Everyday Personal Informatics

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Abstract

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The increase in ubiquity of personal tracking tools has resulted in more people tracking their actions and behaviors, bringing more varied expertise and more diverse goals to the process. Although this increase in access provides great opportunity for more people to benefit from self-monitoring, tracking tools often fail to acknowledge and account for the realities of what it means for this more diverse group to use track in their everyday life. My dissertation provides evidence that accounting for the challenges of everyday life can help people find more value in their data and find more support through their data.

Toward helping people find value in their data, I first describe the *Lived Informatics Model*, a new conceptual model which describes people's use of tracking technology in everyday life. In addition to behavior change, people are also motivated to track out of goals of curiosity and a desire to have a record. I suggest that collecting data and acting on it is part of a larger process

of deciding to track, selecting a tool, and lapsing in tracking. I also surface that people desire additional insight from their data while they are tracking, which motivates the design of the *Visual Cuts* system. Through Visual Cuts, I demonstrate that surfacing correlations between aspects of multi-dimensional tracked data to better help people understand their habits and identify ways they can improve them.

Examining how designs can better help people find support through their data, I describe the *Design Framework for Sharing*, distilling the body of research on sharing tracked data to six dimensions key to creating positive sharing experiences. I analyze and vary Tweets generated by the RunKeeper app to understand how one of these dimensions, post content, can be improved. I show that posts receive more response and interest when they explain a moment's importance to the audience, which motivates the design of the *Yarn* app. Through the design and evaluation of Yarn, I demonstrate that a structured experience for authoring content can help people create posts from their tracked data which explain a moment's importance.

Across these projects, I argue that the common approaches in today's tracking tools for summarizing and presenting data do not provide the benefits promised and the sharing mechanisms do not help people get advice and encouragement they desire. I suggest that accounting for the varied reasons why people track and designing for varied levels of expertise results in designs which better help people understand their habits and get support from others.

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Chapter 1. INTRODUCTION

People often aim to better understand themselves and their habits as a first step toward changing behaviors, increasing awareness, or simply satisfying a curiosity. To achieve this self-understanding, people regularly turn to technology to help them *track* their actions, routines, biological signals, and feelings. Technology with tracking capabilities, often referred to as *personal informatics* systems [95], are becoming increasingly ubiquitous. For example, many smartwatches include the ability to track activity and heart rate (e.g., *Apple Watch*, *Fitbit*). Many smartphones also enable tracking of food, finances, location, and more (e.g., *MyFitnessPal*, *Mint*, *Swarm*). A 2013 Pew survey estimates 21% of U.S. adults use technology to track aspects of their health [58]. In the years since, the increased ubiquity and maturation of tracking technology has likely resulted in more people trying to use technology to track.

Despite of the promise of these tracking technologies, people often stop using them before their needs are met [27,53,93]. A 2016 survey from Gartner Market Research suggests that 30% of people abandon the use of their physical activity trackers after three months or less because they do not find them useful, they get bored of them, or they break [62]. People are more likely to abandon the use of apps and devices in tracking domains where the burdens of collecting data are higher. For example, a study of people's use of *The Eatery*, a photo-based mobile app for food journaling, found that 97% of people stopped regularly using the app within one week of downloading it [71]. Though people may get value out of tracking, the value does not outweigh the collection burdens.

There are many reasons why current technology fails to meet people's needs. My dissertation draws on the *lived informatics* perspective that people's use of personal informatics tools is entangled with other aspects of their everyday lives and that current tracking tools do not account for that reality [131]. This perspective pushes back against personal tracking as a stage-based process in which people make sense on their data after collecting it and act only after careful examination [95]. As more people have begun to use tracking technology, most instead collect data, reflect on it, and act on it simultaneously [20,53,155].

For my thesis, I examined ways to design personal informatics tools which better serve the wide range of goals people bring to tracking, and therefore to better serve people's needs. I address two key problems people face when they use personal tracking tools.

The first problem is that *people struggle to find value in the data they collect*. Many people stop using tracking tools because the data they collect provides limited value to them, and the burdens of tracking outweigh the benefits [47,51]. Others people stop because they got the knowledge they desired out of tracking, learning their typical daily trends for how many steps they walk, calories they consume, or other tracked measurements [27,47,93]. Many early adopters of tracking technology were experts in data analysis and computing, using their skills to find trends in their data [23,95]. As tracking technology has reached a broader audience, and as people's motivations for tracking diversify, there is a need for designs to aid people in extracting value from the data they collect.

The second problem is that *people struggle to find support from others* around the reasons they are collecting data. People often try to share the data they collect as part of asking others for advice, reach out for support, or celebrate achievements [50,111,118,143,149]. However, many people worry their needs and accomplishments are too trivial and elect not to share [114]. When people do share, they often do not receive the interest or response they desired [50,101]. There is a need for designs to help people surface what is important about the data they are collecting and convey it to an interested audience who is willing to engage.

1.1 Thesis Statement

My thesis claim is summarized in the following statement:

Personal informatics tools that acknowledge and account for the challenges of everyday life can help people (T1) find more value in their data and (T2) find more support through their data.

Though *tool*, *design*, and *system* have varied definitions depending on one's epistemological background, I use the terms interchangeably in future sections to refer to any interface which people can use to engage with tracking technology. Depending on the context, I similarly refer to person who is collecting data or engaging with tracking technology as a *tracker* or *self-tracker*.

1.2 THESIS OVERVIEW

I report on findings from four investigations that examine how the design of personal informatics tools can help people find more value in their data (T1) and more support through their data (T2). Toward each thesis claim, I first build an empirical understanding about who is using tracking technology today, exposing why and how they are using the technology. I then synthesize the empirical findings into conceptual models and frameworks which span tracking domains and extend to new ones (Chapter 3 and Chapter 5). I finally implement novel systems and designs which target opportunities exposed by the models and frameworks (Chapter 4 and Chapter 6).

Table 1 describes the research questions I examine. The structure of the rest of my dissertation follows below.

Table 1. Research Questions and Thesis Organization.

Thesis claim	Research Question	Addressed in
T1, Finding more value in data	**RQ1**: How do people use tracking technology in their everyday lives?	**Chapter 3**, through the creation of the *Lived Informatics Model*, which expands on prior conceptual understandings of how people use tracking technology.
	RQ2: How can a design help people get additional value from multi-dimensional tracked data?	**Chapter 4**, through the design and evaluation of *Visual Cuts*, a technique for surfacing how one aspect of tracked data correlates with another.
T2, Finding more support through data	**RQ3**: How have prior research designs supported people in sharing the data they collect? **RQ4**: How can the content of posts elicit additional response and interest from potential audiences?	**Chapter 5**, through development of the *Design Framework for Sharing*, which describes six dimensions key to developing positive experiences sharing tracked data. Additionally, through two quantitative studies of interest and responses to post content in Tweets generated by the *RunKeeper* app.
	RQ5: How can a design support authoring of interesting content using tracked personal data?	**Chapter 6**, through the design and evaluation of *Yarn*, a mobile app to support authoring of interesting content through tracked data.

Chapter 2 surveys how designs have supported people in collecting personal data and making sense of it in. I describe how the literature has characterized people's use of tracking technology for self-improvement, with particular emphasis on Li et al.'s stage-based model of personal informatics systems [95]. I then summarize literature describing other motivations people have for using self-tracking technology, especially Rooksby et al.'s perspective of tracking as lived informatics [131]. I finally describe common design principles in research and commercial applications for tracking physical activity and food. These principles and perspectives on how people use tracking technology inform my research questions on how designs can best support people in getting additional value and support from their tracked data.

Chapter 3 reports on a project where I examined how people use tracking technology in their everyday lives through a qualitative study triangulating people's use of technology for tracking physical activity, location, and finances. This study informed the creation of the *Lived Informatics Model*, a new conceptual model of how people use tracking tools in their everyday lives. The Lived Informatics Model extends prior conceptual understandings of how people use tracking technology (e.g., [20,95,155]). The model uncovers a need for designs to support tracking goals beyond behavior change, to provide insight to people while they are tracking, and to offer further support to people who lapse in their use of tracking technology.

Chapter 4 describes the implementation of a novel design, building upon a design need that people seek additional insight from their data while they are tracking. I conducted a qualitative survey which surfaced the types of questions people seek to answer with the data they track about themselves. These findings led me to develop *Visual Cuts*, a technique involving a visualization and a summary caption to surface correlations between two aspects of multi-dimensional tracked data. In a field evaluation of cuts through physical activity and location data from the Moves app, I demonstrate that the technique helps people find patterns in their data and discover changes they can make to their routines.

Chapter 5 pivots to designing to help people find support through their data. I describe a literature review I conducted to understand how designs in prior research projects have supported sharing of tracked data. This review informed the creation of the *Design Framework for Sharing*, a set of six dimensions key to developing positive experiences when sharing tracked data. I then focused in on one how one dimension, *post content*, can be improved to elicit more response and interest. I conducted two quantitative studies where I analyzed and then varied the post content in Tweets generated by the *RunKeeper* app to understand what about post content elicits more interest and response. These studies found that audiences are more likely to respond when a post explains what is important about the moment being shared.

Chapter 6 applies these recommendations to the design and implementation of *Yarn*, a mobile app that provides a structured experience for authoring content which others find interesting to engage with. I conducted two qualitative studies to understand the types of narratives in which people want to include tracked data. Yarn supports telling stories of accomplishment by guiding people to describe the importance of a tracked moment through text prompts and select a visual template which reflects their motivation for sharing. Through two field evaluations of Yarn, I demonstrate that the authoring process encouraged people to create appealing visual content that friends and family members found interesting to engage with and discuss.

Chapter 7 discusses how the projects presented in the prior chapters provide evidence in support of my thesis claim. I conclude by briefly describing a few projects I plan to pursue in the future.

As with much of research, the work in my dissertation was done in collaboration with others. In each chapter I describe my own contributions and the contributions of others.

Chapter 2. BACKGROUND ON PERSONAL TRACKING

The popularity of digital devices for tracking physical activity increased rapidly in the early 2010s through products like the *Fitbit*, *Jawbone UP*, and *Nike FuelBand*. Mobile phones and smartwatches later began including the ability to track activity, such as via *Apple HealthKit* and *Android Wear*. Mobile applications for tracking became more available and popular in other domains as well, such as *MyFitnessPal* and *Lose It!* for eating, *Mint* and *Quicken* for personal finances, *Clue* and *P. Tracker* for menstruation, and many other domains. As of 2017, 16% of adults in the United States have some sort of wearable device with physical activity tracking capabilities [117]. Estimates suggest tens of millions of people use *Mint* [128], hundreds of millions use *MyFitnessPal* [78], and nearly a third of the world population (2.1 billion) own a smartphone with the ability to download one of these apps [126].

The advent of mobile apps and development of dedicated devices for personal tracking have changed how people collect and engage with their tracked data. I describe prior literature's understanding of how people engage in the practice of tracking by first summarizing Li et al.'s prior model of personal informatics tool use [95], then describing a line of work on the use of tracking technology in everyday life, particularly Rooksby et al.'s perspective of tracking as *Lived Informatics* [131]. I then review common design principles in tracking technology in two domains, physical activity and food, as well as how designs have approached social engagement around the collected data. Reviewing these domains offers insight into key design principles and challenges across personal tracking. I conclude by re-stating the goals of my thesis in light of the related literature.

2.1 USING TRACKING TECHNOLOGY FOR SELF-IMPROVEMENT

Systems for tracking and reflecting on personal data are commonly referred to as *personal informatics systems* in the research literature. Li et al. define personal informatics systems as those which "*help people collect personally information for the purpose of self-reflection and gaining self-knowledge*" [95].

Early work into how people use tracking technology focused on how self-reflection and gaining self-knowledge could support people in improving themselves. Informed by Prochaska & Velicer's Transtheoretical Model of Health Behavior Change [129], Li et al. develop a Stage-Based Model depicting people's use of personal informatics systems, as shown in Figure 1. The model has five stages:

(1) *Preparation*, or starting to collect data and thinking about what information to record and how to collect it.

(2) *Collection*, or gathering data.

(3) *Integration*, or preparing data to reflect upon.

(4) *Reflection*, or examining and exploring data.

(5) *Action*, or taking one's newfound understanding of themselves to inform changes.

The tracking process is iterative; actions inform new thoughts about what information to record, and experiences offer new insight into how to collect it. Problems which people face in earlier stages then affect the later stages. For example, collecting the "wrong" or "insufficient" data can make it difficult to draw conclusions from the data during the later reflection stage.

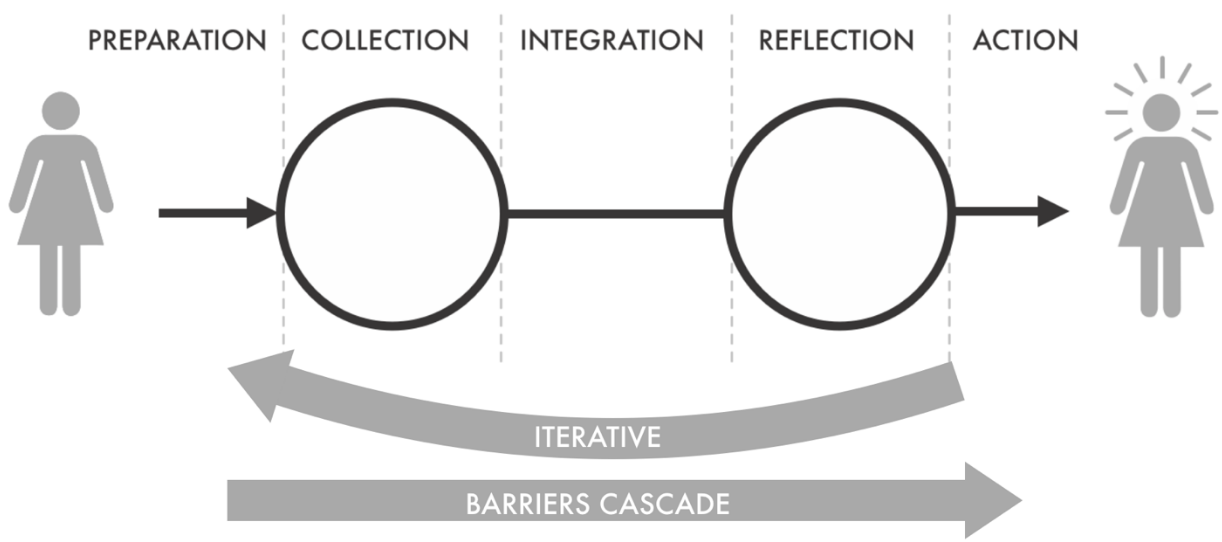


Figure 1. Li et al.'s five-stage model of personal informatics [95]. Primarily informed by tracking toward behavior change, the model emphasizes data barriers toward a presumed action.

Li et al. later identify two phases of reflection, *discovery* and *maintenance*, and note that people ask different types of questions in each phase [96]. From studying practices of the Quantified Self movement, Choe et al. learn that reflection often occurs when data is captured [23] and propose a new model for self-monitoring technology, including reflection through data capture as well as through feedback [20]. Similarly, Whooley et al. note the potential for personal informatics tools to support Schön's reflection-in-action [137], where self-trackers contemplate their data and change their behavior while tracking [155].

Many early adopters of these personal informatics systems were in technology-related fields like computer science, information technology, or data analytics [22,95]. The development of Li et al.'s stage-based model and refinements of it therefore drew heavily from an understanding of how experts in technology development and data analysis approached collecting and making sense of data. Further research studied the visualizations these experts created to understand their data [22] and the common pitfalls they experienced when trying to collect it [23].

Though experts in technology development and data analysis continue to use personal informatics systems, the majority of people who track themselves today do not have that expertise. As I discuss in the next section, today people track for diverse reasons, and current designs often fail to account for these realities.

2.2 USE OF TRACKING TECHNOLOGY IN EVERYDAY LIFE

People's use of tracking technology rarely follows the five-stage process of self-improvement outlined by Li et al.

People track for reasons beyond self-improvement. Many people are motivated to track by rewards, such as discounts or badges (e.g., tracking location on Foursquare [100]). Some people start tracking physical activity to generate income (e.g., recording workouts on Pact) [131]. Many Foursquare users also start tracking to offer awareness to friends and to see where they are, or simply as a record of places they have been (e.g., bars and restaurants they like) [95]. People also start tracking to keep a record for later retrieval, such as TV shows and movies watched [96]. Another common motivation to start tracking is out of curiosity [100] or an interest in quantitative data [95]. Some food journalers [34] and physical activity trackers [131] start tracking to learn more about their behavior, such as their eating habits or steps walked in their daily commute. With these other goals, people may not intend to reach an end stage of *action*, instead feeling like they have succeeded once they have *collected* the data to receive the rewards or after their curiosity has been met upon *reflection*.

Some people undergo careful *preparation* to track. People select tracking tools based on features, branding, form factor, recommendations from friends and relatives, and reviews in app stores and media [95,96,131]. But others undergo no such intentional preparation, receiving tracking tools as gifts or as part of a health insurance plan [131].

Li et al.'s model describes the self-tracking process as iterative. Lessons learned from one tracking experience inform what data someone collects the next time they track and what tools they use to do so [95]. In practice, people rarely maintain use of the same tool and often switch and mix tools when tracking [102,131]. Some people track the same habit with multiple tools, which leads to synchronization complications (e.g., step tracking with a pedometer and a phone app syncing to MyFitnessPal) [95]. Others track different types of activities with different tools (e.g., MapMyRun for running and Wii Fit for weight monitoring [131]), which usually leads to difficulties in organizing and reviewing data across separate tools and formats [95].

People change their goals and practices over time, which is not well-supported by personal informatics systems [96]. These changes sometimes lead to selecting a new tool [95]. Some people who start without clear goals narrow their data collection once they identify actionable goals, moving from *discovery* phase to *maintenance* phase of reflecting [96]. People also switch tools as their practices evolve over time and they find a system no longer supports their priorities (e.g., a jogger starting to do yoga) [60].

People abandon tracking tools because the data is too inaccurate or unreliable, surfaced in Li et al.'s model as a barrier in the *collection* phase. [27,47,70,93]. Beyond barriers in collecting, reflecting, and acting on data, people also stop tracking because of thoughts and feelings they have had surrounding the tracking process. People stop tracking because the process reveals something they find uncomfortable reflecting on (e.g., poor eating habits or a poor financial situation) [34,47]. Others stop because they learned enough about their habits succeeded in changing them toward their desired goal [27,47]. Some people feel they gained little from the tracking experience, while others continue to use the knowledge they gained [47,51].

2.3 Principles for Designing Tracking Technology

Early research prototypes examined how to support people in collecting data about themselves and how to then present the collected data usefully and meaningfully. Many characteristics of supporting efficient data collection and useful data presentation have been adopted in popular commercial systems, such as Fitbit and Apple Watch for physical activity and MyFitnessPal for food journaling.

2.3.1 *Physical Activity Tracking*

The Houston research system enabled people to keep a record of how much they walked and compare it with others by manually entering data from a digital pedometer, the Omron HJ-112, to an early smartphone, the Nokia 6600 [28]. Later research systems automatically synced activity data from an accelerometer-based devices to smartphones and desktops, easing the collection burden [29,31,99,152]. The popularity of commercial devices for physical activity tracking rapidly grew in the early 2010s. Some early devices the *Nike FuelBand* used abstract measures to represent any activity. Walking, running, and lifting weights all contributed to a person's "fuel". Other devices like the *Fitbit* and *Jawbone Up* used "steps" as a unifying measure of activity, allowing for manual entry of other activities. As of the late-2010s, most new smartwatches and smartphones include activity tracking features by default through platforms like *Apple HealthKit* and *Android Wear*.

Many tracking apps use *visual metaphor* to convey how active someone has been. Visual metaphor is effective at communicating tracked information in an interpretable, motivating, and entertaining way [55]. As shown in Figure 2, the Fish'N'Steps system used a growing fish to convey how much someone had walked in a week [99]. UbiFit garden similarly created a garden where cardio, strength training, flexibility training, and walking were all represented by different flowers and goal achievement was rewarded with butterflies [29]. Early Fitbit devices also used a growing flower to represent daily activity levels.

Physical activity tracking apps and devices also regularly use *visualization* to demonstrate someone's progress, such as the progress rings in the Apple Watch's Activity app. Similar representations appear in the interfaces of more recent Fitbit devices and their corresponding mobile apps. People often aim to use personal tracking tools to answer diverse questions about their data and their routines [22,23]. Interactive visualization of activity data allows people to explore their data to answer a question or satisfy a curiosity, while metaphor-based representations are typically scoped to answer a limited set of questions (e.g., did I walk a lot or a little today? Did I reach my primary or secondary goal?). However, the benefit of answering more questions comes at a tradeoff with the attentional demand required to benefit from the data [74].

Figure 2. Physical activity tracking apps and devices often use visual metaphor and visualization to convey how active someone has been. From left to right, activity progress presented in Fish'N'Steps [99], UbiFit Garden [29], Fitbit, and Apple Watch.

Nearly all physical activity apps and devices include *goal setting and achievement* as key features. Most systems include a default goal of 10,000 steps, a common goal popularized by a public health campaign around the Manpo-Kei (万歩計) in the 1960s [154]. Most systems include a reward for achieving step goals, drawing on strategies from *persuasive technology* and *behavior change* technology [1,57,108]. Figure 3 shows common examples of how goal achievement is rewarded.

Figure 3. Setting goals and rewarding achievement are key features of physical activity tracking apps. From left to right, goal rewards in Houston [28], Fish'N'Steps [99], GoalPost [114], and Fitbit.

Houston denoted goal achievement by labeling days with an asterisk [28]. Other designs have encoded goal achievement in the visual metaphor, like happy fish if the daily goal was reached in Fish'N'Steps [99] or butterflies in the UbiFit Garden [29]. Some systems have examined the idea of having multiple goals (e.g., a primary and secondary step goal) [29,114]. These systems include multiple types of badges and a page for looking at badges. More recently, insurance providers have begun providing discounts to individuals who wear activity tracking devices and achieve their goals [26]. Though employees often appreciate the incentives provided by these programs, and the shared community they create [66], they also express concerns about disclosing tracked data about themselves to their employer and insurance provider [26,65].

Beyond goal monitoring and achievement, people often use tracked data to better understand their routines [95]. People often track other aspects of their lives alongside their physical activity to better understand their routines, such as their weight, food intake, or mood [11,95]. However, integrating one or more of these types of data can be a challenge for people who are not data scientists or computer scientists [23,95]. To better support people in answering questions which span tracking domains, systems like Salud! have examined how to design platforms for aggregating tracked data from different services [106]. The Health Mashups system automatically detected correlations between data streams, converting them to simple natural-language summaries to improve interpretability (e.g., "you weigh less when you walk more", "on weekdays you are less happy than on weekends") [11].

Many systems include opportunities for *social comparison and support* through two methods: (1) supporting people in seeing and responding to other's activity in-app, and (2) providing mechanisms for sharing on other platforms like Facebook, Instagram, Twitter, or email. Figure 4 includes examples of these features from research prototypes and commercial apps. Houston and Chick Clique recruited sets of friends and family members to use the app together [28,152]. Participants appreciated being able to send and receive messages of encouragement. The HeartLink system demonstrated that people are willing to provide live support on Facebook when heart rate data is shared during a running race [38]. Feedback about other systems which share to broader social networking sites is typically more mixed. Some participants using GoalPost felt sharing increased their accountability [114]. But others worried about sharing trivial accomplishments, and thus opted not to share at all. Participants using the CommitToSteps system were less likely to set activity goals when they were shared on Facebook, but received supportive replies from friends and family when they did [115].

Figure 4. Physical activity tracking apps often include the ability to compare activity with others or share accomplishments and goals with a social networking site. From left to right, comparison and sharing features in Chick Clique [152], Fitbit, HeartLink [38], and CommitToSteps [115].

2.3.2 *Food Tracking*

Design principles common to physical activity tracking also appear in many designs for tracking food. Most apps include a calorie goal or budget as a key feature, visualizing daily progress toward that goal or budget. Many include reminders to track foods eaten. A few applications use visual metaphor alongside or in place of visualization, like a virtual pet for tracking children's eating behavior [17]. Systems have similarly examined how to foster social support, such as a community of peers all tracking their food in VERA [8].

Although sensor-based methods are able to reliably detect many types of physical activity, food tracking is notoriously more difficult. There is a long line of research examining how to automatically detect when someone is eating, what they have eaten, and how much they have eaten [3]. Other research has instead examined *journaling*-based approaches to collect more accurate and useful data than sensor-only methods.

Systems for food journaling have taken varied approaches to lowering the burden of collecting data (Figure 5). Both research and commercial systems have incorporated food dictionaries to provide general estimates about the nutritional value of a food (e.g., PmEB [153], MyFitnessPal). To reduce the entry burden further, both PmEB and MyFitnessPal support favoriting meals or re-entering previous meals. Barcode Ed [141] and MyFitnessPal additionally support scanning barcodes of packaged foods.

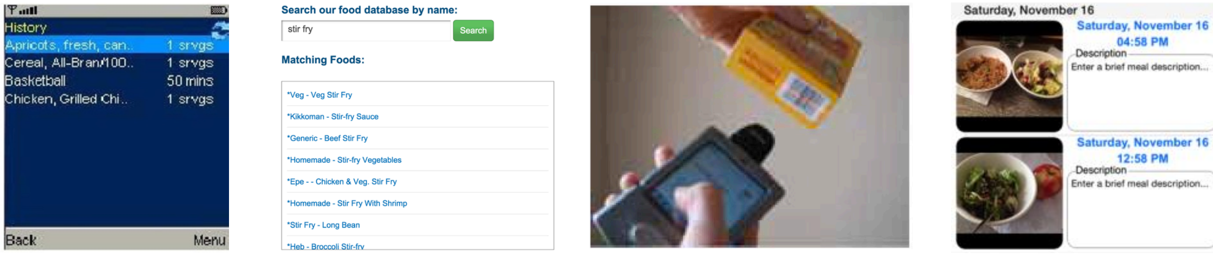


Figure 5. Food journaling apps and tools aim to lower the burden of collecting data.
From left to right, food dictionaries in PmEB [153] and MyFitnessPal,
barcode scanning in Barcode Ed [141], and photo-based food journaling in DECAF [33].

Many apps also remind people to journal their food daily, adopting the persuasive design strategy of reminders of people's ability to accomplish a simple task toward a larger goal [57]. Informed by the daily SMS reminders in PmEB [153], the Health Mashups system demonstrated that people are five times more likely to journal their food when sent a reminder. MyFitnessPal uses a similar reminder strategy, sending a notification when no meals have been logged recently.

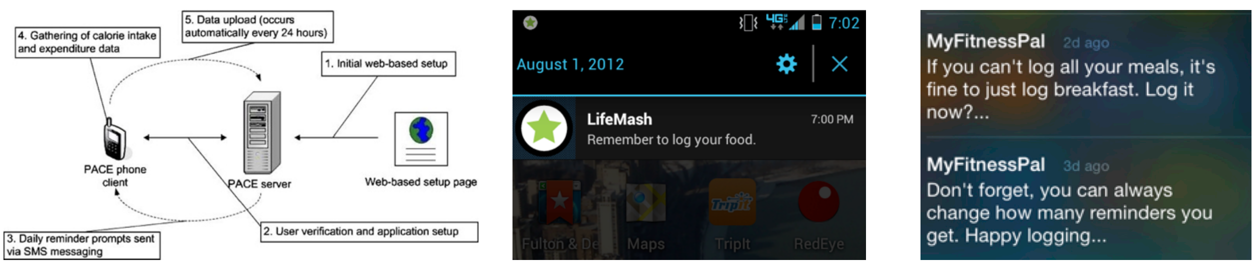


Figure 6. Daily mobile notifications can be effective reminders to journal food. From left to right,
the architecture of PmEB [153], sample notifications from Health Mashups [10] and MyFitnessPal.

Despite their strengths, these lower-burden design approaches for food journaling can also result in nudging people toward undesirable or unwanted behaviors. For example, barcode-based systems can encourage eating more packaged foods, and therefore less produce [34,141]. The difficulty of entering ingredients for home-cooked meals via food dictionaries, like salads, has a similar nudging effect [34]. Calorie-based budgets also make many people feel guilty for exceeding their budget, to which many people respond by electing not to journal everything they eat [34]. People with eating disorders can feel pride in staying under calorie budgets [41]. Designs need to be careful what practices goal setting and lower-burden tracking encourage.

To avoid some of these negative nudges, research has examined photo-based food journals [8,33]. Photo-based journals level the challenge between journaling home-cooked meals and packaged meals. Learning from the collected data can be a challenge in photo-based food journals, as traditional visualizations tend to not be appropriate. However, people often have a sense of how their diet was in a given day or in the week when they review their photos [33].

The dichotomy between fully-automated tracking common in physical activity tracking and fully-manual tracking typical of food journaling depicts a challenge in designing personal informatics apps and devices. Fully-automated systems have lower burden to collecting data and are thus easier to maintain long-term use. But the benefits of tracking are limited if people do not review the data they collect. The act of entering data into fully-manual systems ensures that people spend some time reflecting on the data they collect, but the data collection process is often too burdensome to maintain long-term. Recent work has therefore suggested that designs undertake a *semi-automated* approach to tracking, supporting both automatic and manual capture while promoting awareness about the data collected [21]. Toward semi-automated tracking, designs can support editing or labeling of automatically tracked data. For example, a sleep tracking system can use automatically-collected video and activity data, but support editing times woken up [81]. Designs can also prompt someone to journal when an interesting moment is taking place, such as using wearable sensors to detect when someone is eating [150].

2.4 Summary

Prior research has described how people approach personal tracking when they have a clear question in mind and the expertise and diligence to collect and analyze their data. Research has also demonstrated that people today tend to track for a range of reasons, regularly switching between tools. Despite attempts in designs to help people set goals, interpret their data, and share it with others for support, people often abandon the practice of tracking before the desired benefit has been reached. This occurs because tracking is high-effort, the data is hard to integrate across devices, and people worry about sharing trivial accomplishments with friends and family.

The difficulties people face when tracking motivates my perspective that designing with the realities of everyday life in mind can lead to tracking tools which better help people find value and find support through their data. I next describe a new conceptual model of how people use tracking tools which accounts for these realities and surfaces opportunities for improving design.

Chapter 3. A LIVED INFORMATICS MODEL OF PERSONAL INFORMATICS

As discussed in Chapter 2, self-tracking tools are now a part of everyday life, discussed in the literature as "lived informatics" [131]. For example, people switch what tracking tools to find one which better fits their information needs [95]. But they also switch because their devices break [60,131], they change or upgrade their phone [131], or because they receive a new recommendation for a tool they should use [131]. People also fail to sustain the habit of tracking or get frustrated and give up on their tools [27,34,93].

In this chapter, I describe a project where I extended and adjusted Li et al.'s stage-based model of how people use personal informatics systems (Figure 1 on page 7 and [95]). I develop a new model which acknowledges and accounts for the challenges of people using tracking technology in their everyday lives. This new model can offer better guidance to designers because it describes people's actual uses of tracking technology beyond the ideal case. In developing this model, I answer the following research question:

RQ1: How do people use tracking technology in their everyday lives?

Answering this question surfaced opportunities where people are not receiving the value they desire from their tracking tools, which allowed me to demonstrate how the design I developed in my case study (Chapter 4) solved a problem people face when using tracking technology in their everyday lives.

This project was published in UbiComp 2015 with co-authors An Ping, James Fogarty, and Sean Munson and additional contributors Kelly Campbell, Monica Caraway, Season Dai, Yoanna Desouto, Nicole Fugere, Coimbra Jackson, Chuck Johnston, Kim Lambert, Sreedev Sidharthan, Maria Suhardi, and Frank Xu [53]. I led development of the survey and interview protocols and writing and revising drafts of the paper. Analysis of the qualitative survey results was done in collaboration with An.

3.1 METHODS

Similar to Li et al.'s five-stage model [95] and its expansions and clarifications [20,96,155], I strove to examine diversity in the types of data people tracked about themselves. I therefore selected three domains of self-tracking to study: physical activity, location, and finances. Physical activity was selected because it was perhaps the most widely-used and widely-studied form of self-tracking at the time of the study, included by default in many wearables and phones. Physical activity is often studied when making broader claims about people's use of personal informatics systems (e.g., people's use of persuasive technology [60], opportunities for personalization [94]). Finances were selected because people have historically tracked them manually (e.g., ledgers and then spreadsheets) and there are now tools that support tracking automatically (e.g., tools from banks, aggregators such as Mint.com). Location tracking is a common and historically important branch of research in the HCI and UbiComp communities (e.g., [75,100,147,148]). Prior work suggests that people's goals for location tracking may differ from goals in other domains. For example, location tracking is often socially motivated and goals tend to be less numeric [148]. The equivalent of "walk 10,000 steps" or "save $1,000" is unclear for location tracking.

3.1.1 *Survey Methods*

I surveyed people on Amazon Mechanical Turk (AMT) in Winter 2015, which has been shown to be closer to U.S. demographics than conventional convenience samples [12]. One potential is concern is that people on AMT potentially represent a younger, more technologically literate population. This was is perhaps consistent with the demographics of self-trackers at the time of the study [58]. However, the growing ubiquity of tracking devices warrants considering how the broader population's uses of self-tracking technology differ from these findings.

