From “nobody cares” to “way to go!”: A Design Framework for Social Sharing in Personal Informatics

Daniel A. Epstein[1], Bradley H. Jacobson[2], Elizabeth Bales[1,2], David W. McDonald[2], Sean A. Munson[2]
[1]Computer Science & Engineering, [2]Human Centered Design & Engineering
DUB Group, University of Washington
{depstein, lizbales}@cs.washington.edu, {bhjacobs, dwmc, smunson}@uw.edu

ABSTRACT

Many research applications and popular commercial applications include features for sharing personally collected data with others in social awareness streams. Prior work has identified several barriers to use as well as discrepancies between designer goals and how these features are used in practice. We develop a framework for designing and evaluating these features based on an extensive review of prior literature. We demonstrate the value of this framework by analyzing physical activity sharing on Twitter, coding 4,771 tweets and their responses and gathering 444 reactions from 97 potential tweet recipients, learning that specific user-generated content leads to more responses and is better received by the post audience. We conclude by extending our findings to other sharing problems and discussing the value of our design framework.

Author Keywords

Personal Informatics; Social Sharing; Self-Tracking; Health; Social Network Sites; Social Awareness Streams

ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI).

INTRODUCTION

Technological devices and applications for tracking personal data have become increasingly ubiquitous. The motivations for tracking vary by application and person, from curiosity and fascination with data [32] to having a record [19,33,36] to motivating behavior change [19,42] to engaging with others [3,24,46].

Many applications, both research (e.g. [11,15,27,35]) and commercial (e.g., *FitBit*, *Spotify*, *FourSquare*), have integrated features for sharing this data with others. Considerable research attention has been paid to sharing with others who have similar goals or who are in the same situation (referred to in this paper as *peer support networks*). In particular, research has considered online support communities [26,51] and in-application comparison features [11,56], and has identified several best practices [47]. This form of sharing specifically articulates a set of friends who will share data with each other. Within the group, known individuals directly share information with each other.

A second form of sharing – sharing through social awareness streams (SAS) such as timelines and newsfeeds in Twitter or Facebook – is also commonly used in practice. The use of SAS is a more indirect form of sharing amongst individuals who may or may not be known to each other. Sharing personal informatics data (defined by Li et al. as personal information collected for self-reflection [32]) through SAS can help people reach friends, family, acquaintances, coworkers and others with whom they wish to stay connected. People who collect and post personal informatics data (referred to in this paper as *sharers*) often hope to gain emotional support or communicate their identity as someone engaged in these activities [20,24,44,55]. This form of sharing can also help identify potential activity partners [18,42], create sources of accountability and motivation [43,44], and elicit advice from people who know them and their context [44,51].

Despite reported interest in and a prevalence of features supporting sharing personal data through SAS, these features often find limited or problematic use. While usage data from commercial systems is hard to obtain, the record from 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 [35,37,42,56]. Prior work (e.g., [11,35,42]) has identified several barriers to their use, including not wanting to share a trivial accomplishment and feeling uncomfortable sharing with an unfamiliar audience. Other work has pointed out the importance of finding an appropriate audience [21] or that the responsibility of choosing to ignore or engage with shared content is left to the recipient [55].

In this paper, we reconcile the gap between social sharers’ aspirations and their actual behaviors and outcomes. We develop a descriptive framework of social sharing research, consolidating findings in this space and identifying underexplored design alternatives. We demonstrate the value of this framework by using a subset of the dimensions to analyze how and why people use one popular application to share physical activity information on Twitter and how the details of the sharing affect responses. We consider perspectives of both sharers and their audiences, conducting

CSCW 2014, March 14–18, 2015, Vancouver, BC, Canada.

http://dx.doi.org/10.1145/2675133.2675135

two studies to learn what sharers post to SAS and how the audience views these posts. This combined analysis allows us to make design recommendations for sharing physical activity information on Twitter and broader recommendations for sharing personal informatics data, including how the design framework we developed can be used in future studies.

Specifically, we address the following questions:

RQ1: What design space of social sharing has been explored by prior research and practice in personal informatics and what conclusions can be drawn from this body of work?

RQ2: How do self-trackers presently share physical activity data in SAS, and how do recipients respond to seeing posts with this content?

RQ3: How do potential recipients feel about seeing this data in SAS, and what content features elicit replies or other positive reactions?

