OmniTrack: A Flexible Self-Tracking Approach Leveraging Semi-Automated Tracking

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We now see an increasing number of self-tracking apps and wearable devices. Despite the vast number of available tools, however, it is still challenging for self-trackers to find apps that suit their unique tracking needs, preferences, and commitments. Furthermore, people are bounded by the tracking tools' initial design because it is difficult to modify, extend, or mash up existing tools. In this paper, we present OmniTrack, a mobile self-tracking system, which enables self-trackers to construct their own trackers and customize tracking items to meet their individual tracking needs. To inform the OmniTrack design, we first conducted semi-structured interviews (N = 12) and analyzed existing mobile tracking apps (N = 62). We then designed and developed OmniTrack as an Android mobile app, leveraging a semi-automated tracking approach that combines manual and automated tracking methods. We evaluated OmniTrack through a usability study (N = 10) and improved its interfaces based on the feedback. Finally, we conducted a 3-week deployment study (N = 21) to assess if people can capitalize on OmniTrack's flexible and customizable design to meet their tracking needs. From the study, we showed how participants used OmniTrack to create, revise, and appropriate trackers—ranging from a simple mood tracker to a sophisticated daily activity tracker. We discuss how OmniTrack positively influences and supports self-trackers' tracking practices over time, and how to further improve OmniTrack by providing more appropriate visualizations and sharable templates, incorporating external contexts, and supporting researchers' unique data collection needs.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing**; *Ubiquitous and mobile computing systems and tools*;

Additional Key Words and Phrases: Self-tracking, self-monitoring, semi-automated tracking, personal informatics, tracking apps, mobile apps, health, wellness, customization.

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1 INTRODUCTION

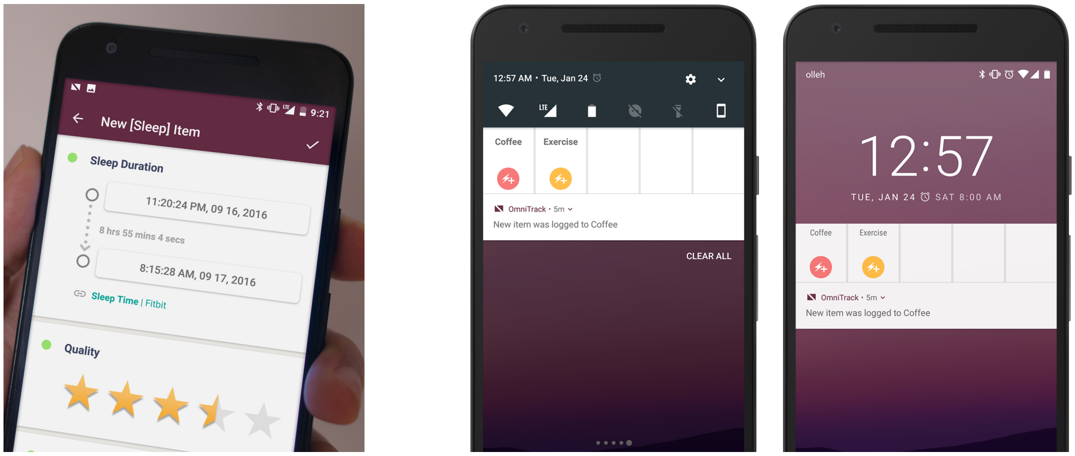
We witness a dramatic increase of health and fitness apps; as of 2016, the number of mHealth apps increased to about 259,000 [30]. In addition, wearable devices such as Fitbit [25], Mi Band [67], and Microsoft Band [44] have become more affordable and more prevalent; market research conducted in 2015 shows that 21% of American adults use wearable devices such as activity trackers or smart watches [26]. Using these apps and devices, people can track various data about themselves, including activity (e.g., [2, 25, 44, 48, 67]), sleep (e.g., [2, 15, 25, 44, 67]), weight (e.g., [6]), diet (e.g., [51]), mood (e.g., [47]), period, breastfeeding, productivity (e.g., [36, 57]), and reading (e.g., [7]). Collecting multiple data streams has recently become more prevalent [16, 59], and yet, most people, including Quantified Selfers, fail to fully leverage their personal data even if they desire to do so [16]. Because tools are scattered across multiple platforms, it is challenging for non-technical people to download data from various tracking platforms.

Despite the vast number of available tracking apps and devices, it can be challenging to find a tool that perfectly suits one's tracking needs, preferences, and commitments. Commercial tracking apps are often highly specialized, providing little or no flexibility over what and how to track. For example, people may want to track their reading activity in different ways: the title and author of the books they read along with a short review; the detailed reading progress (e.g., pages by day); or the time they spent for reading for each day. Yet, because most apps do not allow people to customize the tracking items, people's tracking abilities are bounded by how an app is originally designed. When people cannot find the tool that meets their needs, some people appropriate general-purpose tools (e.g., calendar, spreadsheet, or freeform notes) [17] or even a social media tool (e.g., Instagram [18]) for flexible tracking. Only a few people with technical proficiency build their own tracking tools while others give up tracking entirely if they cannot tolerate the inconvenience of existing tools [17].

We propose OmniTrack (Figure 1), a novel self-tracking approach that provides self-trackers with a high level of flexibility to construct their own tracking tool. OmniTrack enables people to create their own trackers, customizing tracking items to meet their personal needs. To enhance self-awareness while lowering the capture burden, OmniTrack takes a semi-automated tracking approach [13], allowing people to combine manual tracking and automated tracking. With OmniTrack, people can retrieve data from external data sources in addition to customizing manual tracking fields. For example, Ravichandran and colleagues recently pointed out that existing sleep devices mainly focus on supporting automated sleep sensing, despite the importance of integrating one's subjective sleep quality for self-reflection [55]. With OmniTrack, people can easily create a semi-automated sleep tracker, consisting of manual fields (e.g., subjective sleep quality from self-report) and automated fields (e.g., sleep duration retrieved from Fitbit).

To inform the OmniTrack design, we first conducted preliminary interviews with 12 self-trackers to understand their tracking practices, from which we learned how they use and appropriate existing tools to suit their diverse tracking needs. We also analyzed 62 tracking apps (from Apple's App Store) to identify data types of tracking items used in the apps. Based on the two studies, we designed and developed OmniTrack, and demonstrated three use cases to illustrate its broad coverage ranging from mostly manual tracking to mostly automated tracking.

We evaluated OmniTrack through a usability study (N = 10) followed by a deployment study (N = 21). From the usability study, we learned that participants could understand the core concepts of OmniTrack; they favorably responded to OmniTrack's flexibility and semi-automated tracking features. Furthermore, after a short tutorial, they successfully performed tasks that required to create trackers. After addressing OmniTrack's usability issues identified from the usability study, we deployed OmniTrack for 3 weeks to learn how people use OmniTrack's flexible and customizable design over time in their natural environment. Through the deployment study, we showed that participants used OmniTrack in many unique ways to fulfill their personal preferences. In addition, we identified common mistakes people made during the configuration as well as edge tracking cases that cannot be easily covered with our current system, which could lead to opportunities to improve OmniTrack further.



(a) Data Capture Page

(b) Shortcuts for Quick Data Capture

Fig. 1. A semi-automated sleep tracker constructed with OmniTrack. Data Capture page (a) and shortcuts to sleep-related factor trackers (coffee tracker, exercise tracker) located on a phone's notification drawer and the lock screen (b). Note that the "Sleep Duration" field is connected with Fitbit to automatically receive the values tracked by the Fitbit device.

The core contributions of this paper are threefold: (1) we described the design space of flexible and customizable self-tracking informed by preliminary interviews and mobile app analysis; (2) we designed and implemented OmniTrack (Figure 1), a customizable mobile tracking platform that facilitates a semi-automated approach; and (3) we evaluated OmniTrack through usability and field deployment studies to understand how people create, modify, and refine trackers in the lab and in people's natural environment.

2 RELATED WORK

Many research communities—such as human-computer interaction, ubiquitous computing, and behavioral sciences—have been examining ways to support people's self-tracking practices. Specifically, our work builds upon the following three research areas: (1) personal data tracking, (2) universal tracking systems, and (3) semi-automated tracking.

2.1 Personal Data Tracking

People's tracking needs and goals have diversified [59], and so have the available tracking tools [30]. Yet, despite the increasing number of available tracking tools, it is difficult to find a tool that perfectly suits individuals' tracking needs and their diverse goals [38]. For example, numerous food journaling tools exist to help people capture food items and nutritional information. However, these tools fail to fully support the broad range of food tracking goals (e.g., lose weight, identify food triggers, understand food habits) [19]. Due to the mismatch between people's goals and tracking systems' features, many people look for workarounds. A few people with technical skills build custom tools that support specific tracking goals such as self-experimentation [17, 38]. Others have to adapt themselves to existing tools or use generic tools such as spreadsheets or pen & paper [17]. Survey tools also provide customization capabilities to a certain degree for people' diverse data collection needs. For example, Google Forms [29] allows people to collect data in a user-defined format using a familiar form-based interface. Alternatively, people appropriate existing tools (e.g., calendars, instant messengers, Instagram [18]) for tracking purposes. However, these generic tools do not incorporate reminders, tracking-specific assessments, and feedback, all of which could facilitate tracking and help maintain self-awareness.

2.2 Universal Tracking System

Tracking systems for health and wellness (e.g., Apple Health [3], Google Fit [28], and MyFitnessPal [50]) support capturing of health-related behaviors such as steps, calories, weight, and physical activities. They take both manual entries via mobile apps or website and automatic entries from sensors on a smartphone or from an external tracking app. Although these systems allow people to track multiple behaviors, the set of target behaviors is mainly health-related and is predefined by developers. These systems also provide little to no support for configuring data field types and data granularity.

Some systems support end-users to flexibly modify data formats and use tracking facilitators such as notification alarms and triggers. For example, KeepTrack [35], one of the most flexible tracking apps we found, allows people to build their own trackers by combining multiple data types as input components (e.g., numbers, free texts). It also visualizes collected data using basic charts and sets off notifications for awareness and self-reflection. Daytum [11], a web/mobile application which was designed in line with Felton's Annual Report [22], allows to log text-number pairs (e.g., coffee:3) and visualizes the collected data. Felton later released Reporter [23], which asks people to answer customized questions at random times leveraging ecological momentary assessment. Daytum and Reporter help people manually collect personal data in a systematic way. However, all of these systems are tailored to manual tracking only, and do not make use of the external tracking services.

