Semi-Automated Tracking: A Balanced Approach for Self-Monitoring Applications

Semi-automated tracking combines both manual and automated data collection methods. The approach aims to lower the capture burdens, collect data that is typically difficult to track automatically, and promote awareness to help people achieve their self-monitoring goals.

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Self-monitoring for health behavior change is an important practice across numerous domains, including diet, physical activity, sleep, and stress. Studies have shown that self-monitoring can enable greater awareness of behaviors and create reactive effects, yielding positive, therapeutic behavior changes.[1] Although self-monitoring has been used successfully for behavior change interventions (see the "Related Work" sidebar), it has high data capture burdens—with both paper and electronic tools—hindering people from adopting long-term self-monitoring practices.[2] For example, food tracking can help achieve positive behavior change for weight loss and other food-related issues, but the high burdens of such tracking limit its effectiveness.[3]

To counter high data capture burdens, an increasing number of research and consumer applications employ sensing for automated data collection to support self-monitoring. These sensing applications are often deployed via mobile phones, wearable devices, or systems embedded in the home. One of the goals for these automated systems is to lower the capture burdens so that a person can achieve the benefits of self-monitoring without the time and difficulty of manual data capture. Although this approach seems intuitive, little evidence shows that automated health activity tracking leads to behavior change.[4] We suspect that this is partially because the complete automation of data collection significantly reduces the awareness, accountability, and involvement achieved compared to when a person actively engages in manual tracking.[5]

To better achieve the benefits of self-monitoring, we argue that designers need to find the right balance between manual and automated tracking, combining each of their benefits while minimizing their associated limitations. In the following, we define and characterize semi-automated tracking, examine three related design considerations, and provide examples of semi-automated tracking applications in the domains of sleep, mood, and food tracking to demonstrate strategies we developed.

Characterizing Semi-Automated Tracking

We define a semi-automated tracking approach as *any combination of manual and automated tracking approaches*. Semi-automated tracking therefore encompasses a broad spectrum of designs between the extremes of fully manual or fully automated tracking (see Figure 1).

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Related Work in Self-Monitoring Technology

Recognizing the benefits of self-monitoring in promoting health behavior change, both researchers and commercial product developers have been increasingly incorporating automated sensing and manual tracking features into self-monitoring technology. Such technology has been designed for tracking fitness,[1] sleep, moods, and diet (see the main article's Figures 2, 5, and 6, respectively), and for tracking energy and water usage.[2,3]

Ecological momentary assessment (EMA) refers to a collection of methods by which research participants repeatedly report on symptoms, affect, behavior, and cognitions close in time to when they were experienced, in their natural environment.[4] Combined with the prevalent use of smartphones, EMA helps to accurately capture real-time data with minimal intrusiveness, and thus it has been broadly used in the research setting for both assessment and behavior change intervention purposes. With EMA, researchers can capture passive data combined with self-reported data, leveraging smartphone embedded sensors and notifications. For example, EMA has been particularly helpful in tracking people's subjective well-being.[5]

Self-monitoring has recently become popular outside the research or clinical setting. For example, the Quantified Self (http://quantifiedself.com) movement has been increasingly popular since 2008.[6] Initially started in the Silicon Valley area among technology enthusiasts, the Quantified Self has become an international community of people who practice self-monitoring and build self-monitoring technology. Community members also share their self-monitoring practices and experiences through a blog (http://quantifiedself.com), meetup talks, and conference presentations. Researchers have analyzed Quantified Self presentations to understand what barriers are experienced and what insights are gained from the personal data.[7] Although those in the Quantified Self community are dedicated to self-monitoring, they have had difficulties keeping up with self-monitoring when the tracking burden was too high. However, they also share workarounds to alleviate the tracking burden, such as automating the data collection when possible, lowering the data granularity, and making manual capture very easy.[7] These are insightful findings that we reflect on when considering our own designs for semi-automated tracking.

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Semi-automated tracking can range from mostly manual tracking to mostly automated tracking. In fully manual tracking, all data is explicitly captured by people, though they might use a system to help with the capturing (a spreadsheet for data entry, for example). In mostly manual tracking, a system provides light assistance (automatically timestamping an otherwise manual data entry, for example). In mostly automated tracking, a system collects the majority of the data, but people can help by manually confirming or correcting the data that the system collected, measured, or estimated. In fully automated tracking, all data is collected by a system, but people consume the data (viewing a visualization of the automatically collected data, for example). Figure 1 summarizes definitions, strengths, and weaknesses of fully manual, semi-automated, and fully automated tracking.

