, a minimum interval of 30 minutes was enforced between prompts. When triggered, the mobile phone played a wake-up command (e.g., "Hey Google, please run the survey program") to activate the smart speaker. Upon recognizing the command, the speaker launched the survey program and delivered the ESM prompt. Participants received at least six ESM prompts per day within a user-defined 10-hour window (e.g., 10 AM–8 PM). Each prompt inquired about their emotional state over the preceding 1–2 hours. This time interval was intentionally selected to align with the system's triggering frequency, typically prompting participants every 30 to 90 minutes. By asking about recent emotional states within this interval, the system captured fine-grained affective dynamics throughout the day, closely tied to participants' everyday experiences. The ESM survey interface was adapted from validated designs in prior work [56] and tailored to the current study context (Figure 4). The questions used in the survey were based on validated mental health questionnaires, as listed in Table 3. Although the study primarily focuses on tracking domestic routines, the ESM questions were designed to capture participants' overall emotional state, including those influenced by external contexts such as work-related stress. These emotional experiences, even when originating outside the home, may manifest as changes in domestic behaviors (e.g., sleep patterns, movement, or

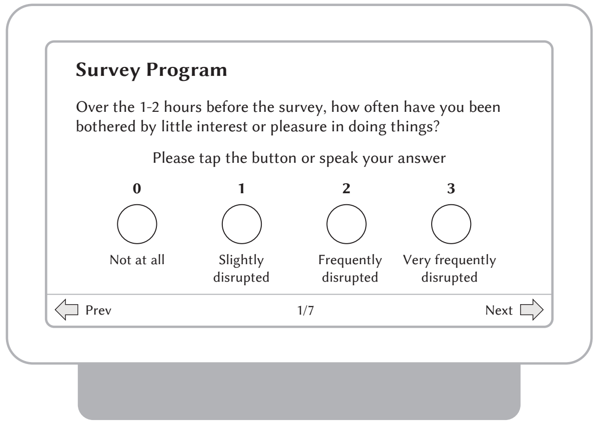


Fig. 4. Multimodal interface displayed on the smart speaker during the ESM task. Participants responded via touch or voice.

household activities). Accordingly, we examined how such emotional states relate to sensor-based representations of daily routines.

Table 3. Mental health ESM questions

Category	Questions	Answers
Depression	1. Over the 1-2 hours before the survey, how often have you been bothered by little interest or pleasure in doing things? 2. Over the 1-2 hours before the survey, how often have you been feeling down, depressed, or hopeless?	Not at all (0) - Very frequently (3)
Anxiety	3. Over the 1-2 hours before the survey, how often have you been feeling nervous, anxious, or on edge? 4. Over the 1-2 hours before the survey, how often have you been unable to stop or control worrying?	Not at all (0) - Very frequently (3)
Stress	5. Over the 1-2 hours before the survey, what was your stress level?	Not stressed at all (1) - Very stressed (5)
Emotional Valence	6. Over the 1-2 hours before the survey, how was your emotion?	Very negative (1) - Very positive (5)
Emotional Arousal	7. Over the 1-2 hours before the survey, how was your emotion?	Very calm (1) - Very excited (5)

3.3 Post-collection Data Reflection

3.3.1 Data Visualization Tool. After data collection, the next step was to present data in a way that users could easily interpret and reflect on their daily behaviors. To achieve this, we considered several design possibilities to make the collected data more comprehensible to individuals. Since visualization is a common approach for quantifying self-tracking data [60, 72], we developed a visualization tool that supports the tracking sensor data related to emotional wellbeing (Figure 5). The system was designed to make the data easy to understand and navigate, allowing users to intuitively explore behavioral and emotional patterns. The tool supports two main tasks: (i) exploring an overview of the collected data and (ii) supporting self-reflection on the relationships between one's domestic activities and emotional wellbeing.

For the first task, the system provides a descriptive overview of general trends in users' daily activities and emotional wellbeing. Users can select specific periods and data types via the left panel for focused exploration. To visualize numerical trends, line graphs were used for environmental data to highlight changes over time, while bar graphs were applied to data like appliance usage and emotional states to emphasize individual values within broader patterns [30, 93].

For the second task, the system offers a correlation view to illustrate relationships between sensor data and emotional wellbeing. Correlation analysis, commonly used in personal informatics [11, 18], helps users intuitively understand these connections. Pearson's correlation coefficients were calculated using daily-averaged emotional wellbeing risk scores (depression, anxiety, stress, emotional arousal, and valence) and aggregated daily sensor data. The most highly correlated factors are displayed in descending order. To further assist users in interpreting the correlation results, textual explanations were added alongside the correlation values. These explanations describe in natural language how each sensor data feature is associated with emotional wellbeing factors. Because many users often find it challenging to directly interpret numerical charts or raw correlation coefficients [11], providing a natural language summary was intended to make the findings more accessible and easier to understand.

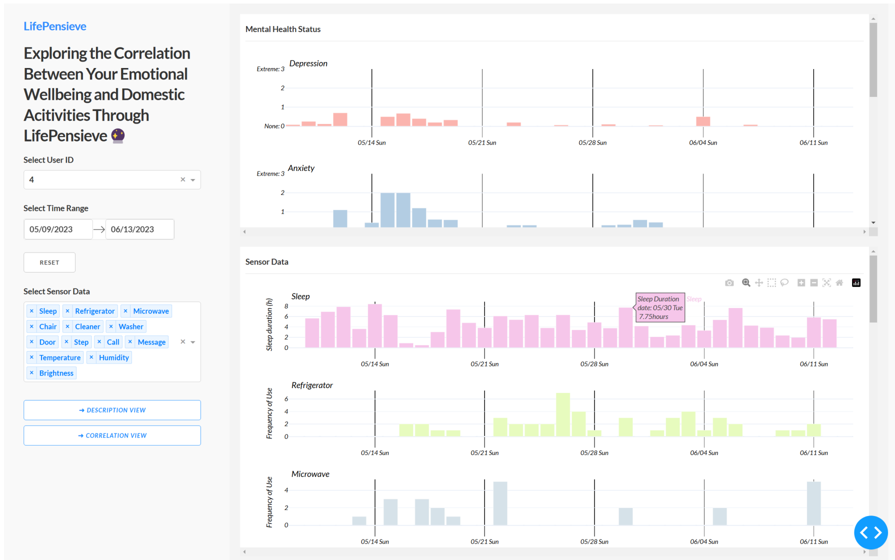
Note that the visualization tool is designed to inform users of strong correlations found by data analysis to avoid information overload. Its goal is to assist users in self-reflecting on their emotional wellbeing and daily domestic routines. It is ultimately up to the user to draw their own conclusions from data sensemaking regarding behavior patterns related to their emotional wellbeing or sources of mental health issues, based on the insights offered by the tool.

3.3.2 User Study on Data Reflection. After data collection ended, we analyzed each participant's data and loaded the results into the visualization tool to help participants engage with their own data and self-reflect on their behavioral patterns and associations related to everyday emotional wellbeing. We explained to participants that the purpose of the system is to visually represent behavioral and environmental factors that might be associated with one's emotional wellbeing. The visualization tool was deployed on a laptop provided by the researchers. Participants individually explored their own data using the laptop in a lab setting. Each session lasted approximately 45–60 minutes and was conducted in a one-on-one, in-person format, so that participants could independently interact with the data without researcher interference. Participants explored the visualization tool on their own, while researchers were present to provide technical support or clarification if needed. After data exploration, we conducted an exit interview and survey. During the interviews, participants were asked about 1) how they explored the data using the provided tool, 2) how they reflected on the relationships between data and emotional wellbeing 3) what insights they gained about their daily patterns and emotional wellbeing, and 4) privacy concerns or other issues with the data utilization. Additionally, participants completed a post-survey assessing their perceptions of privacy acceptability after the data collection period.

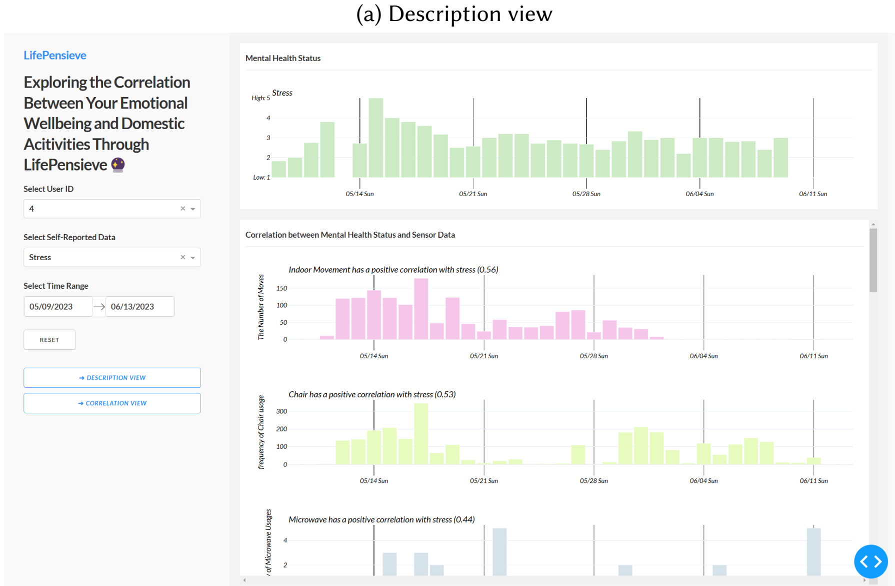
3.4 Data Analysis Methods

We used a mixed method to examine the relationship between home IoT data and emotional wellbeing. The quantitative analysis assessed whether sensor data showed significant associations with risks to emotional wellbeing, while the qualitative analysis explored how participants interpreted these relationships.

For quantitative analysis, we first conducted a multilevel logistic regression, classifying participants' emotional wellbeing states as higher risk (coded as 1) or lower risk (coded as 0). We adapted the PHQ-2 that consists of two questions, assessing the frequency of "depressed mood" and "loss of interest" in the past few hours, each ranging from 0 to 3 (not at all vs. very frequently) and the GAD-2 similarly measuring, "nervousness" and "uncontrollable worrying." For each scale, the score is calculated by adding each question's rating, ranging from 0 to 6. For the PHQ-2 and GAD-2 scales, we followed prior clinical studies identifying a score of *three points* as a validated screening cut-off for detecting individuals at risk of depression and anxiety [48, 74]. For stress, emotional arousal, and emotional valence measures, which were scored on 1–5 Likert scale, we used the neutral midpoint of *three*, as the threshold: scores of *three or above* were categorized as higher risk, and scores below three as lower risk. For emotional valence, specifically, the coding was reversed, because higher valence scores



(a) Description view



(b) Correlation view

Fig. 5. An overview of the data visualization tool

indicate more positive emotions, whereas lower scores are indicative of emotional wellbeing risks. We reported marginal and conditional R^2 to summarize the model fit [65]. Marginal R^2 represents variance explained by fixed factors, while the conditional R^2 accounts for the variance explained by both fixed and random effects, including individual differences. We also conducted a Likelihood Ratio Test (LRT) [110] to compare a full model (mobile, wearable, and home IoT data) with a reduced model (mobile and wearable only), assessing its added value beyond mobile and wearable data. The LRT statistic, computed as twice the difference between the model log-likelihoods, was evaluated against a chi-square distribution.

Next, we analyzed individual-level correlations to identify personalized associations between sensor data and emotional wellbeing. We also investigated whether variability in sensor data (or domestic activities) could serve as an indicator of emotional wellbeing, given prior evidence linking day-to-day behavior variability to emotional wellbeing risks such as depression [66, 107]. We measured this variability using the standard deviation (SD) of daily aggregated sensor data, a common metric for assessing behavioral variability [108]. For each IoT sensor that detects interaction counts, we applied a quantile-based transformation to each feature to standardize the scale while preserving rank order. We then computed the standard deviation of each quantile-ranked feature and averaged these values across features to obtain a participant-level behavioral variability score. Environmental sensors were excluded because of a lack of direct user interactions and their continuous nature of measurements. Participants were divided into two groups based on the median value of their overall normalized variability score in terms of interaction frequencies. High- and low-variability groups were assigned based on whether their overall variability score was above or below the median, respectively. Then, Mann-Whitney U tests were used to compare emotional wellbeing differences between the groups.