In contrast to the tools that directly support end-user configuration, there are several tools designed to support researchers and developers to create experiment conditions (or apps) and conduct studies. For example, PACO [52] provides a web-based interface for researchers to create and publish experiments. To define an experiment condition, researchers design questionnaires and decide on triggers, which can be deployed to participants' mobile phone. Apple ResearchKit and CareKit [4] allow developers to make their own tracking applications for medical data collections and interventions. Their software development kit (SDK) provides a variety of tracking facilitators so the developer can combine them. However, they are tailored to developing applications for specific clinical research problems so the end-user's tracking flexibility is bounded by how the developer designed the tool. The AWARE framework [24] is a mobile context information instrumentation framework, which supports gathering peoples' input through questionnaires and helps collect their smartphone interaction and sensor information. It provides an SDK for developing a mobile app that collects the data and emits context built based on the events. However, this framework is targeted to developers who want to infer highly-personalized contexts that can be used in other context-aware applications. Therefore, it is not suitable for end-users to create their self-tracking apps on their own. Additionally, Salud! [43] is a software infrastructure designed to support other developers and researchers who want to build personal health applications. Salud! shares a similar goal with OmniTrack: to support flexible, end-user configurable tracking. However, Salud! is predominantly a web application supporting researchers, although end-users can create and configure *Logbooks*, named collections of timestamped data entries. Moreover, end-users cannot integrate external services (e.g., automated tracking apps and devices) as it requires programming. In contrast, we designed OmniTrack based on empirical data and evaluated the system through usability and deployment studies, from which we assessed if and how end-users can create and modify diverse trackers to meet their tracking needs.

In summary, prior works show various approaches to collect data in a flexible way—both for researchers and end-users. However, each of them lacks one or more important components for supporting people' self-tracking needs. On the other hand, OmniTrack takes a semi-automated tracking approach to fulfill self-trackers' diverse tracking needs, leveraging the benefits of manual and automated tracking approaches, which we describe in the following section.

2.3 Semi-Automated Tracking

Both manual and automated tracking approaches have advantages and drawbacks. Manual tracking engages people during the data capture, thereby enhancing their awareness, but it can impose a high data capture burden. On the other hand, automated tracking can reduce the efforts needed to capture data, but people might be less aware of the data unless they diligently check the feedback [40]. Incorporating manual and automated tracking can be highly beneficial in balancing the capture burden and awareness. Recognizing the potential synergy between manual and automated tracking methods, Choe and colleagues defined **semi-automated tracking** as any combination of manual and automated tracking approaches and suggested to leverage semi-automated tracking in designing self-monitoring systems [13]. They discuss three design considerations for designing semi-automated tracking tools—(1) data capture feasibility; (2) purpose of self-monitoring; and (3) self-trackers' motivation level.

Semi-automated tracking encompasses a broad spectrum of designs between the extremes of fully manual or fully automated tracking, ranging from the mostly manual tracking to mostly automated tracking [13]. Many self-monitoring systems have incorporated the semi-automated tracking approach (e.g., [1, 15, 19, 34, 54]). For example, Lullaby demonstrates the mostly automated side of the semi-automated tracking spectrum; it helps people track their sleep duration (Fitbit—automatic) and sleep quality (paper-based sleep diary—manual) in conjunction with potential environmental disruptors, such as bedroom light and temperature levels (off-the-shelf sensors—automatic) [34]. On the other hand, SleepTight examplifies semi-automated tracking toward the mostly manual side of the spectrum; it helps people manually capture various sleep-related behavioral factors (e.g., alcoholic beverages, caffeine intake, exercise) and their timestamps by tapping an icon placed on a mobile phone's lock screen widget to lower the capture burden [15]. Although these systems strive to balance the tracking burden and data capture needs, people are still bounded by how the systems are initially designed. They cannot freely add external services (e.g., SleepTight incorporating the Fitbit's sleep data or Lullaby incorporating Microsoft Band in addition to Fitbit for sleep data) or manual tracking fields (e.g., Lullaby incorporating the stress level).

In this research, we set out to explore how to support highly flexible tracking on a mobile phone, allowing people to dynamically create a new tracker, while leveraging the semi-automated tracking approach. We enable people to reuse existing wearable trackers and to configure manual tracking fields of their choice. Depending on how people construct a tracker combining manual and automated tracking, it can be characterized as mostly manual tracking, a combination of manual and automated tracking, or mostly automated tracking. In our work, we demonstrate how our proposed method can cover this broad spectrum of the flexible semi-automated approach.

3 PRELIMINARY STUDY

To understand people's personalized tracking needs, practices with existing tools, and workarounds, we conducted a preliminary study starting with semi-structured interviews with self-trackers in November 2015. We then analyzed 62 mobile tracking apps from Apple's App Store to identify how they support flexible tracking, and what data types they support.

3.1 Self-tracker Interviews

We recruited 12 (7 female) self-trackers who record at least one daily routine, including workout, studying, sleep pattern, and food intake. We used convenience sampling to recruit the interviewees on a university campus in South Korea. Among those who showed interests in participating, we recruited people only if their recordings were relevant to self-tracking. For example, we did not interview people if they used a calendar for a purely scheduling purpose. Participants' ages ranged from 24 to 34 (M = 26.6). Five participants were graduate students, four were undergraduate students, two were self-employed, and one was a full-time employee. We note that none of our participants were using wearable tracking devices at the time of the study; these devices were not as common as in the U.S. To thank the participants, we compensated them through a gift card equivalent to 4,100 KRW (about 3.50 USD).

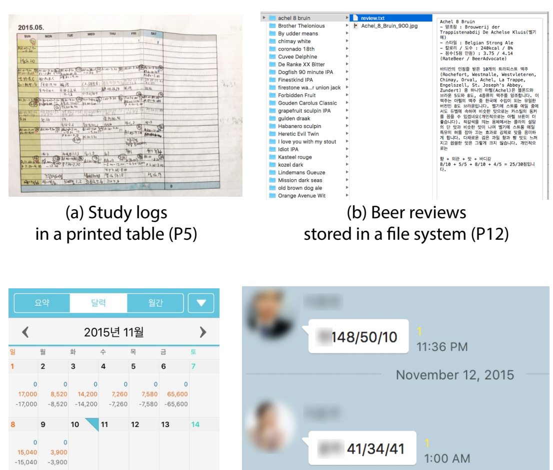
The interview questions covered: (1) target behaviors to track, (2) reasons for tracking, (3) recorded variables to capture the target behaviors, and (4) tracking methods. On average, each interview lasted for about 30 minutes. We took a detailed note while conducting the interviews, which was shared within the research team to identify common themes, which we describe in the following. We also encouraged participants to bring their own tracking data and artifacts (Figure 2). Participants recorded the data in many different ways, including Excel spreadsheets and hand-written logs. In Table 1, we describe what items participants recorded and how they recorded them.

3.1.1 Appropriations of General-purpose Apps for Tracking. We found that participants commonly appropriate general-purpose tools for tracking purposes. Such tools include spreadsheets, note taking apps, messaging apps, photo-sharing social networks, and internet forums/blogs. Participants appropriated these tools for two main reasons: (1) eight (67%) participants manually recorded a target behavior on general-purpose tools because automatic tracking was unavailable; (2) four (33%) participants wanted to leverage the sharing feature supported by existing applications—for example, P8 posted his exercise logs on a shared online space such as a group chat room where each member share their exercise logs to encourage one another. P8 remarked, *"I've been posting the duration of the plank exercise I've done every day on my chat room with exercise club members."*

3.1.2 Switching from Tracking Apps to General-purpose Apps. At the beginning of a self-tracking practice, most participants had tried using various tracking apps before they soon switched to their current methods. They switched to general-purpose apps when (1) tracking apps imposed heavy tracking burden by asking to fill in too many mandatory fields for each entry or (2) existing tracking apps did not support their tracking needs. Appropriating communication tools (e.g., Figure 2d) such as messaging apps or social networking apps effectively reduced the tracking burden because participants were already using those tools for communicating purposes. Simplicity of the input interface was one of the main criteria for choosing a tracking tool to use. P2 remarked,

ID	Tracked Items	Dominant Methods
P1	Exercise, Movie, Food, Ballet, Study	Google Docs with others
P2	Expense, Food, Period	Calendar, Note taking app
P3	Exercise, Expense, Food	Share on messenger, Budgeting app
P4	Food, Study, Step count	Share on messenger
P5	Expense, Trip log	Paper-based diary
P6	Delicious food, Study, Places	Paper-based diary
P7	Exercise, Sleep time	Calendar, Excel
P8	Exercise, Movie, Book, Study	Evernote, Group chat
P9	Book, Places	Note taking app
P10	Exercise, Movie	Paper-based diary
P11	Expense	Budgeting app
P12	Beer Review	Plain text files and photos

Table 1. Summary of the interview participants' information.



(a) Study logs in a printed table (P5)
(b) Beer reviews stored in a file system (P12)
(c) Expense with a dedicated app (P11)
(d) Exercise logs in a messenger (P3)

Fig. 2. Examples of the interview participants' current tracking practice.

"I uninstalled a diet app because it required too many fields on every input. I started using this [note-taking app] because I can log data in a single line."

3.2 Analysis of Tracking Apps in the Market

To better understand common field types that can cover people's diverse tracking needs, we analyzed what field types existing tracking apps support. We searched for tracking apps from Apple's App Store using the keywords, "tracking," "logging," and "recording" in January 2016. We used the App Market Explorer [5] to search for tracking apps with our search criteria because the App Store did not allow custom filtering and sorting. We sorted the retrieved results by total rating count and filtered out the apps with zero rating count. We also removed the apps unrelated to self-tracking from the final set (e.g., music tracks). To ensure a broad topical coverage, we selected up to five apps with best ratings for each App Store category. We installed each app and checked if the app supports self-tracking. The following 16 categories contained at least one self-tracking app: business (5); education (5); finance (5); health & fitness (5); lifestyle (5); medical (5); productivity (5); sports (5); travel (5); utilities (5); book (4); entertainment (3); games (2); music (1); navigation (1); and weather (1). All 62 apps and their field types are documented in the supplementary material available at https://omnitrack.github.io/ubicomp2017.

We identified 12 unique data field types these apps support (Table 2). Overall, textual data field type was the most prevalent. Textual data field types include long text that is usually in the form of notes, or single-line short text that is usually used for simple delineation of an activity. Time-related data field types were also common, and had various forms to support duration capture, time stamping, timer, and stopwatch. Numeric data field types were widely used as well because most health-related variables (e.g., height, weight, distance) are in a numeric form. Other types included choice fields that are supported by either check boxes or radio buttons; boolean types (e.g., indicating if an event was completed or not); locations; images; and ratings (e.g., star ratings, Likert scales). Interestingly, we found several apps that do not have input fields ("No fields" in Table 2), but allow people to add a new entry by just tapping a button to capture the timestamp of the entry or the total number of entries (e.g., goals in a soccer game, prayers in a day).

