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

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Abstract

We present an approach for designing self-monitoring technology called semi-automated tracking, which combines both manual and automated data collection methods. Through this approach, we aim to lower the capture burdens, collect data that is typically hard to track automatically, and promote awareness to help people achieve the goals of self-monitoring. We first specify three design considerations for semi-automated tracking—(1) data capture feasibility; (2) purpose of self-monitoring; and (3) motivation level. We then provide examples of semi-automated tracking applications in the domains of sleep, mood, and food tracking to demonstrate strategies we have developed to find the right balance between manual tracking and automated tracking, combining each of their benefits while minimizing their associated limitations.

Keywords

Self-monitoring; semi-automated tracking; personal informatics; sleep tracking; food tracking; mood tracking.

1. Introduction

Self-monitoring for health behavior change is an important practice across numerous domains (e.g., diet, physical activity, sleep, stress). Studies have shown that self-monitoring can enable greater awareness of behaviors and can create a reactive effect yielding positive, therapeutic behavior changes (see [1] for a review of self-monitoring research). Although self-monitoring has been used successfully for behavior change interventions, its high data collection burdens in both paper and electronic tools hinder 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 food tracking limit their effectiveness [3].

To counter the high data collection 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 such that a person can achieve the benefits of self-monitoring without the time and difficulty of manual data collection. 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 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 tracking and automated tracking, combining each of their benefits while minimizing their associated limitations. We call this hybrid approach ***semi-automated tracking*** and define it as ***any combination of manual and automated tracking approaches***. Semi-automated tracking therefore encompasses a broad spectrum of designs (a double-headed arrow in Figure 1) between the extremes of fully manual or fully automated tracking (two circles in Figure 1). Semi-automated tracking ranges from the *mostly* manual tracking to *mostly* automated tracking. In fully manual tracking, all data is explicitly captured by a person, though they may use a system for capture (e.g., a spreadsheet for data entry). In mostly manual tracking, a system provides light assistance to manual capture (e.g., a system automatically timestamping an otherwise manual entry). In mostly automated tracking, a system collects most data but can be assisted by a person (e.g., manual confirmation or correction of data collected, measured, or estimated by a system). In fully automated tracking, all data is collected by a system, though a person may consume that data (e.g., viewing a visualization of automatically collected data). Figure 1 summarizes definitions, strengths, and weaknesses of fully manual, semi-automated, and fully automated tracking.