For qualitative analysis, we conducted semi-structured interviews to explore participants' reflection process on the relationships between domestic activities and everyday emotional wellbeing. We transcribed and analyzed conversations during the interview by conducting thematic analysis [13]. Two researchers individually read the interview transcripts and assigned thematic codes. Then, the whole research team iteratively reviewed and refined the themes until a consensus was reached.

Finally, we examined whether participants' privacy concerns changed by analyzing the survey data that assesses users' perception of privacy acceptability before and after the data collection period. We conducted a Wilcoxon Signed-Rank Test to statistically analyze differences in acceptability ratings.

4 RESULTS

4.1 RQ1. Exploring Home IoT Data Associated with Everyday Emotional Wellbeing

In this section, we report the results of our quantitative analysis on the relationship between home IoT data and emotional wellbeing. First, we present statistical findings on whether home IoT data is significantly associated with emotional wellbeing states. Next, we identify individual behavioral patterns by analyzing personalized correlations between sensor data and emotional states. Finally, we examine whether the variability of domestic activities captured via home IoT data can serve as a potential indicator for detecting emotional wellbeing.

4.1.1 Association Between Home IoT Data and Emotional Wellbeing. To analyze the relationship between mobile, wearable, and home IoT data and participants' emotional wellbeing, we conducted a multilevel logistic regression. Participants' daily emotional wellbeing risk scores were categorized into two groups (e.g., depressed vs. non-depressed), serving as the dependent variable. Data from mobile, wearable, and home IoT sensors (i.e., fixed effects) and participants (i.e., random effects) were set as independent variables. Mobile and wearable data were used as the baseline because they have been widely adopted as standard data sources in emotional wellbeing research [11, 43, 106]. We first established this baseline to evaluate the additional value of incorporating home IoT data. We then examined how home IoT data influences emotional wellbeing compared to mobile and wearable data using a Likelihood Ratio Test (LRT) [110]. The results are shown in Table 4. Block 1 includes only mobile and wearable features as predictors, serving as the baseline. Block 2 incorporates additional home IoT features. The β coefficients represent the size and direction of the relationship between each sensor-derived feature and the emotional wellbeing risk scores. Positive coefficients indicate that an increase in the feature is associated with higher scores on the corresponding wellbeing measure, while negative coefficients indicate an association with lower scores. Notably, higher scores on depression, anxiety, and stress measures reflect greater emotional risk, whereas higher valence scores reflect more positive emotional states. The likelihood ratio test (LRT) assesses whether adding home IoT data significantly improves model fit compared to the baseline model. Empty beta (β) values in the first block indicate variables that were removed during the modeling process. A significant LRT result suggests that the more complex model provides a significantly better fit to the observed data. Our results indicate that adding home IoT data significantly improved the model fit for depression (χ^2 = 36.01, p < 0.001), anxiety (χ^2 = 38.49, p < 0.001), and stress (χ^2 = 23.68, p = 0.014). However, for valence and arousal, the inclusion of home IoT data did not show significant improvements.

To further explore which specific home IoT features were closely related to emotional wellbeing, we examined the feature-level coefficients from the regression models. Notably, reduced sleep duration showed significant associations with depression, anxiety, and stress, and increased sleep duration was linked to more positive emotional valence. Higher indoor temperatures were associated with elevated depression and anxiety levels. Additionally, certain behavioral indicators, such as increased washing machine usage (related to depression and arousal) and frequent main door open-close events (related to stress), emerged as significant predictors. Full statistical details, estimated coefficients, standard errors, and p-values, are provided in Appendix B Table 8–12.

Table 4. Results of multilevel logistic regression analysis predicting emotional wellbeing outcomes (Depression, Anxiety, Stress, Emotional Valence, Emotional Arousal) based on mobile, wearable, and home IoT data. Block 1 includes mobile and wearable data; Block 2 adds home IoT data. Coefficients (β) describe the size and direction of the relationship between a predictor and the response variable. Likelihood ratio test (LRT) results compare model fit between Block 1 and Block 2 (*p<0.05, **p<0.01, ***p<0.001).

		Depression		**Anxiety**		**Stress**		**Emotional Valence**		**Emotional Arousal**	
	Independent Variables	Block 1	Block 2	Block 1	Block 2	Block 1	Block 2	Block 1	Block 2	Block 1	Block 2
		β	β	β	β	β	β	β	β	β	β
Mobile and Wearable Data	Call	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Message	0.05	0.01	0.03	0.01	0.08*	0.08*	0.05	0.05	0.04	0.02
	Step	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Home IoT Data	Brightness		-0.01		0.00		0.00		0.01		0.00
	Tempearture		0.77***		0.74***		0.23		-0.16		-0.19
	Humidity		-0.23		-0.23		-0.17		0.26		-0.08
	Sleep		-0.21**		-0.33***		-0.12*		0.11*		-0.03
	Cleaner		0.08		0.07		0.02		-0.05		-0.02
	Washer		0.22*		0.03		0.09		0.04		0.17**
	Fridge		0.02		0.07		-0.04		0.01		-0.03
	Microwave		-0.06		-0.01		0.00		-0.08		-0.02
	Indoor Movemnt		0.00		0.00		0.00		0.00		0.00
	Chair		-0.01		0.00		0.00		0.00		0.00
	Door		0.01		-0.10		0.10**		-0.01		0.02
Marginal R^2		0.02	0.43	0.00	0.36	0.05	0.15	0.01	0.11	0.01	0.08
Conditional R^2		0.56	0.68	0.53	0.65	0.41	0.55	0.53	0.57	0.51	0.58
Likelihood Test for Model Comparison											
Log Likelihood		-113.83	-95.83	-113.63	-94.39	-217.81	-205.97	-204.12	-196.28	-210.65	-202.25
χ^2			36.01***		38.49***		23.68*		15.67		16.79

4.1.2 Individual Differences in the Association Between Home IoT Data and Emotional Wellbeing. From the previous analysis, we found that accounting for individual differences in home IoT data is important in explaining emotional wellbeing. To consider personal differences, for each participant, we calculated correlation coefficients between home IoT data and overall emotional wellbeing risk scores of each participant. These correlations were computed by aggregating daily self-reported scores for three key mental health indicators, i.e., depression, anxiety, and stress, which were collected through ESM surveys. Overall emotional wellbeing risk scores were derived from these three sub-dimensions, as is commonly done in psychometric scales, where individual dimension scores are

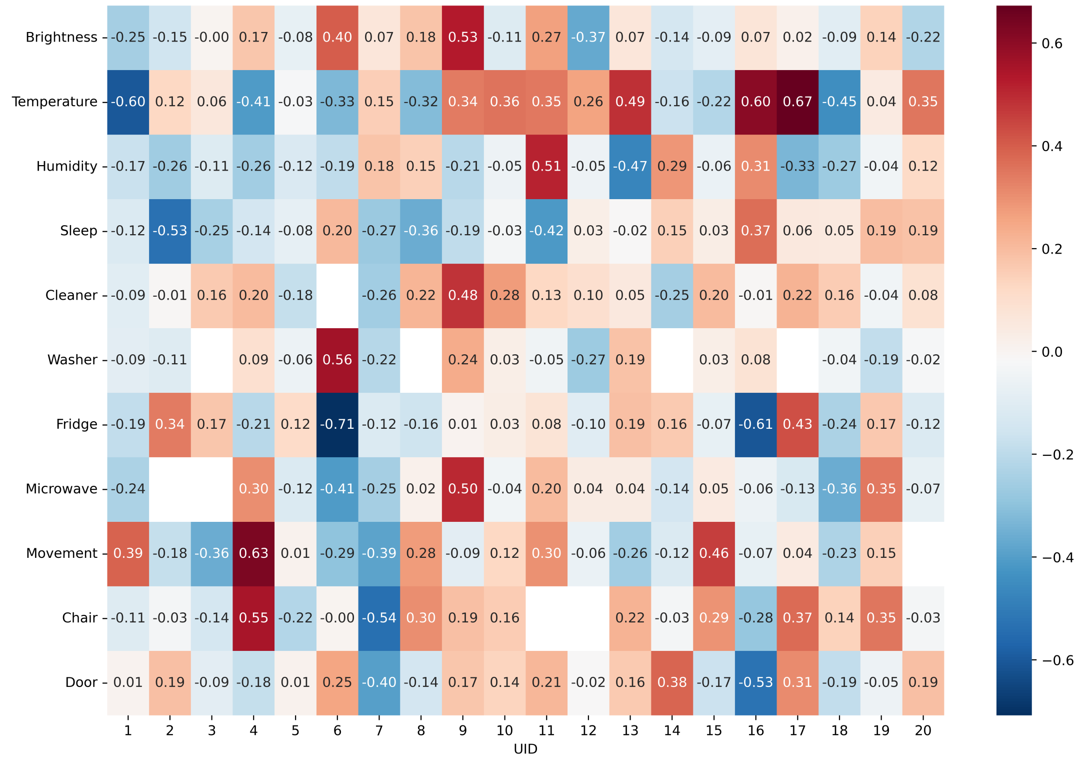


Fig. 6. The correlation heatmap of users (X-axis, user ID) and sensor data (Y-axis) and for emotional wellbeing risk scores

aggregated to generate an overall score. As illustrated in Figure 6, domestic behavioral patterns (Y-axes) varied among individuals (X-axes) based on their emotional wellbeing risk scores. For instance, P16 exhibited decreased refrigerator usage when experiencing high emotional wellbeing risks (r = -0.61), while P17 showed increased refrigerator usage under similar conditions (r = 0.43).

Furthermore, the domestic activities associated with emotional wellbeing varied significantly among individuals. While not statistically significant for all participants, certain data types showed strong correlations with emotional wellbeing for specific individuals. For example, P9 showed a high correlation between microwave usage and overall emotional wellbeing risk (r = 0.5), whereas for P4, chair movements (r = 0.55) and indoor movement counts (r = 0.63) showed stronger associations. To illustrate these patterns, we included a user profile table summarizing the top three correlations between behavioral patterns and emotional wellbeing risk (Figure 7). This figure includes user demographics, such as depression, anxiety, and stress levels from pre-surveys.

4.1.3 Home IoT Data Variability and Emotional Wellbeing. As highlighted in the previous section, individuals exhibit distinct behavioral patterns in relation to their emotional wellbeing states. Despite these variations, we aimed to investigate whether any common pattern could still be identified by examining behavioral variability. Previous studies have also underscored that day-to-day variability in behaviors is closely associated with mental health symptoms [66, 107]. For instance, increased variability in activities such as eating and sleeping may indicate an irregular lifestyle, potentially contributing to poorer mental health outcomes [80]. This aligns with the diagnostic framework outlined in the DSM-5 [8], which emphasizes changes in major behaviors (e.g., sleep, eating)

UID	Gender	Age	PHQ9	GAD7	PSS	Top 1	Top 2	Top 3
User 01	M	25	17	11	25	TEMP (-0.6)	MVT (+0.39)	BRT (-0.25)
User 02	M	25	10	6	15	Sleep (-0.53)	Fridge (+0.34)	HUM (-0.26)
User 03	M	24	12	7	17	MVT (-0.36)	Sleep (-0.25)	Fridge (+0.17)
User 04	M	26	7	5	18	MVT (+0.63)	Chair (+0.55)	TEMP (-0.41)
User 05	M	24	10	2	12	Chair (-0.22)	Cleaner (-0.18)	HUM (-0.12)
User 06	M	26	15	1	25	Fridge (-0.71)	Washer (+0.56)	MW (-0.41)
User 07	F	25	11	6	30	Chair (-0.54)	Door (-0.4)	MVT (-0.39)
User 08	M	26	7	7	15	Sleep (-0.36)	TEMP (-0.32)	Chair (+0.3)
User 09	M	30	11	10	26	BRT (+0.53)	MW (+0.5)	Cleaner (+0.48)
User 10	M	24	4	4	16	TEMP (+0.36)	Cleaner (+0.28)	Chair (+0.16)
User 11	F	20	7	5	23	HUM (+0.51)	Sleep (-0.42)	TEMP (+0.35)
User 12	M	25	3	0	15	BRT (-0.37)	Washer (-0.27)	TEMP (+0.26)
User 13	F	28	16	13	28	TEMP (+0.49)	HUM (-0.47)	MVT (-0.26)
User 14	F	23	3	4	13	Door (+0.38)	HUM (+0.29)	Cleaner (-0.25)
User 15	M	24	0	0	5	MVT (+0.46)	Chair (+0.29)	TEMP (-0.22)
User 16	F	26	19	15	26	Fridge (-0.61)	TEMP (+0.6)	Door (-0.53)
User 17	M	23	10	7	11	TEMP (+0.67)	Fridge (+0.43)	Chair (+0.37)
User 18	F	18	17	14	27	TEMP (-0.45)	MW (-0.36)	HUM (-0.27)
User 19	F	25	0	0	4	Chair (+0.35)	MW (+0.35)	Sleep (+0.19)
User 20	M	29	7	1	16	TEMP (+0.35)	BRT (-0.22)	Door (+0.19)

Fig. 7. User demographics and top three dominant features associated with emotional wellbeing risks (TEMP: Temperature, HUM: Humidity, MVT: Movement, BRT: Brightness, MW: Microwave)

as critical indicators of depression and anxiety symptoms. Based on this rationale, we examined the day-to-day variability of domestic activities and their relationships with emotional wellbeing. While such variability might not fully capture lifestyle irregularities, as it does not take into account factors such as different personal contexts or specific times of day, it can still serve as a useful proxy for estimating the overall consistency or inconsistency of lifestyle patterns. To calculate day-to-day variability, we aggregated the standard deviations of home IoT sensor data for each participant; here, we only considered IoT sensors that detect "interaction counts," and environmental data were excluded due to a lack of direct user interactions and the continuous nature of measurements.