Field Types	Example Field Semantics	App Count	
Long text	Notes	28	(45%)
Numeric	Book page, Height, Weight	23	(37%)
Date	Semester duration, Event date	20	(32%)
Radio button	Type of book (Soft/hard cover)	20	(32%)
Single-lined text	Title, Name	16	(26%)
Boolean	Yes/No/Skip	16	(26%)
Location	Visited place	11	(17%)
Time	Sleep duration, Event occurred at, Exercise stopwatch	10	(16%)
Image	Food photo	5	(8%)
No fields	Log counting	5	(8%)
Checkbox	Predefined mood tags	4	(6%)
Likert scale	Mood score	2	(3%)
Miscellaneous	Weather, Address book entry	2	(3%)

Table 2. Summary of field types from app market survey.

4 OMNITRACK

Motivated and informed by the two preliminary studies, we designed OmniTrack. In this section, we describe OmniTrack's design rationale and the system along with its user interface.

4.1 Design Goals and Rationales

In designing OmniTrack, we had four design goals:

G1. Cover a broad range of tracking practices, and fulfill individualized and sophisticated tracking needs.
G2. Lower the data capture burden to reduce tracking fatigue.
G3. Enable lay individuals to easily create, manipulate, and modify a tracker and tracking facilitators.
G4. Support the tracker authoring on the phone.

We specifically aimed to address barriers identified in the *preparation* (i.e., when people prepare to start new tracking) and the *collection* stages of Li and colleagues' stage-based model of personal informatics system [39] because problems in earlier stages cascade to later ones. For example, people have difficulty reformatting the exported data when they switch over to a new tracking tool, or abandon their previous data entirely [39]. To address these issues, we enabled people to design and revise the data schema of each tracker during the *preparation* stage (G3). One common barrier in the *collection* stage is a disengagement problem: people may be demotivated or forget to track [15, 17, 39]. To alleviate this issue, we employed *reminders* (Section 4.2.1) and *shortcut panel* (Section 4.2.4). To further lower the capture burden, people can utilize existing automated tracking devices (e.g., Fitbit measuring step counts and sleep duration), which complement OmniTrack's manual tracking features (G2).

Designing flexible tools naturally involves tradeoff between flexibility and usability [41]. In designing the user interface, we decided to cut off several functions and detailed configuration options to keep the interface easy to use for lay individuals (G1) while making the authoring process feasible on a mobile device (G4).

4.2 System Design and User Interfaces

We implemented OmniTrack as an Android app, written in Kotlin [37]. The OmniTrack app consists of three main components: *trackers*, *triggers*, and *external services* (Figure 3). OmniTrack's home screen has three corresponding tabs: (1) *Trackers* tab lists all the existing trackers the user created (Figure 3a), (2) *Triggers* tab lists all the triggers (both *time-based* and *data-driven* ones) the user created (Figure 3c), and (3) *Services* tab shows all the external services that OmniTrack supports (Figure 3d).

After conducting the usability study (later described in Section 6), we connected OmniTrack to our server using Google Firebase [27] to upload and synchronize the tracking data in real-time. When people do not have network connectivity, we cached the tracking data in the device's local database until it is uploaded and synchronized.

4.2.1 Trackers: Enabling Flexible Data Inputs. In the **Trackers** tab (Figure 3a), users can start creating their own tracker by tapping the "+" button, which will lead them to the **Edit Tracker** page (Figure 3b). Users can add diverse data fields such as short text, long text, number, ratings, time point, time span, choice, location, image, and audio record. We determined these field types based on the tracking app analysis (Section 3.2). Each field type has its own input graphical user interface that can be configured in the **Field Details** page (Figure 4a).

Tapping on a tracker in the tracker list opens the **Data Capture** page of the tracker (Figure 8a, left), where users can enter data in a form configured in the Edit Tracker page. While each field can be manually filled in, OmniTrack also provides various options for setting default values, such as values based on internal semantics of field type (e.g., present time for time field, current GPS position for location field) or the last logged value. Furthermore, the field can be automatically filled with a value retrieved from existing commercial trackers such as Fitbit and Misfit.

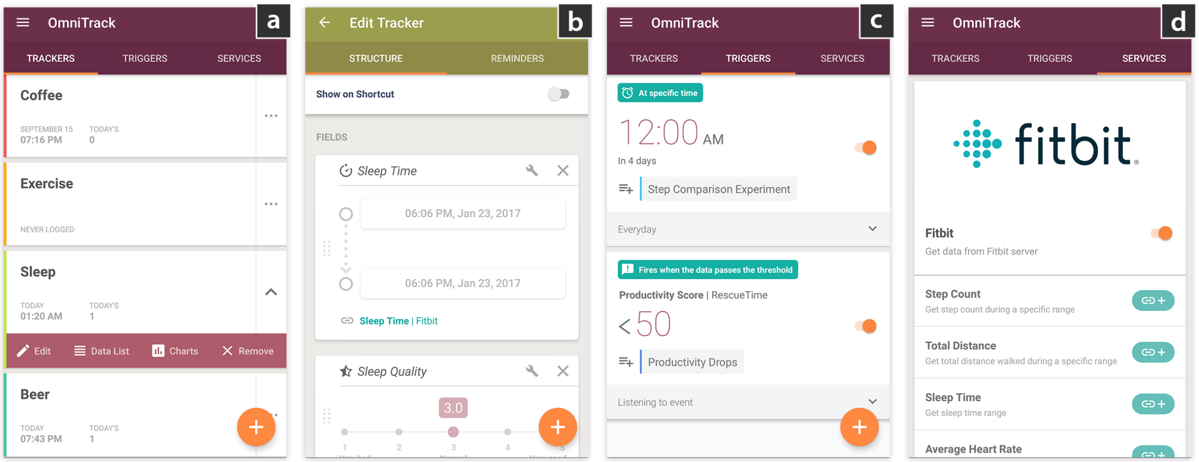


Fig. 3. The OmniTrack interface. A list of existing trackers are shown on the Trackers tab (a), where people click the "Edit" button to open the Edit Tracker page (b) for modifying the trackers. The automatic triggers are listed on the Triggers tab (c), and the external services are listed on the Services tab (d).

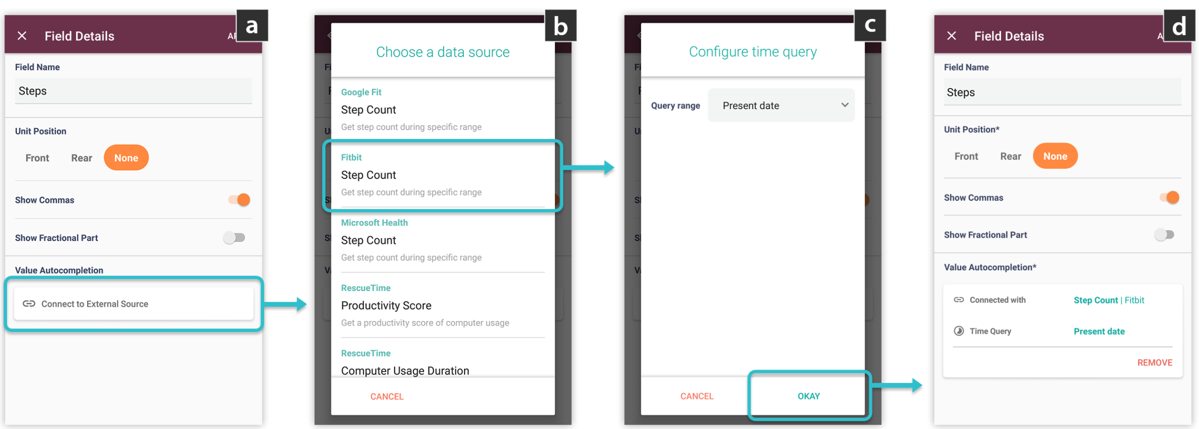


Fig. 4. A process of connecting a measure factory to a data field: (a) tap on the value connection button in the Field Details page, (b) choose which data source to connect, (c) configure time query range, and (d) check the configuration result.

People can also configure **reminders** to inform themselves to input a new tracking entry, listing them on the system notification drawer. They can open the Data Capture page of a tracker by tapping a corresponding reminder item. Given that notifications increase tracking adherence [9], the reminders can support people when the OmniTrack tracker need to be manually recorded punctually and periodically.

4.2.2 Services: Integrating External Trackers and Other Services. Those who are already using external tracking devices, such as Fitbit, Misfit, and RescueTime can integrate data from those devices to OmniTrack. In the **Services** tab (Figure 3d), users can choose and activate the external services that they are currently using. Connecting to the existing sources using the APIs or SDKs requires authentication or similar setup process before they can be activated on OmniTrack. Each external service provides multiple types of **measure factories**, a data provider unit which yields a field value from the service. For example, a Fitbit service provides several measure factories including step count, distance, and sleep duration.

The measure factories can be attached to each tracker's data field through **value connection** settings (Figure 4, Figure 5b). Users can designate a measure factory and set parameters needed to query the measure factory (Figure 4c). Measure factories need query scope, which specifies time range (starting from 12:00 AM) for the query relative to the tracking moment. We simplified the configuration and allowed people to select one query scope among predefined presets (i.e., present day, previous day, recent 1 hour, and recent 24 hours.) using a combo box. For example, 'present day' stands for the scope from 12:00 AM to the tracking moment for the same day. The value-connected fields are automatically filled in when triggers are fired to query the factories.

External services and measure factories that OmniTrack currently supports are as follows: Microsoft Health [45] (synchronized with MS band [44]'s step count and sleep time), Fitbit [25] (step count, distance walked, average heart rate, and sleep time), Misfit [46] (step count and sleep time), UP by Jawbone [62] (step count and distance walked), Google Fit [28] (step count), and RescueTime [57] (productivity and computer usage duration).

4.2.3 Triggers: Retrieving Values Automatically. OmniTrack takes a semi-automated tracking approach by combining manual capture and automated capture using triggers (Figure 3c, Figure 5d). Once triggers are fired, OmniTrack retrieves tracking values from external services and automatically logs the values. Users can manage triggers in the **Triggers** tab (Figure 3c).

OmniTrack supports two types of triggers (Figure 3c): time-based and data-driven. Time-based triggers can be fired either at the preset time or at periodic intervals. For example, using time-based trigger, previous night's sleep data from Fitbit can be retrieved at 9AM the next morning, and automatically filled in every day. Data-driven triggers are associated with the external services. A measure factory (Figure 5c) can be attached to a trigger along with a threshold value so that the trigger sets off an action when a tracking value passes the threshold. For example, people can set a trigger to automatically record the time they achieve the daily 10,000 step count goal (i.e., step count = 10,000).