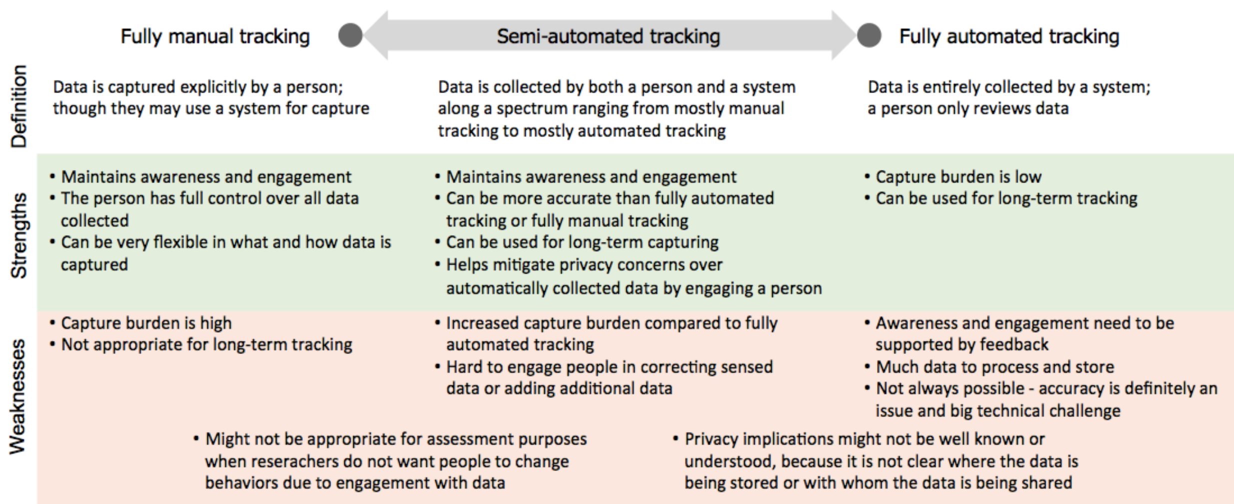

Figure 1: Definitions and comparisons of the strengths and weaknesses for fully manual tracking, semi-automated tracking, and fully automated tracking.

Li and colleagues explored the concept of semi-automated tracking in their work with IMPACT, finding that automated systems can lower the capture burden but may undermine immediate awareness in comparison to manual capture [5]. We build upon this work as we particularly address the following 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 [6,7,8,9, 10,11]. Here, we highlight how we capitalize on the semi-automated tracking approach in each work. After describing design considerations of semi-automated tracking, we map our work and other existing systems onto the design space of semi-automated tracking. We conclude with providing further design opportunities in the semi-automated tracking design space.

2. 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 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 capturing. In designing semi-automated tracking tools, we thus need to 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 semi-automated tracking approaches: (1) data capture feasibility, (2) the purpose of self-monitoring, and (3) 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 ***type*** of data (e.g., subjective vs. objective, qualitative vs. quantitative) and the ***frequency*** of capture.

Data types that are subjective and qualitative in nature are difficult or impossible to automatically capture, but are easier for people to record. For example, subjective sleep quality by definition can only be captured manually, as it requires a person's own perception of their 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 sense the presence of a stressful event (e.g., [12]), but subjective response or severity of the event must be manually captured as ground truth. However, note that even if subjective measures are considered and used as ground truth, people are prone to forgetfulness, unintentional recall bias, delayed recording, and backfilling (i.e., generating fake data to give the appearance of good compliance), resulting in low data quality. Low data quality can also result from limitations in the system's data capture feasibility, which might compromise the overall effectiveness of the system and lead to people's lack of trust in 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 expensive instruments (e.g., polysomnography) and sleep technologists as in the sleep lab.

Data capture feasibility is also shaped by the **frequency of capture**. For example, although a person can accurately count steps for a short period (e.g., 100 steps), it is 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 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 (e.g., tracking location during a run). Alternatively, a system might employ continuous automatic data capture, with an option for manual correction or confirmation (e.g., automatically identifying runs in a continuous location trace while allowing manual correction or identification of runs that were not detected). Mostly manual tracking can also be assisted by automated reminders to manually capture (e.g., experience sampling techniques for subjective capture, context-aware approaches to prompting people to capture).

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, which therefore provides benefits toward behavior change. Therefore, when researchers employ self-monitoring for the purpose of assessment and do not 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 is important to guarantee **accuracy** of the captured data. For example, data accuracy matters for a person with diabetes monitoring blood glucose and insulin level because a doctor's diagnosis and prescription rely on the collected data. When self-monitoring is used for treatment, it is important to enhance **awareness** to facilitate reactive effects to maximize the therapeutic outcome. For example, people may 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 may be less important or even unnecessary. Finally, we also note that it is common to employ self-monitoring for the simultaneous purposes of assessment and treatment. In this case, the design challenge for self-monitoring is both to enhance data accuracy toward better assessment and to promote reactive effects toward a therapeutic outcome.

Designers need to 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

In our experience designing semi-automated tracking applications, we have also found that designers must consider a person's level of motivation and its implication for acceptable burdens of manual capture. High-burden manual capture may be appropriate for highly-motivated people (e.g., an athlete training for an event). On the other hand, low-burden approaches employing more automation might be necessary for less motivated people (e.g., a person curious about their habits, a person casually interested in wellness). Motivation can also be shaped by how self-monitoring is initiated (e.g., self-initiated, in response to a clinician request, in response to receiving a tracking device as a gift). Designers need to account for different levels of motivation in considering how manual capture burdens can be balanced against other aspects of self-monitoring applications.