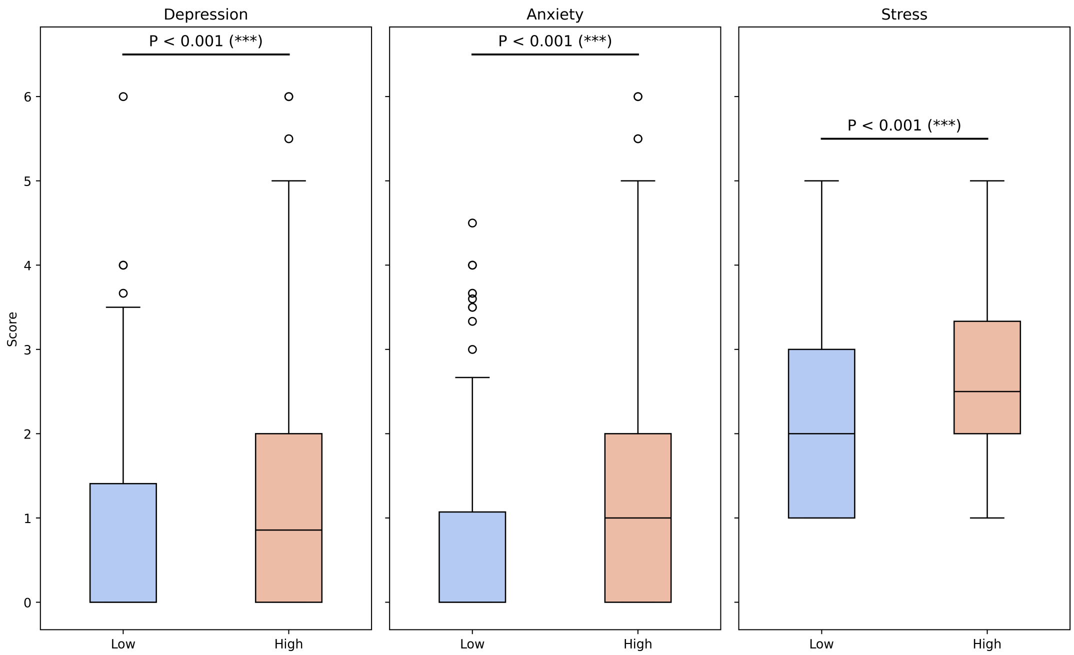


Fig. 8. Comparison of depression, anxiety, and stress scores between low and high variability groups

Based on this metric, participants were divided into two groups: the top 50% with higher domestic activity variability were categorized as the "High Variability Group," and the bottom 50% with lower variability were categorized as the "Low Variability Group." Subsequently, we compared the emotional wellbeing risk scores of the two groups (Figure 8). As the normality test indicated that neither group followed a normal distribution, we conducted a Mann-Whitney U Test for statistical analysis. Although the emotional wellbeing risk scores were relatively low in both groups, as the study was conducted with a general population rather than individuals diagnosed with severe mental illness, the results revealed that the high variability group had significantly higher scores for depression, anxiety, and stress. These findings suggest that the variability in home IoT data itself could serve as an important indicator of emotional wellbeing.

To delve deeper into group-specific behavioral patterns, we examined the correlations between home IoT features and emotional wellbeing risk scores across two groups (Figure 9). The red lines in the boxplot indicate the mean values of the emotional wellbeing correlation with the features for each group. Notably, sleep showed a consistent negative correlation with emotional wellbeing in both groups. This trend aligns with our previous observations, suggesting that poorer mental health tends to be associated with shorter duration of sleep. Other features, such as washer and cleaner usage, showed more discernible group differences, with the high variability group exhibiting positive correlations with emotional wellbeing risk, and the low variability group exhibiting weaker or negative correlations. These findings suggest that the relationship between behavioral patterns and emotional wellbeing may vary depending on domestic behavioral variability.

While these personalized patterns highlight the potential of home IoT data in reflecting emotional wellbeing, interpreting the direction and relevance of these correlations remains challenging without contextual understanding. Thus, to better distinguish between meaningful and spurious associations, we conducted follow-up interviews with participants, as described in the following section.

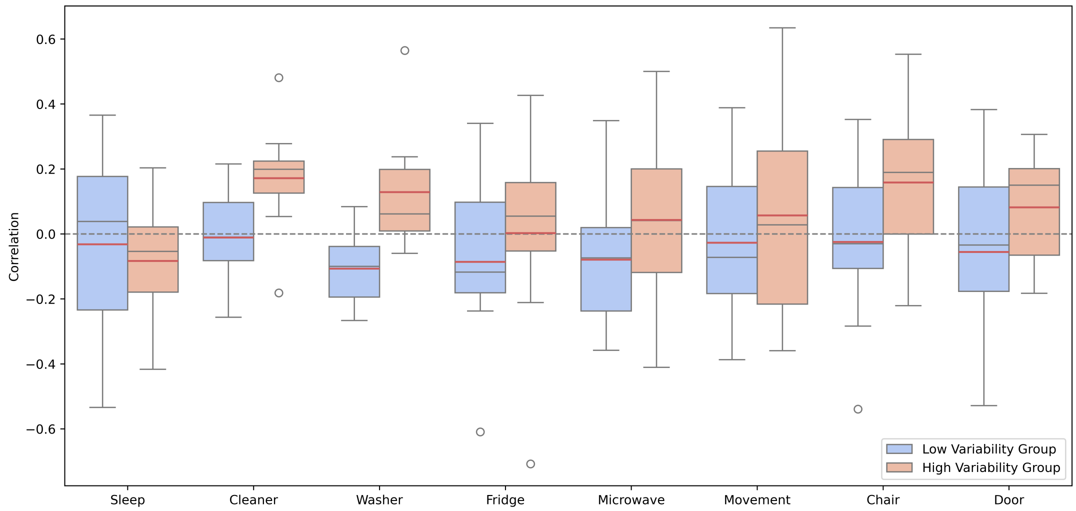


Fig. 9. Correlation of home IoT sensor data with emotional wellbeing in low and high variability groups

4.2 RQ2. User Perceptions of Behavioral Indicators for Emotional Wellbeing Self-reflection

We report our findings on participants' overall self-reflection patterns, focusing on the patterns of initial data exploration, the ways they made sense of data in relation to their emotional wellbeing, and the challenges they faced during the interpretation process.

4.2.1 Initial Data Exploration. When exploring the data, most participants initially focused on data types they were already familiar with, particularly those known to be associated with emotional wellbeing, such as sleep. P3 noted, *"I already know that sleep affects my mood and mental health, so I took a look at it first."* Some participants reported that they focused more on days when the frequency of event occurrences was higher or lower than on other days. For example, P7 said, *"I originally thought I used a vacuum machine almost every other day, but the data shows I didn't clean for quite a long time. This was the first thing that caught my eye."* while P2 explained that *"I first looked at the days when my mental health risk scores such as depression or stress were high, and then checked which home data might be related."*

Participants also replied that the process of understanding their data with the system was straightforward, and the graphs presented the information clearly. P8 said, *"Since the data itself was meaningful, like the number of times I opened the fridge, I didn't feel any difficulty in understanding it."* P17 also mentioned, *"The graphs in the system were quite simple because they showed the data on a daily level. It was intuitive to know how I lived for a month and what my mental health state was like."* However, as shown later, there were also challenges in interpreting certain data types across different individuals.

4.2.2 Patterns in Understanding Emotional Wellbeing Through Home IoT Data. Although statistically significant correlations were limited, many participants reflected during follow-up interviews on the connection between their home IoT data and their emotional wellbeing. Among various daily domestic activities, kitchen appliance usage (e.g., fridge use) was frequently mentioned by participants as an important factor influencing their emotional wellbeing. However, the patterns varied depending on individual behavioral traits. For instance, P17 explained his stress-related routine in association with his behavioral traits. He noted, *"I've always known that I enjoy* *eating. There's just something about treating myself with tasty food that lifts my spirits. However, I've noticed that on days when I'm particularly stressed, I tend to use kitchen appliances more often. It makes me think that perhaps I subconsciously eat more to improve my mood."* Meanwhile, P16 noted that her refrigerator usage decreased when she was depressed. She reported, *"On June 4th, I felt particularly depressed. I noticed that my sleep duration significantly increased while my refrigerator use drastically decreased. I wasn't cooking at all and spent the entire day in bed. I barely moved around and didn't even drink water because I wasn't using the refrigerator. Just lying there, ordering takeout, it's no surprise I felt depressed."*

Participants also reflected on specific past contexts to better interpret the patterns observed in their home IoT data. For example, they reflected on their sleep duration during exam periods to understand its correlation with emotional wellbeing. P3 commented, *"When I'm really stressed, my sleep time tends to decrease. I stayed up all night studying during exams, which added more stress. Not sleeping enough made me even more stressed, and it became a vicious cycle. Plus, during those exam times, I was also snoozing at my desk rather than in my bed. That's probably why my sleep tracking isn't quite catching everything."*

Moreover, some participants integrated insights from multiple types of home IoT data to deepen their understanding of their emotional wellbeing. They leveraged additional contextual cues from diverse data sources, particularly when routines inferred from single sensor data were perceived as inaccurate or incomplete. For example, P13 stated, *"I think the whole combination of these home sensor data reveals a lot about who I am. I easily get sensitive and stressed when things around me are distracting. To keep myself from hitting rock bottom, I try to maintain a clean environment. Seeing even a single hair on the floor can bring me down, so I vacuum daily–sometimes even every hour. I change my bedsheets and do laundry every week. Since I was keeping up with these chores, I didn't notice any major spikes in stress or depression. Looking back, maybe I felt better because of my routines, but this data also makes me wonder if I might have OCD! (laughs)."* Similarly, P19 initially questioned the increase in refrigerator usage captured in her data, which did not immediately align with her understanding of how she typically responded to stress. However, after reviewing additional data on her reduced outings, she recalled how exam pressures had led to significant behavioral changes. She reflected, *"I'm not the kind of person who eats when I'm stressed. I'm very outgoing and love spending time outside doing stuff like seeing friends. I don't usually eat at home. But like I said earlier, I was depressed for some time. I think it was because of the exam and other pressures. During that time, I spent most of my time at home. See the chair movement? I was stressed, but I had to study... Interesting... that explains a lot."*

4.2.3 Challenges in Understanding Home IoT Data for Emotional Wellbeing. While participants generally accepted the results from the system showing the associations between IoT data and emotional wellbeing, some questioned whether certain data types were reliable indicators. This is because they sometimes struggled to establish a clear semantic link between activities tracked by sensors and their emotional wellbeing states.