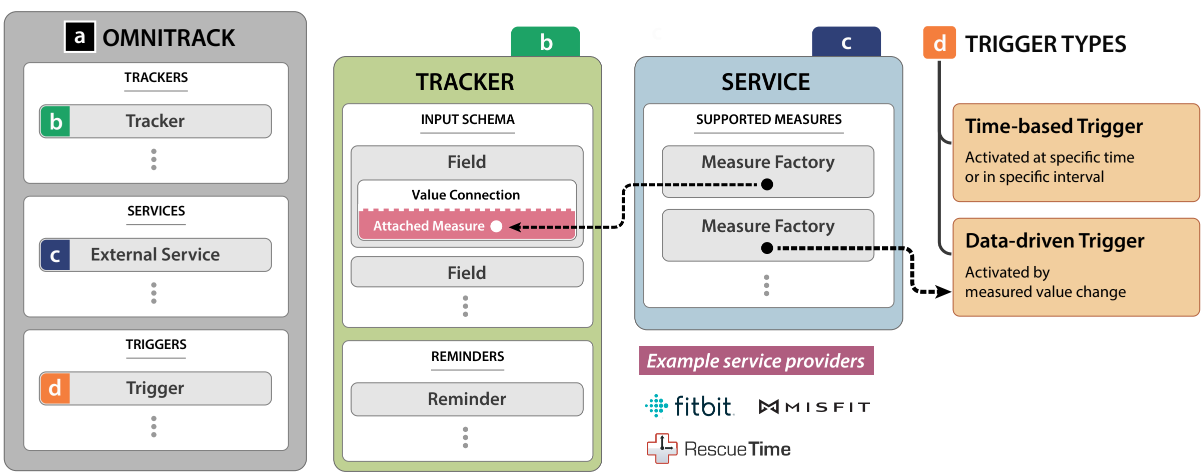


Fig. 5. The OmniTrack system architecture. The OmniTrack app (a) consists of multiple trackers and connects to services. Each tracker (b) has user-defined fields and reminders that notify at specific time or periodically. Services (c) are connected to the existing tracking systems and provided measures that can be leveraged as a field value (b) or to fire a trigger (d). Triggers (d) are used to log the tracker entry with automatically filled values in the background.

Triggers and trackers can be connected with a many-to-many relationship; for example, one trigger can feed in data fields in multiple trackers, and one tracker can be activated by multiple triggers. Triggers are designed based on the *trigger-action model* [64], which is actively employed in many end-user Internet of Things (IoT) configuration interfaces. The trigger-action model is a straightforward approach to command user-defined tasks and it is known to be learnable and understandable to non-programmers [63].

4.2.4 Streamlining Tracking and Lowering the User Burden. Promoting self-awareness and lowering the capture burden are key issues in designing a tracking tool [15, 17]. We designed OmniTrack to deploy the **shortcut panel** (Figure 1b) on the system notification drawer or on the lock screen, which provides easy access to the trackers, thereby increasing the tracking adherence rate [15]. People can select up to five trackers to be displayed in the shortcut panel. Depending on the configuration, tapping on a tracker icon (e.g., coffee) either invokes the Data Capture page to provide easy access to the tracker, or instantly captures the timestamp without requiring additional manual inputs. We learned from the app analysis that the latter case (i.e., 'No fields' in Table 2) was a simple and efficient way for counting items or capturing a single time stamp. For example, to make a simple sneeze tracker that records the moment of sneezing, a tracker with a single time point field can meet the tracking needs. As the user taps on the tracker icon upon sneezing, a new entry is immediately created with the time point field filled with the current time.

4.2.5 Visualization and Feedback. We designed two visualization components to provide feedback on tracked items: the **Item List** page (Figure 8a, right) and the **Visualization Dashboard** page (Figure 8b). The item list displays a list of all the entries of a tracker. The entries can be sorted by any data field. Users can review, edit, or remove each entry. Although it does not provide a comprehensive overview of the data, the list is suitable for browsing the data tracked for the journaling purpose such as book reviews and diaries. The visualization dashboard consists of charts recommended by the system. Because the semantic of each field and relationships among the fields are not determined a priori, OmniTrack determines the type of visualization and encodings based on the field types used in the tracker. OmniTrack currently provides the following four charts: (1) a heatmap timeline that displays the timestamps for all the entries in a single tracker (Figure 6a), (2) a duration chart that shows durations on timeline for each time span fields (Figure 6b), (3) a line chart with x-axis representing time and y-axis representing the numeric ranges of the number fields in a tracker (Figure 6c), and (4) a histogram for each single choice field (Figure 6d). Users can select a specific duration of time using the time range bar (Figure 8b) to see charts for the data within the selected time range.

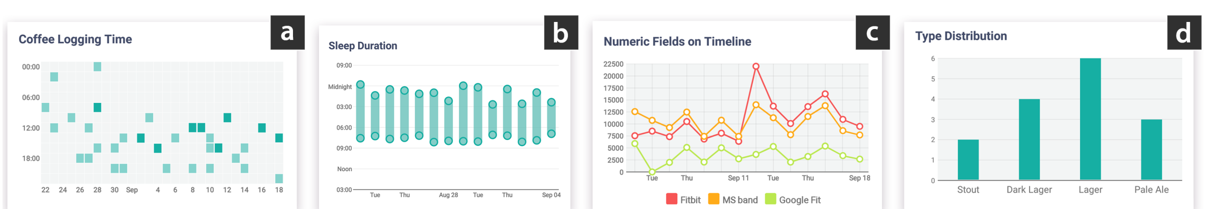


Fig. 6. Visualizations used in the visualization dashboard. Each chart is recommended based on a tracker's schema. A logging time heatmap (a), a duration timeline chart (b), line chart (c), and a histogram chart (d).

5 OMNITRACK USE CASES

In this section, we demonstrate three use cases—ranging from mostly manual tracking to mostly automated tracking [13]—to demonstrate OmniTrack's broad spectrum of coverage in terms of tracking mode (Figure 7). For each case, we describe a self-tracking scenario drawn either from the preliminary interviews or from prior research. Refer to our supplementary video to see how to construct and interact with each tracker.

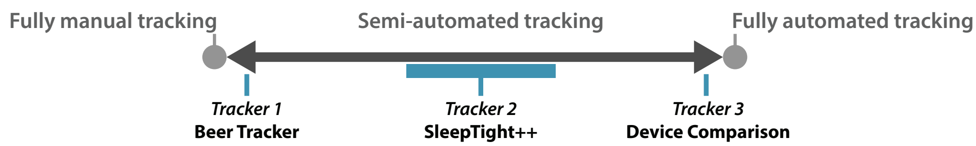


Fig. 7. Example trackers mapped on the semi-automated tracking spectrum.

5.1 Tracker 1: Beer Tracker

This use case is inspired from the interview with P12, who tracks what beer he drinks. David, an enthusiastic beer drinker, enjoys trying out new beers and wants to document the experience. For each beer, David wants to record (1) a photo of the beer, (2) drinking date, (3) beer name, (4) beer type, (5) beer taste (i.e., a review score for the beer), and (6) written review. David needs to enter most of these data manually except for the drinking date, which can be automatically captured. Thus, this scenario represents a case toward the mostly manual side of the semi-automated tracking spectrum. The primary goal of the self-tracker in this scenario is journaling (i.e., documentary tracking in [59]), rather than changing behavior or gaining comprehensive knowledge [59].

5.1.1 Tracker Construction. A single tracker named "Beer Journal" containing the following six fields was designed. The field configuration settings are shown inside the parentheses:

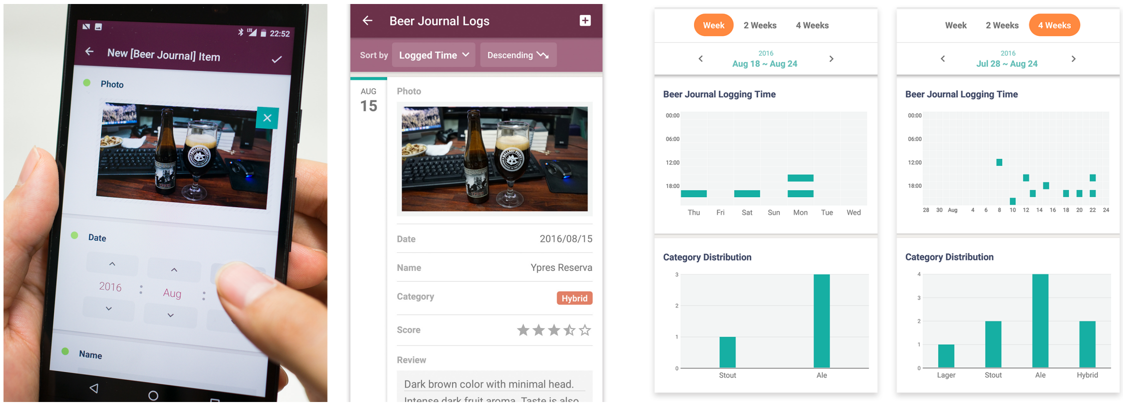
(1) Photo of beer: Image
(2) Drinking date: Time (granularity=date)
(3) Beer name: Short Text
(4) Beer type: Choice (multiple selections=false)
(5) Taste Score: Rating (style=stars, max score=5)
(6) Review: Long Text

For easy access, the tracker was put in a *shortcut panel*.

5.1.2 Usage. When trying a new beer, David taps on the beer tracker icon in the shortcut panel, which opens the Data Capture page. In the form, he takes a picture of the beer (Figure 8a, left). After he tastes the beer, he enters the rating when the memory is fresh. If he is not in a situation to write a review (e.g., being with his friends in a pub), he can complete the rest of the review and push the entry later because the tracker preserves the data already filled in. At the end of each month, David reviews his Beer Journal. He first opens an Item List page to see the list of the tracked beer entries (Figure 8a, right). He sorts the entries by rating to see the beers he liked the most. Then, David opens a Visualization Dashboard page to check out any interesting patterns. A heatmap (Figure 8b, upper right) reveals the time he usually drinks beer, and a histogram shows the distribution by beer type (Figure 8b, bottom right). David switches to a different time range to see if the distribution of beer type has changed (Figure 8b).

5.2 Tracker 2: SleepTight++

This use case is inspired by SleepTight [15], a prior research project aimed to support self-awareness of sleep behaviors through self-monitoring. The original SleepTight design requires users to manually track most of the tracking fields (e.g., sleep measures and sleep-related factors). To lower the capture burden of manual tracking, OmniTrack can be used to build SleepTight++ by leveraging existing sleep tracking devices such as Fitbit, which automatically captures sleep. This scenario represents balanced semi-automated tracking. For the sake of demonstration, we condense the variables and types of factors from the original SleepTight by skipping elements that need redundant descriptions. Like SleepTight, current OmniTrack does support visualizing data from multiple trackers together to see the relationships between two factors.



(a) Capturing and Browsing Beer Review

(b) Visualizations of the Beer Tracker

Fig. 8. Data Capture page of the beer tracker (a-left) and the item list showing a previously captured entry (a-right). Summary visualizations showing different time range: 1-week view (b-left) and 4-week view (b-right).