3. Example Applications of Semi-Automated Tracking

We have 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. In this section, we describe our projects across these domains and summarize how we balanced manual and automated approaches accounting for data capture feasibility, self-monitoring goal, 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 are comparing self-monitoring systems within each domain and not between 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 is that there are many potentially relevant things to capture (e.g., sleep duration, sleep quality, behavioral disruptors, 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.

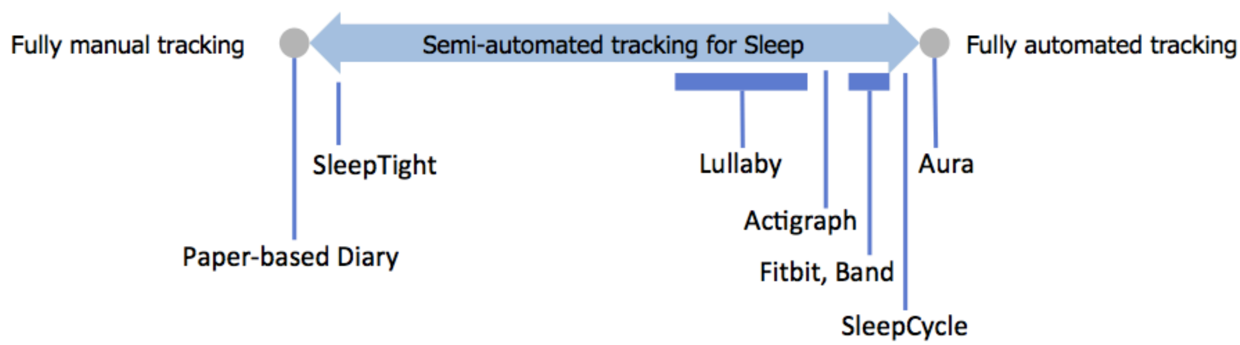

Figure 2. SleepTight's main mode of capture is streamlined manual tracking [6]. Lullaby incorporates automated tracking with manual tracking [7]. Although Actigraph, Fitbit [13], and Band [14] all use wearable sensing, Fitbit and Band do not require manual marking, thereby imposing less burden than Actigraph. SleepCycle [15] only requires placing a smartphone on a mattress. Aura [16] uses sleep sensors that do not require any interaction to capture sleep, thereby representing the "Fully automated tracking" approach.

Lullaby

Lullaby is a self-monitoring application to help people capture their sleep duration and quality in conjunction 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 to continuously capture aspects of the sleep environment (e.g., light, temperature, infrared images) than manual tracking. 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 do not capture subjective sleep quality (important to understand sleep, particularly when polysomnography is not 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 (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 integrated in sleep activities (Figure 3 left).

SleepTight

SleepTight [6] is a mobile sleep application designed to help people capture sleep measures together with various behavioral factors (e.g., alcoholic beverages, before-bedtime activities, caffeine intake, exercise). As many behavioral factors potentially impact sleep quality, SleepTight enables people to customize which behavior 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 aimed to make capture easy by leveraging the lockscreen widget of a mobile phone. For example, a person captures a caffeinated beverage by simply pulling out their phone and tapping a coffee icon on the widget accessible on their phone's lockscreen (Figure 3 right). 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 (i.e., behavior type, time) and not requiring details (e.g., amount of caffeine, 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 mobile phone's easily accessible widget for data capture and feedback.