I restricted participation to Turkers in the United States. To ensure response quality, I further restricted participation to Turkers who had a task acceptance rate of at least 95% and had completed at least 1,000 tasks. I surveyed 200 Turkers, compensating each with $0.50 for a short screener survey (less than 2 minutes) in which they indicated all (if any) self-tracking tools they had used previously in my three domains of interest. Finally, Turkers were presented with a short free-response question about their experience tracking that I analyzed for quality, a recommended practice in AMT surveys [40]. I rejected three responses as spam: two left the free response question effectively blank (e.g., "*N/A*"); one did not enter a code showing they had completed the survey.

I invited each Turker who had self-tracked in a domain (i.e., physical activity, location, finances) to complete a longer survey for that domain. They were compensated $2.00 for completing the approximately 15-minute survey. A single Turker could therefore complete three surveys, one for each domain. 105, 99, and 83 Turkers completed the survey for physical activity, finances, ad location (81.4%, 81.8%, and 76.1% of those who qualified).

In total, 168 unique people of the 169 eligible completed the full survey in at least one domain. I rejected two additional responses (one physical activity, one location) because the Turker indicated they did not use any self-tracking tools in the full survey. Table 2 contains a summary of the demographics from the survey.

Table 2. I surveyed demographically diverse participants using a variety of tracking tools in three distinct self-tracking domains.

Domain	Demographics	Temporal use (average # of tools)	Tools mentioned
Physical Activity	N=105 44 Female, 6 Male, 1 Female-To-Male Age: average 31.47, min 19, max 63	93 current (1.25)	Fitbit (19), MapMyRun (18), RunKeeper (13), MyFitnessPal (12), Nike+ (10)
		53 stopped (1.16)	RunKeeper (12), MapMyRun (9), Fitbit (8), Nike+ (8), MyFitnessPal (4)
Finances	N=99 46 Female, 52 Male, 1 Female-To-Male Age: average 33.46, min 19, max 70	96 current (1.58)	Spreadsheets (60), Credit Card Tools (34), Mint (34), Quicken (11)
		43 stopped (1.07)	Quicken (21), Mint (4), Spreadsheets (7), Credit Card Tools (7)
Location	N=83 36 Female, 46 Male, 1 no answer Age: average 30.75, min 19, max 70	80 current (1.86)	Facebook (56), Instagram (23), Google Latitude (19), Twitter (17), Foursquare (16), FindMyFriends (8)
		44 stopped (1.29)	Foursquare (24), Facebook (9), Google Latitude (7), Instagram (5), Twitter (5), FindMyFriends (4)

The full survey consisted of free response questions about each current and previous tool, asking why they started and stopped using that tool. We affinity diagramed these responses and identify themes. We then separately qualitatively coded the responses, iteratively refining codes through discussion.

3.1.2 *Interview Methods*

After we finished qualitatively coding the survey data, some of the questions I intended to answer in the study required further in-depth interviews to answer. Of Turkers who indicated in the survey that they were willing to be contacted for follow-up interviews, I identified 36 respondents who had representative tracking motivations, behaviors, and experiences and were verbose in responses. 6 Turkers responded to my request for an interview. I therefore supplemented these interviews with another 16 recruited through University mailing lists and posts to social media. These interviewees were screened with the same criteria as the Turkers.

Interviews lasted an average of 38 minutes (min 16, max 59) and were conducted by two members of the research team. 9 interviewees identified as male, 13 as female. They ranged in age from 24 to 39 (median 29.7, median 29.5). Interview participants were compensated with a $20 Amazon gift card. The interviewers discussed trends to identify themes and create codes. Two interviewers qualitatively coded each interview, iteratively refining codes through discussion.

Interviews took place in Spring 2015. The screener survey, full survey, and interview protocol are publicly available at https://github.com/depstein/lived-informatics.

3.1.3 *Limitations of Study Methods*

I focused on three common, yet diverse domains in which people track themselves. People self-track in many other domains in which people might have different motivations or tracking habits, including to manage chronic illnesses. Although I believe our findings are generalizable to domains other than three we report on (e.g., biometric or food tracking), they do not necessarily cover all motivations and usages. For example, in later work I observed that many people are motivated to track their menstrual cycles in order to inform conversations with their healthcare providers [52].

Some people track the domains we study using different classes of tools that we do not extensively report on. For example, tools like Moves and SenseCam [72] support passive recording of location. My findings suggest that these tools are used relatively infrequently (or point to possible limitations of my recruitment techniques). That said, my findings on tracking in a particular domain may not generalize to all tools or people tracking that type of data.

The recruitment techniques in this study overrepresent people who currently identify as self-trackers. The recruitment materials were likely to draw in people who were currently interested in self-tracking (e.g., posting the task on AMT as a "Survey on Location, Physical Activity, and Finance Tracking"). Other research by Lazar et al. [93] and Clawson et al. [27] describe a set of reasons why people stop using activity and health tracking technologies. I extended this understanding in follow-up work understanding how people who have stopped tracking feel about their experience [47]. I additionally triangulate Lazar et al. and Clawson et al.'s findings by describing why people stop in the same three domains as the work in this chapter (physical activity, location, and finances).

3.2 Development of a Lived Informatics Model

Based on the results of my survey and interviews, I developed a new model of personal informatics reflecting a "lived informatics" [131] view of usage, shown in Figure 7.

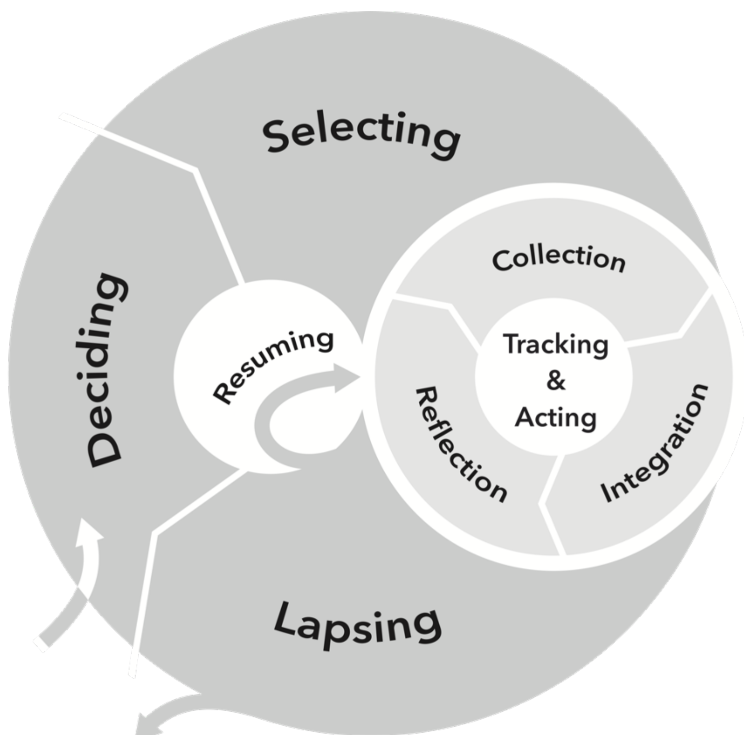


Figure 7. My lived informatics model of personal informatics. It includes the process of *deciding* to track and *selecting* tools, *tracking and acting* as an ongoing process of collection, integration, and reflection, and *lapsing* of tracking that may later be resumed.

3.2.1 *Deciding to Track*

I divide the preparation stage of Li et al.'s model [95] into two stages: *deciding* and *selecting*. The *deciding* stage refers to the decision to track personal data. This stage mirrors the precontemplation and contemplation stages of Prochaska and Velcier's Transtheoretical Model of how people approach health behavior change goals [129]. People decide to track for varied reasons, including to see each other's activity, to share activity with others, to receive rewards, or out of curiosity. People can decide to track having never tracked before or can return to tracking from a prior experience.

3.2.2 *Selecting Tools*

Following the decision to track, people select a tool with which to track. This is sometimes minimal or coupled with the decision to track, such as when someone received a tracking tool as a gift and decides to use it. The decision can alternatively require extensive comparison of tools (e.g., online, through trying out multiple tools). Tool selection can depend on features, aesthetics, and convenience. Choices available can also be limited by the tracker's mobile platform or budget.

3.2.3 *Tracking and Acting*

Choe [20] and Whooley et al. [155] indicate that self-trackers learn about their behavior and make changes to their practices while they collect and integrate data (e.g., reflection-in-action [137]). I therefore define the process of *tracking and acting* as the ongoing process of *collecting*, *integrating*, and *reflecting*. These three activities do sometimes have data dependencies. But in contrast to Li et al.'s model [95], I do not separate them into sequential stages. These activities can and do occur simultaneously and are interweaved.

3.2.4 *Lapsing*

The *lapsing* stage occurs when someone stops actively using a self-tracking tool. Lapsing typically begins with barriers to collection, but can also be caused by barriers to integration or reflection [95]. Later in this chapter I describe four categories of lapses: *forgetting*, *upkeep*, *skipping*, and *suspending*. For some, a lapse is a temporary break in tracking. Others do not return to tracking and have no intention to track again.

3.2.5 *Resuming*

Short-term lapses (e.g., forgetting to bring a pedometer on a weekend trip) are often followed by a quick resumption of tracking. In these cases, someone may not revisit their decision to track or the selection of a tool.

After a longer lapse (e.g., stopping tracking for months), the person tracking may not necessarily resume collecting more data with the same tool they used before. Instead, they may resume integrating or reflecting upon their previous data, deciding later whether more collection is needed and what tool to use. This decision varies by the person tracking and the domain.

3.3 Model Stages Across Domains

I next report on themes present across all three domains I studied, noting exceptions specific to particular tracking domains. The similarities in experiences across tracking domains demonstrate the potential for the model's applicability to other domains.

This section contains quotes from the 168 survey and 22 interview participants. I quote participants at p##, where p1-p22 were interviewed and p16-p184 were surveyed. Note this means that p16-p22 were both interviewed and surveyed.

3.3.1 *Different Motivations for Deciding to track*

I describe the three motivations that people mentioned for tracking: *behavior change*, *instrumentation*, and *curiosity*. These initial motivations inform how people select tools, use them, and lapse in their use.

3.3.1.1 Behavior Change Goals

Prior work has described how behavior change goals can motivate someone to start tracking [48,82,96,131]. In Powers' classification of goals, personal informatics tools support principle and program-level goals [127]. Principle-level goals are relatively abstract and ideal guiding principles that one tries to attain, such as goals described by p5 "*get in better shape,*" p86 "*to have more control over my finances,*" and 92 others. Program goals are more specific and actionable (e.g., p89 "*get[ting] out of debt,*" 39 others). We identified 48 financial trackers motivated to receive a financial touch, or a general awareness that their financial situation was as they expected [83]. For example, p90 "*just wanted a clearer snapshot of my finances.*" I believe such trackers intend to change their behavior if they notice something they find concerning, such as p164 "*[I] wanted to know if I should cut down on anything.*"

Even when people track to aid in behavior change, they sometimes track primarily to gain motivation or increase their accountability, rather than for insights or awareness of their behavior [9]. p72 started tracking "*because I felt I needed to get more motivation for my fitness,*" while p73 tracked finances "*to be accountable with how I spend my money*" (a sentiment mentioned by 13 others). Support for these goals may have different design requirements than supporting informational goals. Adding features that let people share progress may create channels for accountability [115,118], but merely having a record can also help motivate people and make them feel accountable to the tool [114]. For some people, the record's support for accountability is more valuable than insights derived.

3.3.1.2 Instrumental Tracking Goals

We define *instrumental tracking* as tracking with the goal of obtaining a record of a particular behavior, such as going to a particular place, watching a particular movie, or running a certain amount. Some are motivated to track by rewards that can be unlocked by data about their behaviors, such as discounts or badges [100]. p162 started tracking his physical activity because he "*got rewards points with my insurance,*" an increasingly common trend for health insurers [121].

Location trackers often instrument to achieve social benefits. 35 mentioned tracking to share where they went, including p173 for practical reasons "*I like to let friends know where I am in case I am in the area*" and p42 for social engagement "*to get likes.*" Others were motivated to start tracking to see where others were "*my friends had it, so I got it too to see where they were*" (p107, 19 others). These social motivations often are related to other goals, such as p82 sharing to inform friends: "*I ate at this Thai restaurant that I loved, so I wanted to share it with friends so they could check it out.*"

3.3.1.3 Curiosity

Many people decide to track without any behavioral goal, but out of curiosity about what tracking would be like or would offer them. People described thinking tracking would be "*fun*", "*cool*", "*neat*", and wanted to "*try it out*" (19, 12, 6, and 5 people, respectively). Curiosity is often driven by a desire to keep up with new technology, such as p68 trying Quicken because "*it seemed like the latest way to keep up with my expenses*." Curiosity also spread socially, such as for p41 "*everyone was using Foursquare and I thought I'd finally jump on a bandwagon*."

Many phones and computers include self-tracking apps and programs by default, such as Google Now, Apple Health, and Quicken. People also start tracking because they receive devices as gifts (10 people), they were free (7 people), or their "*phone asked if I wanted to,*" referring to the permission models for GPS tracking on many common phone apps (p63, 11 others). These events often make people curious enough to start tracking, such as for p150: "*it was offered free of charge so I thought I'd give it a try*."

3.3.1.4 Differences by Domain

The prevalence of tracking motivations varies by domain. Behavior change goals were common for physical activity or financial tracking (82% and 73% of trackers), while instrumental tracking was a major motivator for location trackers (67% of trackers). Curiosity was prevalent across all three domains, but was mentioned by more location trackers (10%, 6%, and 20% of physical activity, finances, and location trackers). Our participants predominantly used socially-oriented location tracking tools. We expect goals of self-oriented location trackers (e.g., location diaries like Moves and SenseCam [72]) would be more similar to physical activity or financial trackers.

3.3.2 *Selecting Tools Which Support Tracking Motivation*

Rooksby et al. describe reasons why people pick tools for self-tracking, including recommendations for others, reading media articles, and online reviews [131]. We note the same practices. Recommendations from friends (28 people) or family and significant others (9 people) were the most common means of selection. 10 people mentioned online reviews, such as p7 "*it was the first result on Amazon, and it had good reviews*."

Trackers motivated by behavior change try to select applications with features that best support their goals [60]. p177 chose RunKeeper because it integrated with another tool he was already using: "*it works well… with my other app… Nexercise.*" p78 was seeking a specific feature, "*I wanted to be able to download and import my bank statements so I could keep track of my spending,*" and decided Quicken best fit his needs. People motivated to track by a behavior change goal typically do substantial background research when selecting a tool, such as looking at many reviews. For example, p19 said, "*I read a lot of tech blogs… Fitbit has consistently gotten really good reviews*" (7 others described similar behaviors). 3 participants described seeking opinions on tracking tools from their online social networks. p5 said, "*a lot of times if I know that I'm looking for something new, I will quite often ask around on Facebook and such, 'has anyone tried this'?*"

Instrumental trackers look to maximize benefit they receive from a tool based on social influence or potential rewards. For instrumental trackers who are interested in social influence, selecting a tool is largely dependent on what tools the people they want to connect with are using. Location tagging on large social networks is popular because "*everyone else is using it*" (p57) and it is easy to engage with a large audience. People also look to maximize the rewards they receive, such as selecting a Fitbit because it is supported by a work wellness program (p18).

Trackers motivated by curiosity often do not actively think about selecting a tool, instead beginning to use whatever tool prompted their initial curiosity or is most readily available. Frequent media references led p154 to be curious about self-tracking: "*I started using Apple HealthKit since there was hype in the media about how great this app is,*" but it did not live up to his expectations "*I used it for less than a week and was not impressed.*"

3.3.3 *Using Tools for Value and Insight*

People's tracking motivations influence how they use their tools during the *collection*, *integration*, and *reflection* stages of Li et al.'s stage-based model [95]. We define this use of tracking tools as a unified process of *tracking and acting*. This section separately discusses how people *collect*, *integrate*, and *reflect* on data, but we reiterate that these processes occur simultaneously in practice. I report and discuss how both data domain and motivation influence usage.

3.3.3.1 Collection

Among the usage patterns of the survey participants, I observed a trend toward long-term use of current tracking tools (e.g., people who were currently tracking had used their tools for months or years). Figure 8 shows the usage durations we observed.

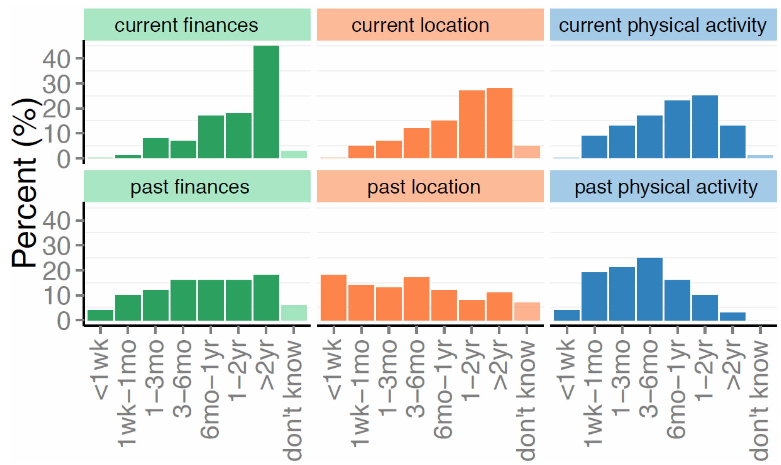


Figure 8. Respondents reported using financial tracking tools for longer than other tracking tools. They were quickest to abandon the use of location tracking tools.

Our data suggests that people abandon location and physical activity tracking tools more quickly than financial tracking tools. Among the participants who were no longer tracking, 45% and 44% of people stopped using location and physical activity tracking tools within three months, versus 26% for financial tools. Figure 9 shows that respondents also used location tracking tools less frequently than other tools.

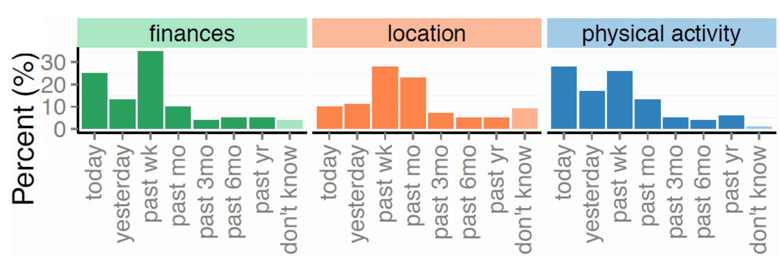


Figure 9. Respondents often made daily or weekly use of physical activity and financial tracking tools.

Figure 10 shows participant usage patterns around collecting tracked data. Many respondents reviewed physical activity every day. I infer that people have a daily or weekly habit of collecting their finances or physical activity, while location tracking appears more intermittent. However, many participants reported having not used their tracking tools in the past week (24%, 26%, and 36% of physical activity, finances, and location trackers).

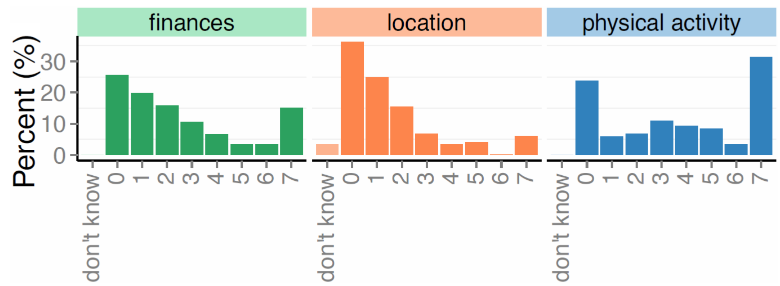


Figure 10. Location tools were typically used less than twice per week.
The plurality of participants reviewed their physical activity tools every day.

People who track to support behavior change tend to collect data frequently, such as p21 "*the Fitbit's on every day, almost 24 hours.*" Behavior change trackers were bothered when records were not accurate, "*I had a few accounts that I could never get added properly… it was an inaccurate picture of our finances*" (p19). p162 wanted credit for his activity "*[my app] wouldn't always acknowledge when I was at the gym,*" a common problem in prior work [28,60,70]. For people trying to maintain a level of activity, accuracy was less important. p11 noted "*I do keep an eye on trends. If I'm trending negative, or trending positive in my accounts,*" and emphasized trying to keep his spending constant. Kay et al. previously noticed trends matter more than accuracy for people who were trying to maintain, not lose, weight [82].

Financial tracking participants typically had behavior change motivations, and their usage of tools reflected this. 45% of financial trackers reported using their current tool for at least two years, with 73% reporting having used their tool within the past week. 63% of financial tracking participants were currently using spreadsheets, which require substantial manual entry. This level of sustained and frequent engagement with financial tracking is notable given the high burdens of data entry relative to our other domains. Kaye et al. suggest people are willing to exert this effort to manage their finances and often prefer it to using financial aggregation tools [83].

Instrumental trackers tend to engage in tracking when the benefits of doing so exceed the costs, such as the effort to record activities or to remember to charge and wear a device. For p143, this meant tracking when he was somewhere interesting: "*to brag about a cool place I'm at like Disneyworld.*" p18 was motivated to track by the incentives of her health insurance plan, and she continues tracking. She says, "*I get rewards [from my health insurance plan] for making so many steps a day and for logging my food daily*."

The frequency with which curiosity-driven trackers collect data is inconsistent. It primarily depends on how compelling they find the data they track. Many people motivated to track by curiosity will discover another value to tracking and increase their tool use, such as p85, who started tracking location because it "*was a trendy thing to do, but later on I've realized its benefits*." p132 started tracking physical activity because an app came preinstalled on his phone, and later realized the app was "*an ideal tool to record my physical activity*."

Location trackers tended to have instrumental or curiosity motivations, use their tracking tools less frequently (only 49% report tracking in the past week), and abandon tracking most quickly (18% of past trackers used their tool for less than one week). We note that 75% of current location trackers reported using their tools for at least a year prior to the study. This roughly coincides with when the feature appeared in popular social networking apps in mid-2013.

3.3.3.2 Integration

People integrate self-tracking data to help make sense of it. Integration can be trivial or time-consuming, depending on how much responsibility the person bears in preparing the collected data for reflection [95]. Many of the tools used by participants did not require integration, such as for MapMyRun "there is this whole dashboard on the website" (p16). For some behavior change tools, such as Mint, the primary purpose of the app is integration: "*I thought it would be beneficial to have all my finances in one place and see what I spend my money on*" (p178).

For instrumental trackers, it is important the data they track integrate into the system that provides the corresponding benefits. Tracking location for social reasons is only valuable if the audience a person cares about can see it. For p6, it was important to select a tracker that integrates with his insurance program. He describes the integration process: "*Fitbit sends [my data] to the health plan, then you can view it through the health plan's app to track your progress*." Trackers in the study who were motivated by curiosity did not describe any integration work, but integration can surface habits that self-trackers want to know more about [48].

3.3.3.3 Reflection

Survey respondents reported reviewing their physical activity most regularly (Figure 11), and most current location trackers had not reviewed their location in the past 7 days. Financial trackers reported reviewing weekly (35% and 33% of current and past trackers), while location trackers reported reviewing once a month or less (44% and 45% of current and past trackers). We note some respondents across all domains made a daily habit out of reviewing their data (20%, 12%, and 4% of physical activity, financial, and location trackers reported reviewing their data every day for the past 7 days).

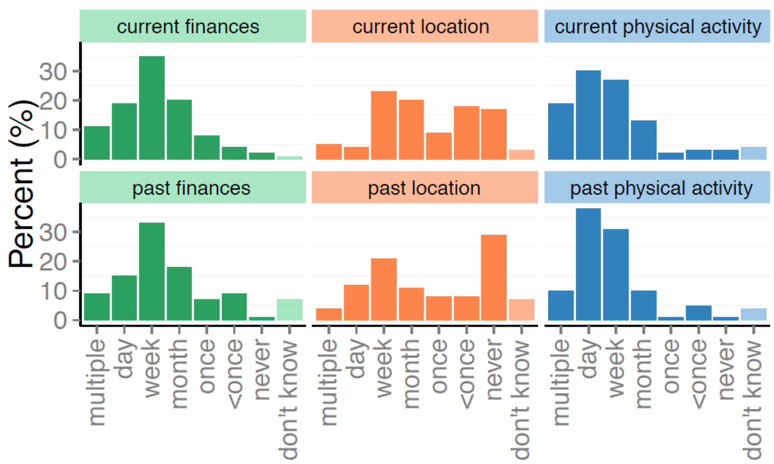


Figure 11. Respondents often reviewed physical activity data at least weekly. Respondents reviewed financial data slightly less frequently, and many location trackers rarely or never reviewed their data.

Trackers motivated by behavior change regularly reviewed their data, such as p22 "*I usually log into Mint almost every day. Sometimes I check a couple times a day when I am expecting a big expense.*" Physical activity trackers reviewed their data most frequently (Figure 12). For example, p17 said, "*I guess I would check in pretty much daily on how many steps I had taken, maybe 2 or 3 times a day.*" Aggregation across a week or month may be enough for people to receive value from financial data.

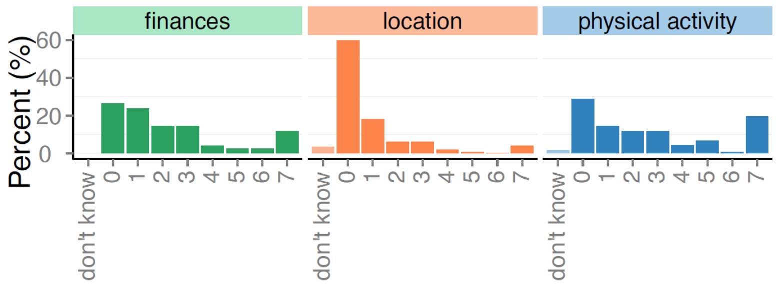


Figure 12. The majority of location trackers had not reviewed their data in the past week. Nearly 20% of physical activity and financial trackers had reviewed their data in each of the past 7 days.

Instrumental and curiosity-driven trackers tended not to frequently review or reflect on their data, such as p2 "*I would say a couple times a week. Not that frequently*." For instrumental-motivated trackers, the act of tracking was more important than looking back later: "*it's just about entering it in that moment*" (p16).

3.3.4 *Four Categories of Lapsing*

15%, 14%, and 17% of physical activity, finances, and location trackers identified as current trackers despite having not used their tool for a month or more. These participants seemed to still see themselves as trackers and participate in the underlying behavior. p30 identified he was no longer tracking, and when asked why he stopped, he stated, "*technically, I haven't [stopped]—I am just in between usages…*"

Participants in my study described four types of lapses: *forgetting*, *upkeep*, *skipping*, and *suspending*. I discuss the causes of each of these lapses and how they manifest. Lapsing may be intentional or unintentional and may or may not lead to stopping entirely.

Forgetting. People do not always remember to use their tracking tools, or cannot use them, regardless of whether they intended to and their original motivations for tracking. p13 states she "*never purposefully stopped using*" her Fitbit, but she has "*left it in a coworkers car after happy hour once. That was embarrassing.*" Substantial personal informatics research has explored how to reduce the likelihood of forgetting, including providing reminders [10] and automatically sensing behaviors that are typically journaled [151].

Although forgetting typically results in a short-term lapse, people may decide that the benefits of tracking are not worth the trouble of trying to remember to track. For example, p177 stopped using RunKeeper, explaining "*[I] haven't used it as much as I would want to. I guess I forget to use it.*" p3 mentions falling out of the habit: "*I just didn't make it a habit and then kind of forgot about it.*"

Upkeep. Devices and tools often require maintenance to continue tracking. The simplest example is charging the battery of a wearable device. 8 people mentioned forgetting to charge their devices, leaving them unable to track for an extended period of time. When talking about her Fitbit, p19 said, "*right now it's out of battery, so I haven't used it all week.*" Although she intends to continue using it, she often needs a reminder to resume tracking: "*I'll probably charge it tonight, just because we're talking about it.*"

Upkeep becomes a barrier to success for people motivated to track out of a behavior change goal. p19, who used spreadsheets to track her finances, said "*we just kind of stopped updating it because it was too much work to keep up to date,*" with p174 adding that he "*grew tired of managing it.*" For curiosity-driven trackers, upkeep becomes a barrier to usage. p20 wanted to use the lifelogging app Saga, "*it would log everything… that sounds exactly like [what] I'd wanted*" but gave up quickly because "*I felt it was eating too much of my battery.*"

Skipping. People make the decision not to log everything they track. Sometimes, tracking would not teach them anything new because they had already seen the data: "*I run this one little loop that I already know the distance, so I don't really bother with keeping track on the app*" (p11). p20 mentions that some locations represent events too private to record: "*some of these appointments are personal private things… 'do I check in publicly so that I can keep track?'*" The desire to maintain a complete record is often in tension with privacy in systems that emphasize sharing.

People also skip tracking entries when creating the entry is too difficult, such as entering every ingredient in a recipe [34]. This difficulty led p16 to stop tracking food entirely "*what caused me to stop is that… you have to break down every single thing you eat into all these component ingredients.*"

Suspending. People temporarily suspend tracking because they do not need or want to track during a time period. p122 stopped using Nike+ because of the winter holiday season "*the holidays and family visiting me has stopped me from using it.*" p12 does not food journal while she is on vacation: "*I put [entries] in MyFitnesPal every single day, except if I'm on a holiday or something.*"

p6 notes that he has "*taken breaks during the winter season from [activity] tracking.*" p180 describes taking a break from Mint and later returning: "*because I didn't really have the financial need at the time—not much money was coming in. But I recently started using it again.*"

Suspending tracking differs from suspending the activity that is being tracked. Examples of suspending activities include injuries (e.g., "*I got injured and stopped running*" p106, "*I stopped running due to knee injury*" p16) or changing life habits "*I travel less now*" (p46). In these examples, the tracking tool no longer serves a purpose for the person. Although these suspensions may be temporary and may appear the same from the perspective of what data is captured, this distinction is important in how people think about and use their tools.

3.3.5 *Transitioning to a New Tool*

Self-trackers regularly transition to new tools. In my survey, 53%, 72%, and 78% of physical activity, finances, and location trackers had used more than one tool. Changes are sometimes forced by reasons outside of tool selection, such as changing phones ([131], "*I switched mobile platforms*" p22, 3 others) or because the tool stopped being supported (e.g., "*Microsoft Money quit supporting their software*" p77, 5 others). We focus on people choosing to stop using a tool and beginning to use another, with or without a lapse in between.

As suggested by Li et al. [95], people who have behavior change motivations for tracking often switch to tools that better meet their information needs. 25 people described switching to a new tool that was "*better*", such as p186 switching from Quicken because "*someone recommended MoneyDance and I liked it a lot better*" and p95 from RunKeeper because "*found a better alternative (MapMyRun).*" People often describe what is better about a new tool in terms of features (e.g., p47 said, "*I wanted a more robust app option that would keep my weight and body measurements,*" 12 others agreed), ease of use (e.g., p72 said, "*I like my online banking app better and it is easier*"), or accuracy (e.g., p54 said, "*I upgraded to a smartphone with data that could track my actual location more accurately*").

Trackers motivated by behavior change often use and compare multiple tools at once, then decide what tool they prefer. When p5 decided to try switching from an analog pedometer to a Fitbit, she wore both of them: "*I put them both on to see what the Fitbit would be like and compare* *them*" and later abandoned the Fitbit because it was "*way off in comparison*." p121 started using their bank's tracking tools "*to compare it to other software tools,*" but later decided that other tools were better and stopped using her bank tools.

For instrumental trackers, tool switching often occurs when a new tool offers more benefits. p57 switched from location tagging on Facebook to using Twitter and Instagram because "*everyone moved in to other social media platforms… so I followed those trends instead*." p6 described using multiple pedometers at once because his health plan would "*pick the best numbers from all of these*." He later settled on the pedometer which gave the largest rewards.

I did not observe many instances of curiosity-motivated trackers switching tools, perhaps because use of one tool tended to satisfy their curiosity. After trying tracking, some of these trackers developed behavior change goals and switched to tools that better matched their new goals.

3.3.6 *Stopping Tracking*

Although extended or repeated lapses often lead people to stop tracking, people also stop tracking for other reasons. Some trackers motivated by behavior change stop tracking when they successfully change their behavior and move on to maintaining their desired behavior [129]. p142 and 2 others stopped tracking because they "*met my weight goal*." For others, the behavior change is no longer necessary, "*I'm not as financially strapped as when I was using Mint, so that's a big reason why I stopped using it*" (p15).

Instrumental trackers stop tracking when the benefits from instrumenting fade or are withdrawn. p164 stopped using Foursquare because "*the possibility of deals wasn't enticing enough*." For many social-oriented location trackers, this occurs when others stopped using the tool: "*everyone else stopped using it*" (p170, 10 others). However, some people who start as instrumental trackers find other benefits for tracking. Although p18 would not have purchased her Fitbit except for her work wellness program, she said she would continue to use it if the wellness program no longer supported it.

Some people who are motivated to track by curiosity stop when that curiosity fades. p109 stopped using Foursquare when "*the novelty wore off*" and p72 stopped using Google Latitude because “*it was boring*.” p27 and 2 others described starting to track because they “*like new technology*.” They may have moved onto a new curiosity when the novelty of the tool faded.

Stopping tracking is not necessarily a permanent decision, and people sometimes return to tracking. Finding a new tool to use may motivate someone to resume tracking. p20 stopped using Foursquare because there was “*less of a motivation to check in,*” but later resumed because she “*got a Pebble and you can check in on Foursquare from your Pebble*.” People also return to tools when their goals align with what the goals can support. p18 used MyFitnessPal to help her lose weight, lost interest in the tool, and resumed using MyFitnessPal to help with weight loss two years later.

