Towards a Typology of Self-Tracking Gaps

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ABSTRACT

This paper introduces an emerging typology of the 'absences' that confound the study of self-tracking. A review of the literature, and the ongoing work of the authors on the long-term value of self-tracking data, is used as a resource to develop descriptions of levels and types of 'gaps' that emerge as part of the activities, behaviors, technologies, and data practices of self-tracking. Such gaps are shown to be both common and insightful, highlighting the economic, social, behavioral, and psychological layers that undergird self-tracking.

KEYWORDS

Personal informatics; quantified-self; self-tracking; personal data; small data; data practices; data gaps

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TRACE & ZHANG, WORK-IN-PROGRESS

Participants: 18 participants (10 females and 8 males) between the ages of 18 and 42 were recruited for the study in fall 2017. Fourteen participants identified as white, (3 of whom identified as Hispanic or Latino), three as Asian, and one as African American.

All had used a smartphone app to track their health, wellness, or fitness for at least 6 months. In addition, 13 had tracked some aspect of their personal finances, 11 had tracked body and medical symptoms, and 8 had tracked some aspects of their environment.

Fourteen participants also noted that they had tracked other aspects of their lives including habits and goals, travel/location, schedule/ due dates, useful information, public transportation usage, computer usage/productivity, dreams, sociability, and utilities.

Methods: Participants who signed up for the study were directed to complete an online questionnaire. The survey gathered demographic data and participants' basic characteristics vis-à-vis their self-tracking behavior and their experience in using self-tracking apps. In-person interviews were then conducted to ascertain participants' beliefs regarding the long-term use and value of quantified-self data. Interviews ranged from 44 to 153 minutes in length (Mean = 72 minutes).

Analysis: Survey data was analyzed using descriptive statistics. All interviews were recorded and transcribed in full. The resulting 590 pages of qualitative data were coded using the software program, MAXQDA.

INTRODUCTION

Most self-tracking research focuses on understanding motivations and barriers for self-tracking and on developing tools and techniques to collect, represent, analyze, and visualize data to assist reflective learning and behavioral or psychological change [3]. Recent HCI literature has also argued for the importance of studying peoples' long-term (retrospective and future) use of self-tracking data [5], where the emphasis shifts from human motivation and behavioral change to the "documentary potential" of quantified data [4]. In either case, the study of self-tracking brings with it a concern for studying the patterns of life, whether it be the nature of the activities or routines that make up the human condition, the behaviors that inhibit or support the quest for digital and quantified self-knowledge, or peoples' associated data practices as behaviors and activities are transformed into personal digital traces that must be captured, managed and understood.

As demonstrated below, this research has established that there are 'absences' that confound the study of self-tracking activities, behaviors, devices, and data practices. We define these absences or gaps as residual questions, or issues left over from the study of self-tracking. In this work-in-progress paper, we draw from the literature and our own ongoing study of the long-term personal and societal value of health and fitness data (see sidebar 1), to present an emerging typology of these self-tracking 'gaps.' In doing so, we demarcate the cascading levels and types of self-tracking gaps that exist and draw out their associated reach, frequency, duration, and impact.

EMERGING TYPOLOGY OF GAPS

Systemic Gaps

Systemic Gaps exist at the macro level as an unfilled space or a deficiency. Structural (including economic and social) in nature, these gaps reveal that self-tracking, and the adoption of digital devices to manage this activity, is incomplete as a universal pursuit. A 2016 GfK (Growth from Knowledge) survey (https://www.gfk.com/global-studies/global-studies-fitness-tracking/, retrieved October 2018), for example, found that 52% of American online consumers had never tracked or monitored their health and fitness using a mobile, online, or wearable device, with the highest percentage in the 40+ age category. A French study on the use of diet and fitness apps adds nuance to such statistics by highlighting how social, economic, and cultural conditions influence the use of digital self-tracking devices. The study confirmed the existence of a 'social gap,' a digital divide in which more affluent individuals were most likely to use self-tracking apps, while individuals from lower socio-economic classes (predominantly older women) showed the most resistance to the use of digital devices and to participating in self-quantification efforts. The gap stemming from structural inequalities that resulted in different health priorities and technological skills [15].

Activity Gaps

Activity Gaps exist due to differences in peoples' life circumstances which translate into disparities in daily activities or routines, in turn impacting the type, temporality, frequency and/or efficacy of

AN EMERGING TYPOLOGY OF SELF-TRACKING GAPS

Macro Level Gaps

Systemic Gaps exist as impediments to self-tracking and associated technology use. Structural (including economic and social) in nature, these gaps reveal that self-tracking, and the adoption of digital devices to manage this activity, is incomplete as a universal pursuit.

Meso Level Gaps

Activity Gaps result from differences in the broader environment and in life circumstances, which translate into disparities in daily activities and associated tracking, in turn impacting the type, temporality, frequency and/or efficacy of self-tracking.

Micro Level Gaps

Usage Gaps exist due to incomplete patterns of personal use of self-tracking tools and devices in and over time. These gaps are tied to behavior, personality, and motivation and reflect the reality that people move through different states of self-tracking (streaks, breaks, and abandonment).