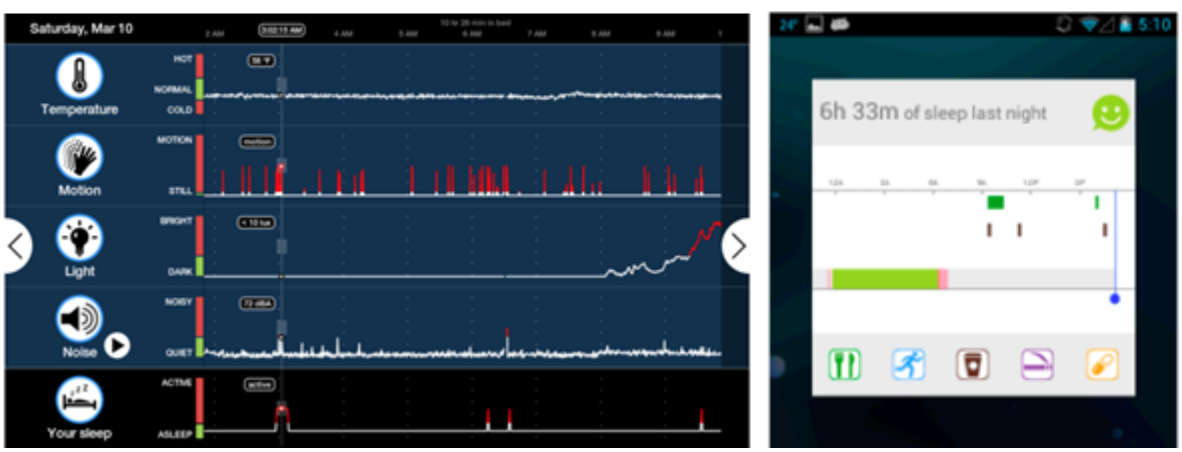

Figure 3: Lullaby's data review screen (left) and SleepTight's data capture widget on Android's lockscreen (right).

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. Prolonged exposure to such stress can result in life-threatening physical (e.g., hypertension) and mental illness (e.g., depression). Tracking mood and stress can be a part of coping, but it is difficult to fully automate due to the subjective nature of the data. Self-monitoring of mood and stress can therefore benefit from semi-automated approaches, which we explored in our work on supporting mood tracking for people with bipolar disorder and our work in semi-automated stress tracking [8].

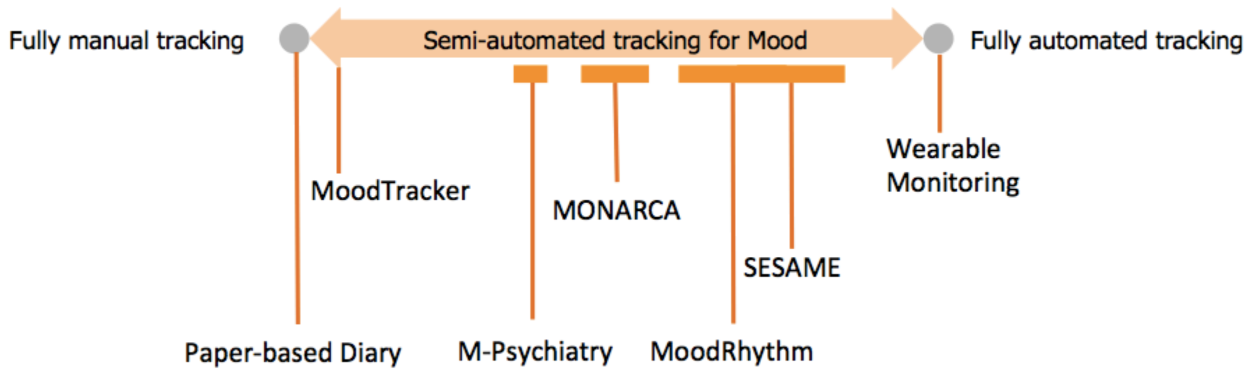

Figure 4. MoodTracker [17] is a manual mood tracking web application. M-Psychiatry [18] leverages sensor networks to augment patient reported data. MONARCA [19] collects self-report data with several sensor data from a phone. MoodRhythm [20] enables manual tracking as well as a wide range of automated tracking and inference of patient behaviors relevant to bipolar disorder. SESAME [8] employs automated tracking of stress with optional manual tracking. Wearable technology (e.g., shirt with integrated fabric electrodes and sensors [21]) can allow fully automated mood tracking.