5.2.1 Tracker Construction. SleepTight supports people to track sleep-related information (e.g., the time span of sleep, sleep quality) and occurrences of sleep-related factors (e.g., smoking, coffee intake, and exercise). While the sleep information needs to be tracked once a day (and everyday), sleep-related factors usually occur multiple times a day or once every few days. Therefore, it is better to construct multiple trackers to track sleep and sleep-related factors separately. The first part of SleepTight++ is a daily sleep diary, which consists of the following field types:

(1) Sleep duration: Time Span
(2) Date of sleep: Time (granularity=date)
(3) Quality of sleep: Rating (style=stars, max score=5)

The next step is to connect the sleep duration field to an external device such as a Fitbit service via value connection; in the case of Fitbit, the query scope is set to “today” because Fitbit API sets the date of sleep as the date of waking up. In addition, a reminder is set to 9:00 AM every morning to increase the tracking adherence.

To capture sleep-related factors manually, two additional trackers are added: coffee tracker and exercise tracker, each with a single time field. Mimicking SleepTight’s lock screen widget, the **instant logging buttons** for the two trackers are placed in the shortcut panel for easy access.

5.2.2 Usage. At 9:00 AM every morning, Kai receives a reminder to enter the previous night’s sleep summary. When he taps on a reminder notification and accesses the Data Capture page, the sleep duration field is automatically filled in by the Fitbit service and the date of sleep field is set as today. If he notices a definite error in sleep duration captured by Fitbit, he can manually correct the error. Now Kai only has to enter sleep quality to complete the sleep diary entry (Figure 1a). During the day when he drinks a coffee or exercises, he just taps on the tracker icon in the shortcut panel to instantly record the timestamp of each activity (Figure 1b). From time to time, Kai checks his sleep pattern using the duration chart (Figure 6b) in the Visualization Dashboard page.

5.3 Tracker 3: Comparison of Automated Trackers

Because most commercial activity trackers store their data in a separate service database, it is not easy to gather data from multiple sources. Yet, prior research reports that some people have a tendency to use multiple trackers measuring the same behavior [59] and attempt to compare the measures from the devices [17, 31, 68]. Based on this finding, we created a scenario of Zoe, who is curious about differences across activity measures collected from multiple sources. Zoe owns two activity trackers (Fitbit and Microsoft Band) and also uses Google Fit, an embedded sensor in an Android device. Reading reviews about some trackers overestimating step counts than others, she decides to compare her step count measures from all three sources. This scenario represents a case more toward the *mostly automated* side of the semi-automated tracking spectrum.

5.3.1 Tracker Construction. A single tracker containing three number fields is created as follows:

(1) Fitbit steps: Number (type=integer)
(2) MS Band steps: Number (type=integer)
(3) Google Fit steps: Number (type=integer)

To automatically pull the total daily step count, Zoe sets the trigger to log the entry at 12:00 AM every day. Then she connects each field to corresponding services using a measure factory. She configures the query scope to be "yesterday" to record the total daily step counts.

5.3.2 Usage. Zoe makes sure that she wears the two activity trackers and carries her smartphone as much as possible. At midnight every day, the device comparison tracker automatically retrieves the total daily step counts from the three services and logs the data in the background. Once a week, Zoe compares the step counts collected from the three services by looking at the time-series visualization; a line chart with each line indicating a different service, x-axis indicating date, and y-axis indicating the total step counts (Figure 6c). Using this visualization, Zoe checks the overall trends and constructs a preliminary hypothesis before conducting further analyses. After collecting additional data for a month, Zoe exports the data into a CSV file to conduct detailed analyses using her favorite data analysis tool.

6 USABILITY STUDY

We first evaluated OmniTrack through a usability study in the lab, from which we wanted to learn whether people can understand OmniTrack's core concepts and create trackers leveraging OmniTrack's various features.

6.1 Participants

We advertised the study on Facebook and the university's research participants recruiting website. We recruited 10 participants (referred to as U1–U10 later) who met the following inclusion criteria: (1) have used an Android smartphone for 6 months or longer; (2) have self-tracking experience using either manual or automated method; and (3) have motivation for self-tracking. Participants' ages ranged from 22 to 31 (M = 26.8) and half of the participants were female. Seven participants were graduate students, two were undergraduate students, and one was a full-time employee. Two had experience using one or more wearable tracking devices. One participant had used form builders such as Google Form [29] and Survey Monkey [61] for data collection purposes.

6.2 Procedure and Study Setup

At the beginning of each session, we asked participants to fill out a pre-study questionnaire to collect their background information about tracking practices and their experience with form builders. Then we gave participants a 15-minute tutorial, which covered OmniTrack's core features, including schema design, external service connection, and triggers. The tutorial also covered several tracking scenarios that OmniTrack support. After the tutorial, we asked participants to perform four tasks. The experimenter did not intervene unless participants asked for a hint. After participants completed the main tasks, we employed the System Usability Scale (SUS) questionnaire [10], a quick way to collect quantitative feedback on usability. SUS consists of 10 questions (e.g., "I think that I would like to use this system frequently."), which can be answered using a 5-point Likert scale anchored by strongly disagree–strongly agree. Finally, we debriefed the participants to learn about their experiences and to gather any feedback or suggestion to improve OmniTrack. The whole session lasted about an hour.

We conducted the study on a Google Nexus 5x smartphone with a 5.2" touchscreen. We recorded participants' interactions using a video camera positioned directly above the study device, and audio recorded the debriefing sessions. We offered 15,000 KRW (about 12 USD) to thank the participants.

6.3 Tasks

The first three tasks involved building trackers from scratch based on a given scenario and specifications of a tracker, and the last task involved building any custom tracker that participants want to use. We designed the tasks that required participants to use a variety of configurable options supported by OmniTrack, including diverse field types and the advanced components such as triggers and the external services. The tasks and their key components are similar to the ones presented in the OmniTrack use cases (Section 5): (1) a beer tracker (a basic schema design and a shortcut panel); (2) a sleep tracker (value connections with external services and constructing multiple trackers for a particular purpose); (3) a 10,000-step tracker (incorporating a data-driven trigger observing the step count measured by Fitbit); and (4) the custom tracking system. Refer to the supplementary material for detailed task scenarios and requirements.

6.4 Results and Discussion

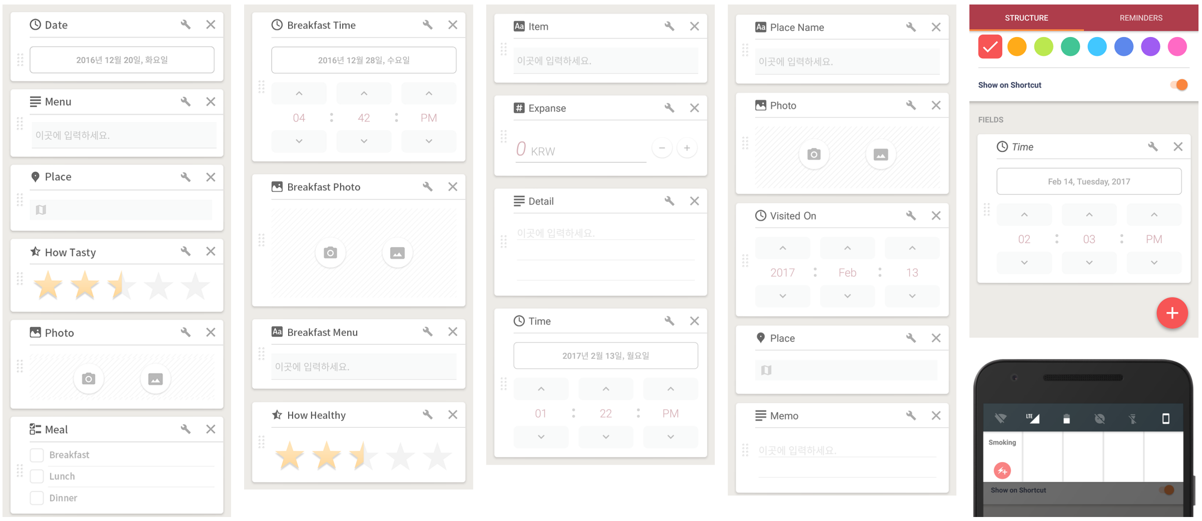
6.4.1 Task Completion. All participants were able to complete all four tasks; seven participants completed them without any hint, and three requested one hint throughout the tasks: U2 inquired from where to configure a reminder during Task 2, U5 could not find a setting (switch) to locate a tracker in a shortcut panel during Task 1, and U10 forgot how to connect Fitbit's sleep duration measure to his tracker during Task 2.

On average, it took 2 minutes and 26 seconds (*SD* = 32 seconds) to complete Task 1, which was the easiest task that involves creating six data fields. Participants spent much time on typing the names for each field. It took on average 2 minutes and 34 seconds (*SD* = 49 seconds) to complete Task 2, which involves value connection feature and making additional coffee tracker. Completing Task 3 took one minute and 17 seconds (*SD* = 21 seconds), which was the shortest due to the simple schema of the tracker. During the task 2, some participants went through trial and error because they were confused by data-driven trigger and value connection.

In Task 4, all participants successfully created a custom tracker that they would like to use in their everyday life. Trackers that participants built included breakfast tracker, meal tracker, expense tracker, travel log, scheduler, smoking behavior tracker, meal time tracker, pill tracker, and a complex tracker containing variables asking detailed daily routines (see Figure 9). One participant created an exercise tracker that leverages data-driven trigger, which automatically logs his exercise event when Fitbit's heart rate is above a certain threshold. As we expected, trackers were designed to serve different purposes and had different schemas. Interestingly, among the trackers participants designed, there were three versions of a meal tracker (Meal tracker, Breakfast tracker, and Meal time tracker), but with different schema serving different scenarios.

No participant used value connection to build a semi-automated tracker. We suspect that participants' tracking experiences were biased toward either mostly manual tracking (e.g., paper diary or calendar apps) or mostly automated tracking (e.g., Samsung S Health [32], which involves background sensing of physical activity). Thus, participants might have been unfamiliar with the concept of combining manual input and automated sensing.