Ian Li and his colleagues explored the concept of semi-automated tracking in their work on the *I*mproving *M*onitoring of *P*hysical Activity using *C*on*t*ext (Impact) approach. They found that automated systems can lower the capture burdens but might undermine immediate awareness in comparison to manual capture.[5] We build upon this work as we address three questions:

- What are important design considerations for semi-automated tracking?
- What are example methods and successful practices to design semi-automated tracking?
- What are design opportunities and challenges for semi-automated tracking?

We discuss these questions as we reflect on our work of designing and studying semi-automated tracking systems. Details of each work are presented in other papers.[6–11]

Design Considerations for Semi-Automated Tracking

Although semi-automated tracking can have distinct benefits over fully manual or fully automated tracking, balancing the two approaches requires careful

	Fully manual tracking	Semi-automated tracking	Fully automated tracking
Definition	Data is captured explicitly by a person, though he or she can use a system for capture	Data is collected by both a person and a system along a spectrum ranging from mostly manual tracking to mostly automated tracking	Data is entirely collected by a system; a person only reviews data
Strengths	• Supports awareness and engagement • Provides full control over collected data • Offers flexibility in what data is captured and how	• Supports awareness and engagement • Offers better accuracy than fully automated tracking or fully manual tracking • Offers long-term capturing • Helps mitigate privacy concerns over automatically collected data by engaging a person	• Has a low capture burden • Supports long-term tracking
Weaknesses	• Has a high capture burden • Doesn't support long-term tracking	• Has an increased capture burden compared to fully automated tracking • Needs to provide opportunities for people to engage—such as correcting sensed data or adding more data—which is often difficult	• Requires feedback to support awareness and engagement • Requires processing and storing a lot of data • Isn't always possible—accuracy is a big technical challenge
	• Might not be appropriate for assessment purposes when researchers don't want people to change behaviors due to engagement with data		• Privacy implications might not be well known or understood, because it is not clear where the data is being stored or with whom the data is being shared

Figure 1. The spectrum of self-tracking approaches. Definitions and comparisons of the strengths and weaknesses for fully manual tracking, semi-automated tracking, and fully automated tracking.

design considerations. Self-monitoring technology involves three components: the person who tracks, the behavior of interest captured through data, and the system that assists with the data capture. In designing semi-automated tracking tools, we thus must consider the capabilities and limitations of a person and a system, and the nature of the data being captured. Reflecting upon these three components and the interactions among them, we suggest three important parameters to consider in designing successful semi-automated tracking approaches:

- data capture feasibility,
- the purpose of self-monitoring, and
- a person's motivation level.

We believe these parameters are essential to successfully achieve the benefits of self-monitoring.

Data Capture Feasibility

The design of semi-automated tracking must consider the feasibility of data capture by a person versus a system, including both the *data type* (such as subjective vs. objective or qualitative vs. quantitative) and the *frequency* of capture.

Data types. When data types are subjective and qualitative in nature, they can be difficult (if not impossible) to automatically capture, but they're easier for people to record. For example, subjective sleep quality by definition can be captured only manually, because it requires the sleeper's own perception of his or her sleep quality. Similarly, automated tracking cannot completely capture stressful events. Objective and quantitative proxies, such as heart rate variability, can be measured and used to infer the presence of a stressful event,[12] but subjective response or the event's severity must be manually captured as ground truth. However, even if subjective measures are considered and used as ground truth, people are prone to forgetfulness, unintentional recall bias, delayed recording, and backfilling (that is, generating fake data to give the appearance of good compliance), resulting in low data quality. Limitations in the system's data capture feasibility can also lead to low data quality, compromising the system's overall effectiveness and leading people to distrust the system entirely.

Some data types are difficult to capture at high quality in any practical manner. For example, comprehensive and reliable calorie-level food tracking remains difficult to manually capture and beyond the reach of more automated systems. For sleep tracking, automated systems can estimate aspects of sleep, such as duration and number of awakenings, but accurate sleep staging remains elusive for manual or automated capture in the wild, where we cannot have the sleep lab's expensive instruments (such as for polysomnography tests) and sleep technicians.

Capture frequency. The frequency of capture also shapes data capture feasibility. For example, although a person can accurately count steps for a short period (such as 100 steps), it's nearly impossible to manually count steps for even a single day. In contrast, a variety of pedometers can automatically capture this behavior with relatively high reliability. As another example, tracking a single food item is easy, but tracking complete meals over time is more difficult.