MoodRhythm

MoodRhythm (Figure 5 left) is a mobile application that leverages semi-automated tracking to support the long-term management of bipolar disorder through interpersonal social rhythm therapy [20]. A person's daily stability and rhythmicity is assessed by the Social Rhythm Metric, which has traditionally been manually captured via pencil and paper. 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 burden while aiming to retain the therapeutic aspects associated with self-tracking (e.g., having a sense of involvement with treatment), which might be lost in a fully-automated system. Patients use 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 capability of reliable recording 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, MoodRhythm continuously and automatically captures data to allow monitoring of potentially relevant contextual and behavioral trends (e.g., sleep, social interaction) by leveraging smartphone embedded sensors. MoodRhythm's semi-automated tracking approach for better data coverage and 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 (Figure 5 right) examines a semi-automated and minimally invasive approach to capture stress using a mobile phone [8]. SESAME automatically captures 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 severity of the stressful condition. 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 one hand, self-reports provided subjective severity of the stressful moments detected via speech and also gave insight into stressful moments when there was lack of speech. On the other hand, speech-based measures captured high-stress situations in which people did not respond to prompt for self-reports. These results suggest that a low-burden semi-automated approach can achieve a more comprehensive view on stress, including necessary subjective and physiological responses, in contrast to a fully automated or fully manual approach.

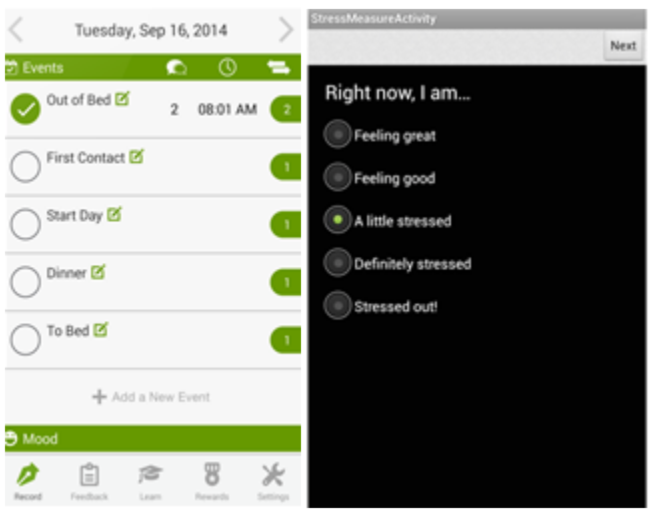

Figure 5: Screens from the MoodRhythm app (left) and SESAME (right). Bipolar patients can use MoodRhythm app to manually track clinically relevant targets (left). SESAME allows entering self-report using a single-item stress measure (right).

Self-Monitoring of Food

Self-monitoring of food can support a variety of goals (e.g., weight loss, healthier choices, identifying allergies or other food triggers), but reliable capture of food consumption remains elusive and burdensome [3]. Our research on semi-automated approaches has examined detecting eating moments, calorie-level food tracking with crowdsourcing, and photo-based capture and reflection. Each approach is shaped by different specific goals in self-monitoring food.