3.4 Discussion

My model of lived informatics offers guidance and design challenges for the personal informatics research community. Some guidelines are consistent with those suggested by Rooksby et al., including to consider the agency of people and how they want to self-track [131]. I supplement these guidelines by recommending that designers help people make sense of their data during the tracking process, plan for lapsing and resumption, consider people migrating between goals, and support people adjusting their tracking goals.

3.4.1 *Making Sense of Data During the Tracking Process*

Because people aim to make sense of their data and act on it during collection, collection tools could better support integration and reflection. Toward integration, tracking tools can better support combining and comparing data across tracking domains. For example, MyFitnessPal enables importing activity data from Fitbit to enable correlating the data to weight and food consumption. Toward reflection, tools can offer insights from data as it is collected, such as surfacing recent trends or comparing data collected across days.

There is a need for designs to move beyond logs and daily goals to help people answer the types of questions which motivated them to begin tracking. Tracking tools today most effectively help people understand how much of a particular behavior they are exhibiting (e.g., “how much am I walking per day?”, “how much do I spend in a typical month?”). This likely meets the needs of people tracking with instrumental goals. But it satisfies only a basic level of curiosity and falls short of helping behavior change trackers find opportunities to change or improve their habits. Future designs should examine how to use people's collected data to answer the questions people are curious about beyond "what and how much" and should begin to surface opportunities for improvement for people motivated to change their habits.

3.4.2 *Returning to Tracking with the Same Tool after a Lapse*

It is unclear how personal informatics tools should behave when someone decides to resume use after a lapse. A person's historical data may be helpful for setting new goals, such as defining a new budget based on their previous spending habits. However, seeing potential failures surfaced in historical data may be demotivating for someone looking to resume use of a calorie-tracking app to lose weight. Historical data offers opportunities to bootstrap the data collection process, but its use requires careful consideration.

Some self-tracking tools passively collect information for as long as the tool is not disabled or uninstalled (e.g., Apple Health, Moves, Mint). Although someone may not look at their data for months or even years, the tool continues to collect and store their information. It is unclear what, if anything, the tool should do with this historical data when someone resumes using the tool after an extended lapse. Although research has considered the challenge of presenting a large amount of personal data in an easily consumable manner [11], it remains unclear how to summarize this data based on the reason the person resumed tracking. Furthermore, perhaps the passively collected data should not be summarized at all. Instead, the person may want to start over with a clean slate, and looking at their previous data may create a negative reaction if they view their previous tracking experience as a failure.

3.4.3 *Effective Migration Between Tools*

Although many tools are free, some self-trackers are concerned with the cost of others. Loss can cause a lapse when someone cannot afford a replacement, such as Fitbit wearer p155 "*it got lost or stolen and I didn't want to spend the money to replace [it]*" and Quicken user p53 "*it costs money, and I realized I could do everything I wanted with Excel.*" More commonly, people change their motivation and needs for tracking, such that tools no longer support the new needs.

Although some self-trackers are not concerned with abandoning tools and the data they have collected, others avoid switching tools, even when a better tool for their goals exists. p11 describes why he avoids switching tools: "*I try to avoid it as much as possible… When you transition from tools, there's a lot of transaction costs in terms of switching between one and the other. You just have to get your profile set up again, you have to learn to interact with a tool. There's potential data loss. I don't know if that matters, sometimes it does, but usually it's something that I just kind of gave up on.*"

The overhead of setting up a profile, learning a new interface, and losing his data were too much for p11 to consider switching tools. When he desires other features, saying "*I want to have an aggregate sense of how many miles I've run for the past three months,*" he is unwilling to switch to a new tool and lose all of his built-up knowledge. Lock-in may be desirable from an application or device manufacturer's point of view. However, personal informatics tools could better support their users with designs that support evolving motivations and feature needs and allow people to migrate when the tool no longer best supports their goals.

3.4.4 *Supporting Migration Between Goals*

Some curiosity and instrumentally-motivated participants found other benefits from their tracking tools that motivated their sustained tracking, even as they satisfied their initial curiosity or as the instrumental benefits faded. Others did not find such alternative benefits. This suggests that designers may be able to do more to help people find benefits in continuing to track. This might include realizing the value of tracking to support behavior change goals they already have, or even setting new goals. For example, an app that someone starts to use out of curiosity regarding how active they are could illustrate benefits achieved by others who started from the same activity level and walked a bit more each week.

In other cases, data from personal informatics applications may prompt people to question their behavior. For example, someone who tracks their location to share with friends or receive discounts might receive a badge for eating out often, or realize they check-in at restaurants much more than their friends, and wonder how much they could save by cooking at home more often instead.

3.4.5 *Conclusion*

I offer a model of personal informatics informed by the perspective of lived informatics, expanding upon prior models that were based primarily in behavior change and maintenance. I identify three initial motivations for tracking: the desire to change a behavior, instrumenting a habit for rewards or social engagement, and curiosity regarding data and habits. The new model captures the practices of self-trackers with such diverse goals, offers a better understanding of how they use self-tracking tools, and helps surface relatively unexplored challenges for future designers and researchers.

The model I developed has also given other researchers a language for articulating the experiences people have and barriers people face integrating tracking technology into their lives. For example, Pina et al. examine how families with shared health goals work together to decide what to track, collect, reflect, and act on data, and lapse in tracking [124]. Individual family members may be responsible for collecting data, making sense of it, and implementing an action plan, and may stop and resume tracking independently. The work further points out that tracking roles are not static. Beyond supporting fluidity between tracking tools, systems to support family informatics should support members switching roles.

The Tracker Goal Evolution Model [119] describes a subordinate construct within the *tracking and acting* stage of the model I developed. The model, shown in Figure 13, describes how people's goals evolve from abstract needs to feel good and be happy to more qualitative goals which can be verbalized and described to quantitative goals which can be effectively measured by tracking technology. To facilitate people migrating their qualitative goals like "having an active lifestyle" or "losing weight" to quantitative, measurable goals, the model surfaces a need for tracking tools to facilitate trust that the tool accurately measures what a person is doing and to support reflecting on the qualitative goals.

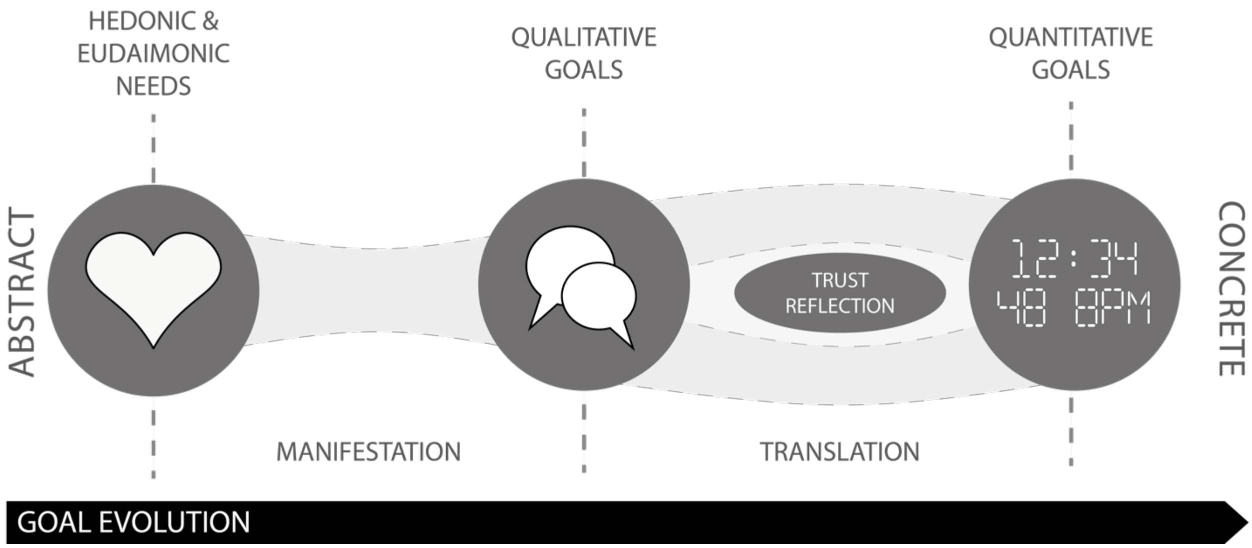


Figure 13. Niess & Wozniak's Tracker Goal Evolution Model describes how qualitative, and eventually quantitative goals emerge from people's hedonic and eudaimonic needs to feel good or be a better person.

The lived informatics model contributes an empirical understanding of how and why people use personal tracking tools in their everyday lives, answering RQ1. I build on this understanding in Chapter 4 by designing a system which helps people find additional value from their data while they are in the phase of tracking and acting.

Chapter 4. VISUAL CUTS AS A CASE STUDY OF DESIGNING FOR FINDING VALUE IN DATA

Development of the lived informatics model uncovered a variety of design challenges for the community related to supporting migration between tools and goals as well as returning to tracking. In this chapter, I focus on a case study toward another challenge highlighted by the model: how designs can help people make sense of multi-dimensional data and get value during the tracking process. Tools today often combine multiple types of data. For example, Moves and Saga passively record location and physical activity, and platforms like Apple HealthKit aim to aggregate data across tracking tools. This style of tracking tool is often described as a *lifelog*, or a record of what people are experiencing [64].

As shown in Figure 14, commercial tools generally use simple presentations which allow for minimal interpretation, such as extremely low-level views (e.g., step counts for every 15 minute interval), high-level aggregation over time (e.g., step count for a day or month), or long historical event streams (e.g., steps with location traces). These place the burden of synthesis on the self-tracker. Trackers with expertise in data analysis may notice high-level patterns (e.g., "*I get the most walking done to and from work*" [97]). However, the rise in popularity of tracking tools now means that most people using them do not have this expertise. Tools to help people extract more complex or actionable correlations may allow people to gain more value from their collected data.

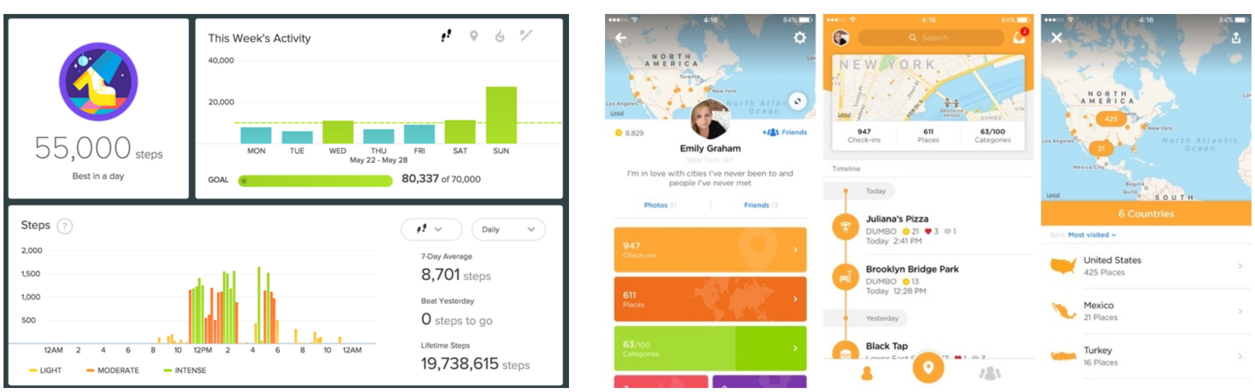


Figure 14. Most commercial applications give low-level minute-by-minute views of tracked data, provide simple aggregations like step count per day, or give a historical event stream.
The desktop dashboard for Fitbit appears on the left, the mobile view of Swarm on the right.

Applications have aimed to infer and surface more complex concepts from the data people collect. A selling point of the now-defunct *Saga* app was its inclusion of a traits feature, which reported basic findings the application has made based on a tracker's location history. However, these traits tended to emphasize information the tracker is already likely to know. As in Figure 15, examples included the type of building a person lives in (e.g., "*Saga has determined that you live in an apartment or condo.*") or a type of place they frequently visit (e.g., "*Saga has noticed that you visit bus stations.*"). Bentley et al. also present trackers with day-level correlations identified in their activities (e.g., "*You walk significantly more on Fridays.*") [11]. However, participants often reported these were "obvious".

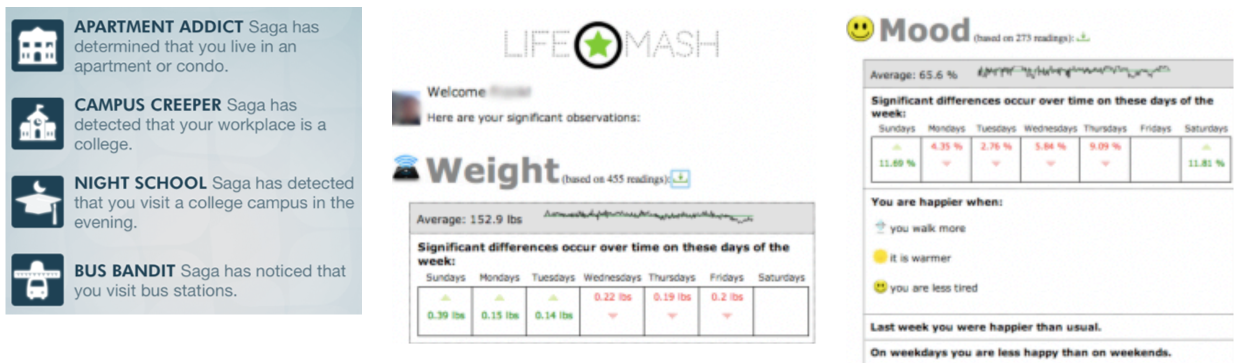


Figure 15. Commercial and research applications have aimed to provide higher-level inference from the data people collect. People tended to find early inferences relatively obvious. On the left, traits uncovered by the Saga app. On the right, correlations noticed and summarized by Health Mashups [11].

The increased need for designs to help people get value out of complex data and the limited success of prior designs led me to ask the research question:

RQ2: How can a design help people get additional value from multi-dimensional tracked data?

My approach, *Visual Cuts*, involves identifying data which answers a question people often have about their habits and visualizing it in an appropriate way. I begin by defining a *cut* as a subset of data people collect with some shared feature. Most prior work focuses on temporal cuts (e.g., [11,63]), but other cuts are possible. For example, a cut may focus on data from whenever a tracker visits a particular type of location (e.g., a restaurant, a gym) or follows a transit pattern (e.g., commuting to work). Cuts can also be projected onto each other to explore how one factor relates to another. Importantly, cuts characterize a subset of data that can then be presented in different ways. Prior work has been relatively ad-hoc, considering visualization techniques including maps [63,79], one-sentence summaries [11,85], graphs [11,46], and visual metaphor [31,55,99]. I therefore began by conducting a formative survey to help identify cuts that people might find valuable in exploring their tracked data. Based on the identified cuts, I considered visualizations that can help support tracker goals. Finally, I evaluated these ideas with a month-long field deployment with 14 people.

This project was published at DIS 2014 with co-authors Felicia Cordeiro, Elizabeth Bales, James Fogarty, and Sean Munson [48]. I led development of the survey protocol, analysis the survey results, and writing and revising drafts of the paper. Specific cuts were implemented in collaboration with Felicia. The interviews at the end of the study were collaboratively conducted by Felicia, Elizabeth, and me.

4.1 EXAMINING LOCATION AND ACTIVITY DATA

In the development of Visual Cuts, I extend prior work by examining designs to help self-trackers synthesize and examine data collected from multiple sources. I start with location tracking and tagging, activity recognition, and weather. Location tracking and activity recognition were both provided in the Moves app (Figure 16). Moves runs passively throughout the day, recording locations and activity. It presents this lifelog to the self-tracker in a timeline view. When a person visits a new location, they can tag the location with a name. Potential tags are generated by searching through the Foursquare database for nearby businesses (this switched to Facebook places in 2015, after the company acquired Moves), and a handful of special tags are supported (e.g., “Home”, “Work”, “School”). After a person tags a location, Moves passively infers the tag on future visits and allows correction of inferred tags as necessary. I supplemented this with additional Foursquare data about visited locations. I also expected weather to impact the decisions people make about transportation and activity, so I used the Forecast API to sample local weather each time the self-tracker arrived at or left a location.

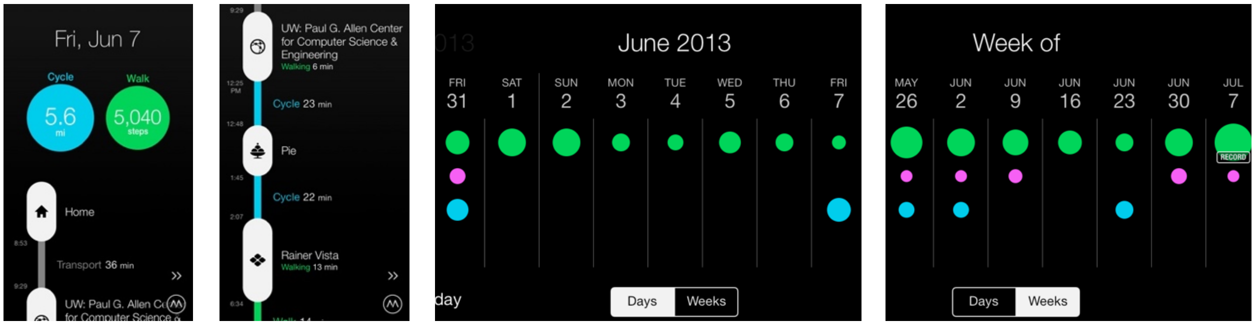


Figure 16. The Moves app collects a tagged log of the places people visit and how they get between places. Moves has limited support for people to explore trends across days. The person tracking can zoom out to compare daily and weekly activity totals, but have to infer what caused those differences on their own.

The techniques and insights developed in this chapter can also apply to other types of personal informatics data, as I explore in a later study of helping people understand their work-break habits [45]. My focus on location, activity, and weather in this chapter allowed leveraging polished commercial products for data collection, focusing the research on data synthesis.

4.2 Visualizing Cuts in Personal Informatics Data

Lifelog data is complex and multi-faceted. Prior work has focused on presenting a subset of the data using a visualization technique chosen to be appropriate. In my approach to presenting different potential cuts of a tracker's data, a challenge is that visualizations appropriate for some cuts may not be appropriate for others. For example, a visualization that surfaces an interesting routine in one cut may lack detail needed to get value from another cut. Conversely, a detailed view effective for one cut may be overwhelming with another cut. I therefore developed a set of visualizations that can cover a range of approaches to presenting the data from a cut. Each visualization was implemented using D3 [15]. I first review the visualizations, then introduce the cuts to which I apply these visualizations.

4.2.1 *Tables*

When a cut reduces data to a small number of values in a single dimension, it is often effective and precise to simply present the data in a table. We therefore summarize data in a table when there is only one variable to represent (e.g., data cut by day of week or other categories). Figure

17 shows one such table, supporting comparison between the amount of time spent at work by the day of the week.

Day of week	Time (in hours)
Sunday (0 days)	--
Monday (4 days)	10 hours, 6 minutes
Tuesday (4 days)	10 hours, 14 minutes
Wednesday (4 days)	8 hours, 35 minutes
Thursday (4 days)	8 hours, 38 minutes
Friday (3 days)	7 hours, 22 minutes
Saturday (0 days)	--
On average, you spend 1.6 fewer hours at work on Fridays.	

Figure 17. A table allowing comparison between the amount of time spent at work and the day of the week.

4.2.2 *Graphs*

Stacked bar charts can be effective for showing how one cut through data relates to another cut. For example, Figure 18 (next page) shows how a person's transportation mode correlates with the length of trip they take. This shows a correlation between short trips and walking. Hovering over a bar reveals more details (e.g., the exact number of trips in the transportation mode).

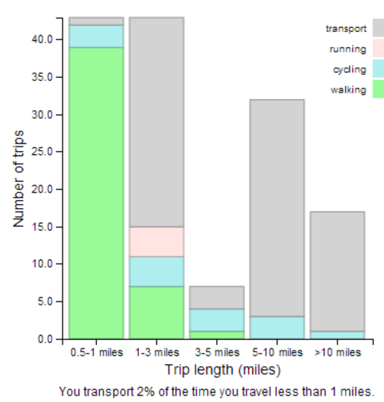


Figure 18. A graph showing how a person's transportation mode varies based on trip length.

4.2.3 *Captions*

Similar to Bentley et al. [11], we distill correlations into single-sentence natural language summaries called *captions*. We present these with tables and graphs (see Figure 17), but explicitly sought participant feedback on captions separate from their table or graph. Captions highlight either the most significant difference in the visualization (e.g., "*On average, you take 2404 more steps on Wednesdays*") or a potential reason for the difference (e.g., "*On your most active days, you went to 2 more Parks than usual*"). The caption in Figure 18 notes a person uses transit on few of their short trips, a potential opportunity for an increase in walking.

4.2.4 *Maps*

Extensive prior work uses maps to visualize location data (e.g., [63,79]). Maps can highlight places visited, routes taken, or other cuts. For example, Figure 19 shows transportation mode for all trips of lengths in a given range. Following recommendations to enable examination of details on demand [140], the mapped locations and routes can be clicked for more detail, such as the location name or the route length. Maps were created using the Google Maps API.

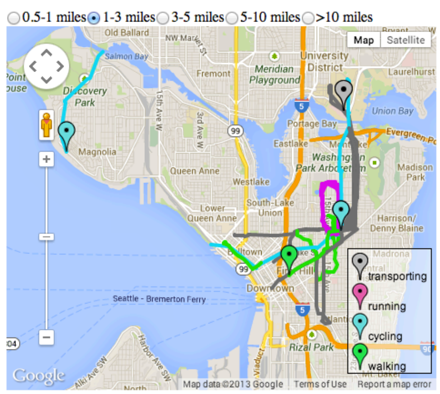


Figure 19. A map showing the routes a person travels on all trips of a certain length.

4.2.5 *Sankey*

Sankey diagrams can be used to visualize energy flow [130], and we applied them to show overall trends in a person's movements. Figure 20 shows an overall flow of starting the day at home, visiting Corbis in the middle of the day (a work location), and returning home. Single trips are visible, as are infrequent clusters (e.g., a few days spent at Mom's house). To remove some clutter and help surface patterns, I combined locations that were visited once, were of the same high-level Foursquare category, and were visited at approximately the same time of day (within two hours, either within the same day or on different days at the same time). Figure 20's "Food" and "Shop & Service" correspond to visiting different locations of those types at approximately the same time. Trackers can also add or remove days of the week from a cut to use the Sankey diagram to find day-specific patterns.

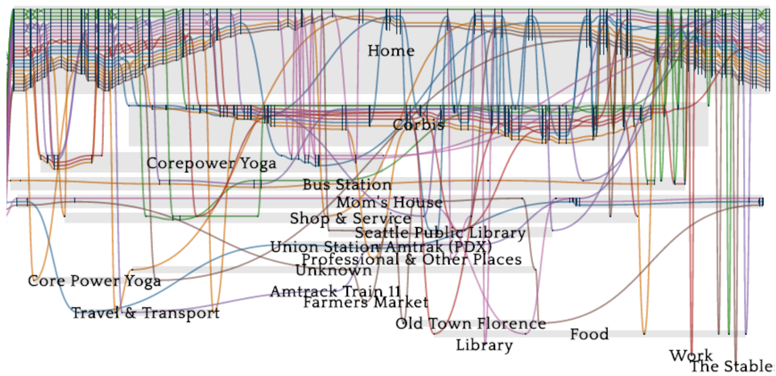


Figure 20. A Sankey diagram showing a participant's overall flow between places each day.

4.2.6 *Daily Lifelog*

Moves and other lifelogging applications provide lifelog views as feeds of data, as in Figure 16. A self-tracker can switch between days, viewing activity for each day. To enable comparison between cuts, I implemented daily lifelog visualization as a selectable calendar. We did not re-implement the Moves timeline, but asked participants to consider it when interacting with the daily lifelog (participants were already highly familiar with the view after using Moves for approximately one month). Although other visualizations of lifelogs exist in prior work [63,79], we asked participants to consider the timeline for familiarity.

4.3 CHOOSING CUTS THROUGH DATA

With these visualizations in mind, I looked to develop a set of meaningful cuts to present to self-trackers. I sought a better understanding of the motivations of current self-trackers, to identify what cuts might be meaningful to people.

4.3.1 *Formative Survey*

I recruited survey respondents in Spring 2013 from a variety of sources, including university mailing lists and Fitbit and Quantified Self forums. 139 people who use commercial self-tracking applications completed the survey. The vast majority (81.3%) used physical activity tracking tools. As a result, I concentrated the development of cuts to meet the goals of physical activity trackers. Respondents who tracked other categories had different goals, and I later discuss extending the findings to developing cuts for other tracking domains.

The survey was a set of free response questions. We analyzed participant responses using an open coding scheme. Respondents indicated what factors they believed impacted their activity level. To help stimulate identification, I asked participants to use a Likert scale to rate how their activity or location was impacted by several factors. The survey then encouraged respondents to list at least three other factors. Table 3 summarizes results.

Table 3. Formative survey respondents reported a wide variety of self-tracking goals, factors they believe impacted their activity level, and daily routines.

Question	Most common responses (# responses)
Tracking tools used	*Fitbit* (104), *RunKeeper* (9), *Nike+* (7), *MapMyRun* (5), other (17), multiple tools (24)
Length of time tracking	Less than a month (23), 1-3 months (27), 4-6 months (12), 7-12 months (22), more than 12 months (29)
Goals for self-tracking	Maintain / increase activity (41), maintain / lose weight (35), awareness of activity levels (34), increase motivation (14), be held accountable (10), have a record of activity (8), find patterns (7), competition (6)
Factors that impact activity level	Work schedule (35), weather (29), travel (21), injury and fatigue (20), changes in daily schedule (18), sleep amount and quality (16), schedule of partners and children (13), stress and mood (13), socializing (12), food consumption (11), errands (7)
Daily activities	Commuting to and from work (44), gym (25), take care of pets or children (18), errands (6)

Of 113 respondents who track physical activity, 68 (60%) identified as female. Median age was 46 (mean 44.7, stdev 13.0). This suggests my survey reached a broader variety of people using self-tracking tools than prior work. For example, Choe et al.'s sample of Quantified Self videos were 79% male [22], though Pew Research suggests that men and women are equally likely to track physical activity [58]. Similarly, Li et al. report a median age of 26 to 30 [95], younger than our participants. Including this more diverse population helps us understand people's broad range of motivations for tracking.

Respondents identified an average of 1.6 goals, typically in two categories: tracking goals (e.g., having a record of activity, finding patterns) and long-term health goals (e.g., maintaining or improving activity and weight).

The most commonly described daily activity was commuting to and from work (44 respondents). Work schedule was the activity with the greatest perceived impact on physical activity (35 respondents). This indicates the importance of commuting in daily activity and the importance to people when they are considering their physical activity trends.

Respondents said their typical activity varied by day of the week. 50% of participants believed that "*being a weekend*" increased their activity, but 24% of participants also believed that weekends decreased their activity. Day-specific activities that respondents mentioned included running or going to the gym, meetings or lunch events in distant buildings, and scheduled errands (e.g., visits to a grocery store). Participants also mentioned additional sources of activity related to walking pets and activities with children (e.g., going to a park, picking up children from daycare).

Variations in the weather (29 respondents), a person's routine (21), or the schedule of a partner or child (18 and 13, e.g., picking them up from work or daycare) also created or limited opportunities for physical activity. Respondents indicated poor weather negatively impacted activity, while abnormally good weather motivated outdoor exercise.

Internal factors were also perceived as influential, such as injury and fatigue (20 respondents), sleep quantity and quality (16), and stress and mood (13). Some respondents used physical activity as a stress relief mechanism, while others reported that physical activity caused them stress.

Respondents also mentioned socializing (12 respondents) and food consumption (11). 44% said that "*being with friends*" increased their activity, while 28% of participants indicated the opposite sentiment. Eating also influenced activity patterns, with respondents not wanting to exercise immediately after eating or feeling the need to exercise more after unhealthy eating.

4.3.2 *Cuts Selected*

Based on the results of the formative survey, I developed 13 cuts through location and activity data to evaluate in a field deployment. Table 4 summarizes the cuts developed. The cuts represent a variety of tracker motivations and were designed to offer interesting points for self-trackers to reflect upon. Participants also interacted with a daily lifelog (DL) view through Moves and a Sankey diagram (SD) of all of their activity.

Table 4. Informed by the formative survey, I selected 13 cuts through location and activity data. These cuts were visualized using graphs, tables, and maps. All cuts included a summary caption.

Cut short name	Description	Visualization technique
TT1	Average time in different modes of transit (walking, running, cycling, and transporting) by day of week	Graph, map
TT2	All trips to and from the same location by transit type	Graph, map
TT3	Number of trips in each transit mode by trip distance	Graph, map
CM1	Amount of time spent at each of home and work by the day of the week	Table
CM2	Average arrival time at work and departure time from work by the day of the week	Table, map
CM3	Time taken to commute to and from work by the type of weather (e.g., clear, partly cloudy, rainy)	Graph, map
FD1	Categories of food places visited by day of the week	Graph, map
FD2	Categories of food places visited by time of day	Graph, map
AB1	5 days with the most and least number of places visited	Graph, map
AB2	10 days with the most physical activity	Graph, map
WW1	Total minutes of physical activity by week	Graph, map
WW2	Number of unique places visited by week	Graph, map
WW3	All places visited only on weekdays or weekends	Graph, map
DL	Daily lifelog view of all activity and locations	
SD	Sankey diagram of all activity	

4.3.2.1 Transit Type and Physical Activity (TT)

Cuts TT1, TT2, and TT3 focus on Transit Types and their relation to physical activity. TT1 overviews transit by day of the week, motivated by respondents identifying day-specific activities (e.g., going running on certain days). TT2 shows trips which start and end in the same location in an attempt to capture common daily activities in our formative survey like pet walks and running routes. TT3 showed differences in transit mode by length of the trip. We expected participants to walk and bike more often on short trips and use transit for longer trips (i.e., cars, public transit). The caption for TT3 showed for what percentage of trips less than one mile the participant had used transit, a threshold selected as a generally "walkable" trip.

4.3.2.2 Commutes (CM)

Because participants most frequently mentioned their work schedule as affecting their activity, I included cuts for commute between home and work due to work schedule. CM1 shows average time spent at work and home, while CM2 shows average arrival and departure time from work. For both, the average excludes days where trackers did not go to work. CM3 presents differences in commute time and weather, assuming that commutes take longer in poor weather.

4.3.2.3 Food Places (FD)

Survey respondents included food consumption as a factor impacting activity (e.g., overeating, not eating). We also anticipated that, apart from home and work, places that serve food would be the most common type of location for people to visit (e.g., restaurants, cafés). These places are also common for socializing, another factor indicated by participants. I therefore created two food place cuts, showing patterns in food places by the day of the week in FD1 (Figure 21) and by the time of the day in FD2.

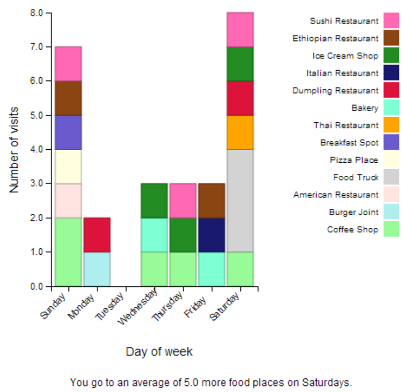


Figure 21. An example of cut FD1 through participant data.

4.3.2.4 Abnormal Days (AB)

Survey respondents noted that changes in daily schedule and deviations from routine to run errands influenced their physical activity, leading me to design cuts to try to highlight such days. AB1 is based on the intuition that the number of places visited in a day could serve as a proxy for how busy a person was with errands and other location-based tasks. The cut could help reveal a person's most busy and least busy days. AB2 shows the day a person tracking was most active, highlighting their accomplishments and potentially helping them identify aspects of those days they may want to repeat more regularly.

4.3.2.5 Week-to-Week Summaries (WW)

Finally, I created cuts that summarize activity from week to week. WW1 (Figure 22) showed total physical activity levels by week, surfacing particularly active or inactive weeks. WW2 helped identify potential abnormal weeks by comparing the number of unique places visited each week.

WW3 showed places only visited on weekdays or weekends, a distinction that survey respondents made when describing their routines.

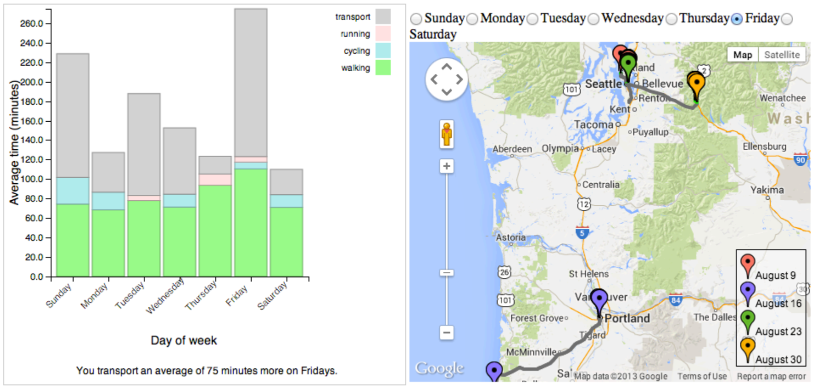


Figure 22. An example of cut WW1 through participant data.