Balancing manual and automated capture therefore requires considering the complementary dimensions of data capture feasibility for a person versus a system, with the goal of enhancing data accuracy and minimizing the capture burden. Automated tracking can often be combined with manual input, with the primary mode of capture determined according to the type and frequency of capture. For example, a person might initiate and end capture, with the system automatically collecting and processing data (such as tracking location during a run). Alternatively, a system might employ continuous automatic data capture, with an option for manual correction or confirmation (for example, automatically identifying runs in a continuous location trace while allowing manual correction or identification of runs that weren't detected). Mostly manual tracking can also be assisted by automated reminders (such as experience-sampling techniques and context-aware approaches that leverage smartphone notifications to prompt people).

Purpose of Self-Monitoring

Self-monitoring has traditionally been employed in clinical and research settings for both assessment and as part of treatment.[1] Although self-monitoring provides clinicians or therapists with data to assess a person's progress, it can also change the behavior under observation. Known as reactive effects (or reactivity), self-monitoring often results in a change in frequency of the target behavior, typically in a desired, positive direction. Therefore, when researchers employ self-monitoring for the purpose of assessment and don't want people to be affected by it, manual tracking might not be an ideal method. In such a case, increased awareness and engagement with data is merely an unwanted side effect.

When self-monitoring is used as an assessment tool, it's important to enhance the captured data's accuracy. For example, data accuracy matters for a person with diabetes monitoring blood glucose and insulin levels, because a doctor's diagnosis and prescription rely on the collected data. When self-monitoring is used for treatment, it's important to enhance awareness to facilitate reactive effects to maximize the therapeutic outcome. For example, people might track food and mood with the goal of being mindful of their mood and its relationship to the types of food they eat, in which case detailed calorie estimates might be less important or even unnecessary. Finally, it's common to employ self-monitoring for the simultaneous purposes of assessment and treatment. In this case, the design challenge for self-monitoring systems is both to enhance data accuracy toward better assessment and to promote reactive effects toward a therapeutic outcome.

Designers must account for the purpose of self-monitoring when choosing a mode of data capture, and this necessarily interacts with data capture feasibility. If enhancing awareness or collecting subjective measures is more important, a semi-automated tracking application might emphasize manual capture. If complete capture of objective measures is more important, an automated approach can be used, but only if an appropriate automatic method is available. Alternatively, a mostly automatic system can be designed to promote awareness through better feedback designs, timely reminders, or just-in-time interventions.

Motivation Level

Our experience in designing semi-automated tracking applications also indicates that designers must consider a person's motivation level and the implication for acceptable burdens of manual capture. High-burden manual capture might be appropriate for highly motivated people (such as athletes training for an event), while low-burden approaches using additional automation might be needed for less-motivated people (such as people curious about their habits or casually interested in wellness). Motivation can also be shaped by how self-monitoring is initiated; for example, it might be self-initiated in response to a clinician request or in response to receiving a tracking device as a gift. Designers must account for these different motivation levels to balance capture burdens against other aspects of self-monitoring applications.

Example Applications of Semi-Automated Tracking

We conducted research exploring semi-automated tracking to support self-monitoring in three distinct domains: sleep, mood and stress, and diet. These domains present different challenges for designing self-monitoring tools. Here, we describe our projects across these domains and summarize how we balanced manual and automated approaches accounting for data capture feasibility, self-monitoring goals, and people's motivation level. We also mapped these projects along with other existing systems onto the semi-automated tracking spectrum in each domain, making it possible to compare various tracking approaches. (Note that we're comparing self-monitoring systems within each domain and not between the different domains.)

Self-Monitoring for Sleep

Sleep impacts many aspects of daily life, including cognitive function, health, mood, and productivity. An important challenge in designing sleep monitoring applications stems from the fact that there are many potentially relevant things to capture (such as sleep duration, sleep quality, behavioral disruptors, and environmental disruptors). SleepTight[6] and Lullaby[7] each propose approaches to combining manual and automated capture to help people self-monitor multiple dimensions of sleep.