Some participants raised concerns that activities tracked via sensors could be interpreted in various ways, making it difficult to assess their relevance as behavioral markers of emotional wellbeing. For example, P4 said, *"Looking at my stress and microwave usage, I assume it's usually meant to infer eating or cooking. But I often open the microwave just to clean it, and it's still counted as usage, even though it wasn't actually used for cooking."* Additionally, P6 noted how his stress-coping strategies influenced the interpretation of certain data, emphasizing that interrelated factors might come into play. He said, *"The system shows that my washing machine usage is higher when I'm stressed, but that's because I tend to work out when I'm feeling stressed. After exercising, I do laundry, so this pattern shows up. It's hard to say that the washing machine usage is directly related to my stress–it's more about the workout routine that follows stress."*

Moreover, participants seemed to lack a clear mental model for understanding how specific behaviors were linked to their emotional wellbeing. For example, P10 mentioned, *"The system says I go out more often when I'm depressed based on the main door data. However, it was hard to fully trust the correlation between going out and*

Table 5. Pre-post acceptability of each sensor data collection (1: Highly Negative – 7: Highly Positive). Statistically significant results are reported as **<0.01.

Data Type	Pre-acceptability Median (IQR)	Post-acceptability Median (IQR)	p	Effect Size (r)
Indoor Environment	6.0 (5.00 − 6.00)	6.0 (4.00 − 7.00)	0.440	0.173
Sleep**	**5.0 (4.75 − 6.00)**	**6.0 (5.00 − 7.00)**	**0.006**	**0.609**
Vacumm Clenaer	5.0 (5.00 − 7.00)	6.0 (4.75 − 7.00)	0.416	0.182
Washing Machine	5.0 (5.00 − 6.25)	6.0 (4.75 − 7.00)	0.429	0.177
Refrigerator	5.0 (4.00 − 7.00)	5.0 (5.00 − 7.00)	0.516	0.145
Microwave	5.0 (5.00 − 6.25)	5.0 (5.00 − 6.25)	1.000	0.000
Indoor Movement**	**4.0 (3.00 − 5.00)**	**5.5 (4.00 − 6.00)**	**0.006**	**0.612**
Chair	5.0 (4.00 − 6.00)	5.0 (4.00 − 6.25)	0.428	-0.145
Main Door	5.5 (4.00 − 6.00)	6.0 (4.75 − 7.00)	0.053	0.433
Mobile	4.5 (4.00 − 6.00)	5.0 (4.00 − 6.25)	0.051	0.437
Wearable	4.0 (1.00 − 5.25)	5.0 (4.00 − 6.00)	0.176	-0.311

feeling depressed. The experiment was during the exam period when I frequently visited the school library, so it was confusing to interpret the data on going out. It seemed like I was just rushing out because I had to, not really because I wanted to." Some participants also found it difficult to understand how environmental factors could be practically relevant. For example, P14 noted, *"Knowing that higher humidity is associated with my stress is interesting, but I'm not sure what I'm supposed to do with that information. Am I supposed to dehumidify my house?"*

4.3 RQ3. Privacy Considerations of Home IoT Data for Self-tracking Emotional Wellbeing

To examine how actual in-the-wild home IoT data collection influences participants' perception of privacy, we statistically compared pre- and post-study acceptability scores for different data types. Participants rated the perceived acceptability of each data type on a 7-point Likert scale. Since the assumption of normality was violated, we employed the Wilcoxon Signed-Rank Test for analysis, as summarized in Table 5.

Overall, participants showed higher levels of acceptability for home IoT data types (e.g., appliance usage, environmental, and movement data) than for mobile and wearable data. In their responses, several participants noted that Home IoT data felt less revealing of personal identity than mobile or wearable data. As P3 noted, *"What my phone records felt really personal. It was like they reflected who I am. But something like how often I open the fridge? Even if someone saw that, it wouldn't really say anything about me."*

While several home IoT data types, such as appliance usage and environmental data, showed relatively high baseline acceptability and remained stable, we observed statistically significant increases in acceptability for sleep data ($p < .01$) and indoor movement data ($p < .01$). Participants explained that, in the case of indoor movement data, they were initially concerned about how precisely their location would be tracked. However, after interacting with the system and seeing the actual data, which simply indicated whether movement occurred, their concerns were reduced. For example, P10 commented, *"I was pretty worried about recording my indoor motion at first because it felt like I was being watched in my private space, which didn't feel right. However, after seeing the data, I was not worried anymore because it only showed whether I moved or not."*

For sleep data, participants described a shift in their attitude after recognizing its relevance to their emotional wellbeing. Participants pointed out that viewing the sleep data helped them recognize patterns related to their emotional wellbeing, which made them feel more comfortable with its collection. P8 shared, *"At first, I was skeptical about the need to collect my sleep data. I thought, 'why is this even necessary?' But after seeing the data, I* *realized that my sleep patterns were directly linked to my mental health, which helped me view the collection of sleep data as a valuable tool for understanding and improving my wellbeing. Realizing its benefits shifted my focus from privacy concerns to how it could support my health.*"

5 DISCUSSION

Our study explored the feasibility of modeling emotional wellbeing by tracking domestic activities with home IoT data, which has traditionally been used to evaluate physical and cognitive health in older adults [21, 53, 105]. By analyzing a dataset from the four-week field study with 20 single-person households, we identified key domestic activity predictors, including their variability, on emotional wellbeing and further showed that interpersonal variations were quite prevalent. We found patterns and challenges of sensemaking domestic activity data for emotional wellbeing. We also observed that sensor-based data collection was positively accepted by participants. In this section, we discuss the considerations for emotional wellbeing modeling, and opportunities and limitations in personal informatics systems using home IoT data. We then propose design implications for emotional wellbeing management systems in home IoT contexts.

5.1 Emotional Wellbeing Modeling using Home IoT Data

Our findings showed that incorporating home IoT data significantly improved the model's ability to explain everyday emotional wellbeing risks, such as depression, anxiety, and stress. Additionally, home IoT data could serve independently as a reliable predictor for emotional wellbeing risks. However, the results also revealed considerable individual differences, indicating the importance of accounting for individual characteristics and contexts when modeling emotional wellbeing with home IoT data.

The heterogeneity in individual-level data is known as distribution shifts [76], and is particularly relevant in generalized models using leave-one-subject-out cross-validation. In such cases, mismatches between training and testing distributions due to inter-individual differences can significantly undermine model generalizability. This observation arises because the relationship between emotional states and actual behaviors is highly individualized. The same behavior may reflect different emotional states across individuals, while similar emotional states may be expressed through different behaviors. In other words, identical behavioral cues can carry opposite meanings, shaped by one's coping mechanisms, routines, or cultural contexts. As a result, models trained on aggregate data may fail to capture these nuances, leading to reduced predictive accuracy when applied to unseen users. For example, Adler et al. [4] highlighted the difficulty in generalizing passive sensing models due to inter-individual heterogeneity, even when data are collected using similar devices and protocols.

From a modeling perspective, this interpersonal variation can be described as a *conditional shift*, where the relationship between input features X (e.g., refrigerator usage) and outcomes Y (e.g., stress) varies depending on individual traits, time, or environmental context [28]. In our study, for example, P16 reported that when feeling depressed, she tended to withdraw from most activities and experienced a loss of appetite, which led to decreased refrigerator usage. In contrast, P17 coped with stress by eating more, resulting in increased refrigerator usage during stressful periods. These contrasting patterns demonstrate how the same feature X can correlate with Y in opposite ways across individuals. This highlights the importance of individual contexts and behavioral patterns in models to better account for such variability.

Our findings highlighted that building generalized emotional wellbeing models requires addressing distribution differences between training and testing data. Leveraging contextual information, such as time of day or user-specific traits, could allow for deeper understanding of the factors influencing emotional wellbeing [113] (e.g., conditional independence). Additionally, we can use domain adaptation or personalization techniques. Domain adaptation could help mitigate or account for these differences by aligning the distributions of the source domain (training data) and the target domain (testing data), thereby enhancing the model's performance as demonstrated in human activity recognition [16]. Personalization enables the model to reflect the user's unique data distribution better and to improve detection accuracy by incorporating a subset of target user data into the training process [62].

5.2 Challenges and Opportunities in Personal Informatics Systems for Emotional Wellbeing Using Home IoT Data

We explored users' experiences with a PI system using home IoT data, and derived key barriers to its effective use from two perspectives: (1) nuances in reflecting on the data, and (2) privacy concerns.

Reflections on data. Interpreting smart home sensor data involves reconstructing behaviors, speculating on and reflecting over data, and contextualizing trends [50]. This sensemaking requires articulation work, such as reasoning about how the home is organized, its routine, and the activities taking place [99, 103]. While prior work emphasized the complexity of this sensemaking process, interestingly, most participants in our study found the reflection process relatively intuitive, possibly due to the simplicity of their living contexts (i.e., living alone in studios or one-bedroom apartments), which helped reduce contextual complexity. They interpreted the data by drawing on situational contexts (e.g., usage scenarios) and behavioral traits (e.g., habitual patterns) and often combining multiple data sources when faced with ambiguity. While participants generally benefited from leveraging home IoT data during the reflection, they also faced challenges due to the following reasons.

Data ambiguity. Home IoT sensor data can often be interpreted in multiple ways due to the limited contextual details. For example, an increase in the value of a main door contact sensor might indicate someone briefly opening the door for ventilation, rather than leaving the home. These data are typically raw and abstract, with limited contextual enrichment, which complicates the accurate interpretation of tracked behaviors. To enhance data interpretability, it is important to provide fine-grained, semantically enriched context recognition (e.g., time of day or contextual annotations) and context-aware data filtering. These enhancements can offer users clearer insights into their tracked behaviors and facilitate more meaningful reflections.

Uncertainty in Exploring Relationships. Some participants noted the challenge of confounding factors, as mental health is influenced by many variables not captured by the system, such as work stress, social relationships, or physical health. Without accounting for these, the system may present spurious correlations, which are statistical associations that do not reflect meaningful or causal relationships. To mitigate this, future systems could adopt multimodal sensor fusion, shifting from isolated, low-level device signals to richer semantic interpretations by clustering related activities and analyzing their temporal sequences [34].

Lack of mental models. Based on our observations, we found that some participants found certain data types, such as environmental factors, difficult to interpret, limiting their ability to reflect and make actionable changes. For example, while P14 easily connected sleep with stress, she struggled to relate humidity to stress. This difference may arise from how closely data aligns with personal experiences. Sleep is tangible and part of daily routines, whereas humidity feels abstract and less connected to direct actions, resulting in a weak and incomplete mental model. One interesting observation to note is that these weak mental models can be explained through the lens of Construal Level Theory (CLT) [101]. According to CLT, people perceive and process information at different levels of abstraction based on their psychological distance. Data such as sleep patterns, closely tied to participants' daily routines, are perceived as psychologically close and processed concretely, making it easier to connect to emotional wellbeing. In contrast, environmental factors like humidity, perceived as psychologically distant, are processed more abstractly. Participants struggled to relate such data to their emotional wellbeing or derive actionable insights because the connection between the data and their personal experiences was not immediately obvious. This underscores the need for systems that make abstract data more relatable by connecting it to users' daily experiences, such as explaining how humidity affects mood or offering specific recommendations. Bridging the gap between abstract data and its implications can help users process and apply insights for emotional wellbeing.

Privacy concerns. Privacy has long been a central consideration in the design of PI systems. In our study, participants' initial concerns about data collection were alleviated after engaging with the data visualization tool for self-reflection. As they gained a clearer understanding of how the data was collected and used, many reported feeling more comfortable with the system. Several factors contributed to this shift in perception.

First, initial privacy concerns stemmed from participants' limited understanding of the data collection process and how the system would represent the collected data. Before using the system, they were uncertain about how their personal information would be handled. However, after reviewing the actual data and seeing how it was abstracted and utilized, their concerns lessened. This transparency alleviated anxiety by clarifying that the system focused on identifying patterns rather than collecting specific, personally invasive details.

Second, participants recognized that the benefits of data collection, such as improvements in emotional wellbeing, outweighed perceived privacy risks. This shift aligns with prior research showing that users often weigh the risks against the benefits of sensor-driven technologies [52]. As participants observed how the system supported their emotional wellbeing, they became more accepting, possibly due to the privacy-utility trade-off [2]. Many participants noted that the advantages of using the system for mental health management overshadowed their initial concerns, leading to increased acceptance of data collection.