4.4 Field Deployment

I next conducted a field deployment to examine how people respond to complex cuts and to better understand how to visualize cuts in an interpretable manner. Each tracker's participation lasted approximately one month and included three interviews. During the first interview, I installed Moves on their personal phone and asked about their initial expectations of the system and the questions they hoped to have answered about their routines. At the two-week interview, I briefly checked in with participants to for their initial reactions to using Moves. Finally, after one month I interviewed participants, presented the visualizations of cuts through their data, and gathered feedback.

It is important to note that cuts were presented only at the end of the study. I did this primarily so I could tailor the visual cuts to the specific questions the participants were hoping to have answered. Delaying the reviewing of cuts also ensured the cuts were populated with substantial data and allowed participants to compare their experience to that with the streaming lifelog presentation found in Moves.

4.4.1 *Study Design and Participants*

I recruited participants from university mailing lists, other local mailing lists, and local self-tracking groups (e.g., Quantified Self meetups). To ensure all participants had equal experience, I excluded any potential participant who had previously used Moves. Because I sought to examine how cuts could support people during their normal routine, I excluded participants likely to have many abnormal days. Specifically, I excluded participants who expected to have more than four days of travel during the study period or expected to move or change jobs. In the previous chapter I discussed how these major life events or changes many motivate someone to resume tracking after a lapse [53]. There is an opportunity for future work to examine how a tracking tool can best support people in comparing their routines before and after a major life change.

I recruited with the goal of obtaining a diverse group of participants, including for gender (4 male, 10 female), age (average 36.2, stdev 12.1), and experience tracking (daily users of another tracking tool, infrequent trackers, people who had never tracked before). 11 participants conducted all of the study interviews in-person, and 3 participated remotely. Table 5 contains participant demographics.

One additional participant dropped out of the study after 11 days due to unanticipated long-term travel. She does not appear in Table 5 and I do not further report on this participant.

Table 5. I conducted a one-month field deployment with 14 people of varying backgrounds, tracking experience, and goals.

	Age & Gender	Self-tracking experience	Occupation	Self-tracking goals (beyond increasing/maintaining activity)
p1	50, F	Infrequently recorded bike route	Researcher	Healthier food
p2	27, M	Daily Fitbit wearer	Graduate student	Recording, finding patterns
p3	40, M	Infrequent Foursquare user	Researcher	Visiting new places, recording, finding patterns, time with friends
p4	26, F	Daily Fitbit wearer	Software engineer	Recording, finding patterns
p5	31, F	Daily Jawbone UP wearer	Researcher	Healthier food, saving money, recording, finding patterns
p6	31, F	Daily Fitbit wearer	Graduate student	Recording
p7	25, F	Infrequent sleep tracker	Graduate student	Recording
p8	31, M	Daily Fitbit wearer	Part-time designer	Recording, finding patterns
p9	44, F	Infrequent RunKeeper user	Librarian	Visiting new places, recording, finding patterns
p10	27, M	Infrequent Fitbit wearer	Software engineer	Recording, finding patterns
p11	32, F	Never tracked	Brokerage assistant	Saving money, visiting new places, finding patterns, time with friends
p12	66, F	Daily Fitbit wearer	Systems business analyst	Healthier food, finding patterns
p13	42, F	Daily ActiveLink wearer	Lawyer	Healthier food, recording
p14	44, F	Never tracked	Fundraiser	Recording, finding patterns

I provided participants a list of potential goals for self-tracking developed from prior literature (e.g., [23,95]) and the formative survey. They were asked to select all goals they felt applied to them or identify another self-tracking goal(s). All 14 indicated they wanted to increase or maintain their level of physical activity. 11 wanted a record of their activity (e.g., instrumental tracking [53]). Other goals were healthier food choices (4 participants), visiting new places (3 participants), finding opportunities to save money (2 participants), and spending more time with friends (2 participants).

I asked participants to launch Moves at least once per day during the study. This ensured participant data was sent to my server and also that participants were reflecting on the data Moves collected. Participants reported checking Moves an average of 3.2 times per day (min 1, max 10, stdev 2.8).

4.4.2 *Moves Usage*

We captured Moves logs from participants for an average of 29.7 days (min 27, max 36, stdev 2.2). Participants visited an average of 4.7 locations per day (min 2.6, max 6.1, stdev 1) and tagged an average of 88% of the locations they were at for longer than 10 minutes (min 67.6%, max 100%, stdev 11.1%). They tagged an average of 38 unique locations (min 18, max 63, stdev 14.9). They tagged an average of 9.6 unique food places (min 0, max 20, stdev 8.9), visiting each food place an average of 1.2 times (min 0, max 2, stdev 0.5), with 3 visiting less than one food place per week. Every participant recorded at least one walk and transit event, 7 participants recorded at least one run, and 8 cycled at least once. 11 participants had no trips to and from the same location, although we had anticipated this would be common activities for pet walks and running routes. 13 participants had a dedicated work location, while 1 participant worked from home.

4.5 RESULTS

I next present participant reactions to seeing their tracking data presented through the cuts and visualizations I developed.

4.5.1 *Feedback on Cuts*

During the final interview, participants gave feedback on the cuts in a talk-aloud format, speaking freely as they examined each cut. At the end of the interview, I asked them to select up to 5 cuts they thought were most valuable, and up to 1 which provided no value. Participants were only presented with cuts appropriate for their activity (e.g., FD1 and FD2 would be very sparse for participants who visited less than one food place per week). Figure 23 shows participant feedback from this think-aloud exercise.

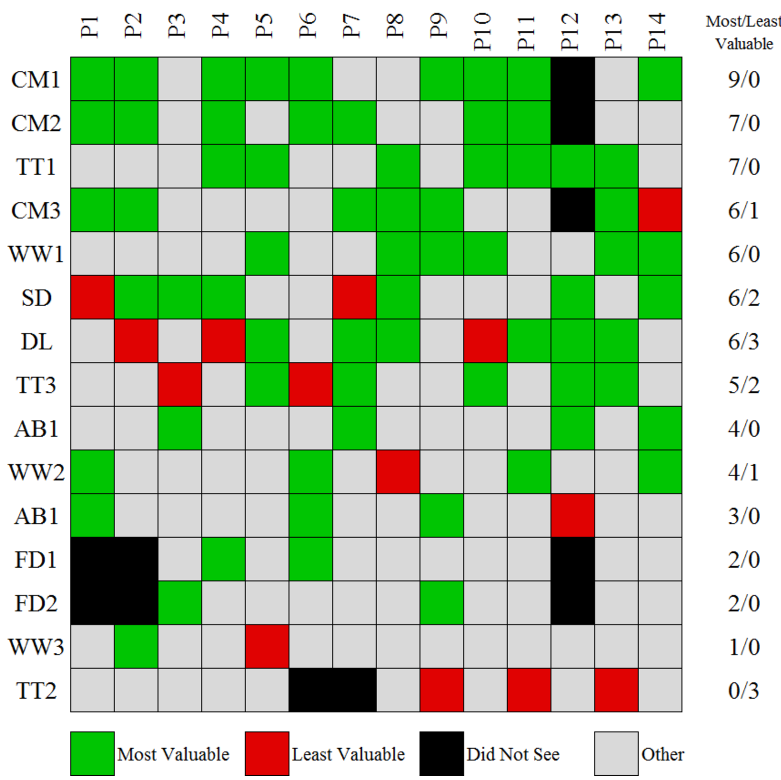


Figure 23. Participants rated the value of each cut, selecting up to 5 most valuable and up to 1 least valuable. There were some cuts which many participants found valuable and one which no participant found most valuable. Most cuts were in the middle; it was valuable for some participants but provided nothing to others.

TT1, CM1, CM2, CM3, and WW1 were valued by nearly half of participants. This indicates that participants wanted an overview of their physical activity and were interested in learning more about their work habits. Because every participant stated a goal of maintaining or increasing their level of physical activity, it was perhaps not surprising they wanted to see their activity patterns. 11 mentioned their work schedules influenced their activity, so it is perhaps similarly unsurprising they reacted positively to work-related visual cuts.

TT3, DL, and SD were more divisive. Some saw TT3 as an opportunity to find ways of incorporating activity into their routine, such as p13: "*Yep, [my husband and I] should be walking on short trips more and biking on medium trips more*." p4 did not appreciate the caption highlighting patterns and anomalies, asking if the system was "*trying to say, 'look punk, you should have been walking there'?*" p12 felt TT3 was more beneficial, saying "*I could quickly compare what days were different, what Thursdays were different*." p1 summarized participant opinions on the Sankey diagram: "*The Sankey had lots of potential, but was hard to interpret*." p7 did not feel the Sankey could ever help them make sense of their habits, saying "*I don't know exactly how a view like [the Sankey diagram] would help me understand my patterns*."

Trends in food places displayed in FD1 and FD2 were not received as well as other cuts. p13, who had the goal of making healthier food choices, suggested that perhaps visiting a food place is not the right metric to support her goal: "*I'm more interested in what I'm eating than where I'm eating*." p8 noted a specific goal supported by FD2: "*some people have goals about [not] eating past 8pm or things like that. Something like this could help me with that*."

I intended TT2 to show dog walks, running routes, and short errands, which survey respondents said impacted their activity. In practice, it was often misunderstood and typically left participants confused. p5 said, "*so I guess I'm having a hard time understanding this view… I'm not sure what I would use it for*." Explanation helped participants begin to understand its purpose, but they ultimately still found it uninspiring.

Participants found reflecting on multiple cuts together, rather than upon one in isolation, helped them gain a more complete picture of their activity. p12 supported this: "*I think that the total of all of the [cuts] made it really interesting… it's like a full picture of what my activity level is and what I've been doing*." This suggests designers should present a swath of cuts, rather than relying on one to summarize activity.

4.5.2 *Cuts and Goals*

Participants selected a variety of cuts as most valuable. Apart from the previously-discussed TT2, every cut was selected as among the most valuable by at least one participant. I did not find any quantitative correlations between valued cuts and the reported goals of participants, despite designing some cuts to support specific goals identified in the formative survey. The participants varied in experience and may not have had a strong attachment to their goals. I additionally suspect participants may have been intrigued by cuts they had not previously considered and marked them valuable because they learned something new and unexpected. This suggests personalization will need to do more than simply generate cuts corresponding to stated goals, as that could deprive trackers of potentially interesting discoveries in their data.

This said, p13 and p8 illustrated different food goals. p13 was only interested in what they were eating, while p8 felt knowing when they were eating would help them regulate their habits. This contrast suggests that whether a cut is valuable is influenced by the goals brought to tracking and the experiences a person has had prior. Niess & Wozniak's Tracker Goal Evolution Model suggests an opportunity for tracking tools to assist people in moving their qualitative goals to quantitative, measurable ones [119]. I anticipate people would find more value in cuts if the personalization process helped people translate their goals from qualitative to quantitative.

4.5.3 *Support from Visualizations*

Participants responded to Likert scales comparing the different visualizations (see Figure 24). The formative survey identified common goals of finding patterns, awareness of activity, and having a record of activity, so I asked participants to compare the visualization types in terms of how they addressed each of these. I also asked about how participants would feel about sharing the visual cuts to better understand whether cuts could help people better find social support through their tracked data.

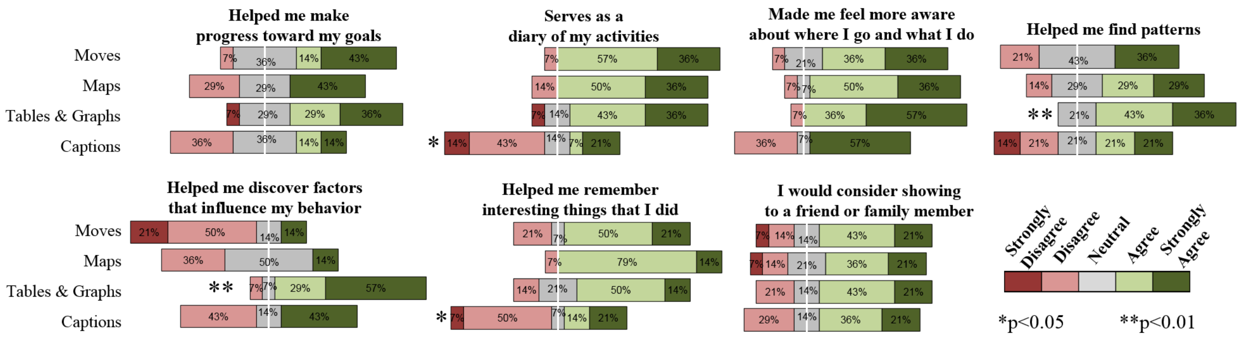


Figure 24. Participants generally preferred tables and graphs from our cuts through their location and activity data. They found these significantly better than the Moves daily lifelog for finding high-level patterns in their data.

Participants generally preferred table and graph presentations, which summarized cuts into easily-consumable formats. I examined whether participants felt visualizations supported common goals better or worse than the daily lifelog visualization in Moves. Because I had ordinal data with multiple measures per participant, I performed a Friedman test for each goal. Where it indicated different distributions, I performed paired Wilcoxon tests correcting for multiple comparisons (treating each question as a family, correcting for six comparisons).

Participants found tables and graphs more useful than Moves at *discovering factors which influence their behavior* ($p<0.01$) and *for finding patterns* ($p<0.01$). This validates cuts as an aggregation tool, highlighting higher-level factors and patterns in a way the Moves daily lifelog does not. Captions were also less effective than Moves for serving *as a diary* ($p<0.05$) or *helping people recall what they do* ($p<0.05$). This is expected, as captions are too distilled to reasonably serve as a diary of their habits.

Participants offered insights into the effectiveness of each visualization. p2 said the graphs were more effective than the maps for learning patterns, "*I think I am finding more information from these charts… the maps are good to view the data… but to get something that you didn't know, I think this is much easier in these charts.*" Some of the aggregate data we presented offered views that better supported visualizing progress toward specific goals. While reading the caption to WW2, p11 stated "*oh, that's cool. 38% of my unique places are food places. That's been a goal of mine, trying to be at different restaurants, try something new.*"

4.5.4 *Supporting Goals and Interests*

Participants found cuts were more effective at supporting their goals than Moves. During both the two-week interview and the final interview, p10 said he did not receive any value from tracking with Moves. However, at the end of the final interview, p10 stated "*all of these graphs totally changed my perspective on this. I was ready to tell you, 'yeah, [Moves] was totally useless', but actually just seeing this at the end, I'm like, 'oh, ok. I can see where you're taking this.' I can see how I might actually want to use this in my every day [life].*"

However, not all participants had the same reaction. p12, a Fitbit wearer, stated "*none of [the visualizations] were really surprising for me, it was just more of a confirmation than anything… since I bought the Fitbit I'm more aware of what I'm doing.*" This supports our prior belief that experienced self-trackers might be more aware of their habits than new trackers, even though neither had experience with Moves. By regularly reflecting on sensed data, experienced self-tracker seems to gain an intuition of their habits.

I presented each visualization for each cut, but some were not valued for specific cuts. The maps for CM1, CM2, and CM3 showed the participant's commuting route, which was typically a predictable route between home and work. p9 commented "*I'm not really getting the map, it's not really relevant to me. I know where home is and where work is.*" However, participants found the map valuable when the cut emphasized either routes or locations. For example, they explored the map in FD1 and FD2 when reminiscing about food places they visited and their weekday versus weekend practices in WW3.

4.5.4.1 Identifying Opportunities for Change

When reflecting on their cuts and visualizations, participants found opportunities to increase their activity or otherwise change their behavior. p8 said, "*maybe on average on Tuesdays I don't cycle much. Maybe there was a day I did. To be able to think about why that was so I could maybe think about how to change what I was doing.*" p10 felt similarly, "*if I notice I'm most active on Tuesdays, then obviously there's something about Tuesdays that I should start doing on other days. That's actionable data.*" Both quotes highlight the value of surfacing positive deviations from routines as potential opportunities for improving activity.

4.5.4.2 Discovery

All participants had moments of discovery, learning something about which they were previously unaware. Many discoveries were previously difficult for participants to quantify on their own, as stated by p10: "*I guess I work 11 to 8, that's my schedule… this is good to keep track of, actually. These are questions I've always wondered.*" Similarly, p11 noticed a pattern in her transportation behavior: "*if it's over 3 miles, I usually drive. It's interesting to see the breaking point between where I decide it's [too far] to walk.*"

Participants often used storytelling to try to reason about patterns. When looking at how her arrival and departure vary by day, p11 said "*I guess it's because I feel guilty for leaving work early [on Tuesdays], so I come in a little bit earlier on Wednesdays. Huh, I didn't even know that.*" Through this process, participants were able to incorporate data they observed into their beliefs about themselves.

Consistent with Schneiderman's task taxonomy of how people examine visualizations [140], participants typically looked at the chart and the caption, then used the map to further explore their data. p10 described this: "*the map was sort of secondary, I would look at the table, and then I would play around with the map, and be like, 'oh, alright… I already knew that.*" Participants also commented the graphs were easier to parse quickly. p5 said, "*I find that I don't really look at the map showing my routes. I just like to see the high-level overview of 'you went here, you were here for 10 minutes'… looking at the map is overwhelming.*" p9 commented the regularity of her schedule limits the value of the map: "*because I go pretty much to the same places all the time, the map wasn't really that telling to me. Even when I go for a walk in the morning, I walk the same route.*"

4.5.4.3 Socializing

Participants also found varied opportunities for socializing. 10 reported showing Moves to at least one other person during the study (7 to a family member or partner, 4 to a friend, 2 to a co-worker). All did so in person, versus via a social network (though Moves included the ability to share a day's record to Facebook or Twitter). p5 showed Moves to her husband after an active day together, stating "*it helped us remember and appreciate the fun activities we engaged in.*" Others showed Moves to explain how it worked, such as p1: "*[I] showed it to friends I was hiking with to see how many steps we'd taken.*"

8 participants felt some of the visualizations were potentially shareable. p10 emphasized the utility of the captions for sharing, saying "*the captions do seem very tweetable. That might be the kind of thing you would share easily on a social network.*" As I explore in Chapter 5, higher-level visualizations are more useful to share online than raw daily lifelogs, as summaries are more likely to get social feedback without revealing private or overwhelming details [46].

4.5.5 *Limitations*

I inferred the purpose of locations using their high-level Foursquare categories, which are not always an effective proxy for a person's activity. For example, coffee shops typically serve multiple roles: places to work, socialize, read, or even just obtain coffee. These differences were not captured, and participants also noticed other incorrect categorizations (e.g., p3's gym was adjacent to his office).

The deployment of visual cuts was conducted during summer on the west coast of the U.S., with typically temperate and consistent weather. 6 participants mentioned that changes in weather would influence their activity. Deployments that are longer, at different times of year, or in a different region might highlight the influence of weather and related cuts. A longer deployment would also enable participants interested in seeing other longer-term trends or seasonal shifts.

Waiting until the final interview to show participants cuts through their data enabled us to personalize the cuts to their goals. However, a clear disadvantage of waiting is that participants were unable to evaluate how their routines changed over time or to measure progress if they made an intentional change.

4.6 DISCUSSION AND EXTENSIONS

The field study surfaced several design considerations and opportunities for future designers and developers. The results also motivated two extensions I conducted beyond the focus of my thesis work.

4.6.1 *Contextually Aware Feedback*

Presenting visualizations after a month of collection led to storytelling and reminiscing about previous events, but did not enable in-the-moment decisions based on prior patterns. Another opportunity is to infer real-time recommendations from prior days. For example, upon arriving home a tracker might be presented a context-aware notification: "*on days when you came home from work at this time, you typically do not reach your step goal. Consider going for a walk this evening.*"

It is unrealistic to think the majority of people who use self-tracking tools will regularly inspect a large number of cuts, and some participants expressed this sentiment. However, selecting a single small set of cuts is not the right solution either, as participants valued different cuts and the discovery of insights or information in unexpected cuts. One approach to this challenge may be to show cuts appropriate for the current context. Perhaps immediately after arriving to work is an appropriate time to highlight average commute duration. Or perhaps immediately after a short drive can be a useful trigger for a cut highlighting transit choices for trips by distance. Positive anomalies could also be highlighted in the moment, helping someone identify and celebrate their successes in achieving greater activity.

In a project published at UbiComp 2016, I examine the *lapsing* stage of the tracking process as a particularly impactful context for people to review cuts through their data [51]. It offers a good opportunity for people to revisit whether or not they could benefit from returning to tracking, serving as a nudge for people who are inclined to return. For people who felt that tracking was a useless or negative experience, reviewing a cut could surface something they did not know about their routines, providing additional value to the time spent tracking.

I conducted a study where 141 lapsed participants saw 7 different cuts through their Fitbit data, drawing on persuasive technology techniques to frame the cut's caption to offer a recommendation or an insight [57,107,108]. The study results demonstrated a need to align cuts with people's tracking experience as well as their perspective (e.g., how long and regularly they have tracked). Figure 25 presents two examples of how cuts through tracked content could be framed for a person who has lapsed. The cut on the left emphasizes high activity days drawn from a long tracking history. This may serve as a reminder of the particularly good days tracked for someone who thought that tracking was a relatively useless or negative experience. The cut on the right highlights the day of the week a tracker averaged the most steps, an approach which can be effective even with a relatively short tracking history. For people interested in returning to tracking, highlighting their success may also help serve as a nudge.

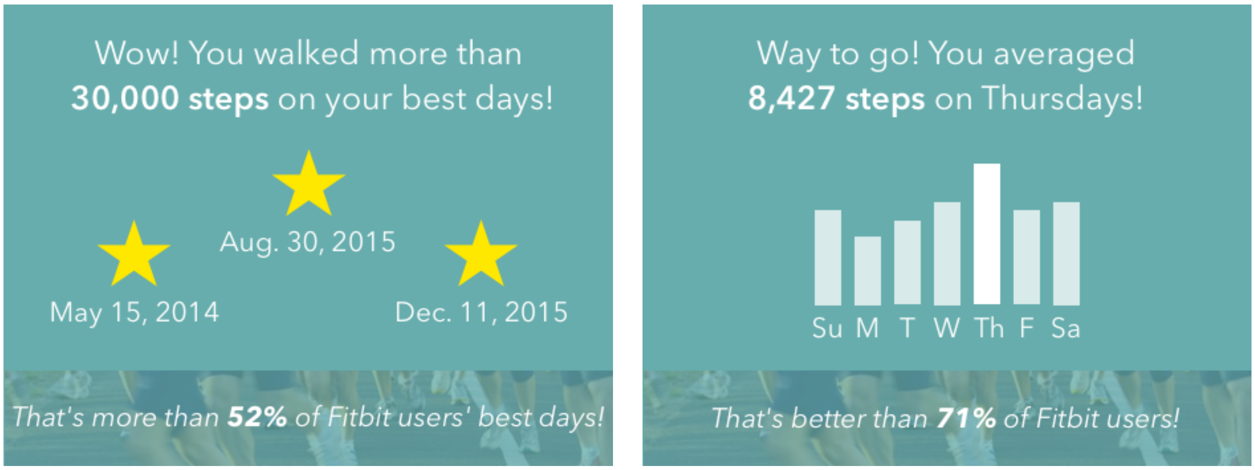


Figure 25. Designs can surface different information for lapsed trackers who do and do not want to return to tracking.

4.6.2 *People Value Different Cuts*

Most participants had goals of increasing or maintaining physical activity and having a record, defined as *behavior change* and *instrumental* goals in the previous chapter. However, as discussed, cuts that participants valued varied dramatically, with all cuts except for TT2 marked as most valuable. Future designs should not attempt to limit cuts based on stated goals and instead should offer a variety of cuts. Future work could leverage collaborative filtering techniques to incorporate feedback based on cut value to predict which cuts will be most valued by a given person at a given time and context.

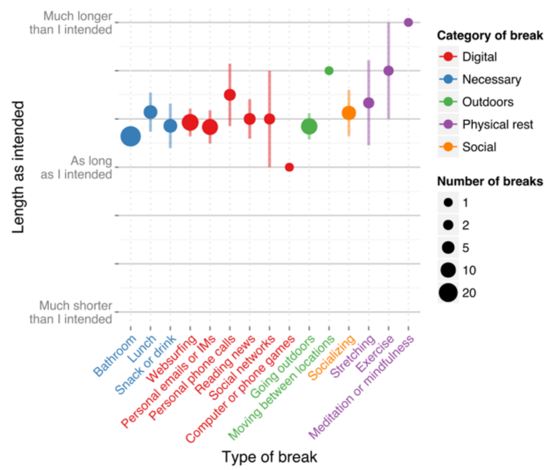
Participant experiences show how visualizations can help trackers at various stages of behavior change [129], and even people who are not thinking about behavior change at all. While viewing TT1, p13 suggested having a conversation with her husband about spending less time at home, even though she may not have previously considered this something that she wanted to change. People contemplating behavior change might benefit from an understanding of their baseline routines and activities, while those who are preparing to change or taking action can use cuts to identify specific ways to effectively change. Highlighting aspects of their storylines that are counter to their goals may also help identify good targets for change. Showing positive anomalies from routines might build better self-efficacy and also suggest how the routines can change. Cuts can also help people satisfy the curiosities they had about their routines, nudging toward self-improvement when appropriate.

4.6.3 *Extension to Other Domains*

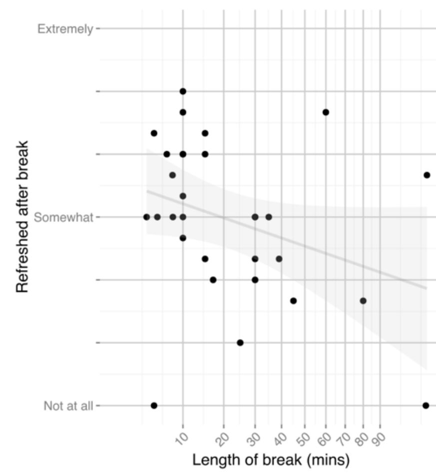
10 of the survey respondents tracked their finance patterns using Mint. Similar to the physical activity trackers, they varied in their beliefs of how factors influenced their spending patterns (e.g., mood, weather). Visualizing these factors and behavior could help lead trackers to new discoveries and potential behavior change. Combining multiple streams might also help self-trackers find a better understanding of their patterns and how they relate. 3 finance respondents believed travel influenced their spending habits, which could be examined with cuts surfacing spending by location.

I focused on physical activity and related goals that could be inferred by location. But many other potential goals could be surfaced through high-level visualizations. A visualization showing spending by location, neighborhood, or commute route might help a tracker identify less expensive places to socialize with friends or surface how much they spend on their commuting coffee routine. A mobile or flexible worker seeking to be more efficient might examine not only when and where they work, but also what kind of work they perform at various times and locations.

In a project published at CHI 2016, I also applied the cuts technique to a new tracking domain, helping people understand their break-taking routines [45]. Through a formative survey, I first identified that people seek to take breaks from work to feel more refreshed and productive in a short amount of time. After logging their breaks for three weeks, 9 information workers reviewed 13 visual cuts designed to help them identify what impacts their break duration and what about breaks leave them feeling refreshed and productive. Figure 26 shows two of the cuts developed. The cuts emphasize how different categories of breaks impact actual duration relative to intended duration and how duration impacts whether or not the person feels refreshed after the break.



Physical rest breaks tend to be longer than you intended more than other breaks.



Longer breaks tend to leave you less refreshed.

Figure 26. I applied the cuts technique in the work-break domain by showing 9 information workers cuts showing patterns in the breaks they logged over a three-week period.

The application of cuts in the work-break domain surfaced many similar findings. Participants were able to identify trends from the cuts and pointed to changes that they could make about their habits. For example, p16 said, "*I have very few breaks after two o'clock. So I probably might be better off trying to even out my breaks more throughout the day.*" p28 found another trend: "*it's pretty clear that the longer my break is, the more likely I am to not feel refreshed… I should probably keep my breaks a little shorter.*" This second demonstration of the benefit of visual cuts suggests the technique can help people find value from tracked data in other domains.

4.7 Conclusion

I have shown that meaningful cuts through personal informatics data can help self-trackers identify correlations and opportunities for self-improvement. I have also found that people value information revealed in cuts even if it does not align to their existing goals. It is important to continue examining how to better support self-trackers in assembling data across multiple domains to enable their self-tracking goals and opportunities.

Chapter 3 and Chapter 4 together point to a need and an opportunity to improve upon how personal informatics systems help people get value out of data. People increasingly aim to draw conclusions from their data and act on those conclusions while they are still collecting data, and a smaller proportion of people have the skills and background to rigorously analyze their data. The visual cuts technique I developed is one way of providing more value. People better helps can more easily find patterns through their data and discover factors that influence their behaviors when the visual representations of data are aligned with the types of questions people ask about their routines.

There are other opportunities to better help people find more value through their data beyond satisfying the instrumental goal of having a record for revisiting later. For example, the Lived Informatics Model points to opportunities for technology to help people decide what to track and select an appropriate way of tracking it. Ensuring that the data collected scaffolds question-answering ensures that people's curiosity, behavior change, and monitoring goals are being satisfied. Colleagues have begun examining how to support diagnostic self-tracking and longer-term monitoring in chronic conditions, specifically Irritable Bowel Syndrome [80] and Migraine [138].

Chapter 5. A DESIGN FRAMEWORK FOR SHARING IN PERSONAL INFORMATICS

In this chapter, I transition to my second thesis claim (**T2**): *designs which acknowledge and account for the challenges of everyday life can help people find more support through their data*.

As discussed in Chapter 2, many applications, both research systems (e.g., Houston [28], HeartLink [38], Sun Valley [77], Fish'N'Steps [99]) and commercial apps (e.g., Fitbit, Spotify, Foursquare) have integrated features for sharing personal informatics data with others. Considerable research attention has been paid to sharing of tracked data in *peer support networks*, defined as sharing with others who have similar goals or who are in the same situation (e.g., social support in online communities [76,143]). People also commonly share through social awareness streams, such as timelines and newsfeeds in Twitter, Facebook, or Instagram. People who collect and post personal informatics data (referred to as *sharers* in this dissertation) often hope to gain emotional support or communicate their identity as someone engaged in the activities they are tracking [61,67,118,149]. Sharing to social awareness streams can also help people identify potential activity partners [46,114], create sources of accountability and motivation [116,118], and elicit advice from others [118,143].

Despite reported interest in and a prevalence of features supporting sharing personal data through social awareness streams, these features often find limited or problematic use. Although usage data from commercial systems is hard to obtain, the record from the research literature is clear: most study participants ignore social sharing features, have concerns that prevent their use, or are disappointed by the reactions they receive when they are used [99,103,114,152]. Prior work (e.g., [28,99,114]) has identified several barriers to their use, including not wanting to share a trivial accomplishment or feeling uncomfortable sharing with an unfamiliar audience. Other work has pointed out the importance of finding an appropriate audience [60] or that the responsibility of choosing to ignore or engage with shared content is left to the recipient [149].

The gap between people's aspirations when sharing tracked data and their actual behaviors and outcomes motivated me to ask the following research questions:

RQ3: How have prior research designs supported people in sharing the data they collect?

RQ4: How can the content of posts elicit additional response and interest from potential audiences?

I developed a descriptive *design framework* to answer **RQ3**, consolidating research findings in this space and identifying underexplored design alternatives. I demonstrated the value of this framework in answering **RQ4**, using a subset of the dimensions to answer how and why people use one popular application to share physical activity information on Twitter and how the details of what was shared affect responses. I considered perspectives of both sharers and their audiences, conducting two studies to learn what sharers post to social awareness streams and how the audience views these posts. This combined analysis enables the development of design recommendations for sharing physical activity information on Twitter. It also suggests broader recommendations for sharing personal informatics data, including how the framework I developed can be used in future studies.

This project was published at CSCW 2015 with co-authors Bradley Jacobson, Elizabeth Bales, David McDonald, and Sean Munson and additional contributors Lindsey Brockish, Danni Hu, Sara Jennings, Chuck Johnston, Rahul Mehan, An Ping, Sreedev Sidharthan, and Melinda Yang [48]. I led the literature analysis, the design of both studies, and the writing and revision of the paper. The statistical analyses for the two studies was done in collaboration with Bradley.

5.1 People's Reasons For Sharing Personal Informatics Data

Having effective social features is key for engagement in personal informatics systems [68]. I briefly review reasons for sharing personal informatics data that have been identified by prior work.

5.1.1 *Request for Information*

Many people share their data and experiences to receive some form of information from their audience. People turn to their social networks for recommendations, advice on how to improve, or for something new to try [111,118,143]. This is a particularly common practice in peer support networks and is often the expressed goal of those networks. The audience has a shared experience to draw upon and the background to offer recommendations [76,143].

5.1.2 *Desire for Emotional Support*

Sharers also seek emotional support, both from peers going through a similar experience and from caring friends and family [118,143]. For example, the HeartLink system enabled a person's social network to cheer them while running a race, which they found motivating [38]. In controlled studies, people have enjoyed receiving encouraging messages sent from others in the study, feeling the messages encouraged them to be more physically active [28,152].

5.1.3 *Seeking Motivation or Accountability from the Audience*

Sharers may seek motivation and accountability by making commitments public, identifying potential activity partners, or creating competitions [114,115,118]. Collaborating in shared activity can create a source of accountability [113]. Social awareness streams can also help foster the accountability people desire. Some people post their plans and goals to Twitter to motivate them to remain active and achieve their goals [149].

5.1.4 *Motivating or Informing the Sharing Audience*

Some people strive to motivate or inform their audience by sharing their experiences collecting personal data [23]. People also share records of activities or goals, such as eating healthy or exercising, to motivate others to act similarly [8]. In location-sharing applications, people may broadcast their location to recommend a cool place they found or to potentially meet up with nearby friends [100].