Lullaby. Lullaby is a self-monitoring application to help people capture their sleep duration and quality in conjunction

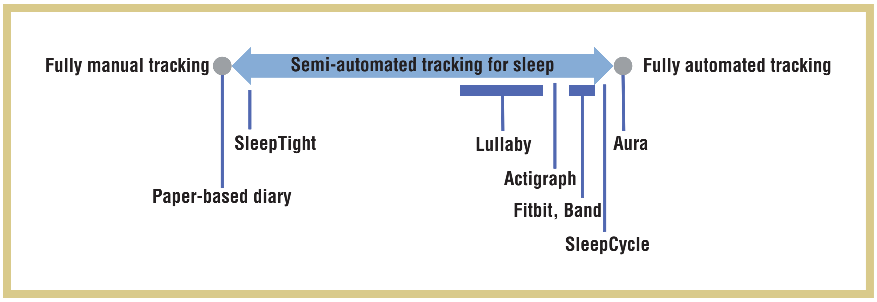

Figure 2. Sleep monitoring application examples. SleepTight's main mode of capture is streamlined manual tracking,[6] while Lullaby incorporates automated tracking with manual tracking.[7] Although Actiwatch (www.actigraphy.com/devices/actigraphy.html), Fitbit (www.fitbit.com), and Microsoft Band (www.microsoft.com/microsoft-band/en-us) all use wearable sensing, Fitbit and Band don't require manual event marking, thereby imposing less burden than Actiwatch. SleepCycle (www.sleepcycle.com) requires placing a smartphone on a mattress, while Aura (www.withings.com/us/en/products/aura) uses sleep sensors that don't require any interaction to capture sleep, thereby representing the "fully automated tracking" approach.

with potential environmental disruptors, such as bedroom light and temperature levels.[7] The system aims to improve sleep quality by helping people assess and improve their sleep environment. We determined that automated tracking was more reliable than manual tracking to continuously capturing aspects of the sleep environment (such as light, temperature, and infrared images).

Participants were particularly intrigued by the way automated tracking exposed events that occurred while they were unconscious. We also used a commercial sleep tracker (Fitbit) to ease the burden of capturing awakenings throughout the night. However, such trackers don't capture subjective sleep quality (which is important to understand sleep, particularly when polysomnography isn't available). Thus, we had people manually rate their sleep quality. Lullaby is therefore more toward the manual side of the semi-automated tracking spectrum than most commercial sleep trackers, including Actiwatch, Fitbit, Microsoft Band, and Aura (see Figure 2). To help people engage with the automatically captured data, we also included data collection and review in the bedside clock, an everyday appliance already associated with sleep activities (Figure 3a).

SleepTight. SleepTight is a mobile sleep application designed to help people capture sleep measures and various behavioral factors related to sleep,[6] such as consumption of alcoholic or caffeinated beverages, before-bedtime activities, and exercise. Because many behavioral factors potentially impact sleep quality, SleepTight enables people to customize which behaviors to track. However, these behavioral factors are hard to automatically sense. We therefore chose a self-monitoring technique more toward the manual capture side of semi-automated tracking (Figure 2), but we aimed to make capture easy by leveraging the lockscreen widget of a mobile phone.