In the remainder of this paper, we review motivations and benefits associated with social sharing, the ways in which systems support this form of sharing, and how well these features support sharers' goals and how they break down. To support our discussion, we draw on prior work on people who socially share personal informatics data and an analysis of tweets from the popular fitness application *RunKeeper*. We conclude by discussing possible implications of these findings for other sharing domains within personal informatics.

SOCIALLY SHARING PERSONAL INFORMATICS DATA

While the majority of personal informatics research focuses on helping individuals improve themselves by reducing barriers to collecting and making sense of data, research and commercial applications have included features to share collected data with others. In this paper, we consider the sharing of self-tracked data to online social networks with a target audience of friends and family.

Many systems support symmetric sharing among groups [4,26,51] or pairs [40] in peer support networks. With peer groups, people can receive and offer experience-based advice, identify mentors and other motivators, and have a sense of shared experience. The audience – other members of the group – has personal experience with the sort the data shared. This helps people share it without needing to provide much additional context about the data. Sharing with peer strangers, on the other hand, may mean that they have to provide additional context about themselves.

Sharing personal informatics data through SAS creates opportunities not possible in peer support networks, such as reaching an audience of people whose opinions matter for emotional support. However, this space has challenges distinct from those in peer support networks, such as how to frame data for an audience potentially unfamiliar with the domain or goals. We continue to compare sharing personal informatics data through SAS to peer support networks throughout this paper, but focus on design issues and opportunities for SAS.

Why people share

People have many reasons for sharing their personal informatics data with peers and with their support networks of friends, family, and colleagues [41]. In many domains, such as health, social support is an important factor in behavior change [31,51]. In this section, we review the reasons for social sharing in personal informatics identified in prior work, including sharing intended to support behavior change and other uses of the data.

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 [39,44,51]. This is a common practice in – and often the expressed goal of – peer support networks, as the audience has a shared experience to draw upon and offer recommendations from [26,51].

Desire for emotional support

Sharers also seek emotional support, both from peers going through a similar experience and from caring friends and family [44,51]. For example, the HeartLink system enabled a social network to cheer on participants running a race, which participants found motivating [15]. In controlled studies, participants enjoyed receiving and felt motivated by encouraging messages sent from others in the study [11,56].

Seeking motivation or accountability from audience

Sharers may seek motivation and accountability by making commitments public, identifying potential activity partners, or creating competitions [42,44]. Collaborating in a shared activity can create a source of accountability [40]. Some people post their plans and goals to Twitter to create a commitment mechanism that helps motivate them to remain active and achieve their goals [55].

Motivating or informing the sharing audience

Some people also strive to motivate or inform their audience by sharing their experiences collecting personal data [10]. People also share records of activities and goals, such as eating healthy or exercising, to motivate others to act similarly [7]. In location-sharing applications, people may broadcast their location to recommend a cool place they found or to potentially meet up with nearby friends [36].

Impression management

People use social sharing to communicate an identity to their social networks and achieve impression management goals [20,44], but this also leads to curation and concerns about self-presentation [44,58]. Posts about runs or workouts can communicate that the sharer is an active, fit individual; feeds of music can communicate one's tastes. This also creates challenges; for example, people may curate their music listening histories to remove guilty pleasures [50].

DEVELOPING A DESIGN FRAMEWORK

While substantial prior work has explored social sharing within personal informatics, it remains disparate and unorganized. Systems share data in a multitude of ways, but system evaluations often lack integration with other prior work because each evaluation focuses on a single approach to data sharing. We develop a design framework by looking across many different studies, integrating and synthesizing results.

The framework can facilitate analysis of new sharing features by isolating a single design choice to vary in evaluation. We describe these different design choices along several *dimensions*, discussing factors of social sharing across one dimension. The six dimensions developed and discussed are:

- **Data Domain**: the 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 share is visible
- **Post Content**: what information is shared
- **Audience**: who receives the post

We summarize these dimensions and a selection of prior work representing them in Table 1. These dimensions were created though a bottom-up consideration of related literature; three members of the research team categorized and named identified dimensions. While 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. We believe that other prior work and future work on shared personal informatics data can be categorized according to these dimensions.