5.1.5 *Impression Management*

People use social sharing to communicate an identity to their social networks and achieve impression management goals [56,118]. For example, posts about runs or workouts can communicate that a sharer is an active, fit individual. Similarly, feeds of songs a person has listened to can communicate a person's musical tastes. However, this practice also leads to curation and concerns about self-presentation [118,159]. Prior work has found that in practice, people curate their listening histories to remove guilty pleasures [142].

5.2 DEVELOPING A DESIGN FRAMEWORK

Although substantial prior literature has examined social sharing within personal informatics, the design strategies implemented in the literature rarely build on the knowledge gained from one another. Systems support sharing data in multiple ways, but system evaluations often lack integration with prior work because each evaluation focuses on a single approach to data sharing. I develop a design framework by looking across studies, integrating and synthesizing results. The framework can facilitate analysis of new sharing features by isolating a single design choice to vary in evaluation. The enumeration of design choices made in sharing features also suggests what design choices may be underexplored.

I describe these different design choices across several *dimensions*, discussing factors of social sharing across one dimension. The six dimensions developed and discussed are:

- **Data Domain**: they type of data collected and shared
- **Preprocessing**: transformations applied prior to sharing
- **Sharing Trigger**: what causes the data to be shared
- **Persistence**: how long the shared content is visible
- **Post Content**: what information is shared
- **Audience**: who receives the post

I summarize these dimensions and a selection of prior work representing, them in Table 6. These dimensions were created through a bottom-up analysis of related literature. Although the literature surveyed is not exhaustive, it represents some of the most seminal and influential work on this topic in the CSCW and HCI communities. Other literature which has come since can be categorized according to these dimensions.

Table 6. I developed a design framework for sharing personal informatics data by extensively considering prior literature and the specific designs explored in the space.

Dimension	**Definition**	**Points within dimensions**	**Prior literature**
Data Domain	Type of data collected and shared	Physical activity	[4,23,28,46,48,60,99,110,113,114,131,149,152]
		Biometrics	[23,38,39,113,135]
		Location	[5,6,7,16,32,36,42,48,63,67,77,89,90,91,98,100,122,123,148]
		Pictures	[8,35,63,73]
		Other including environment, food, music	[8,23,56,61,103,142,143]
Preprocessing	Transformations applied prior to sharing	Raw data	[8,23,32,38,46,48,56,63,67,73,100,123,135,142]
		Aggregate daily totals	[4,23,28,46,99,152]
		Goal achievement	[4,28,60,99,114,152]
		Summarization into trends	[23,48]
		Automatic or manual naming of data	[5,6,16,32,77,148]
Sharing Trigger	What causes the data to be shared	Always-on passively streaming	[6,16,46,56,89,123,142]
		Streaming during a special activity or event	[38,39,113,135]
		Arrival at or departure from a location	[5,7,98]
		Once per day	[46,60,152]
		Determined by the self-tracker	[4,8,28,35,36,42,60,63,67,73,77,100,103,114,148,149,152]
		Request by the sharing audience	[32,77]
Persistence	How long the shared content is visible	Transient	[5,6,28,32,35,77,113,135]
		For the lifetime of the system	[8,16,99,152]
		For the lifetime of the social network	[36,38,39,46,56,114,123,142,149]
		Self-tracker can delete content	[46,56,73,142,149]
Post Content	What information is shared	System-generated text	[4,6,28,32,48,114]
		Numerical summaries	[4,28,38,39,99,103,114,152]
		User-generated text	[4,16,28,110,148,149,152]
		Graphs or other visualizations	[4,23,38,39,48,63,103,114,135]
		Passive notification (noise, vibration)	[5,98]
Audience	Who receives the post	Broader social network	[38,39,46,48,60,89,103,114,149]
		Dedicated social network	[36,56,60,67,100,123,142]
		Strangers in a study	[8,99]
		Friends in a study	[4,6,7,28,32,35,77,98,110,113,152]
		Family/significant others in a study	[5,16,110]

5.2.1 *Data Domain*

Self-tracking occurs in a wide variety of domains as people look to quantify various aspects of their lives. Many research systems have incorporated sharing features into tracking physical activity [28,99,110,152], monitoring biological data such as heart rate and ECG data [38,39,113,135], tracking location [7,77,148], journaling ecologically-friendly activities [61,103], and tracking music [56,142]. Sharing features within commercial systems have been studied as well, such as location in Foursquare [36,100] and Google Latitude [123] and Last.fm for music [56,142].

When deciding what is appropriate to share, designers should consider the norms for a particular type of data. For example, biometric data is perhaps more personal than someone's music listening history. Although sharing hourly or real-time data about music listening might be acceptable, people might view sharing fine-grained biometric data as an invasion of privacy.

5.2.2 *Preprocessing*

Personal informatics data can be transformed prior to sharing, such as by filtering or aggregating by time. Some systems immediately share raw data as it is collected [8,38,46,56,113,123], while others have aggregate daily totals [8,28,46,99,114,152]. Content shared can also communicate achievement of a specific goal or milestone [114].

Data is preprocessed prior to sharing for a variety of reasons. One is to maintain privacy. Aggregation can hide potentially private events, such as the specifics of individual purchases. Systems with sharing features have considered transforming tracked data prior to sharing [46,90,91]. Designers of other systems have discussed electing not to disclose potentially sensitive events [103] or sharing less specific information (e.g., a generic place like "Grocery Store" or city-level information) [5,32,148].

Preprocessing tracked data can also prevent inundating audiences with large amounts of data to interpret or frequent posts. Prior work on physical activity has recommended that designers avoid sharing mechanisms that overwhelm the recipient [46,60]. When sharing to social awareness streams, people tend to censor themselves [144] or post something that they later regretted [145]. Aggregation can therefore help ensure the content shared will be welcomed by audiences. Aggregation has the added benefit of allowing private events to contribute to what a person is sharing, but not be specifically disclosed.

5.2.3 *Sharing Trigger*

Many applications stream collected data constantly, with no explicit posting or sharing action. This streaming data may be collected and updated in the background as long as the application is enabled (e.g., steps [46], location [123]) or may be limited to during a specific activity (e.g., while running [38,113], while listening to music [56]). Other applications automatically share when a person arrives at a designated location (e.g., home, work) [5,6] or arrives near another person using the same application [98]. In some applications, content is instead automatically shared once each day [28,99,152]. Another class of features enables the person tracking to trigger sharing on their own [36,100,114]. Some systems enable recipients to solicit data from others, such as asking someone to disclose where they are [28,77].

There are tradeoffs between automatic and manual sharing triggers. In applications which share automatically, the sharer can become disconnected from their data and lose the opportunity to explain its significance. By requiring the self-tracker to share manually, a sharer is encouraged to both reflect upon the data collected and decide whether the post is worth making. However, when sharing is automatic, self-trackers may share more and thus receive more benefits from sharing. For example, automatic sharing may be particularly important for creating accountability.

5.2.4 *Persistence*

Applications can vary how long shared data is available to the recipient. CoupleVibe automatically shared messages about a remote partner's location using short vibrations. If the recipient did not notice when it occurred, the record of the old location was gone forever [5]. This approach is especially applicable for other time-dependent systems, where the data being shared is occurring at the current moment.

Sharing in other research applications, including Chick Clique and Fish'N'Steps, persisted for the life of the research system [99,152]. Posts of personal informatics data made to a social network (versus a research prototype, as in the system designs of [100,114,149]), can exist for as long as the network is relevant. Both groups of systems preserve a record of previous shares for both browsing or searching. These systems may also enable the self-tracker to delete content they previously shared [149].

Maintaining persistence allows for later revisiting of data, which could be beneficial if the posts are contributing to a story taking place over a period of time (e.g., training for an event, saving for a large purchase). However, the permanence of a record can result in paralysis around whether an accomplishment is too trivial to share. In more ephemeral social awareness streams, like Snapchat, people tend to be confident sharing even minor events [105].

5.2.5 *Post Content*

Application designers have different ways of sharing the content people track about themselves. Systems have supported sharing personally collected data through numerical summaries [28,99], maps [100,123], and graphs [38,46,103]. These have varied in level of detail, ranging from a vague sentiment that an activity has been completed to a detailed post. Detailed posts can include, for example, distance, route, time, and location of a run, as well as heart rate and mood [110].

Some applications encourage people to annotate the data they collect with information about its significance, to provide more details, or to include photos [35,63]. This content conveys more context but requires time and effort to generate. Prior work has not examined the importance of content in detail. It is unclear to what extent audiences prefer self-generated content to system-generated content. I focus on this dimension later in this chapter, answering **RQ4.**

5.2.6 *Audience*

Sharers and system designers must also decide who will receive the tracked content. Systems have connected sharers with a variety of audiences, including pre-organized teams of random co-workers at a large corporation [99] to people who are friends or otherwise already know each other [28,77,152] to family and significant others [5,16]. In each of these systems and evaluations of them, both the sharers and recipients were tracking themselves. Thus, they saw each other as peers with similar goals and shared experiences [114]. Other systems and studies explored posting to a broader social network, such as Facebook [114] and Twitter [149]. In a study of GoalPost, participants were discouraged when their posts received few responses [114].

One way systems have examined negotiating post audience is to use a popular social networking site to distribute the post content, but to restrict its distribution to a subset of the network. Research has approached limiting the audience on these social networking sites by building apps on the platform which share only to other participants [49,103] or by encouraging participants to restrict post visibility to a short list of supportive friends [114]. Groups also self-organize on these networks, such as by creating Facebook groups with shared step goals or utilizing the same hashtag on Twitter or Instagram [25].

People have heterogeneous preferences and comfort with different sharing audiences. For example, some people are comfortable sharing their fine-grained physical activity with their entire social network, while others are only willing to share with close friends, or no one at all [46]. For example, although GoalPost participants were encouraged to list supportive friends to share with, some left their list empty, effectively making their posts a private record [114].

Identifying a good audience for tracked data continues to be an important area for future research. Research that I and others have conducted suggest that one promising option is to group individuals by common goals [8,49,99].

5.3 Applying the Design Framework Dimensions

To demonstrate the value of using these sharing dimensions as an analytical framework, I apply the dimensions to a case study of sharing physical activity from the RunKeeper application posted to Twitter. RunKeeper is a commercial smartphone app for tracking physical activity with 45 million users. At the time this study was conducted, runners logged over 2 million miles per day through RunKeeper.

RunKeeper automatically records distance, time, and route, and it supports posting to Twitter, also Facebook, either automatically or manually after each exercise session. The sharer can add personalized text or a picture to each tweet. The app also enables sharing of runs, walks, or bike rides in real time. Figure 27 shows the current sharing screen of RunKeeper, which is similar to the sharing screen at the time of the study.

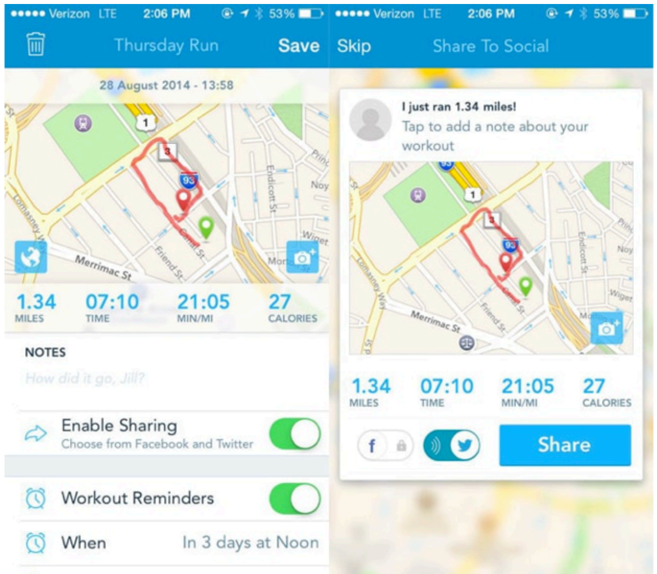


Figure 27. The sharing screen of RunKeeper allows the sharer to add personalized text by adding a note and include photos from their run.

This analysis answers **RQ4** by examining the **Post Content** dimension. The combination of application (RunKeeper) and social awareness stream (Twitter) constrain the remaining dimensions.

- **Data Domain**: I examine running, walking, and biking tracked with RunKeeper. This data falls under the umbrella of physical activity data.
- **Preprocessing**: RunKeeper incorporates minimal preprocessing. The app supports configurable text around activity, pace, distance, and cumulative time.
- **Sharing Trigger**: Posted at the conclusion of an activity, either automatically or manually triggered by the sharer. Live events are shared at the beginning of the activity with a link to follow progress.
- **Persistence**: Posts exist as long as the social network does or until the sharer deletes it.
- **Audience**: My analysis examines followers on Twitter and anyone following the #RunKeeper hashtag.

5.3.1 *Framework Evaluation Methods*

I conducted two evaluations of tweets made through RunKeeper, supported by a formative survey on sharer goals and desired reactions. I first learned about the posts people make by analyzing recent tweets made via RunKeeper, characterizing the types of posts people and what posts generate responses (referred to as the *Collected Tweets study*). I then evaluated audience reactions to similar tweets by generating a set of tweets representing different forms of commonly shared content and then conducting a survey to elicit audience feedback (referred to as the *Generated Tweets study*).

5.3.1.1 Formative Survey: Sharer Goals and Desired Reactions

To identify desirable reactions to sharing, I conducted a formative survey about people's experiences sharing physical activity on a social network. 32 respondents recruited from University mailing lists and self-tracking forums described their best and worst sharing experiences (26 female, 6 male; average age 35.3, median 31, min 21, max 63). Respondents mentioned likes (14 respondents), comments (14), and in-person conversations (2) as important characteristics of their best experiences sharing tracked data. 8 respondents mentioned receiving no feedback (e.g., no likes or comments) as a key characteristic of their worst sharing experience.

From this survey, I learn that self-trackers positively correlate comments and likes to how positive an experience they had making the post. r39 stated that, "*likes and encouraging comments made me feel good about what I did*." r19 strongly stated his feelings when his posts did not receive feedback: "*if a tweet falls in a timeline and nobody's there to hear it… no feedback is the worst feedback!*" These results, and their consistency with prior work (e.g., [114,116]), support the use of social awareness stream feedback mechanisms (e.g., likes or favorites, comments or replies) as measures for how positively a sharer evaluates the success of their posts.

5.3.1.2 Collected Tweets Study

I began the Collected Tweets study analysis by randomly sampling 5,000 tweets from all public tweets posted with the hashtag "#RunKeeper" between late-December 2013 and mid-April 2014. Approximately 652,000 public tweets were posted with this hashtag during this span, so our initial sample represents 0.77% of applicable tweets posted in this span.

The research team coded each tweet for 10 features, described in Table 7. These features were selected to characterize the variability in the post content, therefore highlighting comment trends when posting to Twitter from RunKeeper. We additionally coded for the number of replies, favorites, and retweets as of the time of the analysis (May 2014).

Table 7. Coding scheme for tweet features in the Collected Tweets study.

Tweet feature	Coding
1. Tweet content type	Any combination of: default text, user-generated text, user-generated picture
2. Activity type	Walk, run, bike, other
3. Tweet contains a positive emotion	Yes or No
4. Tweet contains a negative emotion	
5. Tweet link still exists	
6. Tweet contains non-English text	
7. Activity lasts for 0 minutes, 0 seconds	
8. Tweet @mentions another account	
9. Tweet is not sharing someone's activity	
10. Tweet is a live event	

Two researchers coded each tweet. When the assigned codes differed, a third researcher coded the tweet and the dispute was resolved by majority vote. 4,256 of the 5,000 tweets had agreement across all codes after two coders. 19 of the remaining 744 tweets still had disagreement after three coders, each of which occurred as a result of the dimension having more than two levels. These disagreements were resolved through group discussion by five coders.

Eight people coded unequal portions of the tweets. To measure the agreement among the coders, each person coded a set of 100 tweets presented in random order. I used Fleiss' kappa to assess inter-coder reliability among the 10 subjective, nominal codes. Agreement ranged from 0.56 to 1.00, indicating "moderate agreement". All but one code had a kappa value above 0.60, indicating "substantial agreement", and five had kappa values above 0.80, indicating "almost perfect agreement".

The coding process informed the exclusion of a portion of the 5,000 tweets from further analysis. I removed 189 tweets where the sharer deleted their account, changed their privacy settings, or deleted the tweet between capture and analysis (May 2014). I additionally removed 13 tweets where the sharer had no followers, as these tweets were unlikely to receive responses. I finally removed 27 tweets not posted by the RunKeeper application (e.g., recommendations to friends to install RunKeeper or links to news articles mentioning RunKeeper). These tweets differed in content and goals from posts made using the RunKeeper app. The resulting analysis considers only the remaining 4,771 tweets.

5.3.1.3 Statistical Methods in the Collected Tweets Study

We used regression analyses to characterize the correlations between different tweet attributes and responses. We used a Poisson model for the number of favorites and retweets because each favorite or retweet came from one unique account. We used a negative binomial model for if a tweet received replies or not. Many tweets received a high number of replies but involved only a small number of engaged participants and quickly went off-topic, so additional replies rarely offered further support. In all models, we used `log(followers)` as an offset variable (i.e. exposure variable), because one's follower count limited their potential for responses.

4,362 of the 4,771 tweets (91.4%) did not receive any response from Twitter accounts. We used a zero-inflated model in all analyses to differentiate between excess zeros caused by attributes of the user's account versus zeros caused by the attributes of the tweet. To predict excess zeros, we used the presence of the default profile picture (i.e., an egg) and log of the user's tweet frequency.

For the regression analysis, we removed an additional 432 tweets containing non-English text because we were not confident in our ability to code emotion in these tweets. A robustness check, including these tweets and repeating our analysis, does not alter the results.

5.3.1.4 Descriptive Findings from the Collected Tweets Study

74% of the tweets in the Collected Tweets study included only system-generated content. Of the 26% of tweets that included user-generated text, 22% contained positive or negative emotion. We also observed tweets containing advice or support, and additional information such as heart rate or run intervals (e.g., time taken or elevation gained for each mile). 299 runners added pictures in their tweets, typically landscaped, pictures of their running shoes, or selfies.

Analysis of the tweets in the Collected Tweets study only takes into account the observable responses. It cannot measure audience reactions other than a favorite, reply, or retweet (e.g., an in-person conversation around the activity) nor audience opinions on seeing the content. That is, from the Collected Tweets study we can learn *what* tweets get replies, favorites, or retweets, but not *why* or any other ways in which people may have reacted.

5.3.1.5 Generated Tweets Study

Considering the limitations of the Collected Tweets study, I conducted a second study to better understand how a post about physical activity to a social awareness stream would be interpreted by potential audience members. I used the descriptive findings from the Collected Tweets study to generate the parameters for a system to randomly generate tweet-like content similar to those we observed and coded in the Collected Tweets study. Figure 28 shows three tweets generated by my system.

Figure 28. Tweets generated for the Generated Tweets study varied on several dimensions, allowing the role of each feature to be separately evaluated.

I varied nine parameters when generating tweets. Tweets could contain one of three milestone events (i.e., half-marathon, return from surgery, a long-term goal), one of four requests to the audience (i.e., asking for a recommendation, support, accountability, or an activity partner), or details about the sharer's run. Details about the run could include positive emotion (e.g., "felt good", "best run in a while"), negative emotion (e.g., "that sucked", "knee hurt"), and/or information about the weather (e.g., "weather is great", "a little chilly"). The distance of the run was randomly selected between 2 and 15 miles, and could either be live or have already taken place. Finally, the post could include a photo of either the runner's shoes or a landscape depicting the run's location.

For posts that did not include a photo, RunKeeper's default Twitter card was displayed with statistics about pace (i.e., an 8:30 pace per mile regardless of distance) and calorie consumption (calculated using the American College of Sports Medicine metabolic consumption rate formula [2] for a person weighing 150 pounds).

To minimize dissonance created by viewing randomly-generated tweets, care was taken to ensure the tweets were internally consistent. For example, if a tweet communicated poor weather and a picture was to be shown, the picture changed to a rainy park with wet shoes. I additionally removed certain combinations of parameters that did not make sense, such as displaying distance or calorie information for a tweet announcing the beginning of a live run. To ensure short, realistic-sounding tweets, specific information was not combined with life event information or audience requests. Otherwise, generated tweets could exceed 140 characters (a hard limit at the time of the study). I sought to preserve grammar, with tenses corrected for live tweets (e.g., “great” run for a previously-occurring tweet versus “excited to run” for a live tweet) and appropriate use of conjunctions (e.g., “that sucked, but happy I did it” for a tweet containing a positive and negative emotion).

Varying the parameters resulted in 102 possible styles of tweets, plus additional variation in exact wording, content ordering, and run distance. Each tweet contained a randomly-ordered name often associated with both Male and Female genders (Alex, Jamie, Cameron, Kendall, and Taylor), a randomly composed Twitter username (supplementing the name with letters or numbers), and a random profile picture (a landscape). These three parameters had no statistically significant effects on participant responses, and I do not report further on them.

I used a factorial study design to obtain responses to these tweets, surveying 97 respondents recruited from Twitter, Facebook, and University mailing lists in Spring 2014. Respondents were entered into a raffle for one $50 or two $25 Amazon gift cards. Each respondent saw five tweets. The five tweets each respondent saw were selected to overlap on four or fewer parameters to avoid a feeling that respondents were seeing variations of the same tweets multiple times. Finally, the survey enforced that no two tweets among the five an individual saw contained the same picture (e.g., shoe or landscape photo). Tweets containing RunKeeper Twitter cards were oversampled as a result, which corresponds to their more frequent occurrence in the Collected Tweets study.

For each tweet, I asked respondents to select from a list of reasons why they believed the person shared. Reasons were motivated by prior work (e.g., [118,149]), including to receive emotional support, to be held more accountable, and to boast or show off. Respondents were asked to describe their initial reaction to the tweet in a freeform text box. They were additionally asked to indicate on four 5-item Likert scales whether they were happy or annoyed with seeing the post, and whether they found it interesting or boring. Finally, they were asked whether they would reply to the post, and described how they would reply or why not in a text box.

97 people responded to at least one tweet in the survey (62 female, 34 male, 1 blank; average age 28.5, stdev 7.79, median 26, min 18, max 63). 83 responded to all five tweets that they were presented (mean 4.58, stdev 1.06), resulting in 444 total responses to a tweet. 45 participants stated they ran regularly, with 14 of these respondents regularly posting their runs to social media. 18 respondents had used RunKeeper to track their runs before, and 56 used Twitter. The research team affinity diagrammed respondent reactions and reply descriptions and coded according to the identified categories.

5.3.1.6 Statistical Methods in the Generated Tweets Study

We used similar regression analyses to the Collected Tweets study to characterize the correlations between different tweet attributes and audience reactions. We used Ordinal Logistic Regression on results of the 5-item Likert questions, performing multilevel modeling by respondent to control for intrinsic respondent opinions.

5.3.1.7 Limitations

In the Collected Tweets study, we only analyzed tweets that were publicly available in May 2014. As a result, we did not analyze any that a sharer removed after receiving no response or a negative response. Prior work has suggested that people use this as an impression management tactic [145]. We additionally did not collect any replies, favorites, or retweets occurring after that point. I anticipate there were very few, as all tweets had been shared for at least 30 days before reply data was collected. Because follower count can change at any time, the audience count used in the analyses may differ somewhat from the count at the time they were shared. I also noticed some of the accounts tweeting runs had been followed, favorited, and/or retweeted by accounts which represented corporations or products. These responses are included in our analysis even though it may not result in the same feelings of support as reactions from individuals.

The tweets in the Generated Tweets study were all hypothetical, so the actual behavior of respondents may differ from what they described in the survey. Given the frank nature of the responses, I believe respondent reactions to the tweets they saw in the study were authentic. In the Generated Tweets study, 33 respondents said that their willingness to reply depended on how well they knew the person sharing. This ranged from "*if I know the person or not*" (GT14) to "*only if it's a close friend*" (GT23). On a whole, participants seemed more willing to respond to posts made by close friends or family members. Neither study measured the influence of tie strength explicitly, but doing so is an opportunity for future work.

5.4 Results

I triangulated results from the Collected Tweets and Generated Tweets studies to create a more complete understanding of how people post and respond to posts from RunKeeper to Twitter. Results from the regression analyses of the Collected Tweets and Generated Tweets study data appear in Table 8 and Table 9, respectively. Participant tweets and open-ended responses are quoted with the acronym of the corresponding study identifier and number (e.g., CT##, GT##).

Table 8. Regression models from the Collected Tweets study on (a) whether a Tweet received replies, (b) the number of favorites received, and (c) the number of retweets received.

	(a) Tweet received replies (Negative Binomial)			(b) Favorites (Poisson)			(c) Retweets (Poisson)		
	Count Model Coefficients			**Count Model Coefficients**			**Count Model Coefficients**		
Variable	Estimate	Std. Error	p	Estimate	Std. Error	p	Estimate	Std. Error	p
(Intercept)	-8.789	1.092	<0.001***	-7.811	0.801	<0.001***	-6.860	0.828	<0.001***
Default text	0.063	1.073	0.953	0.098	0.788	0.901	-2.056	0.787	0.009**
User text	1.147	0.248	<0.001***	0.806	0.154	<0.001***	0.283	0.543	0.601
User picture	-0.533	0.407	0.190	-0.170	0.208	0.413	-0.053	0.641	0.934
Positive	-0.116	0.409	0.777	-0.153	0.200	0.442	0.833	0.650	0.200
Negative	0.326	0.604	0.590	0.496	0.375	0.187	-13.250	895.397	0.988
Tweet is live	-13.851	671.103	0.984	-0.093	0.466	0.841	0.383	1.163	0.742
@mentions	0.070	0.600	0.907	-0.403	0.289	0.163	1.586	0.832	0.057
0:00	-0.346	0.629	0.582	-1.483	0.787	0.060	0.440	1.180	0.709
	Zero-inflation model coefficients			**Zero-inflation model coefficients**			**Zero-inflation model coefficients**		
Variable	Estimate	Std. Error	p	Estimate	Std. Error	p	Estimate	Std. Error	p
(Intercept)	-0.011	0.392	0.979	-0.351	0.205	0.088	1.552	0.581	0.008***
Egg image	13.456	877.604	0.988	-2.095	9.624	0.828	-14.428	434.771	0.974
log(tweet frequency)	0.440	0.114	<0.001***	0.473	0.076	<0.001***	0.141	0.135	0.294

*** p<0.001, ** p<0.01, * p<0.05

Table 9. Regression models from the Generated Tweets study on how tweet characteristics impacted respondent opinions.

	Annoyed	**Bored**	**Happy**	**Interesting**
User picture	$F_{2,356} = 0.53$	$F_{2,358} = 8.50$ ***	$F_{2,358} = 2.58$	$F_{2,358} = 4.58$*
Positive	$F_{1,360} = 0.19$	$F_{1,362} = 1.74$	$F_{1,362} = 1.68$	$F_{1,363} = 0.17$
Negative	$F_{1,356} = 0.84$	$F_{1,358} = 0.55$	$F_{1,357} = 0.04$	$F_{1,358} = 3.17$
Tweet is live	$F_{1,372} = 0.58$	$F_{1,376} = 0.11$	$F_{1,375} = 2.79$	$F_{1,377} = 0.99$
Distance	$F_{1,374} = 0.73$	$F_{1,378} = 0.77$	$F_{1,377} = 1.43$	$F_{1,378} = 0.04$
Weather	$F_{2,353} = 2.13$	$F_{2,355} = 0.11$	$F_{2,354} = 1.30$	$F_{2,355} = 1.54$
Specific	$F_{1,363} = 15.84$***	$F_{1,365} = 10.35$**	$F_{1,365} = 15.09$***	$F_{1,366} = 6.47$*
Contains ask	$F_{1,362} = 5.58$ *	$F_{1,364} = 7.05$ **	$F_{1,364} = 2.06$	$F_{1,365} = 4.67$*
Number seen	$F_{1,347} = 3.83$	$F_{1,348} = 8.08$ **	$F_{1,348} = 0.003$	$F_{1,348} = 6.89$**

*** p<0.001, ** p<0.01, * p<0.05

5.4.1 *System-Generated Content*

Analysis of tweets from the Collected Tweets study shows that tweets with any text generated by the person tweeting receive more replies (Z=4.63, p<0.001, 95% CI: 1.94-5.12 more replies) and more favorites (Z=5.25, p<0.001, 95% CI: 0.51-1.11 more favorites). Tweets containing any system-generated text receive fewer retweets than those that do not (Z=-2.61, p<0.01, 95% CI 0.51-3.60 fewer retweets). This suggests that adding content to a tweet, even when combined with system-generated content from an application, is more likely to generate responses.

The factorial design in the Generated Tweets study resulted in only 13 respondents viewing a tweet containing only system-generated content. Three of these respondents said such a tweet felt automatic: "*there's no comment attached to this – just an automatic posting*" (GT80). GT49 reacted negatively to the tweet as a result, saying "*this looks more canned, like maybe the app shot it off without Cameron knowing about it… very impersonal.*" GT66 was "*annoyed that they didn't customize their automatic tweets,*" with GT22 and GT44 suggesting that the tweet "*looks like an advertisement.*" GT43 felt the tweets needed to explain the importance of a run, saying, "*It needs more context. Was this related to an event? Or was it a major training run? There is nothing really personal about it. It's just a robot post.*"

Even when a tweet contained content generated by the person tweeting, some Generated Tweets study respondents reacted negatively to the system-generated content. GT2 saw a tweet containing a request for a running buddy, and reacted, "*I wouldn't take the 'run with me next time' thing seriously. It feels impersonal mostly because it's not some kind of direct message to me, but also because it's a part of a canned tweet. Even if they really mean it, I don't believe they do.*"

Respondents also appeared to fatigue after seeing multiple tweets, reporting tweets seen later as more boring ($F_{1,348}$=8.08, p<0.01) and less interesting ($F_{1,348}$=6.89, p<0.01). Respondents appeared to tire of seeing similar content repeatedly, a byproduct of the prevalence of automatically generated content. 5 Generated Tweets study respondents emphasized the importance of "*how often they post content like this*" (GT62, sentiment shared by GT10). After seeing multiple posts, GT97 notes, "*this sense of novelty is wearing off,*" and was left less enthusiastic about posting support.

We conducted a secondary analysis on the 27 tweets from the Collected Tweets study made with the RunKeeper hashtag which did not contain any system-generated text (previously excluded from the analysis). These tweets were more likely to receive responses (χ^2(1,N=4798)=28.14, p<0.001), favorites (χ^2(1,N=4798)=15.63, p<0.001), and retweets (χ^2(1,N=4798)=65.75, p<0.001) than tweets posted through RunKeeper. However, this is dependent on a small proportion of tweets without any system-generated text.

5.4.2 *Details About Activity are Well-Received*

Many sharers in the Collected Tweets study included additional details about the weather in their tweets, such as CT4756: "*Just completed a 10.26 mi run – A cold wind and lovely sunshine*" and CT2912: "*Just completed a 7.49 km run - 6°C, WC: 2°C, 20km/h WSW, 81%.*" Others supplemented their posts with additional statistics about their run, such as biometric or how they were training. For example, in CT1843: "*Just completed a 2.24 mi run – 6x400, pace 09:34/mile, max HR 169*."

RunKeeper includes distance as part of the system-generated content in tweets. Twitter users occasionally responded to this distance, such as in CT2250, which received the response "*only 2.71? ... And you were giving me grief for 4 ;p*." Twelve Generated Tweets study respondents explicitly reacted to the distance of a run. Most were impressed by the sharer, including GT67: "*Holy shit he ran 9 miles?*" Other respondents acknowledged the significance of the event in their response, such as GT23 who wrote "*4 miles for a first run sounds impressive*."

The content of the tweet influenced Generated Tweets study respondent's opinions of the tweet. When a post included a specific reason for the run, respondents found the post less boring ($F_{1,363}$=15.84, $p<0.001$), more interesting ($F_{1,366}$=6.47, $p<0.05$), and were happier to see it ($F_{1,365}$=15.09, $p<0.001$). Consistent with suggestions from prior work [114,118], when a post contains a request of the audience, Generated Tweets study respondents found the post less annoying ($F_{1,362}$=5.57, $p<0.05$), less boring ($F_{1,364}$=7.05, $p<0.01$), and more interesting ($F_{1,365}$=4.67, $p<0.05$).

Generated Tweets study respondents desired more information about the importance of the run when deciding whether or not to reply and responded more positively when this information was provided. GT45 decided to root for a runner "*because it's her first run back from surgery*." GT46 contemplated replying, stating "*if they were working toward a goal, I'd be more likely to reply*." GT92 reports both extremes in their response: "*I don't give a shit about watching people's live runs unless they're in an important race or they're doing an event in which they need support*."

5.4.3 *Pictures in Posts are Seen as Valuable*

In the Collected Tweets study, we did not find a significant effect of the pictures on whether a tweet receives replies (Z=-1.31, n.s.) or how many favorites (Z=-0.82, n.s.) or retweets (Z=-0.08, n.s.) a post receives. The Generated Tweets study identified a significant effect of picture on whether a post was boring ($F_{2,355}$=8.50, $p<0.001$) and interesting ($F_{2,356}$=4.58, $p<0.05$), displayed in Figure 29. Although a picture may not trigger more feedback, tweet audiences still appear to value posts with photos more.