Third, privacy concerns naturally diminished as participants grew more familiar with the technology and its benefits. Initially, there was uncertainty about how sensor data collection might infringe on privacy. However, after living with the sensors for a month and interacting with the system, their concerns were significantly reduced. This reflects the privacy hump hypothesis, which suggests that initial resistance to intrusive technologies fades as users become accustomed to them and understand their value [37]. Similarly, prior work on smart home data privacy [7] suggests that repeated exposure to smart home devices, particularly those with wider market penetration, can lead users to gradually adjust their privacy expectations. As participants in our study became familiar with the IoT sensors and realized that their fears about privacy violations were not realized, their perceived risks diminished. Over time, data practices that were initially seen as unacceptable gradually become normalized, resulting in less concern about data privacy.

5.3 Design Implications

Our study highlighted the potential of home IoT data in supporting emotional wellbeing. Building on these findings, we proposed practical design guidelines for developing user-centered and personalized self-reflection tools for emotional wellbeing. These guidelines focus on supporting diverse home environments and individualized routines in IoT-based tracking, helping users interpret contextual information for meaningful reflection, and improving privacy acceptability through transparency and user control.

Design implication 1: Home IoT self-tracking should account for home-specific variability and individual differences. Our system collected home IoT data to support users in reflecting on their emotional wellbeing. We observed substantial variation not only in participants' domestic routines, but also in how those routines were related to their emotional wellbeing. These differences stemmed from various factors, including home environment characteristics like spatial layout and daily activity patterns [35]. To be effective, tracking systems should account for both the diversity of living situations and individual lifestyles.

Prior work has addressed home-specific variability by introducing personalized bootstrapping techniques. These methods begin with passive data collection and incorporate user feedback through active learning to tailor the system to individuals' homes [34]. Another approach involves developing layout-agnostic models that translate sensor events into natural language descriptions, thereby reducing reliance on physical configuration [98]. These approaches point to the importance of supporting both early-stage personalization and layout-independent interpretation in emotional wellbeing tracking, enabling systems to better adapt across varied home settings.

Individual differences in behavior and tracking preferences also call for user-driven approaches. In the context of chronic condition management, goal-directed self-tracking systems allow users to define what to monitor based on their personal goals, improving relevance and engagement [90, 92]. Another promising direction is involving users in configuring their own tracking logic based on their daily routines, as seen in systems like Routinoscope [111]. Building on this, future emotional wellbeing tracking systems could incorporate interactive feedback mechanisms to support personalized, user-centered tracking experiences.

Design implication 2: PI systems should actively support users in data contextualization for reflection.

Participants attempted to understand their behaviors captured via multiple home IoT sensors by conducting contextualization, adding relevant context to the data to aid sensemaking. For example, some participants interpreted sudden increases in home IoT sensor events as signals indicating the periods of extended time spent at home, which helped them better understand their emotional experiences during those periods. However, when they had difficulty interpreting or noticing such cues, their reflection tended to be shallow or fragmented. Prior studies have also highlighted how contextual cues (e.g., time, location, and activity) could improve the depth of self-reflection [78, 79]. Building on this, PI systems should do more than just display individual time-series sensor data. They should also assist users in providing contextual cues and further integrating them meaningfully into their reflection process. Without such support, users might miss important connections between their behaviors and emotional states.

We suggest two complementary strategies to better support data contextualization for self-reflection. First, temporal interaction can be used to guide users in structuring their reflection. While our system allowed users to filter and examine time-series data, PI systems could build on this by enabling dynamic comparisons between time periods [44], letting users tag time segments they find meaningful [40], or automatically identifying unique time segments deviating from typical behavioral patterns. These tagged segments could then be used to generate personalized insights that highlight recurring emotional patterns [10]. Second, PI systems can support recall by prompting users to revisit specific contextual memories. For instance, Echo [38] encourages reflection through repeated engagement with past journal entries. ReflectiveDiary [86] uses passively collected data (e.g., location, call logs) to create short quizzes that nudge users to remember people or places tied to prior experiences. By helping users reconstruct the context surrounding past events, these systems foster deeper understanding of emotional experiences over time.

Design implication 3: Granular control and explaining benefits and risks help users improve privacy acceptability. Consistent with prior research [1, 115], participants in our study expressed generally low privacy concern regarding IoT data. However, interacting with a data visualization tool appeared to enhance data acceptability by enabling users to explore and interpret the data more directly. We observed that the major factor associated with increased acceptability was perceived personal benefits, such as the association between sleep data and emotional wellbeing. Furthermore, although some data types with low granularity, such as indoor movement, were perceived as intrusive, we found that perceived benefits could potentially offset such concerns.

Building on these findings, we suggest two design strategies to improve privacy acceptability. First, systems should help users understand the concrete benefits of data collection. When users perceive clear personal benefits, they are generally more willing to permit both the collection and sharing of their data [115]. At the same time, highlighting benefits should not come at the cost of obscuring potential risks. Prior work shows that even technically literate users often fail to recognize the privacy risks associated with IoT-based monitoring [12]. Furthermore, users' willingness to disclose personal health data is shaped by their sense of control, with perceived risks and benefits acting as key mediating factors in this relationship [9]. For this reason, explanations should aim to strike a balance by clarifying what users gain while also being transparent about what they are giving up.

Second, systems should make the scope and granularity of data collection explicit. Participants in our study reported feeling less concerned about data collection after reviewing the actual data and concluding it was not personally identifiable. This underscores the importance of data legibility and interpretability in mitigating privacy concerns. When users understand what types of data are collected and at what level of detail, they are better positioned to assess potential privacy implications. Beyond clearly presenting data granularity and scope, prior work has shown that users prefer fine-grained privacy control, particularly in health contexts [15]. Providing adjustable levels of granularity can also improve interpretability, enabling users to better align the data with their personal goals and privacy expectations [70].

6 LIMITATIONS

Our study has several limitations. First, the four-week deployment with 20 single-person households limits the generalizability of the findings. Future long-term studies across more diverse household types are needed to better understand lifestyle patterns and their influence on emotional wellbeing. Second, while we selected sensors based on appliance ownership, this does not guarantee an accurate reflection of actual usage; future work should explore more personalized activity tracking. Third, we did not consider multi-user households, where sensor data may reflect multiple individuals' behaviors, complicating interpretation. Fourth, while most participants lived in studio apartments, variations in living space and layout were not explicitly controlled, which could have influenced some measures such as motion-based indoor movement. Lastly, although we identified quantitative correlations between IoT data and emotional wellbeing, these do not imply causality. We conducted follow-up interviews to provide context, but further methods are needed to distinguish meaningful from spurious associations.

7 CONCLUSION

This study explored the potential of home IoT data as a complementary source for tracking emotional wellbeing, alongside mobile and wearable data. Through a four-week field study with 20 participants in the wild, we demonstrated that home IoT data generates valuable insights into individuals' domestic routines and their associations with emotional wellbeing. Our quantitative analysis revealed that incorporating home IoT data captured major domestic behaviors associated with emotional wellbeing compared to relying solely on mobile and wearable data. However, we observed significant interpersonal differences in behavioral patterns, underscoring the need for personalized approaches to interpreting sensor data in relation to emotional wellbeing. Furthermore, a simple data visualization tool was used to help participants reflect on their behavioral data. The qualitative findings highlighted that participants found home IoT data fairly intuitive and insightful for understanding their relationships with emotional wellbeing. By contextualizing the data within their daily routines, participants were able to identify personalized behavioral markers and gain meaningful reflections on their emotional states. Interestingly, engaging with their own data also led to a positive shift in privacy perceptions, suggesting that transparency and user involvement in data interpretation can mitigate privacy concerns. This study contributes to the growing field of sensor-enabled mental healthcare by offering empirical evidence on the value of home IoT data, user perceptions of behavioral markers, and privacy considerations.

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References

[1] Noura Abdi, Xiao Zhan, Kopo M Ramokapane, and Jose Such. 2021. Privacy norms for smart home personal assistants. In *Proceedings of the 2021 CHI conference on human factors in computing systems*. 1–14.

[2] Alessandro Acquisti, Laura Brandimarte, and George Loewenstein. 2015. Privacy and human behavior in the age of information. *Science* 347, 6221 (2015), 509–514.

[3] Daniel A Adler, Vincent W-S Tseng, Gengmo Qi, Joseph Scarpa, Srijan Sen, and Tanzeem Choudhury. 2021. Identifying mobile sensing indicators of stress-resilience. *Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies* 5, 2 (2021), 1–32.

[4] Daniel A Adler, Yuewen Yang, Thalia Viranda, Xuhai Xu, David C Mohr, Anna R Van Meter, Julia C Tartaglia, Nicholas C Jacobson, Fei Wang, Deborah Estrin, et al. 2024. Beyond Detection: Towards Actionable Sensing Research in Clinical Mental Healthcare. *Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies* 8, 4 (2024), 1–33.

[5] Ane Alberdi, Alyssa Weakley, Maureen Schmitter-Edgecombe, Diane J Cook, Asier Aztiria, Adrian Basarab, and Maitane Barrenechea. 2018. Smart home-based prediction of multidomain symptoms related to Alzheimer's disease. *IEEE journal of biomedical and health informatics* 22, 6 (2018), 1720–1731.

[6] Stelios Andreadis, Thanos G. Stavropoulos, Georgios Meditskos, and Ioannis Kompatsiaris. 2016. Dem@Home: Ambient Intelligence for Clinical Support of People Living with Dementia. In *The Semantic Web*, Harald Sack, Giuseppe Rizzo, Nadine Steinmetz, Dunja Mladenić, Sören Auer, and Christoph Lange (Eds.). Springer International Publishing, Cham, 357–368.

[7] Noah Apthorpe, Yan Shvartzshnaider, Arunesh Mathur, Dillon Reisman, and Nick Feamster. 2018. Discovering smart home internet of things privacy norms using contextual integrity. *Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies* 2, 2 (2018), 1–23.

[8] American Psychiatric Association. 2013. *Diagnostic and statistical manual of mental disorders: DSM-5*. Vol. 5. American psychiatric association Washington, DC, 800 Maine Avenue, S.W., Suite 900, Washington, DC 20024.

[9] Havva Nur Atalay and Şebnem Yücel. 2024. Decoding privacy concerns: the role of perceived risk and benefits in personal health data disclosure. *Archives of Public Health* 82, 1 (2024), 180.

[10] Nikola Banovic, Tofi Buzali, Fanny Chevalier, Jennifer Mankoff, and Anind K Dey. 2016. Modeling and understanding human routine behavior. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. 248–260.

[11] Frank Bentley, Konrad Tollmar, Peter Stephenson, Laura Levy, Brian Jones, Scott Robertson, Ed Price, Richard Catrambone, and Jeff Wilson. 2013. Health Mashups: Presenting statistical patterns between wellbeing data and context in natural language to promote behavior change. *ACM Transactions on Computer-Human Interaction (TOCHI)* 20, 5 (2013), 1–27.

[12] Carlos Bermejo Fernandez, Petteri Nurmi, and Pan Hui. 2021. Seeing is believing? Effects of visualization on smart device privacy perceptions. In *Proceedings of the 29th ACM International Conference on Multimedia*. 4183–4192.

[13] Virginia Braun and Victoria Clarke. 2012. *Thematic analysis.* American Psychological Association, 750 First St. NE, Washington, DC 20002-4242.

[14] Joan Cahill, Raul Portales, Sean McLoughin, Nithia Nagan, Braden Henrichs, and Sean Wetherall. 2019. IoT/sensor-based infrastructures promoting a sense of home, independent living, comfort and wellness. *Sensors* 19, 3 (2019), 485.

[15] Kelly Caine and Rima Hanania. 2013. Patients want granular privacy control over health information in electronic medical records. *Journal of the American Medical Informatics Association* 20, 1 (2013), 7–15.

[16] Youngjae Chang, Akhil Mathur, Anton Isopoussu, Junehwa Song, and Fahim Kawsar. 2020. A systematic study of unsupervised domain adaptation for robust human-activity recognition. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 4, 1 (2020), 1–30.

[17] Eun Kyoung Choe, Sunny Consolvo, Jaeyeon Jung, Beverly Harrison, and Julie A Kientz. 2011. Living in a glass house: a survey of private moments in the home. In *Proceedings of the 13th international conference on Ubiquitous computing*. 41–44.

[18] Eun Kyoung Choe, Bongshin Lee, Matthew Kay, Wanda Pratt, and Julie A Kientz. 2015. SleepTight: low-burden, self-monitoring technology for capturing and reflecting on sleep behaviors. In *Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing*. 121–132.