For example, a person captures caffeinated beverage consumption by

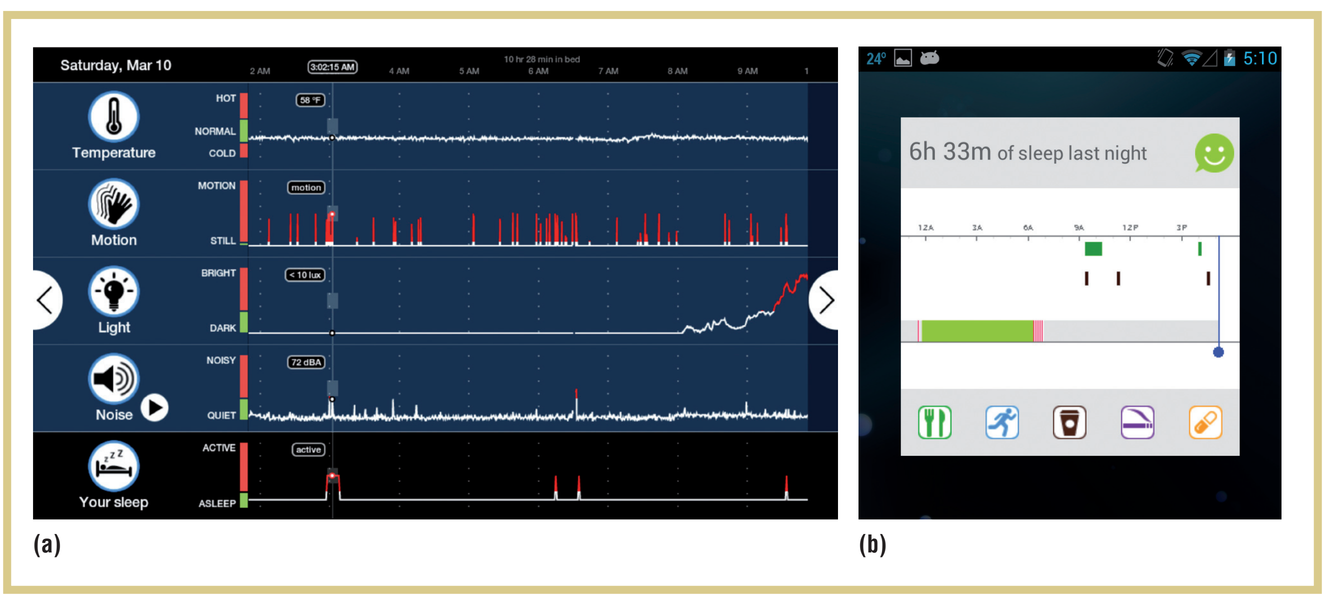

Figure 3. Screenshots from Lullaby and SleepTight: (a) Lullaby's data review screen and (b) SleepTight's data capture widget on Android's lockscreen.

simply pulling out their phone and tapping a coffee icon on the widget accessible on their phone's lockscreen (Figure 3b). SleepTight then automatically timestamps the entry at the current time, thus minimizing the number of steps required to capture that data point. Because the main purpose of self-monitoring was to capture the "when," SleepTight lowers the capture burden by capturing only the necessary information (that is, behavior type and time) and not requiring details (such as the amount of caffeine or type of caffeinated beverage).

In a four-week deployment study, we demonstrated that a semi-automated tracking approach with a heavy emphasis on manual tracking can still achieve high adherence rate when leveraging the mobile phone's easily accessible widget for data capture and feedback.

Self-Monitoring for Mood and Stress

High stress is a pervasive problem in modern life, with three quarters of Americans experiencing some stress-related symptoms.[13] Prolonged exposure to such stress can result in life-threatening physical illness (such as hypertension) and mental illness (such as depression). Tracking mood and stress can facilitate coping, but it's difficult to fully automate due to the subjective nature of the data (with an exception of t-shirt-based wearable technology[14]). Existing tools in this domain include MoodTracker (www.moodtracker.com) and M-Psychiatry,[15] whose main mode of data capture is manual tracking (see Figure 4). MONARCA[16] is an example of a balanced semi-automated self-assessment system that collects self-report data via sensor data from a phone. Here, we feature MoodRhythm (https://moodthythm.com) and Stress Experience Sampling and Measurement Experiment (Sesame)[8] to demonstrate a semi-automated tracking approach that's more toward the automated side of the spectrum (see Figure 5).

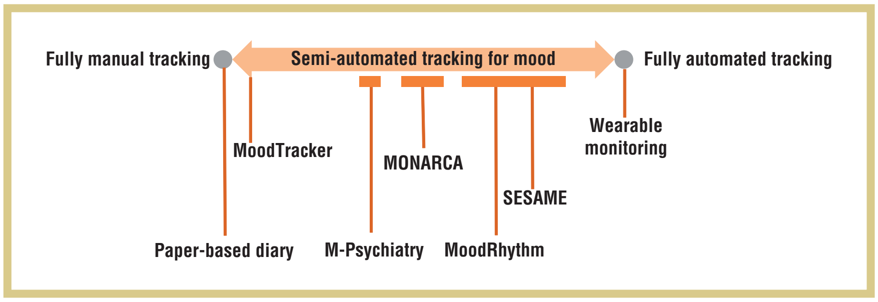

Figure 4. Mood and stress tracking application examples. MoodTracker is a manual mood tracking Web application (www.moodtracker.com), while M-Psychiatry leverages sensor networks to augment patient reported data.[15] MONARCA collects self-report data with several sensor data from a phone.[16] MoodRhythm (https://moodrhythm.com) enables manual tracking as well as a wide range of automated tracking and inference of patient behaviors relevant to bipolar disorder. Sesame employs automated tracking of stress with optional manual tracking.[8] Wearable technology (such as a shirt with integrated fabric electrodes and sensors[14]) can allow fully automated mood tracking.