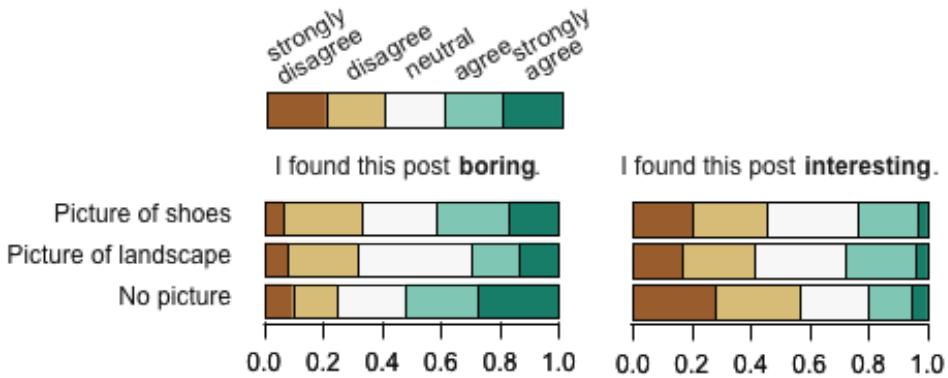


Figure 29. Respondents agreed that posts lacking pictures were more boring and less interesting than pictures of landscapes.

The content of a picture also affected audience responses. We used a Wilcoxon signed rank test to compare impressions of the 54 audience respondents who saw pictures with both a landscape and shoes. Shoe pictures were more boring than pictures of landscapes ($Z=2.36$ $p<0.01$, 95% CI 0.25-4 on a 5-item Likert scale), though there was no difference in interesting rating ($Z=-0.49$, n.s.). Both received primarily positive reactions from the audience, with respondents reacting to the "*nice shoes*" (GT50 and 3 others), "*liking the setting that is pictures*" (GT14 and 9 others), and even "*makes me want to go walk the same location*" (GT55). Others wondered, "*why are you showing me a picture of your shoes?*" (GT93).

5.4.4 *Live Events do not Receive Feedback*

Live tweets were not more likely to receive responses ($Z=-0.02$, n.s.) or influence the number of favorites ($Z=-0.20$, n.s.) or retweets ($Z=0.33$, n.s.). None of the 123 live tweets in the Collected Tweets sample received replies. 8 of the 94 Generated Tweets study respondents who saw a live tweet stated they would follow the link to watch their friend run live. 7 other did not see the value in watching someone else run, such as GT96: "*I have better things to do than watch someone's run online.*"

5.4.5 *Positive Outcomes from Sharing*

Both the Collected Tweets and Generated Tweets studies found positive experiences that could result from sharing, for both the sharer and the audience.

5.4.5.1 Positive Impressions of the Sharer

Generated Tweets study respondents were "*happy for*" the sharer (6 participants). GT66 elaborated more on this sentiment, being "*glad that my friend is making a commitment to being active.*" Providing context for a run tended to support these feelings: "*good to see them back on their feet*" (GT62, a sentiment shared by 2 others) and "*oh good, they're running a half marathon. I hope they do well.*" (GT74, a sentiment shared by GT80, who stated "*I am grinning just looking at this*"). Although these respondents may not reply or interact with the sharer on the social networking site, these positive impressions indicate a potential for in-person conversations about running that might not have occurred without the content being shared.

5.4.5.2 Favoriting

Favoriting a tweet requires little effort from followers but offers an easy way to provide emotional support or motivate the sharer. 6 Generated Tweets study respondents said that they would favorite a tweet, with GT18 noting the lower threshold: "*just a favorite. I don't reply to anything often.*" Text written by the sharer in a tweet seemed to give followers more to respond to. This could be a positive or negative sentiment. CT4204 received four favorites for stating a run was "*Easy Peasy Lemon Squeezy,*" while CT4678 received one favorite for adding "*#dying #turtlesrunfaster.*" Followers may also be more willing to respond when the sharer simply explains what they were thinking. CT508 received one favorite for "*push it to the limits.*"

5.4.5.3 Replying

27 Generated Tweets study respondents indicated they would reply to at least one of the tweets they saw. These replies fell into three general categories. Congratulating the runner was a common type of support, examples including "*good job!*" (8 Generated Tweets study participants responded this way, as well as 5 replies observed in the Collected Tweets study), "*congrats!*" (2 Generated Tweets participants, 2 Collected Tweets replies), "*great work!*" (6 Collected Tweets replies), and simply "*yay!*" (1 Generated Tweets participant and 1 Collected Tweets reply) or "*wow!*" (3 Collected Tweets replies). Others encouraged the runner, with "*come on!*" (2 GT participants), "*you can do it!*" (1 Collected Tweets reply) or "*keep at it!*" (2 Generated Tweets participants). Finally, Generated Tweets study respondents expressed care for the runner "*be careful*" (2 Generated Tweets participants in response to runners who were injured or recovering).

42 tweets in the Collected Tweets study received more than two replies. These posts show conversations occurring over Twitter as a result of the post. Conversations were often follow-ups about how the runner was feeling, such as "*how's the hammy?*" (reply to CT1779) and "*how are you feeling now?*" (reply to CT4170). Generated Tweets study respondents similarly replied with questions for the sharer, such as "*where are you running?*" (GT85). These questions serve as an effective way to engage the runner and can provide useful advice for other followers.

Several tweets prompted Generated Tweets study respondents to say they would offer or solicit advice. 3 respondents offered recommendations on routes, with GT35 saying, "*I might think of my favorite running routes and suggest one to them.*" GT7 indicated they might reply "*if I wanted advice on getting a better time.*" The original sharer of CT4423 offered advice to one of their followers who stopped running: "*joining the running club & #parkrun have got me back into it, I'm loving it!*"

Figure 30 presents how characteristics of the tweet and of the respondent impact the likelihood of Generated Tweets study participants responding. Runners are slightly more likely to respond to tweets than non-runners (χ^2(1, N=444)=2.34, p<0.1), but Twitter users were no more likely to respond than non-Twitter users (χ^2(1, N=444)=0.15, n.s.). Sharing the interest or experience increases a follower's likelihood of reply, and responses may increase with an audience who can better relate to the post content.

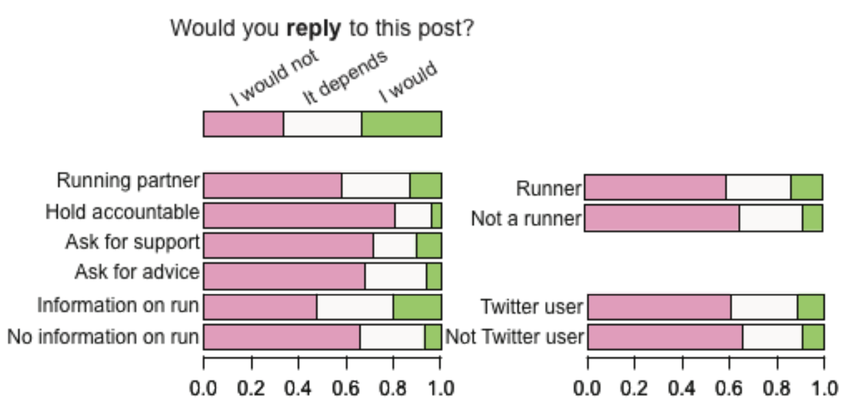


Figure 30. Respondents indicated that they were more likely to respond to posts that indicated information about a run, a request for a running partner, a request for support, or if they were a runner or Twitter user.

5.4.5.4 Responding Beyond Twitter

9 Generated Tweets study respondents indicated they would want to run with the sharer in the future, some in direct response to a request for a running buddy "*let me join next time?*" (GT45, 4 others responded similarly) or following up from an injury recovery "*oh cool, he's back from surgery, let's go on a run together*" (GT24). CT3969 received a response asking to run together: "*nice run, up for 15 [miles] this Sunday?*"

Finally, posts sometimes motivated their audience to go run themselves, such as GT88, "*I wanna go for a run.*" Others posted concerns about their own running habits. A reply to CT763 expressed concerns about starting to run: "*wish I could get myself motivated and off my ass to start running mate. Can't get started.*" The original sharer then offered encouragement back to the friend.

5.4.5.5 Connecting with the Sharer

When tweets made an audience member think of their own experiences, the audience member felt more connected with the sharer and was more inclined to respond. GT80 reminisced about her own running experiences: "*I remember when I was in that place, posting short runs with pictures and training for my first half!*" She would want to reply, adding "*I empathize with this situation and I'd want to encourage this person to keep working toward their goal.*"

Other Generated Tweets study respondents discussed relating to or commiserating with the sharer. GT19 commented, "*seeing as I have knee pain from time to time, I'd be pretty sympathetic to this individual.*" G92 similarly related to the runner, commenting, "*I would commiserate, as I also rarely look forward to runs.*"

The Collected Tweets set also contained several examples of shared experiences between sharers and an audience member. People encouraged their teammates and people who they ran with, such as CT4705 "*motor on teammate!!!*" and CT469 "*great, we have to keep up the momentum*." Some sharers added text to indicate who they were with, (e.g., "*with Dave & Matty*" by CT123 and "*walking with Vinny*" by CT3922) or @mentioning the others (e.g., "*Thanks @[removed] for getting me out of bed!!*" by CT4074).

5.4.6 *Undesired Consequences of Sharing*

A large portion of Generated Tweets study respondents reacted negatively to some or all of the tweets they saw. The Collected Tweets study analysis is unable to capture many of these potential negative reactions. The methods used were unable to observe reactions such as unfollowing the sharer, hiding posts from the RunKeeper app, quickly scrolling past the post, or forming a more negative impression of the sharer.

5.4.6.1 Tweets are Ignored by the Audience

13 of the 97 Generated Tweets study respondents indicated they would ignore at least one of the tweets, with 8 others reacting to a tweet with "*meh*". 73 of the respondents agreed or strongly agreed with the statement "I found this post boring" for at least one tweet, suggesting that survey respondents did not care for this content. GT52 wondered why this content appeared on Twitter: "*I scoff because why do they need to tweet this.*" GT74 and GT93 wondered, "*why would I want to watch you run?*"

55 respondents agreed or strongly agreed with the statement "I would be annoyed if a friend shared this" to at least one tweet. 16 respondents described being annoyed by at least one tweet, with 11 reacting "*ugh*". GT16 reacted "*annoyed, don't care*" and "*I don't want to encourage posts like this.*" GT70 commented, "*really, bro, no one cares.*" 4 respondents said they would unfollow the sharer or try to hide the post.

This sentiment did not appear in the Collected Tweets study, likely because Twitter followers did not want to publicly post negative replies. GT62 stated, "*I dislike this post and would want to keep that negativity off their account.*" GT2 felt similarly: "*I wouldn't reply because if I did it'd be something really rude so it's better to just keep it to myself. Or maybe it's better to unfollow the person.*"

An audience member ignoring or being annoyed by a tweet often appears the same to the person who shared: there is no response. Learning that followers are annoyed by certain posts may lead to changes in tweeting behavior. However, because such a sentiment is rarely publicly expressed, the lack of response makes it difficult for the sharer to learn how to regulate their posting habits.

In the Collected Tweets study analysis, we observed that some sharers created separate accounts for posting only their physical activity. This can complicate the process of following people on Twitter. For example, it can be difficult to identify that someone has a separate feed for physical activity. But it also gives audience members more control to choose whether to follow such accounts and receive physical activity tweets.

5.4.6.2 Negative Impressions of the Sharer

Some Generated Tweets study respondents also expressed negative opinions of the person sharing because of what they tweeted. A few respondents believed that the sharer was posting to brag about their success. For example, GT48 reacted, "*someone likely wants attention,*" with GT49 stating, "*it looks like he's just showing off*." GT35 and GT74 thought that the person tweeting was "*fishing for compliments*." GT90 suggests that posting could cause the sharer to be seen as a braggart, especially when the post is not clear about the sharer's goals: "*I think it's great when people share this kind of stuff because it helps hold them accountable (accountability is the positive byproduct). However, most people are probably posting this because they want to brag about their physical activity and the sweet views they get while running, but that's not a bad thing either if it motivates other people to hit the streets, too*."

For each tweet, respondents were asked to speculate why the tweet was posted from a list of reasons. Respondents marked 55.0% of tweets as posted "to receive emotional support", and 50.9% as posted "to boast/show off", with 25.3% were perceived as motivated by both goals. This shows two different audience interpretations having conflicting sentiments about the sharer. Bragging might be accepted and even encouraged in peer support communities, which GT21 implies: "*I just kind of ignore [posts] unless on [MyFitnessPal] because it is FOR bragging about exercise ;)*." However, participants indicated bragging is less well-received on general-purpose social awareness streams.

5.5 Discussion

The analysis of the Collected Tweets and Generated Tweets studies surfaced both successes in sharing and problems with much of the content that is shared. I next describe some potential causes for the disparity, offer design recommendations, and relate the findings to social sharing in personal informatics more broadly. I then briefly describe two projects which explored different dimensions in the design framework to develop design recommendations.

5.5.1 *System versus Sharer-Generated Content*

Posts in the Generated Tweets study were better received when they contained a request of the audience or substantial context about the importance of a run was provided. While not every run can be a personal best or a major milestone, the findings suggest that describing the importance of a run will lead to more positive responses and support.

These findings demonstrate the importance of supplementing the details of a run with sharer-generated context, such as reporting a personal best. A system can encourage this by prompting the runner to take a picture or answer a question prompt prior to sharing, then including this content in the post. Facebook took steps toward this by encouraging developers to incorporate more personal content into posts made through applications [156]. For example, a sharing application could easily prompt the person sharing with, “why did you run today?” as part of the sharing process.

5.5.2 *Audience and Post Frequency*

Twitter is a broad social network where followers range from close friends to total strangers. It is therefore difficult to frame a post about physical activity to match the expectations of everyone in this audience. Audience fatigue plays a role, especially if a genre of posts appears frequently in a Twitter feed. A highly motivated audience, such as a close friend or a person that can relate to the sharer’s challenges, might suffer from less poster fatigue.

Despite or perhaps because of Twitter’s ability to reach a wide audience, it may not be the best venue for regularly sharing everyday physical activity or other personal informatics data. The design of a potentially improved system could enable sharing physical activity with a smaller audience of close friends or family members, perhaps implemented using lists within a broader social network. A challenge in this implementation is that prior work has found that in practice, many people do not want to spend the effort to configure such lists [114]. Another design approach would be to share only to people interested in running through a dedicated social network, lists of a subset of followers or friends, or dedicated accounts.

The respondents to the Generated Tweets study indicate that people are willing to offer support to a close friend even if they are not collecting the same data themselves. Routing messages to close, supportive friends and to people who have an interest in running or self-tracking may result in a better experience for sharers and their social awareness stream audiences.

Twitter may still be an appropriate venue for sharing significant achievements, such as returning from injury or running a race. An application could recommend sharing these activities to Twitter, while dissuading sharing of other content. Changing the interaction from automatically generating tweets to one that recommends tweeting only if the content is sufficiently important, or novel, would help avoid overloading audiences with content.

5.5.3 *Mismatch Between Sharer Goal and Audience Interpretation*

As discussed previously, sharers have a variety of goals for posting their tracked data to a social networking site. However, these reasons are not always apparent to the post audience. Followers are often left wondering "*why would someone post this?*" (GT57) or believing that there is "*nothing to say*" in reply (GT72, 2 others agreed).

Personal informatics applications should encourage sharers to be more explicit about what feedback they are looking for when they decide to share. People could be asked to answer, "why are you making this post?" prior to sharing. Posting this answer alongside the original post could give the post's audience enough context to provide meaningful feedback for the person sharing.

Although I focused my analysis on audience reactions in the form of replies, favorites, and retweets, some goals may not benefit from more replies. For example, someone seeking advice may need just one or two informative replies, rather than a variety of less accurate replies. Furthermore, for some goals, no specific reply may be necessary. Posts made to foster an impression of oneself as an active, athletic individual might not need replies to achieve their goal. Alternatively, people post goals to social networks to feel more accountable to those goals [115]. If posting alone is sufficient for people to feel committed to their goal, they may not require explicit feedback from their audience. It may be sufficient to acknowledge that a post has been seen.

5.5.4 *Extending Beyond RunKeeper and Twitter*

Many of the design recommendations I described for sharing RunKeeper data on Twitter apply for other domains in which people self-track data as well as for sharing on other social awareness streams. For example, Generated Tweets study respondents felt many posts were made to brag or show off. I expect this occurs regularly when sharing personal informatics data, such as when someone shares that they consumed fewer calories, lost weight, or cut unnecessary spending habits. However, people may not brag in some domains. Some types of data, such as personal finances or health test results, may be seen as more private. But audience members may have a greater desire to see regular updates, such as when someone has an ongoing struggle to manage a chronic illness [118]. Future work should more fully explore heterogeneity between different domains of shared data.

Regardless of the data presented, I believe automatic posts from self-tracking applications are likely to receive negative reactions from audience members. Although perhaps some types of personal data are less annoying or more interesting in a social awareness stream, I anticipate that adverse reactions to automatically generated posts will still be common.

Audience reactions to posts with personal informatics data may correlate to how frequently the posts appear. Current commercial self-tracking applications including Strava, Last.fm, Foursquare, and RunKeeper encourage self-trackers to post to social awareness streams regularly. To create better sharing experiences for both sharers and their audiences, the designs of these applications could encourage fewer, more meaningful posts and could describe the post's importance or what the person sharing hopes to gain from posting.

5.5.5 *Applying the Design Framework in Two Other Projects*

In this chapter, I described a framework for evaluating sharing features in personal informatics systems. Use of this framework can help designers consider each design choice they make when creating a sharing feature for a personal informatics application. I focused on one dimension, *post content*, in evaluating the framework. In other projects, I have begun examining design recommendations in two other dimensions, *preprocessing* and *data domain*.

Toward the preprocessing dimension, I examined perspectives on sharing fine-grained, minute-by-minute tracked data in a project published at UbiComp 2013 [46]. I took a value-sensitive approach to designing transformations of the tracked data, aligning data to people's desire for trust, honesty, support, and accountability as well as privacy [59]. As seen in Figure 31, I developed interactive transformations to preserve privacy. For example, a design could allow a person to shift their mid-afternoon run to later in the day to avoid judgment from coworkers, or someone could remove their late-night walk home from a bar to preserve privacy. To get feedback on these transformations, I interviewed 12 people who used similar tracking tools. Though most could see the benefit of such transformations, their desire to remain honest outweighed privacy concerns and support opportunities. To preserve privacy, participants felt they would prefer their data be coarsely aggregated, in the leftmost transformation of Figure 31.

Figure 31. Three methods for transforming fine-grained tracked physical activity data. The leftmost approach aggregates fine-grained data into a single daily total, preserving privacy at the expense of opportunities for accountability. The middle and right designs explore interactive methods of shifting and deleting activities for impression management goals, trading off honesty for support.

Focusing on the data domain dimension, we examined people's perception of the social feed in Venmo, a peer-to-peer payment application. The project was led by Monica Caraway and published in the Proceedings of the ACM on Human-Computer Interaction (Issue CSCW, 2017) [18]. Venmo's feed is shown in Figure 32. Venmo enables people to see transactions that their friends, and even the entire community participated in and give feedback through likes and comments. This is particularly unusual because people often view financial data as too private to share with others [83,157]. We utilized Uses and Gratifications Theory, which describes how people use media as ritualistic (e.g., habitual, for fun) or instrumental (e.g., goal-directed, purposeful) to understand people's use of Venmo [134]. When sending or receiving money from strangers or weak ties, survey and interview participants often used the feed more instrumentally than a typical social feed, describing the purpose of the transaction. Transactions with friends and family tended to be more ritualistic, including emoji or humor, and more similar to how people share other types of data. Despite some discomfort about revealing finances, participants felt the social feed did not detract from their experience sending money and was occasionally fun or informative.

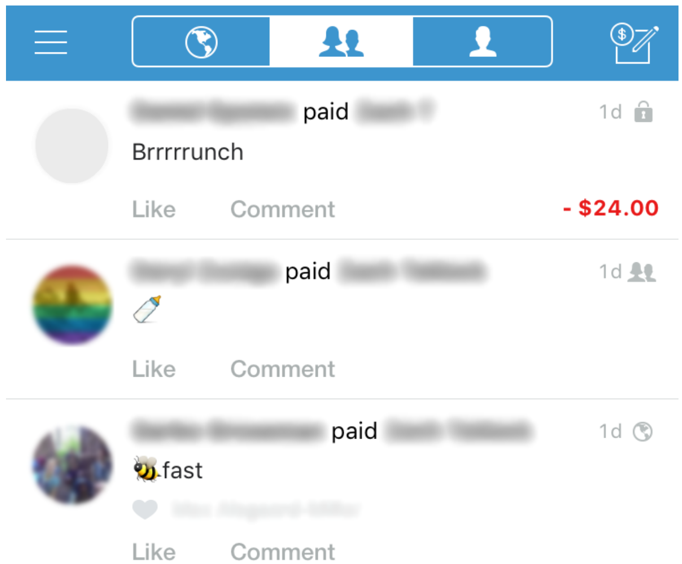


Figure 32. The social feed in Venmo allows people to see transactions they, their friends, and the entire community took part in. The feed includes likes and comments as traditional feedback mechanisms and keeps dollar amounts private to the people involved in the transaction.

These two projects demonstrate how isolating single dimensions in the design framework can surface interesting research questions and useful understanding about how people interact, or want to interact, with features for sharing tracked data.

5.6 Conclusion

This chapter presents a design framework for sharing in personal informatics. The design framework characterizes different design choices for features that can socially support sharing personal informatics data. Designers can use this framework to determine the impact of a single factor in the design of a sharing experience. Researchers can use it to identify unanswered research questions around sharing of personal informatics data and guide further study designs. I characterized prior work into the dimensions of the design framework and summarized findings toward each dimension. I offered design recommendations for improving sharing of physical activity on Twitter through two studies of RunKeeper, and described how these findings can extend to other self-tracking domains and other social awareness streams.

Chapter 6. YARN AS A CASE STUDY OF DESIGNING FOR FINDING SUPPORT THROUGH DATA

The dimensions of the design framework for sharing helped uncover challenges around how designs could help people share their tracked data without overwhelming or boring their audience. In this chapter, I build on the challenge that current designs do not help people create the type of content that others want to respond to. This challenge motivates the research question:

RQ5: How can a design support authoring of interesting content using tracked personal data?

As described in Chapter 5, shared content needs to explain why the tracked moment is important or meaningful. My evaluation of the post content of RunKeeper tweets in Chapter 5 demonstrated that data alone is not enough to explain why a moment is important. People are often tracking data as part of a story in their everyday life, such as trying to lose weight or save money [84,131]. However, these motivations are rarely supported. In a review of people's social needs for personal tracking, Kersten-van Dijk & Ijsselsteign suggest "*to move beyond impersonal, standard messages to fostering true connections between self-trackers and their various audiences, [designs] need to support those users in telling their story and sharing experiences with their data, their way*" [84].

In this chapter, I demonstrate approaches to helping people align data-driven content they collect with their motivations for sharing and connecting it to the broader story they are interested in telling. I developed a mobile app, Yarn, that implements a structured experience of authoring story chapters to help novices quickly create compelling and personally meaningful content they can share. The structured experience uses *visual templates* and *description prompts* to help people clarify their sharing goal and describe how others can help towards it. For example, a visual template for celebrating achievements emphasizes the intermediate steps toward completion of the story (Figure 33), while a template designed for eliciting support emphasizes the difficulty of the current moment. Description prompts then encourage people to explain why a moment was particularly important or difficult.

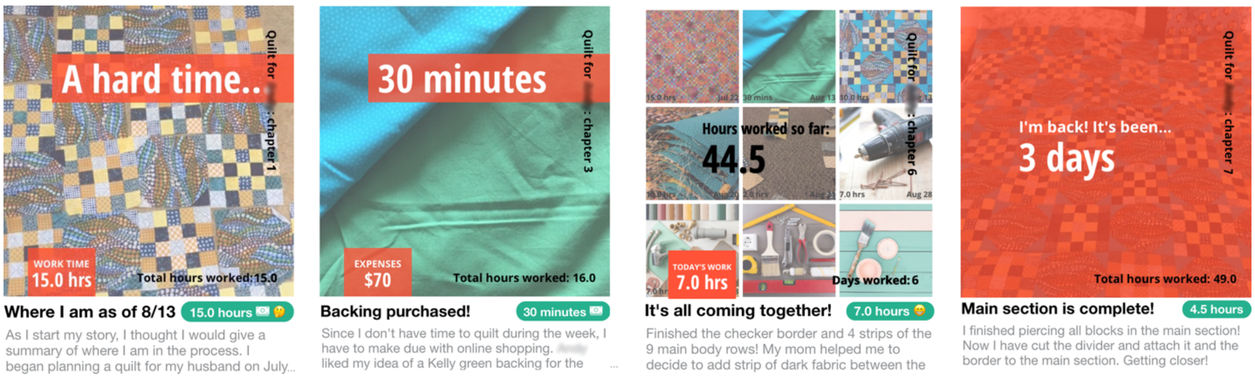


Figure 33. Yarn helps people create content which aligns with their goals for sharing data through a structured authoring process with visual templates and description prompts. This content was created by field study 1 participant F2^{diy} as part of a story about making a quilt.

To design Yarn as an effective tool for helping people author interesting content, I draw from literature on the stories people are interested in telling and design approaches to telling stories. The plots of the stories people tell tend to follow basic themes [14], such as a journey and return to the same place (e.g., sharing photos from a vacation), or overcoming a struggle (e.g., fighting cancer). I focus my investigation on one specific type of plot, supporting *stories of accomplishment*, because people often track moments toward that accomplishment as part of monitoring progress and staying motivated. I specifically designed Yarn for two accomplishments involving different tracked personal data of interest: completion of a running race and of a home Do-It-Yourself (DIY) project. In race training people may track their running distance, heart rate, or pace [38,113], while in DIY projects people may instead collect photos, expenses, or mood [132,133].

Through a review prior work and formative interviews with 23 people, I identified a need for Yarn's structured authoring experience to align shared content with sharing motivations. I conducted two field evaluations where 21 people used Yarn for 4 weeks, finding that participants felt Yarn encouraged them to make more compelling content, and the content resulted in discussions with close friends and family members.

This project is under submission, with Koko Nakajima, Mira Dontcheva, James Fogarty, and Sean Munson as co-authors and additional contributors Madisen Aurang, Sol Choi, Peter Cutler, Maya Klitsner, and Tre Paolini. I conducted all of the formative interviews, led the design of Yarn, implemented all of Yarn, managed the first field study, led data analysis for all studies, and led writing of the paper. The design of the visual templates in Yarn was conducted in collaboration with Koko. Koko also created a video demonstrating the authoring process to help disseminate the research.

6.1 BACKGROUND MOTIVATING THE DESIGN OF YARN

The design of Yarn was motivated by people's varied motivations for sharing personal data. I described these motivations in Chapter 5, but to briefly reiterate, people share to receive *recommendations or advice* [111], for *support or motivation* [149], and to *share an achievement* they are proud of [159]. I next provide more detail on how prior literature has supported authoring stories and on formative interviews which motivated the selection of race training and DIY stories.

6.1.1 *Strategies Used by Designs to Support Authoring Stories*

Storytelling strives to make information understandable, meaningful, and memorable [104]. Yarn leverages design strategies for storytelling to help people create meaningful and memorable content.

One common design strategy is *a structured authoring experience* which describes how experts organize their stories. For example, the Motif system surfaces what video shots will create a good narrative structure, helping people capture and assemble video stories in the moment [87]. Other systems aid people in organizing previously taken photos and videos into a story. The iTell and Storied Navigation systems use prompts to help people effectively brainstorm what they want to highlight and organize any associated data [92,139]. Other systems have instead helped people search within the photos, videos, and location data they collect for relevant or memorable moments. The classic MyLifeBits system included a map and calendar for browsing location-tagged photos [63]. The Raconteur conversational agent mined text conversations with a friend to identify what photos or videos may be appropriate to share [19].

Other designs seek to help people *document the important moments in their progress*, aligning with Rooksby et al.'s documentary-driven tracking style [131]. A record of important moments can help people tell the story of their progress after completion or get advice along the way. For example, the Mosaic system provides a structured process for people to share creative works-in-progress for early feedback [86]. Spyn similarly supports documenting the experience of knitting through photos and location data to help people demonstrate their progress [133]. Smart journals, or digital personal diaries, use a range of media to help people author their own histories [44]. Though journaled data is typically collected for private consumption, Elsden et al. find that the data can serve as a talking point with others when the authored content prompts curiosity [43].

Prominent social networking platforms, including Instagram, Snapchat, and Facebook, have recently added story features aimed at sharing events currently taking place. In these features, people tend not to worry about whether content will be interesting because it is ephemeral and reading is voluntary [105]. When specifically considering stories of accomplishment, designs can offer more helpful guidance on how to make interesting content. Knowing a person's goals, and what progress they have made, can help a system support the person in making content which better describes the importance of an achievement or explains a struggle.

6.2 METHODS

I followed an iterative process to design and evaluate Yarn. I started by conducting two rounds of formative interviews to develop design principles for authoring interesting content. The first round of 16 interviews helped identify a specific type of story which technology could help support people in telling, namely stories of accomplishment. The second round of 7 formative interviews offered guidance toward designing for the two domains I scoped Yarn to support, specifically Do-It-Yourself projects and training for running races. I conducted two evaluations of Yarn. In the first study I sought to understand how Yarn's authoring process helped people create content from their tracked data. The second study examined how people with whom authored content is shared react and engage with it. I iterated on the design of Yarn between studies. 10 participants used Yarn for one month in the first study, 11 in the second study.

Though the sample size of reach study is small, I believe the evaluations offer an initial examination of principles for authoring content through tracked data. Substantial evidence toward the design principles arise from the range of participant stories in the formative interviews and consistency with design recommendations from prior literature. Participant stories in the evaluations of Yarn were similarly varied. Further examination of how a larger, more diverse population responds to principles for authoring with tracked data could help refine design recommendations further.

I now describe the methods used in the formative interviews. I describe methods used in the field studies in the evaluation section of this Chapter (6.5).

6.2.1 *Formative Interviews*

I sought to better characterize the stories people wanted to tell with personal data before narrowing my scope to a specific type of story. I interviewed 16 people in their homes (9 F, 7 M, ages 25-40) in Summer 2017, asking them to describe the personal data they collect and to brainstorm stories they were interested in telling through that data. Interviewees then completed a design activity where they sketched on paper how they would want to tell that story. I then asked questions about the designs they sketched. I took field notes and recorded audio, sending the audio to an external service for transcription.

I recruited participants through posts to community Facebook groups and messages to university email lists. Three participants were currently students, four were in technology-related fields. The remainder ranged from teachers to marketing consultants to customer service representatives. I inductively coded the interviews, wrote memos summarizing themes, and discussed these themes with other members of the research team.

The majority of stories people wanted to tell aligned with three classic narrative plots [13,14]: voyage and return, overcoming a monster, and quests (referred to as *stories of accomplishment* in this research). People telling voyage and return stories wanted to use photos and the places they visited to share a trip that they took. People telling stories about overcoming a monster shared how they used personal tracking to help overcome a personal struggle, such as health problems. These participants wanted to share their method for tracking to help others overcome the same challenge. Finally, people told stories of accomplishment to describe a journey to achieve a goal, using relevant data to share their progress along the way.

I decided to design for authoring stories of accomplishment because designing to encourage social support toward goal achievement has been a recent challenge in research (e.g., [24,30,114,115]). The design needs for telling voyage and return stories have been comparatively well-studied through research on photo-sharing practices (e.g., [109,120]) and in commercial features like Google Photos vacation albums [112]. Participants felt stories about overcoming a monster were more personal, best told in-person to close connections rather than online.

I considered a variety of different specific accomplishments, opting to support telling stories of training for running races and completing home DIY projects. I selected these two as dissimilar examples involving different personal data. Race and DIY accomplishments each have been studied and designed for extensively in the literature (e.g., [38,113,132,133]). Both are areas where the literature has examined structured support for sharing (e.g., [38,133]), making them good examples where technology may be desired or useful. Although I limit my examination to two domains, I intended to develop principles for how technology can guide people to tell stories of accomplishment through a variety of tracked data.

With plot and two domains selected, I sought to better understand how people want to tell those specific types of stories. In Fall 2017, I interviewed 7 people recruited through community Facebook groups. None were students or in technology-related professions. 3 participants were interested in telling running stories (2 F, 1 M) and 4 participants were interested in telling DIY stories (3 F, 1 M), ages 27-35. These participants had all either recently completed or were in the middle of the accomplishment. One race participant was training for her third half marathon, while the other two were training for their first full marathon. DIY projects included a table, a dollhouse, a bookshelf, and a living room renovation. I followed a similar protocol to the previous interviews, framing the interview around their accomplishments and asking participants to design for that story. I coded and analyzed all interviews in a similar manner to the previous interviews. I quote participants with I1-7, with a superscript for type of story (e.g., I1^{run}, I2^{diy}).

6.3 DESIGN PRINCIPLES FOR AUTHORING

I describe three design principles from interviews and prior work: align shared content with sharing motivations, highlight important moments, and include situationally relevant data.

6.3.1 *Align Content with the Reasons People Want to Share*

Prior work suggests designs can automatically add context cues derived from other sensing modalities (e.g., location, mood) [101] or from comparing against previously-tracked data (e.g., a personal best) [50]. Designs can also highlight how personal data contributes to a person's overall goal (e.g., progress toward weight loss or a weekly step goal) [114,115]. Simply including the ability to comment or explain numeric data can help people give context [28]. Designs can further prompt people to explain why they are sharing or what feedback they seek [50]. Personal data can also be presented in a more interesting and visually appealing way, such in as a graph or animation [101] or by supplementing numerical data with photos or videos [50].