[19] Deborah J Cohen, Sara R Keller, Gillian R Hayes, David A Dorr, Joan S Ash, and Dean F Sittig. 2016. Integrating patient-generated health data into clinical care settings or clinical decision-making: lessons learned from project healthdesign. *JMIR human factors* 3, 2 (2016), e5919.

[20] Diane J Cook, Aaron S Crandall, Brian L Thomas, and Narayanan C Krishnan. 2012. CASAS: A smart home in a box. *Computer* 46, 7 (2012), 62–69.

[21] Diane J Cook, Maureen Schmitter-Edgecombe, Linus Jönsson, and Anne V Morant. 2018. Technology-enabled assessment of functional health. *IEEE reviews in biomedical engineering* 12 (2018), 319–332.

[22] Pim Cuijpers, F Smit, and A Van Straten. 2007. Psychological treatments of subthreshold depression: a meta-analytic review. *Acta Psychiatrica Scandinavica* 115, 6 (2007), 434–441.

[23] Jessamyn Dahmen and Diane J Cook. 2021. Indirectly supervised anomaly detection of clinically meaningful health events from smart home data. *ACM Transactions on Intelligent Systems and Technology (TIST)* 12, 2 (2021), 1–18.

[24] Anind K. Dey, Katarzyna Wac, Denzil Ferreira, Kevin Tassini, Jin-Hyuk Hong, and Julian Ramos. 2011. Getting closer: an empirical investigation of the proximity of user to their smart phones. In *Proceedings of the 13th International Conference on Ubiquitous Computing* (Beijing, China) *(UbiComp '11)*. Association for Computing Machinery, New York, NY, USA, 163–172. https://doi.org/10.1145/2030112.2030135

[25] Sophie C Feller, Enrico G Castillo, Jared M Greenberg, Pilar Abascal, Richard Van Horn, Kenneth B Wells, and Los Angeles Community Translational Science Team University of California. 2018. Emotional well-being and public health: Proposal for a model national initiative. *Public Health Reports* 133, 2 (2018), 136–141.

[26] Joseph Firth, John Torous, Rebekah Carney, Jill Newby, Theodore D Cosco, Helen Christensen, and Jerome Sarris. 2018. Digital technologies in the treatment of anxiety: recent innovations and future directions. *Current Psychiatry Reports* 20 (2018), 1–8.

[27] Barbara L Fredrickson and Thomas Joiner. 2002. Positive emotions trigger upward spirals toward emotional well-being. *Psychological science* 13, 2 (2002), 172–175.

[28] João Gama, Indrė Žliobaitė, Albert Bifet, Mykola Pechenizkiy, and Abdelhamid Bouchachia. 2014. A survey on concept drift adaptation. *ACM computing surveys (CSUR)* 46, 4 (2014), 1–37.

[29] Matias Garcia-Constantino, Claire Orr, Jonathan Synnott, Colin Shewell, Andrew Ennis, Ian Cleland, Chris Nugent, Joseph Rafferty, Gareth Morrison, Leona Larkham, et al. 2021. Design and implementation of a smart home in a box to monitor the wellbeing of residents with dementia in care homes. *Frontiers in Digital Health* 3 (2021), 798889.

[30] Nirit Glazer. 2011. Challenges with graph interpretation: A review of the literature. *Studies in science education* 47, 2 (2011), 183–210.

[31] Heidemarie Haller, Holger Cramer, Romy Lauche, Florian Gass, and Gustav J Dobos. 2014. The prevalence and burden of subthreshold generalized anxiety disorder: a systematic review. *BMC psychiatry* 14 (2014), 1–13.

[32] Tamara L Hayes, Francena Abendroth, Andre Adami, Misha Pavel, Tracy A Zitzelberger, and Jeffrey A Kaye. 2008. Unobtrusive assessment of activity patterns associated with mild cognitive impairment. *Alzheimer's & Dementia* 4, 6 (2008), 395–405.

[33] Samar Helou, Victoria Abou-Khalil, Elie El Helou, and Ken Kiyono. 2021. Factors related to personal health data sharing: data usefulness, sensitivity and anonymity. In *Public Health and Informatics*. IOS Press, 1051–1055.

[34] Shruthi K Hiremath, Yasutaka Nishimura, Sonia Chernova, and Thomas Plötz. 2022. Bootstrapping human activity recognition systems for smart homes from scratch. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 6, 3 (2022), 1–27.

[35] Shruthi K Hiremath and Thomas Plötz. 2023. The lifespan of human activity recognition systems for smart homes. *Sensors* 23, 18 (2023), 7729.

[36] Victoria Hollis, Artie Konrad, Aaron Springer, Matthew Antoun, Christopher Antoun, Rob Martin, and Steve Whittaker. 2017. What does all this data mean for my future mood? Actionable analytics and targeted reflection for emotional well-being. *Human–Computer Interaction* 32, 5-6 (2017), 208–267.

[37] Giovanni Iachello, Jason Hong, et al. 2007. End-user privacy in human–computer interaction. *Foundations and Trends® in Human–Computer Interaction* 1, 1 (2007), 1–137.

[38] Ellen Isaacs, Artie Konrad, Alan Walendowski, Thomas Lennig, Victoria Hollis, and Steve Whittaker. 2013. Echoes from the past: how technology mediated reflection improves well-being. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 1071–1080.

[39] Hayeon Jeong, Heepyung Kim, Rihun Kim, Uichin Lee, and Yong Jeong. 2017. Smartwatch wearing behavior analysis: a longitudinal study. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (2017), 1–31.

[40] Matthew Jörke, Yasaman S Sefidgar, Talie Massachi, Jina Suh, and Gonzalo Ramos. 2023. Pearl: A technology probe for machine-assisted reflection on personal data. In *Proceedings of the 28th International Conference on Intelligent User Interfaces*. 902–918.

[41] Soowon Kang, Cheul Young Park, Auk Kim, Narae Cha, and Uichin Lee. 2022. Understanding Emotion Changes in Mobile Experience Sampling. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 198, 14 pages. https://doi.org/10.1145/3491102.3501944

[42] Ronald C Kessler, Wai Tat Chiu, Olga Demler, and Ellen E Walters. 2005. Prevalence, severity, and comorbidity of 12-month DSM-IV disorders in the National Comorbidity Survey Replication. *Archives of general psychiatry* 62, 6 (2005), 617–627.

[43] Taewan Kim, Haesoo Kim, Ha Yeon Lee, Hwarang Goh, Shakhboz Abdigapporov, Mingon Jeong, Hyunsung Cho, Kyungsik Han, Youngtae Noh, Sung-Ju Lee, and Hwajung Hong. 2022. Prediction for Retrospection: Integrating Algorithmic Stress Prediction into Personal Informatics Systems for College Students' Mental Health. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 279, 20 pages. https://doi.org/10.1145/3491102.3517701

[44] Young-Ho Kim, Bongshin Lee, Arjun Srinivasan, and Eun Kyoung Choe. 2021. Data@ hand: Fostering visual exploration of personal data on smartphones leveraging speech and touch interaction. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–17.

[45] Rafal Kocielnik, Fabrizio Maria Maggi, and Natalia Sidorova. 2013. Enabling self-reflection with LifelogExplorer: generating simple views from complex data. In *Proceedings of the 7th International Conference on Pervasive Computing Technologies for Healthcare* (Venice, Italy) *(PervasiveHealth '13)*. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), Brussels, BEL, 184–191.

[46] Ilkka Korhonen, Juha Parkka, and Mark Van Gils. 2003. Health monitoring in the home of the future. *IEEE Engineering in medicine and biology magazine* 22, 3 (2003), 66–73.

[47] K Kroenke, R L Spitzer, and J B Williams. 2001. The PHQ-9: validity of a brief depression severity measure. *J Gen Intern Med* 16, 9 (Sept. 2001), 606–613.

[48] Kurt Kroenke, Robert L Spitzer, and Janet BW Williams. 2003. The Patient Health Questionnaire-2: validity of a two-item depression screener. *Medical care* 41, 11 (2003), 1284–1292.

[49] Kurt Kroenke, Robert L Spitzer, Janet BW Williams, Patrick O Monahan, and Bernd Löwe. 2007. Anxiety disorders in primary care: prevalence, impairment, comorbidity, and detection. *Annals of internal medicine* 146, 5 (2007), 317–325.

[50] Albrecht Kurze, Andreas Bischof, Sören Totzauer, Michael Storz, Maximilian Eibl, Margot Brereton, and Arne Berger. 2020. Guess the Data: Data Work to Understand How People Make Sense of and Use Simple Sensor Data from Homes. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3313831.3376273

[51] Steven Landers, Elizabeth Madigan, Bruce Leff, Robert J Rosati, Barbara A McCann, Rodney Hornbake, Richard MacMillan, Kate Jones, Kathryn Bowles, Dawn Dowding, et al. 2016. The future of home health care: a strategic framework for optimizing value. *Home health care management & practice* 28, 4 (2016), 262–278.

[52] Hyunsoo Lee, Soowon Kang, and Uichin Lee. 2022. Understanding privacy risks and perceived benefits in open dataset collection for mobile affective computing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 6, 2 (2022), 1–26.

[53] Matthew L Lee and Anind K Dey. 2015. Sensor-based observations of daily living for aging in place. *Personal and Ubiquitous Computing* 19 (2015), 27–43.

[54] Ian Li, Anind Dey, and Jodi Forlizzi. 2010. A Stage-Based Model of Personal Informatics Systems. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Atlanta, Georgia, USA) *(CHI '10)*. Association for Computing Machinery, New York, NY, USA, 557–566. https://doi.org/10.1145/1753326.1753409

[55] Robert LiKamWa, Yunxin Liu, Nicholas D. Lane, and Lin Zhong. 2013. MoodScope: building a mood sensor from smartphone usage patterns. In *Proceeding of the 11th Annual International Conference on Mobile Systems, Applications, and Services* (Taipei, Taiwan) *(MobiSys '13)*. Association for Computing Machinery, New York, NY, USA, 389–402. https://doi.org/10.1145/2462456.2464449

[56] Jieun Lim, Youngji Koh, Auk Kim, and Uichin Lee. 2024. Exploring Context-Aware Mental Health Self-Tracking Using Multimodal Smart Speakers in Home Environments. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 699, 18 pages. https://doi.org/10.1145/3613904.3642846

[57] Sheila J Linz and Bonnie A Sturm. 2013. The phenomenon of social isolation in the severely mentally ill. *Perspectives in psychiatric care* 49, 4 (2013), 243–254.

[58] Bernd Löwe, Kurt Kroenke, and Kerstin Gräfe. 2005. Detecting and monitoring depression with a two-item questionnaire (PHQ-2). *Journal of psychosomatic research* 58, 2 (2005), 163–171.

[59] Lucy MacLeod, Banuchitra Suruliraj, Dominik Gall, Kitti Bessenyei, Sara Hamm, Isaac Romkey, Alexa Bagnell, Manuel Mattheisen, Viswanath Muthukumaraswamy, Rita Orji, et al. 2021. A mobile sensing app to monitor youth mental health: observational pilot study. *JMIR mHealth and uHealth* 9, 10 (2021), e20638.

[60] Mark Matthews and Gavin Doherty. 2011. In the Mood: Engaging Teenagers in Psychotherapy Using Mobile Phones. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Vancouver, BC, Canada) *(CHI '11)*. Association for Computing Machinery, New York, NY, USA, 2947–2956. https://doi.org/10.1145/1978942.1979379

[61] Faith McCreary, Alexandra Zafiroglu, and Heather Patterson. 2016. The contextual complexity of privacy in smart homes and smart buildings. In *HCI in Business, Government, and Organizations: Information Systems: Third International Conference, HCIBGO 2016, Held as Part of HCI International 2016, Toronto, Canada, July 17-22, 2016, Proceedings, Part II 3*. Springer, 67–78.

[62] Lakmal Meegahapola, William Droz, Peter Kun, Amalia De Götzen, Chaitanya Nutakki, Shyam Diwakar, Salvador Ruiz Correa, Donglei Song, Hao Xu, Miriam Bidoglia, et al. 2023. Generalization and personalization of mobile sensing-based mood inference models: an analysis of college students in eight countries. *Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies* 6, 4 (2023), 1–32.

[63] Jun-Ki Min, Afsaneh Doryab, Jason Wiese, Shahriyar Amini, John Zimmerman, and Jason I Hong. 2014. Toss'n'turn: smartphone as sleep and sleep quality detector. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 477–486.