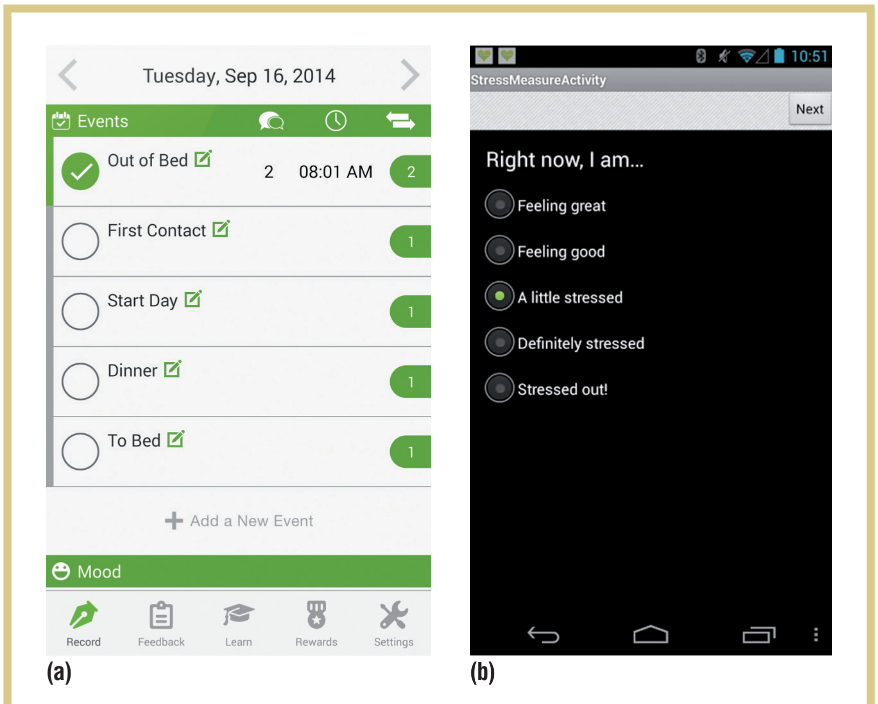

Figure 5. Screenshots from MoodRhythm and Sesame. (a) The MoodRhythm app lets bipolar patients manually track clinically relevant targets. (b) Sesame lets people enter a self-report using a single-item stress measure.

MoodRhythm. MoodRhythm (see Figure 5a) is a mobile application that leverages semi-automated tracking to support the long-term management of bipolar disorder through *interpersonal and social rhythm* therapy.[17] Although there is no permanent cure for bipolar disorder, people can minimize relapses with effective maintenance of daily social rhythms—such as mood, wake time, and bedtime. Traditionally, people have manually captured their stability and rhythmicity using pencil and paper, and they use the Social Rhythm

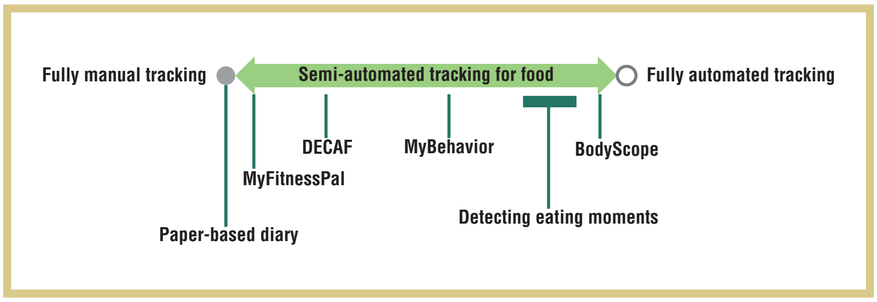

Figure 6. Food tracking application examples. MyFitnessPal (www.myfitnesspal.com) supplements the manual input with food databases. DECAF (Diary of Emotion, Context, and Food) automatically records when and where a person is eating.[11] MyBehavior automatically provides nutritional analysis,[10] although it still requires manual entry of food photos. Detecting eating moments with gestures[9] provides an opportunity for in-the-moment reminders, reducing the burden of remembering to enter food while preserving accuracy and awareness. BodyScope offers automatic detection and classification of eating practices and thus represents "mostly automated tracking."[18]

Metric to assess the data. The inherent characteristics of the illness mean that a person's ability to recall events and self-assess can be compromised, particularly during a relapse. We therefore incorporated passive and automated tracking in MoodRhythm to lower the capture burdens while aiming to retain the therapeutic aspects associated with self-monitoring (such as having a sense of involvement with treatment), which might be lost in a fully automated system.

Patients use the Social Rhythm Metric not only as an assessment tool but also as a planning tool by having explicit target events throughout the day for better stability. Accounting for the patient's ability to reliably record while maximizing the therapeutic goal of self-monitoring, MoodRhythm employs both automated and manual tracking approaches (Figure 4). MoodRhythm allows a person to manually track five core activities of the social rhythm metric along with mood and energy. In addition, it continuously and automatically captures data to allow monitoring of potentially relevant contextual and behavioral trends (such as sleep and social interaction) by leveraging smartphone-embedded sensors. MoodRhythm's semi-automated tracking approach, which promotes the patient's engagement in self-tracking, might be more appropriate than a fully automated system in this challenging domain.