6.3.2 *Support Sharing Throughout a Story's Process, but do not Require it*

Consistent with prior results that people share for different reasons with different groups of people [146,158], some participants only wanted to share with close family, while others preferred sharing only once they accomplished their goal. I5^{diy} imagined keeping most moments private, then sharing her finished dollhouse on Facebook (I2^{diy} and I4^{diy} described the same with their projects). She said, "*I only shared the process photos with my husband and my mom. I feel like the process isn't probably that interesting to other people. Maybe it would be, but from what I've talked with people they like to see the final thing.*" Other participants wanted to share important moments along the way but felt that most people would not find the progress interesting.

6.3.3 *Build Stories as Chronological Chapters, Highlight Important Moments*

All but one participant wanted to present their story chronologically to others, reflecting how they experienced the story and similar to techniques used in prior storytelling designs (e.g., [87,139]). I5^{diy} felt her story "*would just inevitably be chronological… I would never deliberately try to organize it differently.*" Participants drew timelines, calendars, and infinite scrolling to represent this ordered view. Only I4^{diy} imagined another approach, grouping her home renovation by activity (e.g., painting, plastering) rather than the chronology of each room. Interviewees imagined they would add to their story whenever they made progress, much like chapters of a novel. Race training interviewees tended to run a couple times a week, while DIY interviewees tended to make progress in longer stretches of time over weekends.

Participants felt there were many chapters that they wanted to document, but which were minor contributions to the overall story of accomplishment. They expressed concern about sharing trivial accomplishments, similar to prior work [46,50,114]. For running stories, I1^{run} suggested "*some runs are more memorable than other ones*." He explained that setting can influence the importance: "*if you're doing a run that's in the dark in Christmas time when everyone is decorating the city and you go running. That's different than your Tuesday morning run where you force yourself out of bed*." I5^{diy} felt there was no need to highlight chapters which were similar to other chapters. She said, "*I wouldn't want to see repeated steps. I cut wood. I cut more wood. I cut more wood. I painted some and I painted some other things. I painted these. It would be different if it was like, 'I painted and then I put a sealant on it and then this other coat or something.'*"

Participants did not want minor chapters discarded, as they still contributed toward the accomplishment. Despite feeling that many of his runs were minor chapters, I1^{run} felt that "*the most important aspect to convey to people who are not runners is the level of commitment that this takes… Totals are cool to me, how many miles did you run for this marathon, how long did it take*." I1^{run} suggested a design could aggregate and present the total distance he ran to explain the effort to others, aligning with how other storytelling designs enabled people to track their cumulative progress [133].

6.3.4 *Include Situationally Relevant Data, Aligning with the Lived Experience of Tracking*

All three running story participants imagined including the distance or route with each chapter, adding other data types as appropriate or as available. I7^{run} wanted to take a picture of each run, with other data in a box overlaying the image: "*then, this box would be data. I would want to share the distance, and then optionally, duration, pace*." All four DIY participants included one or more pictures in each chapter. Table 10 describes data types participants mentioned.

Table 10. Participants had suggestions for data they wanted to include in each chapter. The (*) indicates data they would expect to always include, without indicates data optional or as-available.

Race Training Suggestions	DIY Suggestions
Distance, route (I1*, I6*, I7*)	Photos (I2*, I3*, I4*, I5*)
Text Description (I1, I6*, I7)	Text Description (I2*, I3*, I4*, I5*)
Photos (I1, I6, I7*)	Expenses (I2, I3)
Pace or time (I1, I6, I7)	Places visited (I2, I4)
Weather (I6, I7)	Emotion (I3, I5)
Emotion (I6, I7)	

Participants were mixed on whether it was necessary to include a text description. All DIY participants felt descriptions were necessary to "*explain what that picture demonstrates*" (I2^{diy}). I1^{run} and I7^{run} felt it would be too burdensome to include text for each chapter. I6^{run} thought text might help someone with whom she shares her story. She felt prompts could encourage her to write a short description.

Participants felt other data types would be situationally interesting or useful to include. Some information, like pace for running, was dependent on audience. I1^{run} felt non-runners "*might not understand… if a ten-minute mile [is] fast or slow*." I6^{run} agreed, instead opting to share how she felt with her non-running friends: "*one thing that the friends I don't tell my pace mileage to, some of them I will talk about more of the emotional side of training, because I think there's some good metaphors and some good lessons*." Participants felt other information could be added as appropriate. For example, I3^{diy} felt it might make sense to include expenses when sharing a chapter about a big purchase toward her home maintenance. I7^{run} felt weather could be appropriate if it affected the run she decided to do.

There are many ways progress toward accomplishments stories can go awry. Much like people track as part of their everyday lives [53,131], people face challenges and opposition in their daily lives which prevent progress. I6^{run} wanted to describe when something prevented her from running as planned (e.g., temporarily *lapsing* in her story due to skipping or suspending [53]): "*it'd be good to have something so you can explain any setbacks, too, because realistically, this is like the training plan, but sometimes you get sick this week and you don't run… injuries would be good to have on there, illnesses. Life stuff, like if you get busy at work and you're working 80 hours that week or something like that.*" Participants described emphasizing text and/or photos in these chapters to describe their setbacks.

6.4 THE DESIGN OF YARN

I designed Yarn for people without storytelling or design expertise, aiming to make authoring of a story that audiences would find interesting. I aimed to make the authoring process as easy and quick as possible to avoid putting excess burden on the person creating a story. I focus on a mobile platform (iOS) to reduce the number of steps between collecting data (e.g., taking photos, logging a run) and writing the story. Yarn automatically gathers as much relevant content as possible (e.g., running route, weather), and automatically composes aesthetic presentations of chapter data using visual templates. Finally, Yarn automatically sizes chapters based on inferring their importance.

The home screen of Yarn lists all the accomplishment stories on which the author is working. Clicking on a story brings up a chronologically sorted feed of the chapters in the story. To add a chapter, the author chooses what data to log and then selects a visual template.

6.4.1 *Support Choosing Appropriate Data to Collect and Share*

I categorized the data type recommendations given by the formative interviewees according to how the data is typically presented (e.g., as an image, as a number, as text) and the importance of that data to the story. These categories are shown in Table 10. I included five categories of data an author can log in Yarn:

- **Visual data**: a visual indication of progress toward the accomplishment. As discussed in the previous chapter, people often find visual data such as photos more interesting than text and numbers in isolation. In DIY projects, photos and videos comprised the visual data. Race training stories also included route maps as visual data.
- **Numeric data**: any numeric measurements of progress toward the accomplishment. I selected *primary* and *secondary* fields based on how formative interviewees imagined tracking their progress. I selected time worked and expenses as primary and secondary numeric fields for DIY projects, and I selected distance and time for race training. I considered supporting a percentage of progress, such how far along a DIY project is or percentage of planned miles in a race training routine. I opted for time because it is easier

to monitor and is not subject to changes in plans (e.g., a project being less far along than anticipated, more or less training required).

- **Description data**: a text title and description of the chapter. Yarn provides a few suggestions for what might be interesting to write about in these fields.
- **Minor data**: data which may be contextually interesting in a chapter, but is only loosely associated with an overall measurement of progress. Drawing from the formative interviews, I included weather information in race training stories and emotion in DIY stories as minor data. These data may help explain a moment, such as why a run was hard or what is important to learn from a DIY picture. However, these data are unlikely to have a strong influence on how the story progresses.
- **Date**: when the chapter being logged occurred. I include this field to allow people to add chapters after the moment, rather than assuming that all chapters are written the same day they occurred.

Figure 34 shows the interface for entering these data fields into Yarn.

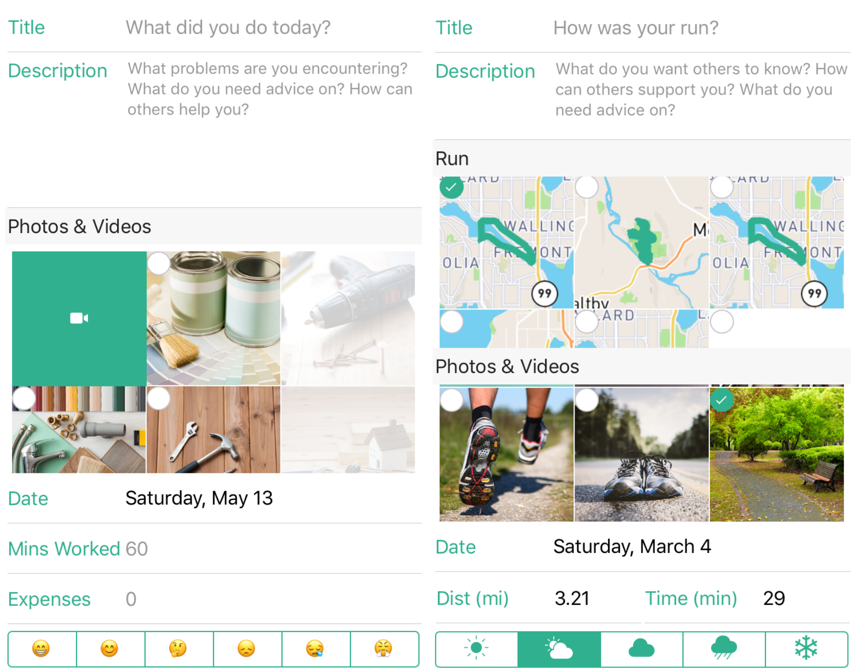


Figure 34. Yarn supports logging five categories of data. To ease the entry process, Yarn automatically infers fields like date and distance based on selected photos or runs and offers writing prompts for description fields. Content shown is illustrative.

I made all data fields optional in Yarn. As suggested in prior work, I connect Yarn with other apps where people already collect data to ease the process of creating chapters [37]. Photos and videos are loaded from the iPhone camera roll. Runs are imported via the Strava API (https://strava.github.io/api/) for race training stories, with weather via the Dark Sky API (https://darksky.net/dev/). Runs are plotted on a map via Mapbox (https://mapbox.com/api-documentation/). To avoid redundancy in the story, authors cannot create two chapters with the same run or photo. Yarn automatically fills out as much data as possible. Race stories use the Strava and Dark Sky metadata to autocomplete runs, date, distance, time, and weather. In DIY projects, the date field is set from photo or video metadata.

Formative interviewees wanted to share single moments and their full story. With Yarn, the author can share their entire story via a URL, which shows the story via a timeline view similar to the author's view. The story links to a page on a publicly accessible server. The author can mark a moment as private if they do not want it to appear in this feed. Drawing on design recommendations I outlined in the previous chapter, Yarn does not automatically share content. Instead, the author can share a single chapter by clicking the icon of a sharing platform (e.g., Twitter, SMS). Yarn then opens a dialog in the platform, including the templated visual data, description data, and a link to the full story. The author can edit the text as they wish for the platform.

Formative interview participant had varied preferences for platforms where they might be interested in sharing their stories. I included the four platforms mentioned most by participants: Facebook, Twitter, Instagram, and SMS. Interview participants were also interested in sharing chapters with Snapchat, but no official API currently exists.

To summarize, including these data types in Yarn follows the design principle of including situationally relevant data. Keeping all fields optional allows people to pick the specific data types relevant to the chapter they created. Keeping fields optional also enables chapters to align with the lived experience of tracking. I wanted to ensure people could use Yarn to log moments related to their story that did not contribute numeric progress toward their accomplishment. For example, a person can create a chapter in Yarn about how an injury prevented them from going on a scheduled training run. Logging this event would be difficult in current commercial tools, requiring creative use of tracking features (e.g., logging a custom exercise or a 0-mile run). Supporting multiple sharing channels and not requiring moments to be shared aligns with my principle that designs should support sharing throughout an accomplishment's progress.

6.4.2 *Visual Templates and Description Suggestions*

Inspired by how running apps annotate photos and routes with information about distance and pace, I explored different methods for annotating Yarn's visual data with numeric data. Each annotation, or *visual template*, connects the logged data to a goal people have for sharing. Visual templates also surface how the full story is progressing by presenting the total numeric data (bottom-right of each template, e.g., "*Total hours worked: 5.0*") and how many chapters have been crated (top-right, e.g., "*Springfield half marathon: chapter 6*").

I created seven templates inspired by prior work on people's sharing motivations. They emphasize:

- **A question** for when the goal is *information or advice*.
- **A hard time** making progress, for moments where *emotional support* might be desired.
- **I'm back!** Describes how the accomplishment intersects with people's everyday lives by pointing out the time since the last chapter. This template is also designed for moments when the author might desire *emotional support*.
- **Today's effort**, designed to align with a desire to *share an achievement* by highlighting the progress which was made.
- **My journey**, summarizing all of the chapters so far to support a desire to *share an achievement* of how much progress has been made. The template is divided into squares of visual data from each chapter. Stock images relating to the accomplishment make up the remaining squares.
- **A long run** relative to the other runs logged, designed to align with a desire to *share an achievement*. I included this template for race training stories only. In the formative interviews, participants wanted a design to reflect when they ran a personal best

distance or time. I felt the DIY parallel (e.g., a personal minimum or maximum time spent) was not a good measure of progress for most people.

- **Nothing special** when someone did not have anything they specifically wished to highlight. This template was not designed to align with a particular goal. It was instead designed to allow people to create chapters they wanted to record but felt were minor contributions to the overall story of accomplishment.

Figure 35 shows the seven templates.

(a) A question (b) A hard time (c) I'm back! (d) Today's effort (e) My journey (f) A long run (g) Nothing special

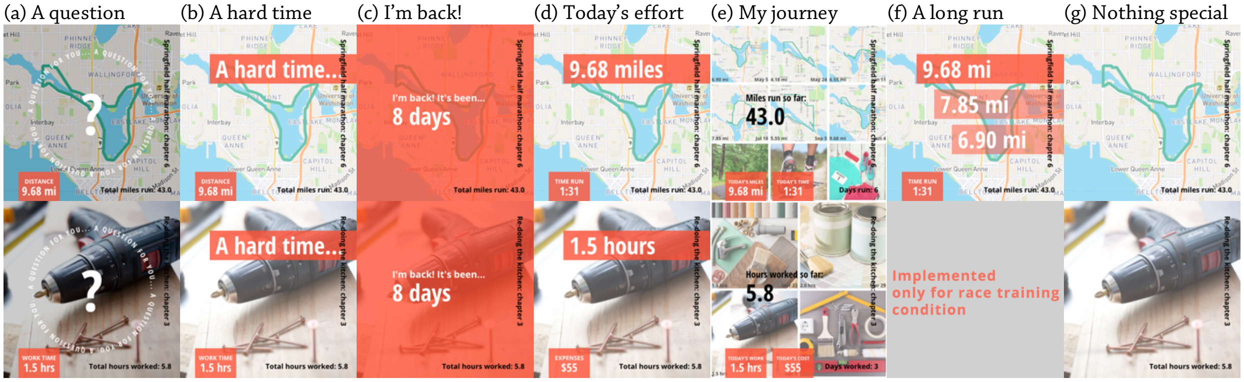


Figure 35. Yarn's templates were designed to support motivations for sharing personal data surfaced in prior work. Template (a) targeted requests for *information or advice*. Templates (b) and (c) aimed to solicit *emotional support*. Templates (d), (e), and (f) were designed to support *sharing an achievement*. (g) supported minor, typically-unshared moments. Content shown is illustrative.

I designed Yarn to support or promote certain templates based on the data entered in a chapter. For example, the **long run** template was only visible when the distance logged was one of the three longest runs. **My journey** was only included as a template option after two chapters had been created. In other cases, Yarn promoted certain templates by defaulting to them. For example, Yarn defaulted to the **I'm back!** template if it had been more than three days since the previous chapter was logged. **A question**, **a hard time**, and **nothing special** were always template options, as was **today's effort** when numeric data was included in the chapter.

Hint text for chapter descriptions contained a few suggestions for what to write, visible in Figure 34. These hints were designed to prompt the author to consider what they might want to share about that moment. For example, I included suggestions on asking for *information or advice* (e.g., "What do you need advice on?"), *emotional support* (e.g., "How can others support you?"), and *achievements* (e.g., "What are you proud of today?"). Yarn randomly picks three suggestions, out of thirteen I wrote to highlight different sharing motivations.

The visual templates were designed to follow my design principle of aligning content with the reasons why people want to share. Most of the templates emphasize a sharing goal, providing a suggestion to audience members about how to engage with the chapter. The prompts I wrote for chapter descriptions also follow this principle, encouraging people to consider and write about the moment's importance.

6.4.3 *Sizing Moments According to Importance*

The chronological feed of chapters is the author's primary view of their story and is also the view others see in the public link. Figure 36 shows the chronological feed in Yarn.

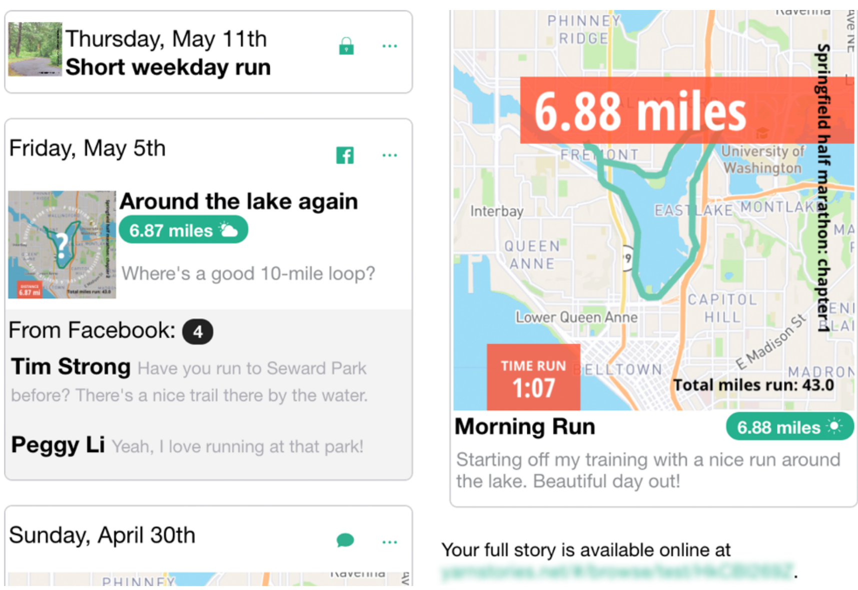


Figure 36. Yarn sizes chapters in a feed based on the numeric and visual data, template selected, and description length. Content shown is illustrative.

When sharing their story, interviewees wanted all chapters to be visible to demonstrate the effort they put into that accomplishment. However, they wanted emphasis placed on the important moments. Yarn uses heuristics to infer how important a chapter might be, sizing chapters as small, medium, or large in Yarn's feed based on those heuristics. Authors could re-size chapters as desired. I considered adding support for updating a chapter's importance based on whether the author shared it online or by comparing the numerical data to chapters added later. However, I decided people might find it unusual if chapters were resized when they revisited the apps days or weeks later. The heuristics therefore rely only on the data logged in the chapter and the chapters which were entered before it.

In decreasing order of weight given, Yarn uses the following to evaluate the importance of a chapter:

- The amount of primary numeric data relative to other chapters (e.g., the number of hours worked or miles run).
- The amount of visual data relative to other chapters (e.g., the number of photos or videos added).
- Whether the template has been selected before, with no weight given for the **nothing special** template.
- The word count of the description data relative to other chapters.

I intended this feature to reflect how the formative interview participants described what makes a chapter important to them. In the field studies, I made a cursory assessment of how participants felt about the sizing of the chapters. I leave it to future work to design and rigorously evaluate an algorithm for weighting chapters, or perhaps other content shared to social media, according to perceptions of importance.

Sizing moments according to importance aligned with my design principle of highlighting important moments. The large size of important moments made them stand out when an audience member scrolled through a person's complete feed of activities.

6.4.4 *Visualize Story Progress and Social Feedback*

In addition to supporting sharing, interview participants hoped a storytelling system would help them understand and document their accomplishment. I therefore supplemented Yarn's main feed with a graph for story authors to track their progress placing the date on the X-axis and the cumulative primary numeric data on the Y-axis (e.g., hours worked, miles ran). This graph enables story authors to monitor how their story is progressing.

Yarn also helps people document when and how they told their story by recording when the author shares via SMS, Twitter, Facebook, or Instagram. I designed this to serve as a memory aid for social discussion. Toward this end, the timeline in Yarn also presents reactions and comments that a Facebook post receives, shown in Figure 36. I included this to explore the concept of presenting social response in a storytelling feed. Future work could explore the appropriateness and usefulness of presenting social data from different channels. For example, I expect SMS responses would help storytellers remember what advice others had, but many people would feel their privacy was invaded if these messages appeared in a public story feed.

The ability to visualize story progress followed the principles of presenting stories chronologically and highlighting important moments. Both the person tracking and their audience could refer to the graph to get an overview of when a person made progress toward their accomplishment ant what moments were particularly noteworthy. Surfacing social feedback into the feed of Yarn did not aid the authoring process, but allowed people collecting data to see their questions answered in the flow of their story.

6.5 Evaluating Yarn Through Two Field Studies

To understand whether the authoring process in Yarn was effective, I sought to have people use Yarn to tell their own DIY and race training accomplishment stories. To answer **RQ5**, which asked how a design can support people in authoring interesting content with tracked data, I specifically sought to understand whether Yarn's authoring process helps people create content which follows principles of what others find interesting and to understand perceptions to the content by a potential audience.

I therefore conducted two field deployments of Yarn for four weeks. The first deployment emphasized whether the authoring process in Yarn resulted in interesting content. The second deployment examined social engagement and responses around authored content with Yarn. In response to participant feedback, I iterated on the design of Yarn between the two studies. To be eligible for either study, participants needed to be actively training for a running race or working on a DIY project. There was no overlap between participants in the formative interviews or either of the field studies.

6.5.1 *Field Study 1. Content Created Through Yarn's Authoring Process*

In summer 2017, I recruited a convenience sample of 10 participants via mailing lists and fliers in a mid-sized technology company. Four participants were working on DIY projects, six were training for running races. One participant (F8^{diy}) was working on a DIY project but began using Yarn to record her runs as well (though she was not training for a race). F1^{diy} was working on multiple home remodeling projects simultaneously and created different stories for each. An eleventh participant (male, DIY project) dropped out of the study prior to creating any chapters. I do not report further on this participant.

Participants had varied levels of experience with the accomplishment they were pursuing and in telling stories about them. F4^{diy} maintained a blog for decades dedicated to DIY projects he had undertaken, while F1^{diy}, F2^{diy}, and F8^{diy} had only done one or two prior DIY projects. All race training participants had run races before, though F5^{run} began using Strava specifically for the study. F6^{run}, F9^{run}, and F10^{run} ran races at least every couple of months. The other participants were running their first race in a year or more. Seven participants identified as female, three as male. Age ranged between 22 and 43 (average 32). Table 11 contains additional demographics.

Table 11. In the field study of the authoring process, 10 participants used Yarn for 4 weeks, authoring 1-3 chapters per week.

ID	Planned Accomplishment(s)	How Far Through Accomplishment(s)	Stories/Chapters Written
F1^{diy} (F, 27)	Remodeling bathroom, laundry room, kitchen	Near end, Beginning	4/11
F2^{diy} (F, 30)	Making a quilt	Midway	1/7
F3^{run} (F, 28)	Half-marathon	Beginning	1/5
F4^{diy} (M, 43)	Upgrading mill, building kinetic sculpture	Midway	2/4
F5^{run} (F, 40)	10K	Beginning	1/10
F6^{run} (M, 22)	5K	Midway	1/6
F7^{run} (F, 24)	10K	Beginning	1/5
F8^{diy} (F, 35)	Designing and building an inspiration wall	Beginning	2/4
F9^{run} (M, 37)	Half-marathon	Midway	2/5
F10^{run} (F, 30)	Half-marathon	Midway	1/7

I anticipated that Yarn would better serve the goals of early adopters of personal tracking technology, as they are already accustomed to collecting personal data and may be interested in sharing it. Choe et al. found Quantified Selfers often work in the technology sector [23], making the convenience sample of a mid-size technology company an appropriate choice for gathering opinions on the design of Yarn.

I scheduled an introductory meeting with participants where I helped them install Yarn, described the remainder of the study, and conducted a short interview about the accomplishment they were pursuing. Participants completed a short survey each week on any bugs they encountered and what they liked and disliked about the app. A longer survey at the end of the study asked participants how they felt about components in the design of Yarn. I also interviewed each participant about their answers to their final survey. Participants were given a $70 gift card to Amazon for their time. Participants could use Yarn after the study to continue telling their story, but I did not compensate them for doing so. F1^{diy} and F3^{run} each wrote one additional chapter after the study (12 and 6 total), and F10^{run} continued using Yarn for another six weeks, logging another 9 chapters (16 total).

I told participants Yarn was designed to help tell DIY and race training stories. I did not offer recommendations for when to add chapters, encouraging them to explore the app and use it to write and tell their story as they saw fit.

Because the experience with Yarn was designed to be similar for DIY and race training participants, I analyzed interview and survey data together rather than contrasting the two participant groups. I quote participants with F1-10, again with a superscript for story type (e.g., F1^{diy}, F3^{run}).

6.5.1.1 Yarn Motivated People to be More Descriptive, Collect More Varied Data

To evaluate the quality of content participants created in Yarn, I use principles on what others want to see from shared personal data outlined in Chapter 5. To reiterate, my prior work specifically suggested that shared content explain the importance of the moment, include visual content beyond numbers (e.g., pictures or graphs over time) and vary between moments.

Yarn's description prompts motivated people to add more detail and explain a moment's importance. F7^{run} felt the prompts encouraged her to think more about how her run went: "*some days, [the prompts] did help me reflect on my run, which was nice*." F2^{diy} agreed, adding "*the prompts were good… having those fields where you could put what you were working on and what things you were actually encountering… it just focused me and allowed me to write a lot*." Other participants ignored the prompts altogether, writing "*based on my feeling*" (F9^{run}). But even those who ignored the prompts still felt they encouraged authoring interesting content. F1^{diy} felt "*I thought [the* *prompts] were actually good ideas for what I might write. I didn't always follow them, but I did usually read them.*"

The emphasis on visual data in the authoring process encouraged participants to consider how they might make their chapters more varied and more interesting. F10^{run} mentioned that Yarn "*kind of motivated me to do different trails, since I'm taking photos and stuff it made me want to venture out to different areas.*" This motivation to create interesting visual content by trying new routes continued in her training after the study. F2^{diy} similarly tried to highlight how her quilt evolved over the weeks, but she struggled because "*once you get to a certain point it doesn't really change.*" She therefore appreciated how the numeric data demonstrated that she had made progress.

Participants appreciated how Yarn inferred importance from the data they entered. F5^{run} liked how the sizing emphasized her longer runs, "*there's so many standard runs you've got to knock out three times a week, and then once a week you have a more challenging, long run… so it is nice to highlight that.*" F2^{diy} thought the moment sizes aligned with her perceptions, but she wished her first chapter was emphasized more: "*it seemed like the entries where I actually spent time on the work, they were the ones which were larger, except for the first entry… this is kind of the intro, so it shouldn't be smaller than others*" (F1^{diy} agreed). Though DIY participants thought time worked was a reasonable measure of importance, they also had other measures in mind (e.g., how they felt, how far along they were).

6.5.1.2 Templates Should Reflect Personal Goals and be More Visually Distinct

On average, participants selected 3 templates during the study (min 1, max 5). Participants overwhelmingly picked the "today's effort" and "nothing special" templates (39% and 32% of templates selected). Some participants, like F7^{run}, felt these two templates depicted everything they wanted to collect and share: "*I pretty much only stuck to the standard [today's effort] template, it just had everything I needed… [adding chapters] wasn't really a creative exercise for me.*" For other participants, the choice was motivated by aesthetics. F4^{diy} said, "*the templates are killing me. I really want one that doesn't touch my image content at all.*" F1^{diy} agreed, "*often when I need to ask a question, there is also an image that communicates [my question] … I wouldn't want to put so much text on top of the image because I want people to study the image to tell me an answer.*"

Participants wanted chapters to be visually distinct and reflect their personal goals. They therefore suggested the visuals and text in templates be more customizable, both in each chapter and thematically across a story. F9^{run} felt templates should be visually distinct: "*they all look very similar… there were 4-5 templates with kind of the same color. It would have been good to have more choice with more diversity*" (F6^{run} and F7^{run} agreed). F1^{diy}, F5^{run}, F7^{run}, and F10^{run} all described Snapchat-like features that would make their story feel more personal, including overlaying emoji or their own text. F10^{run} felt the template choices constrained her ability to be creative: "*if I follow the template exactly then it's not my words… versus how I actually felt that day*." She went on to say, "*I think if someone was a heavy user of the app, then it could get boring after a while if they were limited to just a handful of templates*."

Participants wished templates were more specific to their accomplishment, question, or struggle. For example, when F1^{diy} wanted to celebrate the achievement of her new bathtub arriving, she wished the template had reflected that excitement. She describes how she would have liked the moment presented: "*I tend to be more on the minimalist side, so I might just have the text displayed more beautifully to say 'my bathtub arrived!'. I have some friends who are really into emojis and might cover half the picture with emojis and smiley faces*." Race training participants also imagined a template could highlight more specific accomplishments, such as "*if it was a PR [personal record]*" (F5^{run}) or what kind of run it was "*if I were trying to do a distance run, say 'distance run', or like a 'short run', or some of them are like, 'hill training*'" (F3^{run}). F6^{run} felt "*if a run was hard, I might want [the template] to say something more specific about it*."

Overall, participants were split on whether visual templates should reflect the sharing motivation or whether this should be left to description text. F2^{diy} suggested that a design could prompt people to select a template prior to writing the description. She said, "*selecting at the end kind of made me rethink what I had written earlier. I thought it would be better beforehand so I could kind of frame what I was writing with the template in mind*."

This tension between a design fostering structure and facilitating self-expression parallels research into curation of personal digital information [69] and smart journaling [44]. Participants surfaced concerns about their authored content being in Yarn's voice rather than their own, removing their agency from their story.

6.5.1.3 Participants Desired Communities with Similar Goals

Participants felt they would have liked to have a community with other people using Yarn to tell similar stories, echoing a suggestion from prior work [50,118]. All four DIY participants expressed this sentiment, suggesting features such as making visible what other DIY projects participants were working on. F8^{diy} felt "*I would have liked it to feel more like an Instagram style of app where I can see other people's projects and get also inspired and motivated by them and their projects.*" She contrasted this perspective with her experience using Yarn to track her runs: "*for the running… I didn't find it as useful. The already existing apps like Strava had the features that I was looking for.*" Race training participants agreed, such as F7^{run} who was "*fine sharing it in the Strava app*" and was not interested in sharing through a Yarn community. That said, F3^{run}, F6^{run}, and F9^{run} felt Strava could benefit from including Yarn-like features, such as the ability to signify that a run is part of training for a race. F6^{run} wished that "*in Strava you could create a goal or a story… so you could keep track of these milestones or keep track of these chapters… once you've completed your goal you can look back at what you've done and it would be easy to visualize.*" F9^{run} felt "*even if [other people] are training for different races, you can discover a race you didn't know before. Even if the race is different you may train for the same distance, you could compare their training or you could see in which places they train.*"

6.5.2 *Design Iteration in Response to Feedback*

Informed by the first study, I modified Yarn prior to the second field study focusing on audience reactions. Participant feedback during the first field study suggested that the initial design largely succeeded, but that participants wanted more customizable templates and more emphasis on reaching an interested audience. As a result, I revised Yarn to support more flexible templates and added a dedicated audience. I aimed to maintain aspects of Yarn that participants appreciated. I also fixed bugs participants encountered and made a few minor adjustments to how Yarn emphasized content (e.g., always sizing the first moment in a story as important).

I modified Yarn to include two basic mechanisms for customizing templates. Rather than all templates using an identical color scheme, I developed a set of five schemes which complimented one another. I also added variations in each template's overlay. I added two additional phrasings in the **question**, **hard time**, and **I'm back!** templates, which all use text to direct the audience to the detailed caption. In templates where data is emphasized, (e.g., **today's effort**, **my journey**, **a long run**), I added options for the template to highlight secondary data fields and minor data fields (e.g., **today's effort** can be used to prominently display expenses and emotion in DIY projects, duration or weather in training for a race). To enable people to tailor a template to their specific experiences, I added the ability for people to write a custom phrase for all templates via an "edit" button. Figure 37 illustrates how templates could be customized in the updated design.