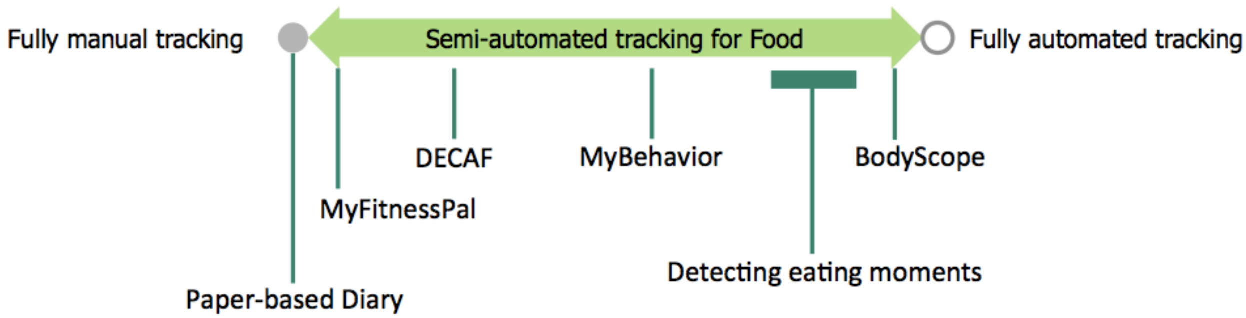

Figure 6. MyFitnessPal [22] supplements the manual input with food databases. DECAF [11] automatically records when and where a person is eating. MyBehavior [10] automatically provides nutritional analysis, though still requires manual entry of food photos. Detecting eating moments with gestures [9] provide an opportunity for in-the-moment reminders, reducing the burden of remembering to enter food while preserving accuracy and awareness. BodyScope [23] offers automatic detection and classification of eating practices representing "Mostly automated tracking."

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. We believe this will remain technologically infeasible in the near future, and that it would also likely undermine the awareness created by the act of tracking. But automated detection of eating moments can help restore the benefits of tracking where people forget or are otherwise unable to track (e.g., social situations where in-the-moment tracking might be considered inappropriate). Toward this goal, we have investigated automatic eating detection using a variety of on-body sensors and sensing modalities [9]. We have found that wrist-mounted devices (e.g., watches) provide a promising platform for recognizing eating gestures (e.g., hand-to-mouth movements) because of their practicality and potential to scale. With a combination of laboratory and in-the-wild 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 (e.g., "It seems you ate at 2 PM 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 have explored semi-automated approaches that employ crowdsourcing to provide nutritional analysis of manually captured food photos. We have 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 (Figure 7). We found that photo-based tracking can reduce capture burdens while supporting reflection toward a diversity of 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 do not include nutritional breakdowns, and the application does not include a calorie budget or other quantitative goals. DECAF therefore may 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 (e.g., more vegetables, a balanced diet, low-processed foods). We found photo-based tracking can support participants in identifying triggers and trends (e.g., "*I didn't eat as many fruit and vegetables as I thought.*") and can promote awareness (e.g., "*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 awareness benefits of self-monitoring.

Figure 7: An example entry in DECAF; no calorie or nutrition information is shown, as the journal instead logs meal enjoyment, location context, and social context.

4. Opportunities & Challenges for Semi-Automated Tracking

In the previous section, we showcased seven semi-automated tracking projects we have conducted in three different domains, demonstrating that semi-automated tracking approach is an effective self-monitoring method for promoting engagement while lowering the capture burden 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 first need to identify the types of data that need to be captured (e.g., potential environmental disruptors such as bedroom light and temperature levels as in Lullaby [7]) to help people achieve their self-monitoring goal (e.g., improve the sleep quality). They then need to 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 burden (e.g., streamline the capture process as shown in SleepTight [6], capture only the necessary data as shown in DECAF [11]). When automated tracking is the main mode of capture, designers should integrate ways to involve people in the self-monitoring process providing feedback to the person and reflecting their input back to the system as in the case of SESAME [8].

Designing and Integrating Effective Feedback

The goal of self-monitoring is not just to engage people in data capture but also to support their goals by helping them draw meaningful insights out of their data. Although we have mainly discussed the data capture aspect of semi-automated tracking, the system can further be 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 engage in exploring and reflecting upon data. It can be provided when more screen space is available to present deeper insights (e.g., long-term trends, comparisons, correlational data). Designing engaging feedback is particularly important for semi-automated tracking systems that are designed for mostly 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 is not 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 bring people to ignore the notifications and related feedback altogether. The frequency and content of notifications therefore need to be carefully designed. Social features allow people to view data associated with their friends (e.g., to compare, compete, or encourage), and can motivate people to engage in data collection and review feedback. More work needs to examine how to create healthy social dynamics while allowing to share personal data in a privacy-preserving manner.