Sesame. In-situ capture of daily stress can enable prompt prevention and coping. To this end, Sesame examines a semi-automated and minimally invasive approach to capture stress using a mobile phone (see Figure 5b).[8] Sesame automatically captures the physiological response to stressful conditions—such as changes in speech production—using a phone's built-in microphone. However, such automated capture fails to assess subjective perception of the stressful condition's severity. Therefore, Sesame employs ecological momentary assessments (EMA) to capture self-reported stress appraisal and related valance.

In a study with Sesame, we observed that the speech-based measures and self-reports complement each other. On the one hand, self-reports provided subjective severity of the stressful moments detected via speech and also gave insight into stressful moments when there was a lack of speech. On the other hand, speech-based measures captured high-stress situations in which people didn't respond to the prompt for self-reports. These results suggest that a low-burden semi-automated approach can achieve a more comprehensive view of stress, including necessary subjective and physiological responses, in contrast to a fully automated or fully manual approach.

Self-Monitoring of Food

Self-monitoring of food can support a variety of goals (such as weight loss, healthier choices, or identifying allergies or other food triggers), but reliable capture of food consumption remains elusive and burdensome.[3] Existing food tracking tools include MyFitnessPal (www.myfitnesspal.com; representing mostly the manual side) and BodyScope (representing the mostly automated side).[18] Our research on semi-automated tracking in this domain examined three approaches: detecting eating moments,[9] calorie-level food tracking with crowdsourcing,[10] and photo-based capture and reflection.[11] Each approach is shaped by different specific goals in self-monitoring of food (see Figure 6).

Detecting eating moments. Motivated by the fact that people often forget to manually capture food in a journal, we have been examining automated detection of eating moments. Importantly, we are not attempting to fully automate food tracking. Such automated tracking will remain technologically infeasible in the near future and could also undermine any awareness created by the act of manual tracking. However, automated detection of eating moments can help restore the benefits of tracking in situations where people typically forget or are otherwise unable to track (such as social situations where in-the-moment tracking might be considered inappropriate).

Toward this goal, we investigated automatic eating detection using a variety of on-body sensors and sensing modalities.[9] We found that wrist-mounted devices (such as watches) provide a promising platform for recognizing eating gestures (such as hand-to-mouth movements) because of their practicality and potential to scale. With a combination of laboratory and field studies, we found that eating moments, such as lunch and dinner, can be successfully inferred from the temporal density of detected intake gestures.[9] Such automated detection might support a variety of semi-automated approaches, including in-the-moment reminders or later prompts to track such as "It seems you ate at 2 p.m. today. Click to enter food items."

Calorie-level food tracking with crowdsourcing. Food tracking often requires a person to manually decompose meals into constituent ingredients that are then matched against a database for detailed caloric content. Only a highly motivated person might continue this difficult and time-consuming process. Therefore, we explored semi-automated approaches that employ crowdsourcing to provide nutritional analysis of manually captured food photos. We extended prior crowdsourcing-based systems with techniques that use machine learning to automatically maintain a list of accurate and low-cost crowd-workers.

In a field study comparing this semi-automated approach to a traditional manual food tracking on a phone, we found that crowdsourcing nutritional analysis leads people to track significantly more foods per day.[10] Participants reported that they were curious to know the crowdsourcing-provided calories and that they often checked or corrected the crowdsourcing-provided labels on meal components. We also found that calories per food intake decreased over time with the crowdsourcing-based approach. These results suggest semi-automated nutritional analysis can both reduce tracking burdens and promote awareness needed to facilitate reactive effects.

Photo-based capture and reflection. As an alternative to highly quantitative methods, we examined lightweight photo-based capture and reflection in the design of DECAF (Diary of Emotion, Context, and Food) (Figure 7). We found that photo-based tracking can reduce capture burdens while supporting reflection toward diverse goals.[11] Specifically, we developed DECAF to track manually captured food photos together with semi-automated (when and where) and manual metadata (with whom, mood, and food enjoyment). Journal entries intentionally don't include nutritional breakdowns, and the application doesn't include a calorie budget or other quantitative goals. DECAF therefore might not be suitable for a person seeking detailed quantitative assessment as part of a serious health condition, but our formative survey found that people have many other food tracking goals (such as eating more vegetables, a balanced diet, or less processed foods).

Figure 7. An example entry in DECAF. Rather than show calorie or nutrition information, the journal focuses on logging meal enjoyment, location, and social context.