Data Domain

Self-tracking occurs in a wide variety of domains as people look to quantify various aspects of their lives. Many systems have been built to examine physical activity [11,35,38,56], bioinformatics data such as heart rate and ECG data [15,16,40,49], location [6,27,54], ecologically friendly activities [22,37], and music [20,50]. These domains are tracked for a variety of reasons, including to make healthier decisions or track health factors [8,38,41,55] or simply to know thyself [19,32,33].

Others have studied the use of commercial applications across these domains as well. Location sharing has been studied in FourSquare [14,36] and Google Latitude [46], now integrated into Google+. Teodoro and Naaman report on the use of Twitter to share physical activity [55] while Fritz et al. [21] and Rooksby et al. [48] consider other sharing networks. Last.fm has been studied for how people share music listening practices [20,50].

When deciding what is appropriate to share, designers should consider the norms attached to that type of data. For example, biometric data is perhaps more personal than someone's music listening history, and thus is more influenced by other dimensions. Sharing hourly data about music listening might be acceptable, while this might be an invasion of privacy for biometric data.

Preprocessing

Personal informatics data can go through a series of transformations prior to sharing, such as filtering or aggregating by time. Some systems immediately share raw data as it is collected [7,15,18,20,40,46], while others share aggregate daily totals [7,11,18,35,42,56]. Other times, shares communicate achievement of a specific goal or milestone [42]. Sharing high level syntheses from the raw data has been considered, such as a sentence describing a trend in activity [19] or a story drawn from collected data [23].

Preprocessing of data occurs for a variety of reasons. One is to maintain privacy, as aggregation can hide potentially private events, such as specific purchases. Social sharing has considered transforming raw data prior to sharing [18,29,30]. Designers of other systems have discussed electing not to disclose potentially sensitive events [37] or sharing less specific information (e.g. a generic place like "Grocery Store" or city-level information) [3,12,54].

Preprocessing data can also prevent inundating recipients with large amounts of data or frequent posts. Prior work on physical activity tracking has recommended that designers avoid sharing mechanisms that overwh the recipient [18,21]. It is common for people to self-censor in these networks [52] or post something that they later regretted [53].

Sharing Trigger

Another important dimension to consider is what triggers a share. Many applications stream data constantly, viewable in a profile or on a webpage. This streaming data may be collected and updated in the background as long as the application is enabled (e.g. steps [18], location [46]) or may be limited to during a specific activity (e.g. while running [15,40], while listening to music [20]). Other applications share when a self-tracker arrives at a designated location [3,5] or arrives near another self-tracker [34]. In other applications, shares are triggered automatically once a day [11,35,56].

All of the above systems implement automatic sharing of activity, but another class of features enable the self-tracker to trigger sharing on their own [14,36,42]. Other systems enable recipients to solicit data from the sharer, giving the sharer the choice to respond [11,27].

In applications that 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, they are required 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. To our knowledge, researchers have not systematically studied the tradeoffs

Dimension	Definition	Points Within Dimensions	Prior Work
Data Domain	Type of data collected and shared	Physical activity	[2,10,11,18,19,21,35,38,40,42,48,55,56]
		Biometrics	[10,15,16,40,49]
		Location	[3,5,6,9,12,14,17,19,23,24,27,28,29,30,34,36,45,46,54]
		Pictures	[7,13,23,25]
		Other, including environment, food, and music	[7,10,20,22,37,50,51]
Preprocessing	Transformations applied prior to sharing	Raw data	[7,10,12,15,18,19,20,23,24,25,36,46,49,50]
		Aggregate daily totals	[2,10,11,18,35,56]
		Goal achievement	[2,11,21,35,42,56]
		Summarization into trends	[10,19]
		Automatic or manual naming of data	[3,5,9,12,27,54]
Sharing Trigger	What causes the data to be shared	Always-on passively streaming	[5,9,18,20,28,46,50]
		Streaming during a special activity or event	[15,16,40,49]
		Arrival at or departure from a location	[3,6,34]
		Once per day	[18,21,56]
		Determined by the self-tracker	[2,7,11,13,14,17,21,23,24,25,27,36,37,42,54,55,56]
		Request by the sharing audience	[12,27]
Persistence	How long the share is visible	Transient	[3,5,11,12,13,27,40,49]
		For the lifetime of the system	[7,9,35,56]
		For the lifetime of the social network	[14,15,16,18,20,42,46,50,55]
		Self-tracker can delete content	[18,20,25,50,55]
Post Content	What information is shared	System-generated text	[2,5,11,12,19,42]
		Numerical summaries	[2,11,15,16,35,37,42,56]
		User-generated text	[2,9,11,38,54,55,56]
		Graphs or other visualizations	[2,10,15,16,19,23,37,42,49]
		Passive notification (noise, vibration)	[3,34]
Audience	Who is receiving the post	Broader social network	[15,16,18,19,21,28,37,42,55]
		Dedicated social network	[14,20,21,24,36,46,50]
		Strangers involved in a study	[7,35]
		Friends involved in a study	[2,5,6,11,12,13,27,34,38,40,56]
		Family or significant others involved in a study	[3,9,38]