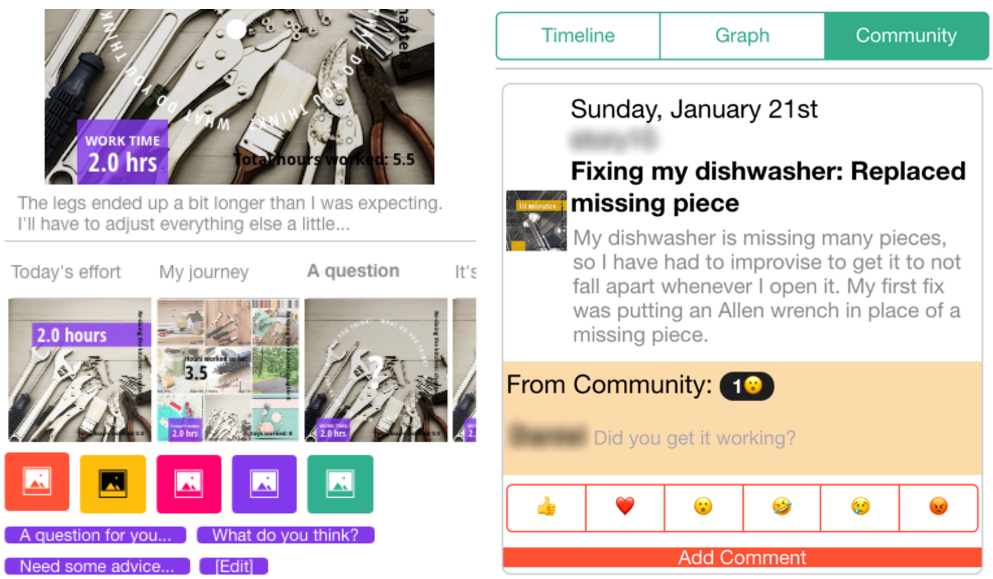


Figure 37. I iterated on the design of Yarn to offer more customizable templates and access to a community of people working toward a similar accomplishment. Content shown is illustrative.

Responding to the participant desire to see each other's progress, I added a community feature within Yarn. The community feature, also shown in Figure 37, displays the most recent chapters created by other study participants and offers commenting and reaction mechanisms similar to other social networking sites. Community reactions and comments are replicated in the main timeline view in Yarn, similar to how Yarn replicates reactions and comments from Facebook into Yarn's main feed. In addition to the feed of recent chapters from the community, people can look at the complete stories of other community members via a separate page. To protect anonymity, all participants select a pseudonym to be used in the chapters and any comments they write. Community engagement is only visible to members who use Yarn. Reactions and comments from the Yarn community are not shared when chapters are posted on social media nor are they visible on the story's public link.

The design of the community feature in Yarn was heavily inspired by the social feature in Food4Thought, an app I helped design. Food4Thought aimed to promote mindfulness about food choices through a photo-based food journal with daily challenges, leveraging prior work showing how challenges can help promote healthy eating [33,34,125]. We incorporated a social feature into Food4Thought to sustain engagement and therefore further promote mindfulness. Food4Thought included a private Facebook group where everyone shared photos of food which completed a daily challenge. Figure 38 shows an example post to Facebook from Food4Thought.

Figure 38. The design of the community feature in Yarn was motivated by the community feature I designed in Food4Thought, a challenge-driven photo-based food journaling app. In evaluating Food4Thought, we found that a private Facebook group where everyone had the same goal encouraged engagement and promoted food mindfulness.

Our evaluation of the design of Food4Thought was published at CHI 2016 [49]. Participants saw the daily challenge and what others were eating to complete the challenge in their regular Facebook feeds. This reminded them to think about their food choices as they checked their feed for other reasons. Having a group of people with a similar challenge created a peer community. Participants felt the group encouraged them to stay engaged and provided a bit of social pressure. I hoped the community in Yarn would foster similar motivation to stay engaged and would make participants feel accountable to one another to make progress toward their accomplishment.

6.5.3 *Field Study 2: Social Interest and Response to Authored Content*

In winter 2018, I recruited 11 participants through local running and making community groups as well as email lists. Five participants were working on DIY projects, six were training for running races. A twelfth participant (female, race training) dropped out of the study after creating one chapter. I do not report further on this participant.

Eight participants identified as female, three as male. Age ranged between 28 and 64 (average 39). Two participants, F16^{diy} and F19^{diy}, knew one another prior to enrolling in the study. All participants were from the same metropolitan area. Participant occupations ranged from artists to homemakers to analysts to retired. Table 12 contains additional demographics.

Table 12. In the field study of social engagement, 11 participants used Yarn for 4 weeks. The (*) indicates social connections that the participants stated they shared their story with, but who did not respond to our survey.

ID	Planned Accomplishment(s)	How Far Through Accomplishment(s)	Social connection(s)	Stories/Chapters Written
F11^{run} (F, 37)	Full-marathon	Beginning	Sister (F, 39), Husband (M, 37)	1/6
F12^{run} (F, 37)	Half-marathon, 5k with son	Midway	Mother (F, 67), Spouse*, Training partner*	2/28
F13^{run} (M, 43)	Half-ironman	Midway	Wife*, Training partner*	4/13 (split by week)
F14^{diy} (F, 31)	Home remodel	Beginning/Midway	None	4/5
F15^{run} (F, 30)	Half-marathon	Beginning	None	1/9
F16^{diy} (F, 28)	Sewing/scrapbooking projects, bullet journals	End/Beginning	Husband (M, 31), Father (M, 57)	4/21
F17^{run} (M, 31)	Half-marathon, Skiing	Midway	Training partner*	2/13
F18^{run} (F, 45)	10K	Beginning	Training partner (F, 51)	1/9
F19^{diy} (F, 32)	Winter cowl, bullet journals	Midway	Husband (M, 35), Friend*	6/8
F20^{diy} (M, 64)	Jeopardy-style buzzer system	Beginning	Partner (F, 52)	1/5
F21^{diy} (F, 51)	Cabinet for litter box	Beginning	Housemate*, Friend*	2/4

The second field study followed a similar protocol to the first study. Participants used Yarn for four weeks and were invited to use Yarn for longer if they wished. We helped participants install Yarn in a short introductory meeting. We sent participants short weekly surveys and conducted an interview at the end of the study to understand their experiences with the app. Participants were given a $70 gift card to Amazon.

In order to understand how people respond to authored content, I wanted to ensure participants had the experience of sharing their content with Yarn. During recruitment, I therefore asked participants to identify a few friends or family members with whom they were interested in sharing their story. After the participant completed the final interview, we sent each social connection a short survey about their experience engaging with the content their participant generated in Yarn. Each participant was given a $10 gift card to Amazon for their time. Though all participants identified friends or family members they wanted to share with, two participants (F14^{diy} and F15^{run}) did not share their story with their social connection(s). They both felt that content created in Yarn had too much overlap with content they shared with their social connections via other platforms (e.g., running data on Strava for F15^{run}, progress photos on Instagram for F14^{diy}). In total, we contacted sixteen social connections (min 0, max 3 per participant), of which eight completed the survey. Table 12 contains demographic and relationship information about the social connections.

I quote participants as F11-21, again with a superscript for story type (e.g., F11^{run}, F14^{diy}). I quote social connections with S##a-c, including the corresponding participant number and using letters to differentiate between multiple social connections for a single participant (e.g., S16a^{diy}, S11b^{run}).

Participants made use of the template customization features I added in Yarn's design iteration. Seven participants created at least one chapter with a template color other than the default (max all 4 non-default colors, average 2.27 colors used per participant). Eight participants created at least one chapter with an alternate phrasing or custom phrase (max 3 chapters with an alternate or custom phrase, average 1.08 alternates per participant). All participants except for one (F17^{run}) created at least one chapter which used the added customization features. Participant's use of the customization features provides evidence that the design iteration improved participants' ability to tell their story how they wanted to. I will later discuss suggestions from participants on how chapters could be made even more distinct from one another.

Most participants shared their chapters with their social connections in-person, tending to do so not long after creating the chapter. Two participants (F16^{diy} and F20^{diy}) shared nearly all of their chapters to one of their social connections via SMS. Six other participants used the SMS feature at least once. Only one participant in the second study used Yarn to share a chapter to social media (F18run shared to Instagram once during the study).

I believe the lack of social media use was caused in part by the identification of specific friends and family members to share with and the inclusion of the community feature. Both outlets offered participants opportunities for feedback and support without reaching out to a broader social network, where people often worry their accomplishment is too trivial [114]. Participants across both field studies suggested that they would be more interested in sharing their story to social media once it neared completion. F8diy felt her project was "*not done, so it's not something to be proud of yet.*" F1diy agreed, stating that "*I might share a before and after photo at the very end of a project, but I don't want to 'show off' by showing people how much work I did or bore people with all the stages*" (5 others expressed a similar sentiment). As a result of this limited sharing, this study describes how peers and small groups of supporters react to seeing Yarn-like content, not a broader social media audience. I return to this point in discussion.

6.5.3.1 Social Connections Appreciated Seeing Author Progress Toward their Accomplishments

I evaluate how audiences react to seeing Yarn's content by describing how people responded and felt about the content authored by their social connections. I draw understanding from how participants and their social connections described their interest level and interaction, as well as how participants felt about seeing and responding to each other's stories through the community feature.

The majority of engagement around Yarn-generated content was encouragement, both among social connections and in the community group. F11run described her engagement as, "*both my sister and husband thought it was interesting… their responses were supportive*" (6 others expressed similar sentiment). F15run found that other participants used the title, description, and templates to garner more encouragement, "*some people put funny titles or commented on what was hard for them, and that makes you want to encourage them more if they maybe show some personality or some progress or something in their little comments.*" By sharing as a story, Yarn also occasionally made the audience aware of otherwise invisible work the author had been doing. F13run described that his wife found out, "*what she didn't realize was that I do a lot of running around work, she never really sees or hears about those. So she found that to be interesting*" (F13run).

Although authors hesitated to share their progress to broader social networks, social connections particularly appreciated being able to see the chapters of the author's progress. S11a^{run} felt that "*I got more details than I normally would about the day-to-day training.*" In particular, S11a^{run} learned that F11^{run}'s training had not progressed smoothly: "*I hadn't realized her recent setback in training and it was interesting to see how she described it on Yarn, and then be able to talk to her about it.*" Social connections added that sharing chapters through Yarn gave organization to the story. S16a^{diy} appreciated that Yarn provided "*regular updates on particular benchmarks with beautiful and concise information. It bundled the information very well instead of hearing things in a haphazard way.*" F19^{diy}, who knew F16^{diy} prior to the study agreed, adding "*even things she hadn't sent me in a text message I saw on [Yarn], and I'm like, 'oh, you completed it.' So it was fun to see the progress she made.*"

Despite appreciating being able to follow progress, some social connections felt the stories in Yarn did not convey the author's motivation or the scale of the accomplishment. S16b^{diy} said, "*it was nice to see [F16^{diy}]'s progress, but I wasn't sure of the context – why was she pursuing a particular project, what the scope of it was, etc.*" F11^{run} felt Yarn could have used better mechanisms for demonstrating how individual training moments contributed to the overall accomplishment. She said, "*[my social connections] might've been more engaged if there were reasons to keep interacting, like watching for milestones or PRs on a progress bar or something.*" S11b^{run} agreed, stating "*progress or milestone markers would have been nice.*" People's stories often deviate from their plans, so it remains challenging to design to support presenting this progress. But participant feedback suggests progress indicators beyond cumulative distance ran or time worked should be examined, like critical milestones.

6.5.3.2 Yarn's Authored Content Helped Drive Social Connection's Interest and Engagement

Social connections felt that templates, visual data, and numeric data added to the content that story authors created. Three social connections mentioned they "*liked the variety of templates*" (S18^{run}), suggesting the variations "*kept things interesting*" (S12^{run}). Two social connections indicated that visual data was most compelling to see and engage around. S16a^{diy} felt his social connection's visuals "*were illustrative of the product she was working on and would show applicable aspects of it.*" S11b^{run} agreed, stating that the inclusion of photos in race training "*was a nice added* *feature that helped visualize the activity*" beyond the map of the route ran. S16b[diy] felt the numeric data "*added impact, meaning, and in case I would do it too, valuable information*."

DIY authors occasionally felt it was inspiring to see each other's visual and numeric data through the community feature. F19[diy] stated "*I feel like not posting a picture, it's like a complete cop-out… like I don't want to see a picture of a paint bucket [the default visual data in the DIY version of Yarn] 'cause that's not inspiring at all*" (1 other participant expressed a similar sentiment). Participants training for races often learned about other places they might run. For example, F18[run] said, "*I'm always looking for new routes. A lot of [other people's] are near or around [where I run] but not exactly the same. So I was like, 'oh, I could go this way.' Yeah, just a bit of change to make it different*" (2 other participants expressed a similar sentiment).

Social connections appreciated how Yarn helped them understand what story authors experienced. S11a[run] liked how the descriptions in Yarn helped her "*get into her head here, how she felt, victories and frustrations – this is important*." Social connections felt other data added to their awareness. S16b[diy] felt F16[diy] used the emotion data field to "*convey her enthusiasm along the way*." S12[run] described how weather data added to what F12[run] shared with her: "*[she] usually shared how she felt when her alarm was going off at 4:45a.m. and what the weather was doing. I loved the times she was running while it tried to snow*."

6.5.3.3 Community Feature Provided Accountability, but Accomplishments were Too Disparate

5 participants wrote at least one comment or sent a reaction in the community feature (responding to a max of 4 chapters). In total, 10 chapters written by 4 unique participants received reactions or comments. 3 participants both sent and received reactions or comments.

In addition to learning from what others were doing, participants felt the community added a sense of accountability to continue making progress toward their accomplishment. F15[run] felt that "*seeing other people running adds like a little motivation for me to keep up with running*." F16[diy] agreed, stating "*I got one or two hearts, and I think it's fun to know that someone is looking at your stuff and a nice boost to keep going*." Though this is similar to prior work involving shared challenges [49] and activity goals [28,152], I note that in our study participants pursued a wider range of accomplishments (e.g., different races, more varied DIY projects).

Because their accomplishments were dissimilar and participants did not know one another, many participants were reluctant to engage or had a hard time deciding how to respond. F12[run] felt, "*it was nice to see other stories out there, but I didn't really dig in too deep. I definitely went through... someone's training for [the] Chicago [marathon], that's cool. I hear that's a good marathon or whatever... it just feels weird to me to go on and be like, 'oh, someone I don't know is training for a race I'm not running, I should go see what they're doing.' Maybe I shouldn't care so much, we fall in the same boat [of runners].*" F20[diy] felt similarly, struggling to see how he might learn from, provide advice to, or be inspired by some of the other DIY projects. He said, "*some people were building a cat house, other people were knitting, other people were doing some quilt thing... I didn't really care about those much, but if someone had been doing a home security thing with cameras or electronics, I might have been like, 'oh, that's interesting and something I might want to do myself.'*" Three participants suggested that Yarn follow a traditional social network setup where people can follow one another. For example, F15[run] said, "*I would prefer if it was just that my friend could also have the app and we can see each other's' [runs] on there... in my mind, then the people are looking at what I'm posting because they're interested in seeing it rather than it be more motivated by me sharing it.*"

Overall, most participants wished they had received more response from the community. F14[diy] felt that having a social response would have been "*a little more encouraging to continue on with whatever story or whatever project I was working on and actually follow through with it to completion.*" But participants felt the varied accomplishments and not knowing the others were barriers to responding. F12[run] said, "*I don't want to be the weirdo that's like, 'here's your thumbs up'... but once that gets going and that's kind of the social norm of it, [then] it wouldn't be a big deal.*" F19[diy] felt the reaction options provided a barrier to further conversation. She said, "*the different emojis made it kind of like a hard stop. Like, oh, you do a face and the conversation is over. I think I'd actually prefer if those faces weren't there... that way would've made it more of a conversation, or the comments probably would've had more usage.*"

To overcome these barriers to participation, some participants recommended grouping strangers by more specifically similar accomplishments, such as the same race or DIY projects involving the same materials. F11[run] felt, "*if it was people that also did similar things, so they ran the same route or were training for a race at the same time... or if there were things that might have similar* *backgrounds, like, 'hey, I'm breaking in a new pair of shoes'... I think that would draw me in.*" 2 other DIY participants agreed, with F21^{diy} saying "*maybe if it was almost like a forum for particular crafts, so you knew your audience was just people who are doing the same sorts of things. Which I guess [Yarn] kind of is actually, but even within the app there's a lot of different things.*"

6.6 Discussion

I developed four principles for authoring stories with tracked data, following these principles in the design of Yarn. Aligning the content people create with the reasons why they want to share ensures that audience members can determine what response would be most beneficial or desirable. Optionally supporting sharing throughout the process of an accomplishment story enables the sharer to frequently reach people who want regular updates while avoiding overburdening others who only care to see the most important moments. Treating moments as variably import allows people to highlight what milestones are reached while ensuring the other moments still contribute to the story. Incorporating, but not requiring, a range of data provides people tools to select how they like to tell their story. Making data optional also accommodates for setbacks where data may be absent.

Participants felt the structured authoring experience helped them create interesting content about their accomplishment journeys, and social connections found the content surfaced what the sharer was experiencing in an engaging way. The use of templates and prompts helped participants describe their process with minimal expertise and effort. To better help people tell stories of accomplishment in the way they desire, templates in future designs should specifically describe a person's accomplishment or struggle and indicate when milestones have been reached.

Participant's use of Yarn demonstrates an approach for how designs can help facilitate documentary informatics [43,131]. Much like the style of content common in journals, Yarn encouraged a person to log how a they were feeling and the importance of the moments they were experiencing. By combining this consideration of emotional state with visual and numeric data about what a person experienced, Yarn facilitates people in revisiting their histories long-term. Yarn's guided authoring approach of combining emotion, description, and data helps the tool be useful for later personal reminiscence, even if a person tracking has no interest or desire to share their story with others. This parallels how people's memories logged on Facebook can facilitate "backstalking", both alone and with others [136].

The current design of Yarn operates as an aggregator of tracked data, translating data collected in another app (e.g., Strava for running) to a story. This structure has the benefit of supporting a range of data collected from other applications to tell stories through other domains, such as incorporating Duolingo data to tell the accomplishment story of learning a language. But as some participants suggested during the study, Yarn may not need to be a standalone app. Rather, structured authoring could be added to personal tracking apps (e.g., Strava, Mint) or to social networking platforms (e.g., Facebook, Instagram, Snapchat). Many of Yarn's mechanisms for measuring progress and reaching interested audiences exist already within these platforms. Participant reactions to Yarn demonstrate how providing continuity across moments can lead to more appreciation for seeing the efforts that contribute to the accomplishment. A design cannot expect that including data from the major moments in a story (e.g., photos from each step, all runs) is sufficient to receive the type of feedback and engagement people desire.

By re-framing sharing as storytelling, personal tracking apps can help people receive support and advice in the process of an accomplishment, in addition to celebrating its completion. Updates to social feeds within tracking apps, such as the latest runs of followers in Strava, could instead emphasize progress made toward accomplishments (if a person has designated a goal). Social networking sites can continue exploring ways to support connecting moments that contribute to a larger accomplishment. One example is the ability to continually add to an album on Facebook, updating the album's followers via their timeline. Drawing inspiration from the recent introduction of "story" features (e.g., in Snapchat, Instagram, and Facebook), future designs could group "stories" by the varied accomplishments an individual is pursuing and could persist stories according to the timeline of an accomplishment (i.e., in contrast to the ephemerality of current "stories" functionality).

To extend a structured authoring process to other stories of accomplishment, a designer would need to identify what constitutes progress toward that accomplishment, how to present that progress, and who would be interested in hearing about progress.

Selecting Measures of Progress: People have varied preferences for what is interesting or informative in personal data [48]. Participants similarly had varied preferences for how they wanted to measure progress toward accomplishments. F2^{diy} felt monitoring the hours she spent on her project helped keep track of her progress, while F1^{diy} and F8^{diy} preferred to think more holistically about their projects (e.g., “did I just start?”, “is there a lot left to do?”). Race training participants also preferred varied measures of progress, including distance (F3^{run}, F7^{run}, F10^{run}), pace (F6^{run}, F9^{run}), and whether they ran at all (F5^{run}). A more flexible self-tracking system (e.g., perhaps using techniques developed in [88]) could help people track a personally meaningful indicator of progress and present it with appropriate visual templates.

Presenting Progress: In designing Yarn, I sought to create a structured yet flexible authoring experience. The results from the first field study indicate I succeeded at creating a structured experience. However, participants wished the content they created better aligned with their specific motivations for tracking and sharing. As F5^{run} and F11^{run} suggested, templates could express different levels of accomplishment (e.g., a minor achievement, a major milestone). Templates could also incorporate measures of progress, like summing numerical data over a week or since the last time the content was shared with a particular audience member. Participants and social connections, particularly F11^{run} and S11b^{run}, expressed interest in sharing and viewing progress bars or other metrics which indicate how far along someone is, or how an individual moment has contributed to the larger accomplishment.

Audiences appreciated how visual data helped them relate to the moments being shared. They also valued how numeric, descriptive, and minor data helped contextualize what was important about a moment and what the author was feeling at that moment. Variation in the presented content helped keep interest across minor moments. When presenting progress, a design should keep moments distinct from one another, present them in visually compelling ways, and ensure content explains what someone did, why they did it, and how they feel. To keep moments distinct, designs could use sticker and filter metaphors in current “story” features as opportunities for incorporating data. For example, a Snapchat filter could incorporate someone’s running route, or a sticker could allow someone to label a snap of a table they built with how long they spent working on it.

Identifying an interested audience: In Chapter 5, I suggested that broad social networking sites like Facebook, Twitter, or Instagram might not be an appropriate place for sharing personal tracked data, and different sharing motivations lend themselves to different audiences [118]. My findings suggest that close ties and communities with similar accomplishments appreciated seeing intermediate progress, and most people feel comfortable sharing their milestones to these groups. Sub-dividing audiences by more specific goals (e.g., length of race, materials used in DIY project) or typical data collected (e.g., running similar distances on the same days of the week, similar schedules for working on projects) could foster additional interest and opportunity for offering advice. Participants whose accomplishments were still weeks or months away indicated that they might be interested in sharing to a broad social networking site when they completed their story, but felt their progress was not sufficient enough to warrant sharing immediately.

Given that social connections were interested in seeing intermediate progress, story authors may have misjudged how interested a broad social networking audience would be in seeing the steps toward their accomplishments. Alternatively, story authors may have successfully identified the few social connections they had who would be interested in offering support and advice on intermediate accomplishments. Future work on understanding how broader social networks respond to Yarn-like content would help designers determine whether to support or even emphasize sharing accomplishment progress to these networks, or instead emphasize keeping strong ties informed.

Participants described a mix of posting and lurking behavior in the community feature. The small size and shared accomplishment goal in the community were such that most participants were comfortable posting their progress. Though participants enjoyed seeing and learning about the accomplishments that each other were pursuing, they used the reaction and comment features sparingly. To help ensure that people receive support, future designs could explore how prompts could offer suggestions for what to include in a response. Alternatively, a design could demonstrate to the storyteller that others are interested in the progress by surfacing how many people in the audience viewed the chapter, even if they did not explicitly respond (e.g., applying techniques from social translucence [54]).

6.7 Conclusion

I contribute design principles for telling stories of accomplishment through personal data, specifically a structured authoring process to help people align the content they create with their motivations for sharing. The mobile app I built, Yarn, demonstrates these design principles by prompting people to explain their reason for sharing in a description and by offering visual templates that emphasize different sharing motivations.

Taken together, Chapter 5 and Chapter 6 indicate a need to prove how personal informatics systems help people find support through the data they capture. People struggle to convey the importance of the moments they track when they do share, and thus tend not to get the response they desire. Through evaluating Yarn, I demonstrate how prompts and templates can create content that friends and family members were interested in engaging with and discussing. Future designs should balance tensions between flexible content versus easy authoring, as well as the content needs of dedicated communities versus broader social networking platforms.

Chapter 7. DISCUSSION AND CONCLUSION

I have examined how people use personal informatics systems in their everyday lives and how the design of technology can be improved to support their uses and needs. Beginning with an examination of who is using tracking technology today, how they are using it, and why they are using it, I have developed a model and framework which expose challenges in designing everyday personal informatics systems. I have implemented and evaluated two novel designs which address some of the challenges people encounter in finding value in their data and support through their data. Through this body of work, I have sought to demonstrate the importance of accounting for the realities of everyday life when designing personal informatics technology. I also aimed to provide design strategies for supporting people toward their goals while acknowledging those realities.

I revisit my thesis statements in context of the work presented in my dissertation.

7.1 Helping People Find More Value in Their Data (T1)

The Lived Informatics Model I presented in Chapter 3 demonstrated opportunities for helping people find more value in their tracked data. The Visual Cuts technique I described in Chapter 4 capitalized on one such opportunity to better help people make sense of their data as they collect it. I now discuss a few of the key findings from these chapters.

7.1.1 *Aim to Satisfy People's Diverse Goals*

Across my formative work I saw that many people's motivations to track themselves and their routines are not squarely in documenting or improving. As discussed in Chapter 3, people are additionally looking to satisfy curiosities they have about themselves, monitor whether their habits are on a good trajectory, and receive social and financial benefit from recording what they do. My work suggests a need for designs of tracking tools to help people monitor their habits as well as record them. In Chapter 4, I demonstrated that interfaces which reflect answers to common questions people have, whether their own questions or questions from others, can help people better understand their habits and make changes. Through this work, I saw an opportunity to shift tracking tools from records of personal data and goal-achievement to examination of a person's habits and opportunities for improvement when appropriate. This may involve applying techniques from analytic workbenches to create tools for interactively exploring personal data. Or it may involve automatically surfacing trends through notifications or in activity feeds.

7.1.2 *Support People During, and After, the Tracking Process*

People's use of tracking tools often does not follow the scientific method of forming a question, collecting data, and evaluating the question with that data. In Chapter 3, I showed that people instead make sense of their routines, and even change their habits, as they collect data. The interfaces I developed in Chapter 4 suggest that to help people who do not have the expertise necessary to analyze their increasingly multi-faceted data, tracking interfaces can provide insight while people are collecting data and trying to make sense of their habits. I have also found that revisiting tracked data can help people reflect on successes after they have stopped tracking. For example, when people return to tracking after a break, tools can help people revisit their previous habits and reevaluate their goals.

7.2 Helping People Find More Support Through Their Data (T2)

The Lived Informatics Model I presented in Chapter 3 demonstrated opportunities for helping people find more value in their tracked data. The Visual Cuts technique I described in Chapter 4 capitalized on one such opportunity to better help people make sense of their data as they collect it. I now discuss a few of the key findings from these chapters.

7.2.1 *Explain the Importance of Tracked Moments*

I have demonstrated that sharing tracked data in isolation is often insufficient for a person's audience to understand why that data is meaningful or noteworthy and can come across as impersonal. In Chapter 5, I show that short contextual explanations, such as identifying a moment as a personal best, can be enough to explain a moment's importance. Incorporating other media, like personal photos taken during the tracking process, can also help contextualize importance. Through evaluating Yarn in Chapter 6, I have shown that audiences appreciate when individual tracked moments are connected to the larger story of what motivated a person to track. Though people often lack the expertise to create these connected stories on their own, an authoring interface can guide them to explain what is important in a tracked moment and to add other related media.

7.2.2 *Find an Appropriate Audience*

When sharing tracked data, the encouragement and advice from a few close connections who may be more understanding of a person's experience can be enough for many people to feel supported. Sharing to a social networking site like Facebook, Twitter, or Instagram enables reaching a broader set of people who may be able to offer more varied advice. In Chapter 5, I show that despite the potential, sharing tracked data on broader social networking sites tends to get limited interest and engagement. Chapter 6 discusses that close ties, or people with a similar tracking goal, are more likely to be interested in hearing about projects and stories which are still in-progress. To help people find more support, designs can help form peer communities within the broader ecosystem (e.g., people with similar running goals) and support sharing major accomplishments and milestones more broadly.

7.3 FUTURE WORK

I aim to continue examining how the design of personal informatics tools can be improved to acknowledge and account for the realities of everyday life and the variety of motivations people have for tracking. Some opportunities for future work include:

- **Migrating between goals**: After people's initial curiosities about their habits are satisfied, people often migrate toward self-improvement or monitoring goals. I am interested in exploring how an interface can draw on these initial curiosities to help people refine their questions into to measurable items to monitor or improve.
- **The resumption experience**: After a major life change, such as a move or a new job, people often resume tracking to see how that change has impacted their habits. There is an opportunity for the design of tracking tools to intelligently summarize key findings

from a person's previous tracking experience and enable comparing data before and after a life change.

- **Supporting monitoring practices**: Some people track for continued assurance that the status quo is fine, rather than with an improvement goal. Drawing from literature on ambient displays could offer some guidance. There is particularly ample opportunity to support monitoring in domains where analyzing detailed records could cause discomfort even when someone's overall state is healthy, such as in finances or weight management.
- **Opportunistically adding tracked data when sharing**: I believe there is an opportunity to consider how tracked data can supplement the content people are already interested in sharing with others on or off of social media, rather than treating the data as the primary content being shared. Using tracked data to explain the context or importance of a moment, rather than requiring a person to explain the context surrounding tracked data, could result in more support, advice, and accountability.
- **Indicating progress toward long-term accomplishments**: There is value in exploring how tracked data can be used to monitor and share progress toward an accomplishment set to occur over weeks, months, or years. The inevitability of changing timelines and evolving accomplishments present a challenge for designers. However, these challenges also present opportunities to examine how to convey setbacks, changes, and challenges.
- **Inclusive tracking technology**: Tracking applications tend to make assumptions about the orientations and abilities of people who use them, such as binary gender classification in fitness apps and heterosexuality in menstrual tracking apps. I hope to continue advocating for the design of tracking applications to avoid excluding people based on their identity. I also plan to take what I have learned about how to help people find value and support through their data to future work exploring how technology can be more understanding of how people's abilities and their environment impact the feasibility of different tracking goals.

7.4 CONCLUSIONS

As phones and wearable technology continue to advance and continue to permeate emerging markets, technology with tracking capability will only become more ubiquitous. Tracking technology has substantial potential to help people monitor and improve their food choices, finances, exercise, and other aspects of their lives. Tools today certainly do help some individuals regulate their wellbeing, but often fail to acknowledge and account for the realities of everyday use by a diverse audience. Designers of tracking tools often assume that people can and will collect data indefinitely and rigorously analyze it to answer their questions.

The field's understanding of how and why people are tracking must continue evolving as the technology changes. For example, advances in sensing placed in people's environments may result in fewer people making an explicit decision to track and making a thoughtful selection of tools. Devices with tracking capabilities may be installed in people's homes or work environments without their explicit decision to track. Or alternatively, people may install sensors or digital assistants without thinking about tracking capabilities and then discover those later.

Similarly, future advances in automatic sensing of eating, sleep, and other habits will change how people reflect and act on their data. As more tracked data becomes passively collected, the reflections people currently have as they collect data will occur less frequently. As research into semi-automated tracking by myself and others suggests, people are unlikely to review automatically-collected data as regularly and will act on trends surfaced less frequently. Lapses may come to be viewed more as lapses in reviewing and engaging with tracked data, rather than lapses in collecting data. New conceptual models accounting for these practices would expose design challenges created by continuing technology changes.

As I saw in my review of research on sharing tracked data, common approaches to designing today's tracking tools often fail to create the mechanics necessary to maintain interest in tracking and therefore lack the ability to provide the promised benefit. Seeing today's tracked data can satisfy a person's initial curiosity, but the tools need to do more to provide people with value based on that data. People often appreciate the record-keeping capabilities of tracking tools and the ability to see their data for the previous day or week. But many of today's tracking tools fail to connect data to the events which influence that data, such as people's routines, weather, work deadlines, major life changes, and more. Connecting data to life events can help people understand the longer-term trends in their habits and what factors influence their activity, finances, or other domains.

Current sharing features in tracking tools similarly lets a person's friends and family follow their early fascination with the technology. But current sharing features fail to provide much more benefit. As I showed in my study of tweets from RunKeeper, the content shared quickly looks repetitive and does not explain its relevance. I believe that a strong opportunity for sharing tracked data on broader social networking sites is as supplemental value or context to the conversations people are already interested in having online. Peer communities that already have substantial domain knowledge and interest may benefit from seeing tracked data, but the design of tracking tools still must encourage people to contextualize that data for the audience.

To live happy, healthy lives, people should not need to manually journal or review many factors about themselves each day. I think it is worthwhile to examine how short bursts of careful reflection or manual tracking, perhaps in response to a life change or other new information, can lead to increased understanding. These periods of close examination of data can also be supported with passive data collection over a longer time. As part of the process of tracking in everyday life, abandoning the collection of data or active engagement with collected data should be considered a normal part of the process. Though people often appreciate when designs encourage them to continue collecting data through notifications and other nudges, designs should be cautious in reprimanding people for stopping.

Conversations in and around the Quantified Self movement have suggested that tracking, or understanding the habits revealed by tracking, has a lot of benefit for providing people with better self-understanding. But across my research on how people track their food, menstruation, and finances, I have also found that tracking can cause people substantial discomfort. A trust in numbers to accurately explain how a person is doing, whether deserved or not, can cause much of this discomfort. One prospect is to instead move toward presenting holistic views of data, such as whether things are going well or could improve. Moving the conversation away from numbers can also lead to more beneficial sharing experiences, as much of the support people desire around their tracked data relate to how they feel and what they are struggling with.

This idea of moving to more holistic presentations of data is in tension to another recommendation from the literature that tools should guide people toward making their goals and questions more specific and measurable. But I believe these two recommendations can coexist in practice. One opportunity is to guide people toward specific and measurable goals when someone is deciding what to track and to aim for more holistic representations when someone is collecting data and reflecting on their habits. Another is to focus on holistic tracking primarily when the domain of the collected data has the opportunity to be sensitive or when the person tracking has indicated that they are often uncomfortable reviewing their data.

My findings help demonstrate the value in understanding and accounting for the implications of everyday life in people's use of tracking technology. Acknowledging the challenges of everyday life leads to designs which better help people draw value from the data they are collecting and gain support from others. These designs ensure that not only the needs of experts are met, but also the needs of people who are new to data and analysis.

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