[64] Mehrab Bin Morshed, Samruddhi Shreeram Kulkarni, Koustuv Saha, Richard Li, Leah G Roper, Lama Nachman, Hong Lu, Lucia Mirabella, Sanjeev Srivastava, Kaya De Barbaro, et al. 2022. Food, mood, context: Examining college students' eating context and mental well-being. *ACM Transactions on Computing for Healthcare* 3, 4 (2022), 1–26.

[65] Shinichi Nakagawa and Holger Schielzeth. 2013. A general and simple method for obtaining R2 from generalized linear mixed-effects models. *Methods in ecology and evolution* 4, 2 (2013), 133–142.

[66] Saida Salima Nawrin, Hitoshi Inada, Haruki Momma, and Ryoichi Nagatomi. 2024. Twenty-four-hour physical activity patterns associated with depressive symptoms: a cross-sectional study using big data-machine learning approach. *BMC public health* 24, 1 (2024), 1254.

[67] Francisco Nunes. 2019. From medicalized to mundane self-care technologies. *Interactions* 26, 3 (2019), 67–69.

[68] World Health Organization. 2001. The World Health Report 2001: Mental health: new understanding, new hope. (2001).

[69] World Health Organization et al. 2017. Depression and other common mental disorders: global health estimates. (2017).
[70] Nels Oscar, Shannon Mejía, Ronald Metoyer, and Karen Hooker. 2017. Towards personalized visualization: Information granularity, situation, and personality. In *Proceedings of the 2017 conference on designing interactive systems*. 811–819.
[71] Crystal L Park, Laura D Kubzansky, Sandra M Chafouleas, Richard J Davidson, Dacher Keltner, Parisa Parsafar, Yeates Conwell, Michelle Y Martin, Janel Hanmer, and Kuan Hong Wang. 2023. Emotional well-being: What it is and why it matters. *Affective Science* 4, 1 (2023), 10–20.
[72] Laura Pina, Sang-Wha Sien, Clarissa Song, Teresa M Ward, James Fogarty, Sean A Munson, and Julie A Kientz. 2020. DreamCatcher: exploring how parents and school-age children can track and review sleep information together. *Proceedings of the ACM on Human-computer Interaction* 4, CSCW1 (2020), 1–25.
[73] Madison C Piotrowski, Julia Lunsford, and Bradley N Gaynes. 2021. Lifestyle psychiatry for depression and anxiety: Beyond diet and exercise. *Lifestyle Medicine* 2, 1 (2021), e21.
[74] Faye Plummer, Laura Manea, Dominic Trepel, and Dean McMillan. 2016. Screening for anxiety disorders with the GAD-7 and GAD-2: a systematic review and diagnostic metaanalysis. *General hospital psychiatry* 39 (2016), 24–31.
[75] Martin Prince, Vikram Patel, Shekhar Saxena, Mario Maj, Joanna Maselko, Michael R Phillips, and Atif Rahman. 2007. No health without mental health. *The lancet* 370, 9590 (2007), 859–877.
[76] Joaquin Quiñonero-Candela, Masashi Sugiyama, Anton Schwaighofer, and Neil D Lawrence. 2022. *Dataset shift in machine learning*. Mit Press.
[77] Joaquim Radua, Alberto Pertusa, and Narcis Cardoner. 2010. Climatic relationships with specific clinical subtypes of depression. *Psychiatry research* 175, 3 (2010), 217–220.
[78] Shriti Raj, Joyce M Lee, Ashley Garrity, and Mark W Newman. 2019. Clinical data in context: towards sensemaking tools for interpreting personal health data. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3, 1 (2019), 1–20.
[79] Shriti Raj, Kelsey Toporski, Ashley Garrity, Joyce M Lee, and Mark W Newman. 2019. " My blood sugar is higher on the weekends" Finding a Role for Context and Context-Awareness in the Design of Health Self-Management Technology. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–13.
[80] Francisco Ramirez and Renan Amon Ramos. 2021. Irregularity In Eating and Sleeping Seems Affect Mental Health. *Current Developments in Nutrition* 5 (2021), 473.
[81] Daniele Riboni, Claudio Bettini, Gabriele Civitarese, Zaffar Haider Janjua, and Rim Helaoui. 2016. SmartFABER: Recognizing fine-grained abnormal behaviors for early detection of mild cognitive impairment. *Artificial intelligence in medicine* 67 (2016), 57–74.
[82] Kelly C Richards, C Estelle Campenni, and Janet L Muse-Burke. 2010. Self-care and well-being in mental health professionals: The mediating effects of self-awareness and mindfulness. *Journal of mental health counseling* 32, 3 (2010), 247–264.
[83] Mar Rivas Rodríguez, Roberto Nuevo, Somnath Chatterji, and José Luis Ayuso-Mateos. 2012. Definitions and factors associated with subthreshold depressive conditions: a systematic review. *BMC psychiatry* 12 (2012), 1–7.
[84] John Rooksby, Alistair Morrison, and Dave Murray-Rust. 2019. Student perspectives on digital phenotyping: The acceptability of using smartphone data to assess mental health. In *Proceedings of the 2019 CHI conference on human factors in computing systems*. 1–14.
[85] John Rooksby, Mattias Rost, Alistair Morrison, and Matthew Chalmers. 2014. Personal tracking as lived informatics. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Toronto, Ontario, Canada) *(CHI '14)*. Association for Computing Machinery, New York, NY, USA, 1163–1172. https://doi.org/10.1145/2556288.2557039
[86] Rufat Rzayev, Tilman Dingler, and Niels Henze. 2018. Reflectivediary: fostering human memory through activity summaries created from implicit data collection. In *Proceedings of the 17th International Conference on Mobile and Ubiquitous Multimedia*. 285–291.
[87] Sohrab Saeb, Mi Zhang, Christopher J Karr, Stephen M Schueller, Marya E Corden, Konrad P Kording, David C Mohr, et al. 2015. Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: an exploratory study. *Journal of medical Internet research* 17, 7 (2015), e4273.
[88] Antti Salovaara, Andrea Bellucci, Andrea Vianello, and Giulio Jacucci. 2021. Programmable smart home toolkits should better address households' social needs. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–14.
[89] Jerome Sarris, Adrienne O'Neil, Carolyn E Coulson, Isaac Schweitzer, and Michael Berk. 2014. Lifestyle medicine for depression. *BMC psychiatry* 14 (2014), 1–13.
[90] Jessica Schroeder, Ravi Karkar, Natalia Murinova, James Fogarty, and Sean A Munson. 2019. Examining opportunities for goal-directed self-tracking to support chronic condition management. *Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies* 3, 4 (2019), 1–26.
[91] Francesca Sciarra, Edoardo Franceschini, Federica Campolo, Daniele Gianfrilli, Francesco Pallotti, Donatella Paoli, Andrea M. Isidori, and Mary Anna Venneri. 2020. Disruption of Circadian Rhythms: A Crucial Factor in the Etiology of Infertility. *International Journal of Molecular Sciences* 21, 11 (2020), 3943. https://doi.org/10.3390/ijms21113943
[92] Yasaman S Sefidgar, Carla L Castillo, Shaan Chopra, Liwei Jiang, Tae Jones, Anant Mittal, Hyeyoung Ryu, Jessica Schroeder, Allison Cole, Natalia Murinova, et al. 2024. MigraineTracker: Examining patient experiences with goal-directed self-tracking for a chronic health condition. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*. 1–19.

[93] William A Simcox. 1984. A method for pragmatic communication in graphic displays. *Human Factors* 26, 4 (1984), 483–487.

[94] Geetika Singla, Diane J Cook, and Maureen Schmitter-Edgecombe. 2010. Recognizing independent and joint activities among multiple residents in smart environments. *Journal of ambient intelligence and humanized computing* 1 (2010), 57–63.

[95] Robert L Spitzer, Kurt Kroenke, Janet B W Williams, and Bernd Löwe. 2006. A brief measure for assessing generalized anxiety disorder: the GAD-7. *Arch Intern Med* 166, 10 (May 2006), 1092–1097.

[96] Aaron Springer, Victoria Hollis, and Steve Whittaker. 2018. Mood modeling: accuracy depends on active logging and reflection. *Personal and Ubiquitous Computing* 22 (2018), 723–737.

[97] Madiha Tabassum, Tomasz Kosiński, and Heather Richter Lipford. 2019. "I don't own the data": end user perceptions of smart home device data practices and risks. In *Proceedings of the Fifteenth USENIX Conference on Usable Privacy and Security* (Santa Clara, CA, USA) *(SOUPS'19)*. USENIX Association, USA, 435–450.

[98] Megha Thukral, Sourish Gunesh Dhekane, Shruthi K Hiremath, Harish Haresamudram, and Thomas Ploetz. 2025. Layout-Agnostic Human Activity Recognition in Smart Homes through Textual Descriptions Of Sensor Triggers (TDOST). *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 9, 1 (2025), 1–38.

[99] Peter Tolmie, Andy Crabtree, Tom Rodden, James Colley, and Ewa Luger. 2016. "This has to be the cats" Personal Data Legibility in Networked Sensing Systems. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*. 491–502.

[100] Peter Tolmie, James Pycock, Tim Diggins, Allan MacLean, and Alain Karsenty. 2002. Unremarkable computing. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 399–406.

[101] Yaacov Trope and Nira Liberman. 2010. Construal-level theory of psychological distance. *Psychological review* 117, 2 (2010), 440.

[102] United Nations, Department of Economic and Social Affairs, Population Division. 2018. World Urbanization Prospects: The 2018 Revision. Available at: https://population.un.org/wup/assets/WUP2018-Report.pdf.

[103] Yasmin van Kasteren, Dana Bradford, Qing Zhang, Mohan Karunanithi, Hang Ding, et al. 2017. Understanding smart home sensor data for ageing in place through everyday household routines: a mixed method case study. *JMIR mHealth and uHealth* 5, 6 (2017), e5773.

[104] Roger Walsh. 2011. Lifestyle and mental health. *American psychologist* 66, 7 (2011), 579.

[105] Ju Wang, Nicolai Spicher, Joana M Warnecke, Mostafa Haghi, Jonas Schwartze, and Thomas M Deserno. 2021. Unobtrusive health monitoring in private spaces: The smart home. *Sensors* 21, 3 (2021), 864.

[106] Rui Wang, Fanglin Chen, Zhenyu Chen, Tianxing Li, Gabriella Harari, Stefanie Tignor, Xia Zhou, Dror Ben-Zeev, and Andrew T. Campbell. 2014. StudentLife: Assessing Mental Health, Academic Performance and Behavioral Trends of College Students Using Smartphones. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (Seattle, Washington) *(UbiComp '14)*. Association for Computing Machinery, New York, NY, USA, 3–14. https://doi.org/10.1145/2632048.2632054

[107] Rui Wang, Weichen Wang, Alex DaSilva, Jeremy F Huckins, William M Kelley, Todd F Heatherton, and Andrew T Campbell. 2018. Tracking depression dynamics in college students using mobile phone and wearable sensing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 1 (2018), 1–26.

[108] Weichen Wang, Gabriella M Harari, Rui Wang, Sandrine R Müller, Shayan Mirjafari, Kizito Masaba, and Andrew T Campbell. 2018. Sensing behavioral change over time: Using within-person variability features from mobile sensing to predict personality traits. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 3 (2018), 1–21.

[109] Jing Wei, Tilman Dingler, and Vassilis Kostakos. 2021. Understanding user perceptions of proactive smart speakers. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 5, 4 (2021), 1–28.

[110] Samuel S Wilks. 1938. The large-sample distribution of the likelihood ratio for testing composite hypotheses. *The annals of mathematical statistics* 9, 1 (1938), 60–62.

[111] Jong-bum Woo and Youn-kyung Lim. 2020. Routinoscope: Collaborative routine reflection for routine-driven do-it-yourself smart homes. *International Journal of Design* 14, 3 (2020), 19.

[112] Daolin Wu and Fuwei Liu. 2022. Assessment of the relationship between living alone and the risk of depression based on longitudinal studies: a systematic review and meta-analysis. *Frontiers in psychiatry* 13 (2022), 954857.

[113] Xuhai Xu, Prerna Chikersal, Afsaneh Doryab, Daniella K Villalba, Janine M Dutcher, Michael J Tumminia, Tim Althoff, Sheldon Cohen, Kasey G Creswell, J David Creswell, et al. 2019. Leveraging routine behavior and contextually-filtered features for depression detection among college students. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3, 3 (2019), 1–33.