Connective Gaps exist as distinct intervals or breaches in self-tracking continuity and their effects are studied in terms of how they disrupt a person's sense of connection to their data.

Accountable & Expressive Gaps reveal the way people perceive, account for, and make meaning from the gaps that exist in personal self-tracking data. Gaps in this scenario are a pass or a way through - a mechanism by which people navigate a world where the rhythms and patterns of life create gaps in activities and associated data.

self-tracking [9, 6]. At a global level, inequality in activity levels have been tied to intrinsic (e.g. gender, weight, age) and extrinsic factors (e.g. walkability of the built environment) [1]. A study from 2012 indicates that worldwide, a little over 31% of adults are physically inactive, with the number rising to 43% in the Americas. Inactivity also increases with age, is higher in women than in men, and is more prevalent in high rather than low-income countries [10].

At the meso level, activity levels also show gradations within populations. For example, research has confirmed a difference between the ambulatory physical activity of American college students and other adult populations. Age and environmental factors help students buck the general trend by being more active on weekdays than weekends [2]. From a self-tracking perspective, Epstein et al. [7] have established that external (weather), internal (injury and fatigue, sleep amount and quality, stress and mood), temporal (work, travel, and partners schedules), and behavioral factors (socializing and food consumption) can affect physical activity levels to a degree that also disrupts an individual's self-tracking activities.

Usage Gaps

Usage Gaps exist due to incomplete patterns of micro level use of self-tracking tools and devices in and over time. Research has established that people move through different states of self-tracking. A person is on a 'streak' if they exhibit an extended uninterrupted period of use days for a self-tracking device [13]. Uninterrupted patterns of non-use days are referred to as 'breaks,' 'pauses,' or 'lapses' [13, 8]. Forgetting, skipping, and suspending are specific forms of lapses based on factors of intentionality and duration [9]. A more relaxed form of a 'streak,' the 'phase', exists when a person's usage encompasses a series of streaks, separated by short breaks and ending with a long break [13]. 'Phases' are further categorized based on how attributes, including duration and density of activity tracker use, are combined [13]. When a lapse, substantial or otherwise, becomes permanent, the person is said to have abandoned self-tracking [3, 8].

These states of self-tracking feed into broader patterns of use over time. Meyer et al. [13] tie such patterns to density of use as well as its temporal boundaries. The early use phase includes people who briefly try and then drop activity trackers (try-and-drop), people who try the tracker for a short period (short-term), and people who take some time to set up the tracker before moving into actual use (slow-starter). Longer-term use includes a different set of patterns: those who periodically try out self-trackers, often for short periods (experimenter); those that often take lengthy breaks but then regularly resume use (hop-on hop-off); those that consistently but sparsely use a self-tracking device (intermittent users); users that track continuously and intensely (power users); and those who are moderate but relatively long-term users of activity trackers (generally consistent users).

In looking at the issue from a behavioral perspective, Jarrahi et al. [11] examine divergent usage patterns of activity trackers (Fitbit devices) through the lens of peoples' pre-existing motivations to act. These motivations are in turn viewed as tied to personality, personal situations, and priorities. In this scenario a total of five categories of users are identified: 'curious immobiles' (no prior motivation to become more active, generally abandon self-trackers after minimal short-term use),

PARTICIPANT QUOTATIONS ABOUT ACCOUNTABLE AND EXPRESSIVE GAPS

"My self-tracking data... has nothing to do with my stress levels, but it's really good at demonstrating my stress ...The amount of thought and effort that I put into...actively trying to be aware of my weight, and my nutrition, and my finances, that starts slipping, because it gets bumped down on my priorities list." [P2]

"In July 2015 I had very few steps. So that's, that might be because I'm back home and I'm relaxing and my mom is cooking great food and I'm not going out and exercising. "[P6]

"I eat a lot alone during the week at work. Whereas, when I'm sitting down during the week at home, there's either a child or a spouse, or somebody else with me. And so, it becomes more important for me to give them that extra 30 seconds that it takes me to track than it does for me to track it...If I have tracked all weekend, it probably was not a great weekend. If I [have] not tracked that weekend, it probably was a very family-centered weekend." [P5]

"I can see patterns where... I wasn't data collecting at all on the weekends... because that was our time together... I actually showed her that, I took a screenshot of my history and I sent it to her. And she's like, "I have no idea what I, what, what you want me to do with this." But I said, "I want you to see that you're so important to me that I don't even track my stuff when I'm with you." [P5]

'aspiring starters' (inactive, somewhat motivated to improve physical activity, generally inconsistent usage of activity trackers); 'motivation seekers' (active, motivated to use devices to improve activity levels, routinely integrate activity trackers into daily routines), 'quantified-selfers' (active, consistently generating targeted information streams, persistently use activity trackers over time), and 'persistent roamers' (highly active, find information streams redundant, often abandon activity trackers because of perceived inadequacies with the technology).