Table 1. We develop a design dimension framework for sharing personal informatics data by extensively considering prior work and the points explored within the space.

between encouraging automatic posts and self-tracker initiated posts.

Persistence

Applications can also vary how long shared data is available. CoupleVibe automatically shared messages about a remote partner's location using short vibrations. If the recipient did not notice when it occurred, the old location was lost forever [3]. This approach is especially applicable for other time-dependent systems, where the relevant data to share is occurring at the current moment.

Other research applications, including Chick Clique and Fish'N'Steps, implement shares persisting for the life of the system [35,56]. Posts of personal informatics data made to a social network (versus a research prototype), including from [36,42,55], exist for as long as the network is relevant. Both groups of systems preserve a record of previous shares for browsing or searching. These systems may also enable the self-tracker to delete a prior share [55].

People sometimes post data to social network sites to create a private record of events in their lives [58]. This, combined with being aware of and finding patterns in their activity [8,19], demonstrates the value of sharing to a persistent social network even when another record does not exist. Enabling the deletion of shares is important for impression management, and deletion is a common strategy for managing regretful posts to social networks [53].

Post Content

Application designers have explored different types of share content. Systems have supported sharing personally collected data through numerical summaries [11,35], maps [36,46], and graphs [15,18,37]. These have varied in level of detail, ranging from a vague statement that an activity has been completed to a detailed post, including, for example, distance, route, time, and location of a run, as well as heart rate and mood [38, RunKeeper]. People have also expressed an interest in having the details hosted outside of the SAS and posting only a link. Apart from providing more detail than possible in a SAS post, people rarely use these features because they lead to uninteresting posts [38].

Some applications encourage users to annotate the tracked data with information about its significance, provide more details, or photos [13,23]. This content conveys more context, but also requires user time and effort to generate.

Prior work has not explored the importance of post content. It is unclear when it is necessary for the self-tracker to provide self-generated content versus system-generated content to receive feedback. Furthermore, what self-generated content posters should add has not been studied; we explore this later in this paper, considering both how self-trackers currently curate their posts, as well as how the audience views these posts.

Audience

Sharers and system designers must also decide who will receive posts. Systems have connected sharers with a variety of audiences, including pre-organized teams of random co-workers at a large corporation [35] to people who are friends or otherwise already know each other [11,27,56] to family and significant others [3,9]. In each of these systems and evaluations, all users were also participating in the activity. Thus, they saw each other as peers with similar goals and shared experiences [42].

Other systems and studies explored posting to a broader social network, such as Facebook [42] and Twitter [55]. GoalPost participants could share physical activity goals and journals to Facebook, but many worried about posting accomplishments that would seem trivial to others. Participants were also underwhelmed and discouraged when their posts received few responses [42]. Teodoro and Naaman found people posted to Twitter to feel accountable to their audience and did not express concern about their audience's opinion on their posts [55].

One way of negotiating post audience is to use a popular social network site to distribute the posts, but to restrict its distribution to a subset of the network. Prior work has limited the audience on these social network sites by building apps on the platform [37] or restricting post visibility to a list of supportive friends identified by the user [42]. Groups also self-organize on these networks, such as by creating Facebook groups with shared step goals or utilizing the same Twitter hashtag.

Post audience in prior work has varied from other study participants (both friends and strangers) to social networks (both specific to the data being tracked and broad). The norms of each of these audiences vary. In self-contained studies where the audience is a part of the study, the audience can relate with the sharer through their joint experience [44].

Despite hopes for using social network sites to share personal informatics data [43,55], there remain many challenges and best practices are not yet well understood [42]. Some social networks include features to help both sharers and their audience navigate sharing challenges. For example, Facebook and some Twitter clients enable hiding posts originating from a certain application or with a certain hashtag.