We found that photo-based tracking can support participants in identifying triggers and trends through participant comments such as "I didn't eat as many fruit and vegetables as I thought." It can also promote awareness, as exemplified in the comment, "Do I really want to eat this? I'm capturing this image." In domains where data capture feasibility is a significant barrier, this work suggests that de-emphasizing detailed measurement in favor of easing capture can reduce burdens while preserving the awareness benefits of self-monitoring.

Opportunities and Challenges

As our seven semi-automated tracking projects in three different domains demonstrate, a semi-automated tracking approach is an effective self-monitoring method for promoting engagement, while also lowering the capture burdens and capturing data that is typically difficult to sense. Here, we describe further opportunities and challenges for semi-automated tracking, including how designers can successfully employ semi-automated tracking and create effective self-monitoring feedback.

Semi-Automated Tracking Design Process

To employ semi-automated tracking in designing self-monitoring applications, designers must first identify the types of data that must be captured—Lullaby, for example, captures potential environmental disruptors, such as bedroom light and temperature levels[7]—to help people achieve their self-monitoring goal (to improve sleep quality). Next, designers must determine which data to automatically capture and which to manually capture, considering the data capture feasibility, the goal of self-monitoring, and the target audience's motivation level. When manual tracking is the main mode of capture, designers should reduce the associated burdens—such as by streamlining the capture process, as in SleepTight,[6] or capturing only the necessary data, as in DECAF.[11] When automated tracking is the main mode of capture, designers should integrate ways to involve people in the self-monitoring process, such as by providing opportunities for people to capture complementary data or to make an appraisal of the captured data.

Designing and Integrating Effective Feedback

The goal of self-monitoring isn't just to engage people in data capture but also to support their goals by helping them draw meaningful insights from their data. Although we mainly discussed the data capture aspect of semi-automated tracking, the system can be further improved by integrating effective feedback, timely notifications, and sharing features, with the goal of helping people create a healthy habit of long-term engagement in self-monitoring.

Self-monitoring feedback can be provided in a variety of forms. For example, real-time feedback usually shows a person's current state and is used as a means to intervene at critical moments. Aggregated feedback can be helpful for people who want to explore and reflect on the data. This type of feedback can be provided when additional screen space is available to present deeper insights, such as long-term trends, comparisons, or correlational data. Designing engaging feedback is particularly important for semi-automated tracking

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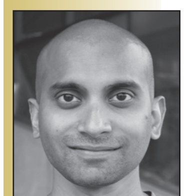

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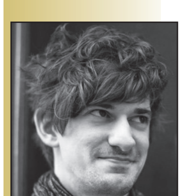

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systems that are designed primarily for automated capture, because feedback can compensate for the reduced engagement relative to more manual capture. Well-designed feedback can thus improve engagement and support self-reflection. For example, an easy-to-understand visual summary of data collected over a long period can help people not only see their progress but also reflect on past and current behavior.

Whether well designed or not, feedback isn't useful unless people actually receive it. Notifications and social features are often employed to focus attention on feedback. Because notifications can also help promote capture, they can create a link between regular data capture and obtaining feedback on that data. However, overuse of notifications can lead to people ignoring the notifications and related feedback altogether. The frequency and content of notifications therefore must be carefully designed.

Finally, social features let people view data associated with their friends (so they can compare their data or compete or encourage each other), and can motivate people to engage in data collection and review feedback. More work is needed to examine how to create healthy social dynamics while allowing people to share personal data in a privacy-preserving manner.

Long-term engagement with self-monitoring applications requires the practice of capturing and reviewing data to become a habit, which can't be based entirely on notifications or external motivations.[19] At the core of semi-automated tracking is the goal of making it easier for people to engage in self-monitoring practices.

We examined making manual capture easy (such as the single tap in SleepTight[6]), capturing complementary data (as in MoodRhythm and Sesame[8]), crowdsourcing more tedious aspects of self-monitoring (such as calorie-level food tracking in MyBehavior[10]), reducing data granularity and capturing the most important data (as in SleepTight[6] and DECAF[11]), and integrating feedback review into daily activities (as in Lullaby's bedside alarm clock[7]). These are just a few examples of designing self-monitoring systems that leverage semi-automated tracking.

To maximize the long-term value of self-monitoring, we must help people create virtuous cycles of capturing data, which in turn supports meaningful feedback and increases awareness through self-reflection, thereby

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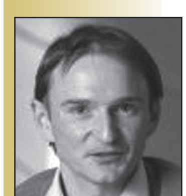

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encouraging continued data capture. Semi-automated tracking approaches seem to be the key to striking the appropriate balance between manual and automated tracking, combining each of their benefits while minimizing their associated limitations.

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