[114] Miao Yu, Adel Rhuma, Syed Mohsen Naqvi, Liang Wang, and Jonathon Chambers. 2012. A posture recognition-based fall detection system for monitoring an elderly person in a smart home environment. *IEEE transactions on information technology in biomedicine* 16, 6 (2012), 1274–1286.

[115] Serena Zheng, Noah Apthorpe, Marshini Chetty, and Nick Feamster. 2018. User perceptions of smart home IoT privacy. *Proceedings of the ACM on human-computer interaction* 2, CSCW (2018), 1–20.

Appendix

A Preliminary Survey Results and Collected Sensor Data

This section presents the preliminary survey results used to guide sensor selection (Table 6) and details of the collected sensor data (Table 7).

Table 6. Number of single-person households owning each home appliance

Category	Appliances	Number of respondents
Kitchen Appliances	Refrigerator	30
	Microwave	29
	Air fryer	16
	Rice cooker	13
	Water purifier	7
	Stove	2
	Dishwasher	2
	Oven	1
Laundry Appliances	Washing machine	29
	Clothes dryer	1
Cleaning Appliances	Vacuum cleaner	25
	Air purifier	5
Entertainment Appliances	Television	20
	Gaming console	1
	Projector	1
	Smart speaker	1

Table 7. Descriptions of collected sensor data

Device Type	Sensor Type	Data Type	Description
Home IoT Sensor	Vibration Sensor	Refrigerator	Number of refrigerator doors opened per day
		Vacuum Cleaner	Number of vacuum cleaner vibrated per day
		Washing Machine	Number of washing machine vibrated per day
		Chair Motion	Number of chair movements detected per day
	Contact Sensor	Microwave	Number of microwave doors opened per day
		Main Door	Number of door open/close per day
	Pressure-based sleep sensor	Sleep	Hours of sleep per day
	Motion Sensor	Indoor Motion	Number of motion detected per day
	Temperature & Humidity Sensor	Temperature & Humidity	Average temperature & humidity of the daily home environment
	Light Sensor	Light	Average light (lx) of the daily home environment
Smartphone		Calls	Call duration per day
		Messages	Number of messages sent and received per day
Wearable Device		Steps	Daily step counts

B Supplementary Multilevel Regression and Temporal Analyses

This section reports detailed multilevel regression results examining the associations between sensor-derived features and emotional wellbeing indicators, as shown in Tables 8, 9, 10, 11, and 12. Reduced sleep duration showed a strong association with multiple emotional wellbeing indicators, including depression (β = -0.21, p = 0.008), anxiety (β = -0.33, p < 0.001), and stress (β = -0.12, p= 0.020). Similarly, increased sleep duration was associated with positive emotional valence (β = 0.11, p = 0.030). Higher indoor temperatures were also significantly linked to increased levels of depression (β = 0.77, p < 0.001) and anxiety (β = 0.74, p < 0.001). Notably, specific behavioral indicators such as an increase in washing machine usage showed a connection to depression (β = 0.22, p = 0.049) and high emotional arousal (β = 0.17, p = 0.007), while a higher frequency of main door open-close events was

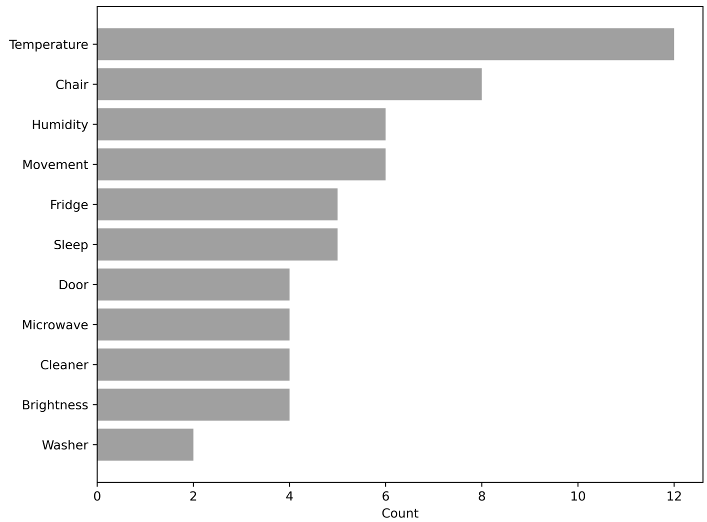

Fig. 10. Frequency of domestic activities showing strong correlations with emotional wellbeing risk across participants

linked to stress (β = 0.10, p = 0.007). Additionally, across five emotional wellbeing indicators (i.e., depression, anxiety, stress, emotional valence, and emotional arousal), the conditional R^2 values consistently exceeded the marginal R^2, demonstrating the importance of accounting for individual differences.

In addition, we observed substantial variability in individual-level correlations across participants (Figure 7), which summarizes the top three associations between behavioral patterns and emotional wellbeing risk for each user. To further explore these patterns, we visualized the most frequently occurring indicators across individuals (Figure 10). Temperature emerged as the most frequently correlated feature (N = 12), likely influenced by seasonal variations during early summer when data collection took place. This was followed by chair movements (N = 8), indoor movement counts, and humidity (N = 6). These findings highlight that even features without statistical significance at the group level may hold considerable relevance when analyzed at the individual level.

Beyond individual-level correlations, we also examined temporal dynamics in emotional wellbeing using Generalized Estimating Equations (GEE), which account for correlations among repeated measures. We specified an exchangeable working correlation structure and an identity link function to model participants' emotional wellbeing risk scores (depression, anxiety, stress, emotional valence, and emotional arousal) over time, with week as the primary predictor. Each participant provided daily self-reported survey responses over four weeks, resulting in repeated measurements clustered within individuals, with participant ID treated as the clustering variable. The GEE analysis did not reveal statistically significant temporal effects.

Table 8. Results of multilevel regression model (Depression)

Depression						
Independent Variables	**Estimate (β)**	**Std. Error (SE)**	**Odds Ratio (OR)**	**95% CI**	***p***	
Call	0.00	0.00	1.00	1.00 − 1.00	0.378	
Message	0.01	0.05	1.01	0.91 − 1.12	0.845	
Step	0.00	0.00	1.00	1.00 − 1.00	0.574	
Brightness	-0.01	0.01	0.99	0.98 − 1.00	0.183	
Temperature	0.77	0.20	2.17	1.45 − 3.24	<0.001	***
Humidity	-0.23	0.37	0.79	0.39 − 1.63	0.529	
Sleep	-0.21	0.08	0.81	0.70 − 0.95	0.008	**
Cleaner	0.08	0.04	1.09	1.00 − 1.18	0.060	
Washer	0.22	0.11	1.24	1.00 − 1.54	0.049	*
Fridge	0.02	0.04	1.02	0.94 − 1.11	0.600	
Microwave	-0.06	0.12	0.94	0.74 − 1.19	0.602	
Movement	0.00	0.00	1.00	0.99 − 1.00	0.674	
Chair	-0.01	0.01	0.99	0.97 − 1.01	0.262	
Door	0.01	0.07	1.01	0.88 − 1.16	0.877	

Table 9. Results of multilevel regression model (Anxiety)

Anxiety						
Independent Variables	**Estimate (β)**	**Std. Error (SE)**	**Odds Ratio (OR)**	**95% CI**	***p***	
Call	0.00	0.00	1.00	1.00 − 1.00	0.439	
Message	0.01	0.06	1.01	0.91 − 1.13	0.816	
Step	0.00	0.00	1.00	1.00 − 1.00	0.608	
Brightness	0.00	0.01	1.00	0.99 − 1.01	0.541	
Temperature	0.74	0.20	2.10	1.41 − 3.13	<0.001	***
Humidity	-0.23	0.37	0.80	0.39 − 1.64	0.536	
Sleep	-0.33	0.08	0.72	0.61 − 0.85	<0.001	***
Cleaner	0.07	0.05	1.08	0.98 − 1.18	0.111	
Washer	0.03	0.12	1.03	0.81 − 1.30	0.809	
Fridge	0.07	0.04	1.07	0.99 − 1.16	0.104	
Microwave	-0.01	0.12	0.99	0.79 − 1.25	0.961	
Movement	0.00	0.00	1.00	0.99 − 1.01	0.921	
Chair	0.00	0.00	1.00	0.99 − 1.01	0.659	
Door	-0.10	0.08	0.91	0.78 − 1.05	0.195	

Table 10. Results of multilevel regression model (Stress)

Stress						
Independent Variables	**Estimate (β)**	**Std. Error (SE)**	**Odds Ratio (OR)**	**95% CI**	p	
Call	0.00	0.00	1.00	1.00 – 1.00	0.624	
Message	0.08	0.04	1.08	1.00 – 1.16	0.040	*
Step	0.00	0.00	1.00	1.00 – 1.00	0.126	
Brightness	0.00	0.00	1.00	1.00 – 1.01	0.483	
Temperature	0.23	0.13	1.26	0.99 – 1.61	0.065	
Humidity	-0.17	0.21	0.85	0.56 – 1.28	0.431	
Sleep	-0.12	0.05	0.89	0.81 – 0.98	0.020	*
Cleaner	0.02	0.03	1.02	0.96 – 1.08	0.555	
Washer	0.09	0.06	1.10	0.97 – 1.25	0.144	
Fridge	-0.04	0.03	0.96	0.91 – 1.01	0.100	
Microwave	0.00	0.07	1.00	0.87 – 1.14	0.986	
Movement	0.00	0.00	1.00	1.00 – 1.00	0.449	
Chair	0.00	0.00	1.00	1.00 – 1.00	0.129	
Door	0.10	0.04	1.11	1.03 – 1.20	0.007	**

Table 11. Results of multilevel regression model (Emotional Valence)

Emotional Valence						
Independent Variables	**Estimate (β)**	**Std. Error (SE)**	**Odds Ratio (OR)**	**95% CI**	p	
Call	0.00	0.00	1.00	1.00 – 1.00	0.507	
Message	0.05	0.04	1.06	0.97 – 1.15	0.194	
Step	0.00	0.00	1.00	1.00 – 1.00	0.581	
Brightness	0.01	0.00	1.01	1.00 – 1.01	0.146	
Temperature	-0.16	0.13	0.86	0.66 – 1.11	0.232	
Humidity	0.26	0.22	1.30	0.84 – 2.01	0.245	
Sleep	0.11	0.05	1.11	1.01 – 1.23	0.030	*
Cleaner	-0.05	0.03	0.95	0.89 – 1.01	0.120	
Washer	0.04	0.08	1.04	0.90 – 1.22	0.583	
Fridge	0.01	0.03	1.01	0.95 – 1.06	0.781	
Microwave	-0.08	0.07	0.93	0.81 – 1.06	0.263	
Movement	0.00	0.00	1.00	1.00 – 1.00	0.723	
Chair	0.00	0.00	1.00	0.99 – 1.00	0.176	
Door	-0.01	0.04	0.99	0.91 – 1.07	0.755	

Table 12. Results of multilevel regression model (Emotional Arousal)

Emotional Arousal						
Independent Variables	**Estimate (β)**	**Std. Error (SE)**	**Odds Ratio (OR)**	**95% CI**	p	
Call	0.00	0.00	1.00	1.00 − 1.00	0.979	
Message	0.02	0.04	1.02	0.95 − 1.09	0.645	
Step	0.00	0.00	1.00	1.00 − 1.00	0.072	
Brightness	0.00	0.00	1.00	1.00 − 1.01	0.678	
Temperature	-0.19	0.13	0.83	0.65 − 1.06	0.141	
Humidity	-0.08	0.21	0.93	0.61 − 1.41	0.721	
Sleep	-0.03	0.05	0.97	0.88 − 1.07	0.558	
Cleaner	-0.02	0.02	0.98	0.95 − 1.02	0.334	
Washer	0.17	0.06	1.18	1.05 − 1.34	0.007	**
Fridge	-0.03	0.03	0.97	0.92 − 1.03	0.332	
Microwave	-0.02	0.07	0.98	0.86 − 1.13	0.815	
Movement	0.00	0.00	1.00	0.99 − 1.00	0.165	
Chair	0.00	0.00	1.00	1.00 − 1.00	0.550	
Door	0.02	0.04	1.02	0.94 − 1.10	0.625	