6.4.2 Debriefing and SUS Questionnaire. Overall, participants liked OmniTrack as a means to design their own trackers. During the debriefing session, eight participants mentioned flexibility as one of the most favored features. Some participants mentioned that OmniTrack's flexibility would alleviate the burden of finding an app that suits their tracking needs. For example, U1 remarked, *"When I start to track a new item, I search the App Store with a keyword and download at least five apps that support my goal. After trying out each app, I remove them except*



(a) Meal Tracker (b) Breakfast Tracker (c) Expense Tracker (d) Travel Log (e) Smoking Tracker

Fig. 9. Screenshots of the custom trackers designed by participants in Task 4. Each tracker is designed by different participant. While both (a) and (b) track meals, they have different schema and level of complexity.

one that best matches the schema I want. This app [OmniTrack], however, will get rid of such a process." Participants also liked *triggers* and the capability to connect to external services. Nine participants mentioned that they will use the *value connection* feature when they use OmniTrack. Another feature they liked was the *shortcut panel* and its *instant logging* functionality because it lowers the capture burden. Participants used the instant logging button when designing trackers such as *location pin tracker*, *smoking tracker*, and *meal time tracker*. Half of the participants mentioned that the interface was intuitive and easy to use. U9 remarked, *"Its design was intuitive and not strange compared to other tracking apps. I just followed the steps naturally [to do what I intended]."* U7 also remarked, *"The app is concise. I think that a broad range of audience can use this [OmniTrack]."*

The average SUS score was 67 (SD = 13.73, ranging from 42.5 to 85), which is evaluated as marginally acceptable according to [8]. It is not recommended to interpret scores of individual SUS questions [8]; instead, we discuss why the total score was marginal based on our observation and the debriefing feedback. We suspect that OmniTrack was perceived to be challenging to learn without any guidance. While performing the tasks, many participants went through trial and error especially when they were learning novel concepts such as value connection and triggers. During the debriefing session, some participants raised concerns about learnability of the triggers and value connections. Three participants pointed out that the tutorial was critical for performing the tasks successfully, and were unsure about how they could have performed without the tutorial. For example, U2 said, *"I could easily use the value connection feature, but I might have had been unable to use this feature if I hadn't learned it from you [experimenter] during the tutorial."* They suggested to show simple instruction tutorial on the first launch of the application to inform people about the unfamiliar features.

6.5 Improvements After the Usability Study

After the usability study, we addressed several usability and design issues raised by the participants. The most confusing workflow was value connection, that is, connecting a specific field in a tracker (e.g., the "sleep duration" field in a "Sleep Tracker") to values provided by an external service (e.g., "Fitbit"). To do this task, participants often went to the Services tab and then tried to connect a service to their tracker, whereas the workflow we designed was to go to the Edit Tracker page of a tracker, select a specific field, and then connect to a service. To address this confusion, we revised the design and allowed to initiate the value connection in both ways. In our final version, people can see the list of available measure factories on each service list item (Figure 3d). Tapping on the measure factory name allows people to choose tracker and its field which the measure can be attached to.

Given the comments that tutorial was crucial in understanding OmniTrack's usage, we added tooltips and simple instruction pages on the app. The instruction pages automatically show up at the first launch, and can be always accessed in the application menu. We believe that such instruction would be effective during the deployment study. We also fixed other minor issues caused by system bugs and GUI design flaws.

7 FIELD DEPLOYMENT STUDY

After addressing the issues identified from the usability study, we conducted a 3-week field deployment study followed by an exit interview. Our goal was to assess if people can capitalize on OmniTrack's flexible and customizable design to meet their tracking needs in their natural environment without a guided tutorial.

7.1 Study Setup

We remotely deployed the Android implementation of OmniTrack via Google Play Store as a private beta release, which exposes the app only to the designated Google accounts. We did not provide an individual training session, but instead included four example trackers shown in the participants' accounts: (1) a coffee intake counter with a shorcut, (2) a diary with a reminder, (3) a daily activity tracker that automatically logs daily step count from Google Fit and sleep duration from Fitbit, and (4) a restaurant tracker to log the time of the visit as well as photo, rating, review, and location of the restaurant. We included these example trackers to demonstrate OmniTrack's capability, helping people who might have difficulty creating trackers from scratch. We allowed participants to edit or delete these example trackers.

After three weeks from the account activation, we arranged an exit interview with each participant (we did not contact participants during the 3-week deployment period.) We conducted semi-structured interviews in our lab or over Skype depending on participants' availability. From the interview, we aimed to learn (1) OmniTrack usage patterns and styles; (2) participant's tracking experiences before and after using OmniTrack; and (3) opportunities to improve OmniTrack. The interviews were audio-recorded to aid in the analysis.

7.2 Participants

We advertised the study on Facebook, campus recruiting website, and internet forums of wearable devices. We emailed the OmniTrack installation manual to 31 people who filled out the screener and met our inclusion criteria: (1) Android smartphone users; (2) have self-tracking experience using any methods (manual or automated) and interested in self-tracking; and (3) not under the situation that prohibits access to their smartphone for more than three consecutive days during the study period. The installation manual contained the Google Play Store link to OmniTrack and study instructions (i.e., install OmniTrack, create at least one tracker within a day, and participate in an interview after the 3-week study period). Among the 31 people who installed the app, we excluded three people who had never created a new tracker. We eventually excluded additional seven participants, who declined or did not respond to participate in an exit interview. We note that some of the participants may have enrolled the study without strong motivation to use OmniTrack and dropped out after a short usage.

Among the final 21 participants (referred to as D1–D21 later), 11 (52.3%) were female. Their ages ranged from 22 to 34 (M = 26.8). Eleven participants were undergraduate students, six were graduate students, and four were full-time employees. Five people were using the extra tracking devices such as Fitbit, Jawbone, and Wi-Fi weight scale. As a compensation, we provided 20,000 KRW (about 18 USD) to the participants who completed the study.

7.3 Data Analysis and Results

We had access to participants' trackers, field types, and field labels (but not the actual data entries). We also captured the app *usage logs* including page sessions and edits (e.g., adding and removing fields). Using the *usage logs*, we classified the trackers into three groups: *example* (the example tracker whose design has not been modified), *example-edited* (the example tracker whose design has been modified by participants), and *custom* (the tracker which was created by participants from scratch). By the end of the study period, participants retained a total of 95 trackers: among these, 46 were *custom*, 40 were *example*, and 9 were *example-edited* trackers.

To understand how participants designed their trackers with OmniTrack, we analyzed their usage behaviors in both qualitative and quantitative ways. As for the qualitative analyses, we labeled and categorized the *custom* and *example-edited* trackers in terms of their styles, target behaviors, and goals. When labeling, we referred to participants' interview comments to understand semantics and intentions of participants. For example, trackers that were designed to capture "study duration" and "online lecture" were both categorized as "study" trackers even though they belong to two different tracker styles (see Table 4). In addition, we identified themes regarding the motivation to use OmniTrack, experience with OmniTrack, and barriers of customization from the exit interviews. As for the quantitative analyses, we reported descriptive statistics on field data types and tracker types, as well as the diversity of the trackers. The supplementary material contains a full list of 21 participants and their tracking experiences.

7.3.1 *OmniTrack Usage.*

Overall, participants actively created and modified their trackers. At the end of the study period, each participant retained an average of 4.52 trackers (SD = 1.62, ranging from 2 to 9). They also removed an average of 3.76 trackers (SD = 2.75, ranging from 0 to 12). At the time of the interview, 18 participants were using customized trackers; the other three participants had created custom trackers but removed them. Table 3 shows the average number of trackers each participant created.

Over the course of three weeks, each participant logged 33.62 items on average (SD = 23.32, ranging from 6 to 116). The daily log count peaked during the first week after the activation and plateaued over time. We found that most participants attempted to use OmniTrack to track behaviors they were originally tracking, except for several edge cases (described below). Nineteen participants were tracking at least one of their original tracking behaviors, and 12 of them successfully migrated all of their original tracking with OmniTrack. Inspired by the *example trackers* and the flexibility of OmniTrack, 17 participants started to track additional items. For example, D8 remarked, *"I had been using Google Calender for recording travel logs. Because it was tedious to access Google Calendar multiple times a day, I recorded multiple items as a single event of a day at once. I used this [OmniTrack] for logging my business trips. [With OmniTrack] It was easy to capture each individual item with an automated timestamp, and I could even upload photos with location tags, which is not possible with Google Calendar."*

Participants also reported several edge cases that were *not* supported by OmniTrack. Mostly, participants did not migrate to OmniTrack if their current offerings provide a very specialized functionality to track specific target behaviors. For example, many participants mentioned personal budgeting apps that automatically parse smartphone's incoming SMS messages of credit card transactions. Some female participants mentioned that they

		Tracker Group			
		Custom	***Example-edited***	***Example***	**Total**
Status	**Retained**	2.19 (SD = 1.93)	0.42 (SD = 0.74)	1.90 (SD = 1.47)	4.52 (SD = 1.62)
	Removed	2.09 (SD = 1.77)	0.09 (SD = 0.29)	1.57 (SD = 1.56)	3.76 (SD = 2.75)

Table 3. The average tracker count per participant (N = 21) by tracker group and by status upon completion of the deployment.

are tracking their menstrual cycles using period-tracking apps, which are calendar-based and predict upcoming cycles. D5 remarked, *"Calendar is really important for period tracking. I can see the dates, next cycles ... Regarding periods, anticipating the upcoming cycle is more important than reviewing my previous period. So the purpose of tracking was a bit different from what's supported by OmniTrack."* One participant did not transfer book tracking to OmniTrack because he was using his custom Google spreadsheet, which is configured to automatically calculate the progress: *"I didn't track my reading with OmniTrack because I'm using my own Google sheet, which is already customized quite a bit. When I enter the number of pages I read and the total page count, this cell automatically calculates the progress in percentage with saturated background. It seemed hard to get that in OmniTrack"* (D13).

7.3.2 Tracker Styles and Style Diversity. We analyzed the 55 *custom* and *example-edited* trackers and identified four tracker styles in terms of data capture method, complexity, and time scope. Fifty out of 55 trackers were categorized to one of the following four styles: in-situ experience tracker; timestamper; daily summary; and archive. The remaining five were To-do lists, which we did not list as a tracker style category because these trackers' main usage—making up for prospective memory—seemed to be an "appropriation" of OmniTrack, which is designed to support retrospective memory. Table 4 shows the summary of target behaviors of the *example-edited* and *custom* trackers by each style. Below we describe each tracker style in detail:

Style 1: In-situ Experience Tracker (17 trackers by 11 participants)
In-situ experience tracker supports the most canonical form of self-tracking, producing a time-series data. Using these types of trackers, participants usually captured an event with surrounding contexts in diverse situations, including mood, exercise, and visited places, with several autocompleted fields such as time and location. These trackers usually represent the mostly-manual side of the semi-automated tracking spectrum.

Style 2: Timestamper (14 trackers by 9 participants)
Timestamper is a special type of the in-situ experience tracker with or without an explicit time field. The captured items contain the occurrences of a target event and its time. In most cases, they were in the shortcut panel and acted as a one-click tracker to lower the capture burden (referred to as "streamlined manual tracking" in [13]). Participants used this type of tracker to capture drinks, medication intake, specific emotions (e.g., sadness), or predefined activities (e.g., one session of a specific exercise).