Promoting Long-term Engagement

Long-term engagement with self-monitoring applications requires the practice of capturing and reviewing data to become a habit, which cannot be based entirely in notifications or external motivations [24]. At the core of the semi-automated tracking is the goal of making it easier for people to engage in self-monitoring practices. We have examined making manual capture easy (e.g., single tap in SleepTight [6]), capturing complementary data (e.g., MoodRhythm [20], SESAME [8]), crowdsourcing more tedious aspects of self-monitoring (e.g., calorie-level food tracking with Crowdsourcing [10]), reducing data granularity and capturing the most important data (e.g., SleepTight [6], DECAF [11]), and integrating feedback review into daily activities (e.g., 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 need to help people create virtuous cycles of capturing data, which in turn supports meaningful feedback, which increases awareness through self-reflection, which encourages continued data capture. We believe semi-automated tracking approaches are 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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References

1. Korotitsch, W. J., & Nelson-Gray, R. O. (1999). An overview of self-monitoring research in assessment and treatment. *Psychological Assessment, 11*(4), 415.
2. Epstein, D. A., Ping, A., Fogarty, J., & Munson, S. A. (2015). A lived informatics model of personal informatics. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing,* 731-742. ACM.
3. Cordeiro, F., Epstein, D. A., Thomaz, E., Bales, E., Jagannathan, A. K., Abowd, G. D., & Fogarty, J. (2015). Barriers and Negative Nudges: Exploring Challenges in Food Journaling. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems,* 1159-1162. ACM.
4. Patel, M. S., Asch, D. A., & Volpp, K. G. (2015). Wearable devices as facilitators, not drivers, of health behavior change. *Jama*, *313*(5), 459-460.

5. Li, I., Dey, A. K., & Forlizzi, J. (2012). Using context to reveal factors that affect physical activity. *ACM Transactions on Computer-Human Interaction (TOCHI)*,*19*(1), 7.
6. Choe, E. K., Lee, B., Kay, M., Pratt, W., & Kientz, J. A. (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. ACM.
7. Kay, M., Choe, E. K., Shepherd, J., Greenstein, B., Watson, N., Consolvo, S., & Kientz, J. A. (2012). Lullaby: a capture & access system for understanding the sleep environment. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing (UbiComp 2012),* 226-234. ACM.
8. Adams, P., Rabbi, M., Rahman, T., Matthews, M., Voida, A., Gay, G., Choudhury, T., & Voida, S. (2014). Towards personal stress informatics: comparing minimally invasive techniques for measuring daily stress in the wild. In *Proceedings of the 8th International Conference on Pervasive Computing Technologies for Healthcare,* 72-79.
9. Thomaz, E., Essa, I., & Abowd, G. D. (2015). A practical approach for recognizing eating moments with wrist-mounted inertial sensing. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 1029-1040. ACM.
10. Rabbi, M., Aung, M. H., Zhang, M., & Choudhury, T. (2015). MyBehavior: automatic personalized health feedback from user behaviors and preferences using smartphones. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing,* 707-718. ACM.
11. Cordeiro, F., Bales, E., Cherry, E., & Fogarty, J. (2015). Rethinking the Mobile Food Journal: Exploring Opportunities for Lightweight Photo-Based Capture. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 3207-3216. ACM.
12. Choi, J., & Gutierrez-Osuna, R. (2009). Using heart rate monitors to detect mental stress. In *Wearable and Implantable Body Sensor Networks, 2009 (BSN 2009),* 219-223. IEEE.
13. fitbit. https://www.fitbit.com.
14. Microsoft Band. https://www.microsoft.com/microsoft-band/en-us.
15. Sleep Cycle. http://www.sleepcycle.com.
16. Withings Aura. https://www.withings.com/us/en/products/aura.
17. MoodTracker. https://www.moodtracker.com.
18. Blum, J., & Magill, E. (2008). M-psychiatry: Sensor networks for psychiatric health monitoring. In *Proceedings of The 9th Annual Postgraduate Symposium The Convergence of Telecommunications, Networking and Broadcasting, Liverpool John Moores University,* 33-37.
19. Bardram, J. E., Frost, M., Szántó, K., Faurholt-Jepsen, M., Vinberg, M., & Kessing, L. V. (2013). Designing mobile health technology for bipolar disorder: a field trial of the monarca system. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems,* 2627-2636. ACM.
20. MoodRhythm. www.moodrhythm.com.
21. Valenza, G., Nardelli, M., Lanata, A., Gentili, C., Bertschy, G., Paradiso, R., & Scilingo, E. P. (2014). Wearable monitoring for mood recognition in bipolar disorder based on history-dependent long-term heart rate variability analysis.*Biomedical and Health Informatics, IEEE Journal of*, *18*(5), 1625-1635.