Connective Gaps

As a concept introduced by Yli-Kauhaluoma & Pantzar [18] *Connective Gaps* are micro level gaps that exist as a distinct interval or a breach in self-tracking continuity and whose effects are studied in terms of how they disrupt a person's sense of connection to their data. From the technological side, such gaps come about because people habitually replace or update self-tracking tools and devices [16, 3]. Other gaps are the result of the mental and physical effort involved in wearing, using, and maintaining the device(s) and in inputting data manually [14, 12, 3, 9, 6]. From the human perspective, such gaps can be behavioral in nature, including a failure of 'adherence' to a self-tracking regime [17, 18]. Other reasons for temporary or permanent abandonment include a disconnect between a person's goals and sense of self and the perceived purposes of and market for the device [12, 3]; a sense that self-tracking is no longer necessary when certain knowledge has been obtained or plans have been put in place [6, 3]; difficulties in developing a routine for using a self-tracking device and in reengaging when such a routine is interrupted [12]; and a sense of discomfort with what is revealed through the data about a person's efforts/progress [6].

Whether technological or human in nature, this failure in transformation means that people experience gaps in their self-tracking data streams, with data rendered in ways that are deemed 'invisible' (data that is missing or fragmentary, or that fails to materialize certain activities), 'inaccurate' (data that disappears or data that doesn't match expectations and is unverifiable), and 'inadequate' (data that is difficult to interpret and make meaningful) [19 and see also 14, 9, 12, 6, 18]. The net effect is to leave people feeling 'indifferent' about their data [18].

Accountable and Expressive Gaps

The notion of *Accountable and Expressive Gaps* attends to the call in the CHI literature to study how people 'perceive,' 'interpret,' or 'explain' the gaps that arise in self-tracking data [5]. Research by Tang & Kay [17] and others [9] have established that people can articulate a reason and a context for such data gaps and speculate on its effects, including in terms of their performance. However, we expand upon these understandings through emergent themes from our work in progress (see sidebar 1). In effect, we see these concepts as illustrating the role played by gaps in the "experience of remembering" with data [15]. By explicitly calling out and naming gaps as 'accountable' and 'expressive' we foreground the work that people do as part of self-tracking to make sense of the world around them and the method by which they do so. Instead of taking these accounts for granted, we argue for them to be studied and embedded within design considerations.

DESIGN CONSIDERATIONS FOR ACCOUNTABLE AND EXPRESSIVE GAPS

- Recognize and design for micro-level gaps as part of the natural order of self-tracking.
- Reorient design from a perspective that seeks to mitigate all data gaps, to one in which data gaps are viewed as an opportunity to connect or reconnect individuals with meaningful changes in the patterns of life.
- Explore ways that app data can be collected and presented so that people can continually orient themselves in time and space, and thus wayfind through their activities in life.
- Explore ways to implicitly design for the social aspects of self-tracking, acknowledging that it is not just the individual but their family and friends that are bound up with the activities documented in self-tracking and its associated absent or present data.
- Explore ways to let people tag or otherwise demarcate and describe meaningful spikes and gaps in accumulated app data, thus making the data more memorable and facilitating its use in reflection and in the telling and sharing of life stories.
- Explore ways to augment data gaps and spikes (represented through numbers and graphs) with other forms of information (e.g. photographs) that help to contextualize and set the story (accounts) in place for the individual and for the system.

Gaps in this scenario are a pass or a way through - a mechanism by which people navigate a world where the rhythms of life create gaps in activities and associated data. While app design generally allows people to uncover and look back on absent data, it is the individual (not the system) that is currently capable of calling it to account. Our research underscores the fact that people can isolate, contextualize and reflect on such absences, and through the expression of feelings and ideas, they can also construct meaning from data gaps (see sidebar 3). While other types of gaps are often viewed as deficiencies, something to be filled in and remedied (by individuals and researchers alike), our research highlights the counter narrative. That people account for gaps as part of the natural and normal order of things. For our participants, data gaps are tied to shifts in daily life as told through personal stories. Stories of transition (e.g. being in college), of upheaval (e.g. personal and family illness), and of shifting priorities (e.g. when family takes precedence over the wants of the individual). Data absences are also tied to changes in routine that speak to joyous life events, where the activity of self-tracking, for example, is set aside to spend quality time relaxing at home or being with family and friends.

Data gaps are seen as an integral part of a larger ecosystem that includes daily data averages and data anomalies (data 'spikes') that presage an increase in self-tracking. It is the element of contrast that is the method by which each state is made especially meaningful. If Tang & Kay [17] argue that design for self-tracking apps needs to take 'incompleteness' into consideration, we propose a design frame (see sidebar 4) that treats certain data gaps as a form of wayfinding through life. In such a scenario, the absence of data is treated as a meaningful connected event, something to actively design for and not just mitigate against.

SUMMARY

This paper outlines our ongoing efforts to develop a typology of the 'absences' that confound the study of self-tracking. In this first stage of the research outlined here, a preliminary review of the literature and our own on-ongoing research identified five types of gap, cascading from the macro to the micro level. In the process their associated reach, frequency, duration, and impact are described. To conclude, preliminary design considerations for *accountable and expressive gaps* are presented, with the intent of facilitating further investigation into how to design for this and other types of self-tracking absences. In all, gaps are shown to be common and insightful, highlighting the social, economic, behavioral, and psychological layers undergirding self-tracking.

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