Style 3: Daily Summary (9 trackers by 8 participants)
Daily summary trackers usually contain a date field and capture summarized or aggregated values of the day. Seven out of 9 trackers in this category were designed to capture health-related data such as step counts, walking distance, or sleep duration of the day. One participant tracked how many cups of coffee he consumed per day in a number field. Participants usually connected these trackers to external activity trackers to automatically pull the value using triggers, or manually entered a value at night when promoted by reminders [15].

Tracker Style	Target Behaviors	Example Custom Trackers
In-situ Experience	Exercise (4), Mood (3), Health (2), Book (2), Study (2), Visited Place (2)	**Mood** [when(datetime), mood(likert scale, negative to positive), emotion(choice)] + shortcut
Timestamper	Study (4), Pill (3), Mood (2)	**Allergy Pill** [taken at(datetime)] + shortcut
Daily Summary	Health (7), Coffee (1), Productivity (1)	**Health** [Date(date), Fitbit steps(today), Fitbit distance(today), Fitbit sleep duration(today)] + time-based trigger
Archive	Wish list (7), Memo (3)	**Restaurant-Wanna-Go** [memo(long text)] + shortcut

Table 4. Four tracker styles with target variables and example of *custom* tracker.

Style 4: Archive (10 trackers by 6 participants)
Although self-tracking is usually time-based, some participants used trackers to capture items that are not related to time. Participants used these trackers in place of a memo app or journal, recording their thoughts or wish list items [59]. Most archive trackers contained a single text field.

To examine the diversity of the tracker styles for each participant, we counted the number of distinct styles each participant used. For this analysis, we included the *example* trackers in the dataset and counted To-Do lists in the fifth style (Note that we did not include them to the tracker styles). On average, participants used 2.52 tracker styles (SD = 0.87), and 10 (47.6%) participants used three or more tracker styles.

7.3.3 Tracker Schemas and Schema Diversity. To examine the diversity of OmniTrack usage, we analyzed the *example-edited* and *custom* trackers in terms of (1) how diverse the field schema of the trackers are and (2) how diverse the tracker design within the trackers that capture similar target behaviors.

The trackers that participants designed or modified had 26 unique schemas. Figure 10 shows the distribution of a unique set of tracker schemas. The long-tailed distribution represents individualized and customized trackers participants created, with more complicated trackers being at the tail end.

We found that participants often used a different schema or tracker styles even for capturing similar target behaviors. Based on tracker's name, schema, and feedback from the exit interview, we labeled each tracker based on the target behavior, producing 21 groups. Eleven out of 21 target behavior groups were captured with at least two uniquely-designed trackers. One prominent group was *health*; seven participants designed nine trackers to capture some aspects of health. Most of the health trackers were *daily summary* trackers, which included fields connected to external activity trackers, or fields for manual inputs such as body fat. For example, D11 designed two health trackers, one for automatically capturing variables from Fitbit using a time-based trigger and another for manually capturing weight and body fat with a reminder setting.

Two participants (D8 and D19) designed five trackers to capture different aspects of *mood*, demonstrating heterogeneous design concepts. D19 designed two mood trackers; one was a *timestamper* designed to capture when he cried, and the other was an *in-situ experience* tracker designed to capture the mood type and rating in a 10-point Likert scale. D8 designed three mood trackers, each of which captured happiness, sadness, and encouraging moments, respectively. The three trackers had a different schema and tracking style: the happiness tracker contained multiple fields including image and audio recording fields to capture context; the sadness tracker contained a text field to capture the causes of sadness; and the encouraging moment tracker contained a *timestamper.* Another high diversity group was *exercise* (5 trackers by 5 participants). For example, D16 captured ping pong games with self-commentary text; D10 captured calories burned; and D5 captured her gym visit.

Participants designed trackers containing a varying number of fields, with more than half of the trackers containing just one field (see Figure 11). Among the 29 trackers containing a single field, 11 were timestampers, eight were archives, seven were in-situ experience trackers, two were To-Do lists, and one was a daily summary (see Figure 11, bottom). The trackers with no field (n = 3) were also timestampers without an explicit time field.

7.3.4 Tracker Refinement. OmniTrack allows people to change tracker design even after they started logging items to accommodate the change of their tracking needs. Although the *usage logs* showed that participants tend to stick with their initial tracker design, we found that seven participants modified 10 trackers after they saved the first entry. During the exit interview, we learned that participants modified the trackers when additional tracking needs arose or when they realized that some fields turned out to be unnecessary in practice. D19 who extended her mood tracker remarked, *"At first, I created a happiness tracker by imitating the coffee tracker [the example tracker]. Later, I added more fields because I thought it would be good to enter a reason [short text] and photo [image]. Few days ago, I added an audio recording field as well."* D8 who also extended his mood tracker mentioned, *"I initially wanted to draw a graph with my mood score. As I was tracking the mood score, however, I got curious about the type of mood I felt. So, I added a checkbox [choice field with multiple selection] and appended new*

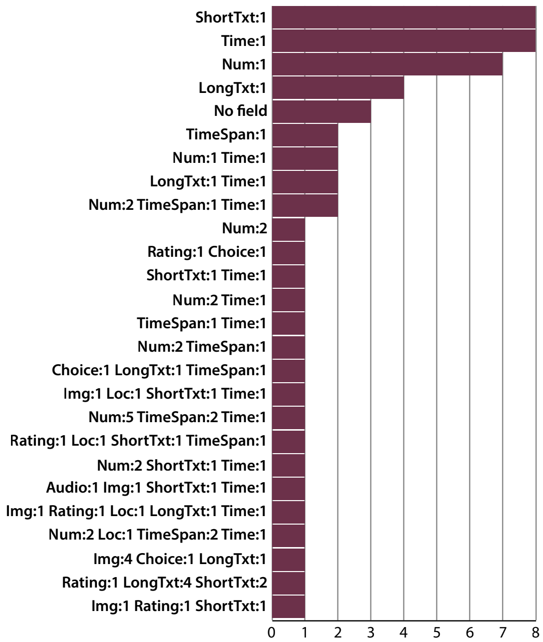


Fig. 10. Distribution of a unique set of tracker schema.

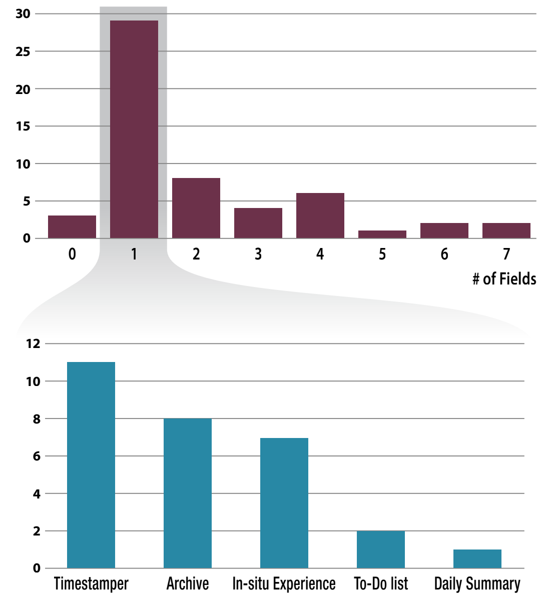


Fig. 11. Distribution of trackers by the number of fields (top) and a breakdown of single-field trackers by tracker style (bottom).

mood types [checkbox item] every time I encountered a new one." At the time of the interview, D8's tracker had 11 mood types (e.g., happy, embarrassed, lonely, worried).

7.4 Reflections on the Deployment Study

7.4.1 Diverse and Dynamic Needs of the Self-Trackers. Our deployment study results showed that participants used OmniTrack in their own unique ways. As we observed in the usability study as well as in the deployment study, participants designed trackers differently even if they had a similar tracking goal. Moreover, we observed that 33% of participants modified trackers as they continue to track. We believe that this "on the go" modification feature will facilitate people to track necessary behaviors and contexts as they gain more experience with self-tracking over time [17]. These findings support that the OmniTrack system well embodies our design goal to cover a broad range of tracking practices and fulfill individualized and sophisticated tracking needs.

7.4.2 Single App for Handling Multiple Tracking Practices. With the OmniTrack system, participants could manage multiple self-tracking practices in one app. During the exit interview, five participants mentioned that the single-app approach was a main motivation to participate in the study. One interesting phenomenon was that most participants attempted to transfer their current tracking practices into OmniTrack. D9 remarked, *"Before this [OmniTrack], I used tracking methods scattered in different platforms—health with Google Fit, some Memo apps, and just in my brain ... It is very convenient to track everything in one app."* D13 also mentioned, *"[Before using the OmniTrack,] I had thought that it is unavoidable to use siloed tracking tools for each tracking because they are domain-specific. But, I had a desire to see the data in one place. OmniTrack satisfied my needs in that it supports both tracking and seeing data in one app."* Despite OmniTrack's strengths of being able to track multiples behaviors and integrate data from external devices, current version does not support elaborated reflection features including inter-tracker visualization. Future research remains to support better visualization and reflection in OmniTrack.

7.4.3 Misconfiguration of Trackers. Several participants reported that they misconfigured some components of trackers (especially the trigger), thereby experiencing their tracker to work somewhat irrationally: D13 described, *"... currently I have Health [step counts from Fitbit] and Weight [manual field] in two different trackers. I initially put them together in the same tracker because I didn't understand how it [trigger] works ... After I realized that empty weight value is recorded when the step count field syncs with Fitbit automatically, I took the weight field out and created a new weight tracker."* This happens partly because we designed the components to be interconnected independently—i.e., tracker, triggers, and value connections are configured independently regardless of their semantics, to maximize flexibility. One way to prevent misconfiguration while preserving the system's flexibility is to provide example trackers that is properly configured. Going further, we envision creating a tracking platform where people can create and share tracking *templates*.

Participants used OmniTrack in an unexpected way. To-Do lists are not considered as self-tracking in general, but three participants attempted to use OmniTrack to manage their To-Dos. For example, participants created a tracker for planning a trip (D9) and for keeping a list of short-term tasks (D3). To-Do apps should effectively handle future events, which is beyond the scope of OmniTrack. However, it might be worth connecting OmniTrack with existing To-Do apps (if they provide an API) to help people keep track of task completion.

Another unexpected OmniTrack usage was combining multiple information in a single long text field [65], which we observed from three participants. For example, the To-Do trackers that D3 and D9 created contained a text field where they typed multiple To-Do tasks in a bulleted list. D16 stored multiple metadata of songs he wants to listen, separated by newlines (i.e., "name of song /newline/ artist"). We believe that supporting additional field types (e.g., per-item level definition of check list) could address some of their needs.