22. MyFitnessPal. https://www.myfitnesspal.com.
23. Yatani, K., & Truong, K. N. (2012). BodyScope: a wearable acoustic sensor for activity recognition. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*, 341-350. ACM.
24. Stawarz, K. M., Cox, A. L., & Blandford, A. (2015). Beyond Self-Tracking and Reminders: Designing Smartphone Apps That Support Habit Formation. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 2653-2662. ACM.

Sidebar – 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 in self-monitoring technology. Self-monitoring technology has been designed for tracking fitness (e.g. [1]), sleep, mood, and diet (see Figures 2, 4, & 6 in the article, respectively), and energy and water usage [2,3].

Ecological momentary assessment (EMA) refers to a collection of methods by which research participants repeatedly reports on symptoms, affect, behavior, and cognitions close in time to experience and 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 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-beings (e.g., [5]).

Self-monitoring has recently become popular outside the research or clinical setting. For example, Quantified Self (QS) movement has been increasing popular since 2008 [6]. Initially started in the Silicon Valley area among technology enthusiasts, QS has become a community of people practicing self-monitoring and building self-monitoring technology. The QS community also shares their self-monitoring practices and experiences through a blog, meetup talks, and conference presentations. Researchers have analyzed QS presentations to understand what barriers Quantified-Selfers have and what insights they gain from their personal data [7]. Although Quantified-Selfers are dedicated to self-monitoring, they had difficulties keeping up with self-monitoring when tracking burden was too high. They offer 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 our design considerations for semi-automated tracking.

1. Consolvo, S., McDonald, D. W., Toscos, T., Chen, M. Y., Froehlich, J., Harrison, B., ... & Smith, I. (2008). Activity sensing in the wild: a field trial of ubifit garden. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems,* 1797-1806. ACM.

2. Froehlich, J., Findlater, L., Ostergren, M., Ramanathan, S., Peterson, J., Wragg, I., ... & Landay, J. A. (2012). The design and evaluation of prototype eco-feedback displays for

fixture-level water usage data. In*Proceedings of the SIGCHI conference on human factors in computing systems,* 2367-2376. ACM.

3. Rodgers, J., & Bartram, L. (2011). Exploring ambient and artistic visualization for residential energy use feedback. *Visualization and Computer Graphics, IEEE Transactions on*, *17*(12), 2489-2497.
4. Stone, A. A., & Shiffman, S. (1994). Ecological momentary assessment (EMA) in behavorial medicine. *Annals of Behavioral Medicine*.
5. Stone, A. A., & Mackie, C. (Eds.). (2014). *Subjective well-being: Measuring happiness, suffering, and other dimensions of experience*. National Academies Press.
6. Quantified Self. http://quantifiedself.com.
7. Choe, E. K., Lee, N. B., Lee, B., Pratt, W., & Kientz, J. A. (2014). Understanding quantified-selfers' practices in collecting and exploring personal data. In *Proceedings of the 32nd annual ACM conference on Human factors in computing systems,* 1143-1152. ACM.

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