7.4.4 Technical Issues, Barriers, and Workarounds of OmniTrack. Deploying the OmniTrack system revealed some technical issues and barriers. Most participants were using Samsung Galaxy smartphone that comes with S Health [32]. The deployed version of OmniTrack did not support S Health as an external service because Samsung opens their API only to the publicly released apps. As a result, many participants failed to connect their health trackers to the S Health app (e.g., step count). Nevertheless, some tech-savvy participants found workarounds such that they configured S Health to synchronize its data with Google Fit, and connected Google Fit with OmniTrack. We are planning to release OmniTrack publicly, so this limitation will be addressed soon.

Although few, several participants reported a battery drain issue. They were using Samsung Galaxy smartphones, which have a built-in warning system of battery consumption. Participants reported that their phones often sent warning notifications that the OmniTrack app was consuming too much battery. We learned that they were using too many time-based triggers and reminders by mistake. We suspect that triggers and reminders frequently wake up the device from the internal battery saver mode, and if the user connects a tracker to external services, the trigger will repeatedly pull the data via network, which consumes system resources. Displaying a warning when people set the battery-consuming configuration will help them use OmniTrack more reliably.

8 DISCUSSION AND FUTURE WORK

In this section, we discuss lessons learned during the process of designing, implementing, and evaluating the OmniTrack system, and future research directions to use and improve OmniTrack.

8.1 Expanding the Design Space for Self-Tracking

Prior studies suggest that people use trackers in different ways; as their interests and needs change over time, they change what items to track [59] or switch over to a new device [38]. People often try to track too many variables at first, and then are demotivated by tracking fatigue [17]. In light of these, if self-tracking tools give little or no flexibility, people could easily disengage with and abandon their self-tracking practice.

In contrast, people can modify the data structure while they are using OmniTrack. They can append new fields to an existing tracker or remove existing fields that are not useful anymore, without putting in additional efforts of making a new tracker or saving the collected data. This capability further differentiates OmniTrack from existing tracking tools, which often have a fixed set of tracking variables determined at the design stage. Although dedicated tracking tools can provide valuable insights for specific aspects of life, we believe that the post-hoc revision of trackers could elicit different tracking behaviors that are not feasible with dedicated trackers. During the deployment study period, 33% of the participants revised their tracker to reflect their changing needs.

Tracker deletion could indicate either people's disengagement or goal accomplishment, although we did not cover in this paper in depth [21]. In addition, examining the life cycle of a tracker—creation, modification, and deletion—in relation to people's corresponding stages of self-tracking might help us understand how OmniTrack affect people's tracking experience over time.

8.2 Leveraging Other Building Blocks for Successful Self-Tracking

In this work, we mainly focused on supporting the preparation and data collection stages in self-tracking. Our future work will go beyond these initial stages of self-tracking by helping people identify insights from the collected data and accomplish their tracking goals. Throughout the usability study and deployment study, some participants requested very specific UI components for self-reflection (e.g., charts, feedback) and gamification (e.g., rewarding mechanisms). For example, U12 and D15 wanted to receive a visual indicator ("goal streak") emphasizing that they have been continuously achieving a daily goal. In addition to reminders, employing gamification and using visual aids could be effective and enjoyable in promoting goal achievement, although they may cause technology dependency [56, 60]. When conveying numeric goals, nudging by *goal setting* [49] and visually emphasizing different direction ("*Visual Framing*") [12, 14, 36] could produce greater effort toward meeting the goal.

8.3 Providing More Appropriate Visualizations

Participants in the usability study frequently asked how OmniTrack visualizes data and supports self-reflection, even though we did not test the visualization component in the study. Some participants actively commented on visualizations (e.g., a horizontal line to indicate a user-defined goal) as a way to better support self-reflection. This implies that visualization would be an important feature for long-term engagement. Currently, OmniTrack supports a set of simple visualizations, choosing a visualization based on the field types and the data schema. We plan to provide additional visualizations such as a word cloud for text fields and a duration chart for time spans, and improve the visualization selection logic by incorporating more heuristics. However, OmniTrack currently does not account for the semantics of trackers, posing a risk of not using the most appropriate visualization. It is challenging to design a generalized visualization interface without knowing in advance the semantics of and relationships among the fields and trackers. In the information visualization field, general visualization tools usually suggest automatically generated alternatives in the form of a gallery to help people choose a proper visualization among them [66]. However, this approach might be unsuitable on a small mobile screen, and usually increases the complexity of interface. Designing a generalized personal data visualization that covers a wide range of semantics warrants further investigation, which is specifically challenging on mobile devices.

8.4 Sharing Trackers with Other People

We envision an online tracking community (e.g., a marketplace in OmniTrack), where people can upload, search, and download the trackers and associated triggers they designed with OmniTrack. The sharing capability could help novices learn how to make trackers by first downloading the trackers designed by experts and customize for their own use, as in the case of sharing IFTTT 'recipes' (a configured set of trigger-action behaviors) [33].

Another opportunity is to enable clinicians to 'prescribe' a tracker to their patients. For example, a clinician might want her patient to collect sleep data in a particular form. Instead of employing a paper-based sleep diary, the clinician can deploy a sleep tracker created with OmniTrack to her patients and have them add a few other sleep-related factors that are of particular interest to them.

In addition to share tracker templates, a group of self-trackers could share tracking logs as a way to provide and receive social support [49]. For example, four interview participants stated that they share their logs (sometimes even by posting the logs on shared places such as a group chat room) with other people with the same tracking goal to encourage each other. Usability study participants also expressed a desire to have sharing features. For example, U3 imagined using OmniTrack for journaling movie reviews, and noted that he wants to share the tracked item (review) on his SNS feed, as most blogging apps support. U6, a product manager, proposed a feature that allows multiple people to track items on a single tracker through network. He imagined using OmniTrack as a milestone tracker with other team members. Future work remains to understand group tracking behaviors around the use of OmniTrack.

8.5 Utilizing External Information and Contexts

Currently, OmniTrack's data-driven triggers are responsive to the changes of the values retrieved from external services. Going forward, we can extend OmniTrack by introducing event-based triggers, which can be fired by external events such as a change of the owner's state measured by smartphone sensors or other IoT devices. One promising direction is to integrate OmniTrack with existing services or frameworks (e.g., IFTTT [33] and AWARE [24]) that allow people to define events with various sources in a high degree of flexibility.

IFTTT recently announced *Webhooks*, a service which allows people to connect their own project to an event triggered by an IFTTT condition [42]. Using the Webhooks service, we can enable OmniTrack users to track more diverse types of contextual events. For example, the following IFTTT recipe, "IF I leave my workplace, THEN fire the event-based trigger in OmniTrack" enables people to easily track the time they leave work.

The AWARE framework [24] provides functionality to listen to the context change events by leveraging smartphone sensors and data sources. While some native programming is needed to build a new context, AWARE provides easy access to the smartphone sensors via APIs specialized for building contextual events, and the context can be distributed as a plugin. We envision that developers can add new contextual events that they want people to track with OmniTrack. For example, we can extract stress level from voice through microphone [1] with AWARE and integrate into OmniTrack. An event-based trigger listening to the stress change event can record the time when the stress level increases, or send a reminder to the person, asking him to journal possible reasons for the stress change in-situ.

8.6 Supporting Researchers with OmniTrack

We can extend OmniTrack to enable researchers to create a data collection tool without programming. To collect behavioral data, a researcher can design a tracker with OmniTrack and deploy it to study participants. Using OmniTrack for research has potential advantages over using other research toolkits: combining traditional manual fields along with automatic inputs connected to the external services will expand the design space of the experiment by increasing the number of target variables due to the lowered input burden. For example, a researcher can collect subjective tiredness scale along with automatically tracked step count and sleep duration.

Supporting research purposes requires additional components to be incorporated. In a typical research context, only a researcher should be able to configure a tracker deployed to participants, which is not supported in the current OmniTrack system. Another important feature is the experiment administration dashboard used for managing the experiment and analyzing the collected data. Because a researcher does not need to design the tracker on a smartphone, it is possible to provide a more convenient and flexible user interface for the tracker design on the desktop environment. The channel for participant recruitment and the process of consent approval are also important features to support researchers; PACO [52] and AWARE [24] allow people to enroll in an experiment easily by taking a photo of QR code. Apple ResearchKit [4] provides APIs to show the informed consent form to participants. Because an ethical consideration on mobile deployment is an important issue [53, 58], providing a proper mechanism for approving consent for private sensing and tracking data is a critical part to make OmniTrack feasible for research purpose. In addition, technical issues raised on sharing tracker packages (Section 8.4) should be addressed to deploy a tracker seamlessly. Extending OmniTrack to support researchers is an interesting future research topic and will contribute to domains that require behavioral data collection, as well as to other HCI researchers studying self-monitoring.

8.7 Studying with a Broader Audience

A majority of our participants of the usability and deployment studies were students in their 20s and 30s. Therefore, our findings regarding the perceived difficulty and tracker usage patterns may not be generalizable across all the education levels and age groups. For example, tracking needs and capabilities of older adults could be different from those of younger people [20]. In addition, many of our deployment study participants did not have activity trackers or had devices that OmniTrack did not support. Our study results are not likely to show the full potential of using OmniTrack in conjunction with existing activity trackers. Conducting a deployment study with a broader audience would provide additional insights with higher external validity (e.g., identifying new tracker styles that were not reported in Section 7.3.2).

9 CONCLUSION

In this paper, we presented OmniTrack, a novel self-tracking approach that provides self-trackers with a high level of flexibility in constructing their own tracking tools. To meet people's diverse tracking needs and leverage existing tracking tools, OmniTrack employs a semi-automated tracking approach, allowing people to combine manual and automated tracking methods. With OmniTrack, people can create a tracker using various field types for flexible data capture. OmniTrack adopts the simple trigger-action model to enable automated logging in the background. OmniTrack also connects to external tracking services to feed the measured values to its data fields or to leverage automated tracking through data-driven triggers. We demonstrated OmniTrack's broad coverage of tracking practices by showcasing three use cases ranging from mostly manual tracking to mostly automated tracking. To identify usability issues and examine how well people learn the core concepts, we conducted a usability study (N = 10). We then conducted a 3-week deployment study (N = 21) to assess if people can capitalize on OmniTrack's flexible and customizable design to meet their tracking needs. Our study results demonstrated that participants can use OmniTrack to fulfill their personal tracking preferences except for some edge cases. Specific areas for future research include examining the life cycle of a tracker in relation to people's tracking behavior, supporting researchers to use OmniTrack as a research platform, providing support for sharing trackers, integrating external contexts drawn from other platforms, and providing more sophisticated visualizations and feedback to enhance self-reflection on a generalized tracking system. In closing, we believe that OmniTrack can empower self-trackers, patients, researchers, and others who have data tracking needs, helping them construct their own trackers to capture their health, wellness, and many other rich life experiences.

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