Individual preferences and comfort with different sharing audiences are heterogeneous. For example, some people are comfortable sharing their fine-grained physical activity with their entire social network, while others were only willing to share with close friends, or no one at all [18]. In the GoalPost study, some participants configured a "support group" of Facebook friends who could view their posts. Some included no one in their support group – making their posts a private record for themselves – and others shared with supportive friends, partners, or teammates; many other participants just chose to share with their entire Facebook network [42].

APPLYING THE DESIGN FRAMEWORK DIMENSIONS

To demonstrate the value of using these sharing dimensions as an analytical framework, we apply the dimensions to a case study of physical activity shares from the RunKeeper application posted on Twitter. RunKeeper is a commercial smartphone physical activity tracker with 25 million users, with runners logging over 2 million miles per day through the application at the time of this publication.

RunKeeper automatically records distance, time, and route, and enables posting to Twitter either automatically or manually after each exercise session. The user can add personalized text or a picture to each tweet. The app also enables sharing of runs, walks, or bike rides in real time.

This analysis focuses on unpacking the dimension of **Post Content** to answer the question: *How does the content of a RunKeeper post to Twitter influence follower impressions and responses*? The results of our analysis are generalized to the other sharing dimensions of our design framework in the discussion section below.

The combination of application (RunKeeper) and social awareness stream (Twitter) constrain the remaining dimensions:

- **Data Domain:** physical activity, specifically RunKeeper
- **Preprocessing:** minimal, 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 user. Live events are shared at the beginning of the activity with a link to follow activity progress
- **Persistent:** exist as long as the social network does or until the poster deletes it
- **Audience:** followers on Twitter social network and anyone following the "#RunKeeper" hashtag

Focusing on the content dimension and fixing the other dimensions in this way facilitated a more tractable analysis.

Framework evaluation methods

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

Formative survey: sharer goals and desired reactions

To identify desirable reactions to sharing, we conducted a formative survey about self-tracker's experiences sharing physical activity on a social network. 32 respondents recruited from University mailing lists and self-tracking forums (26 female, 6 male; average age 35.3, median 31, min

21, max 63) described their best and worst sharing experiences. Likes, comments, and in-person conversations were mentioned important characteristics of their best experiences sharing personal informatics data by 14, 14, and 2 respondents, respectively. Twelve respondents described their worst experience sharing their physical activity; the remainder either stated that they had not had a negative experience or left the question blank. Eight respondents mentioned receiving no feedback (e.g. likes or comments) as part of what made the experience their worst.

From this survey, we learn that self-trackers positively correlate comments or likes to how positive of an experience they had making the post. R39 mentions how feedback on their physical activity made them feel: "*likes and encouraging comments make 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 [42,43], encouraged us to use SAS feedback mechanisms (e.g., likes or favorites, comments or replies) as measures for how positively a sharer evaluates the success of their posts.

Collected Tweets (CT) study

We began our CT 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 all tweets posted in this span with the hashtag "#RunKeeper".

We coded each tweet for 10 features, described in Table 2. These features were selected to characterize the variability in the post content, highlighting common trends when posting to Twitter from RunKeeper. We additionally coded for the number of replies, favorites, and retweets.

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 these disagreements occurred as a result of the dimension having more than two levels), and 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 a random order. We used Fleiss' Kappa to assess inter-coder reliability among our 10 subjective, nominal codes. We received high agreement for "live event", "not an activity share", "activity type", "broken", and "zero minutes ran" (1.00, 1.00, 0.97, 0.96, 0.87) and moderate agreement for "post type", "non-English tweet content", "negative emotion", and "positive emotion" (0.79, 0.76, 0.64, 0.56). Mentions of another user did not occur in the set sampled for inter-coder reliability.

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 user	
9. Tweet is not an activity share	
10. Tweet is a live event	

Table 2. Coding scheme for tweet features in the CT study.

We excluded a portion of these tweets from analysis. Tweets were captured in real-time, so if the tweeter changed their profile settings to make their tweets private or deleted their account or the specific tweets, the tweet became no longer publically accessible. We removed 189 tweets not publically accessible as of mid-May 2014. We additionally removed 13 tweets where the tweeter had no followers, as these tweets were unlikely to receive responses. Finally, we removed 27 tweets not posted by the RunKeeper application (such as recommendations to friends to install RunKeeper or links to news articles mentioning RunKeeper). These tweets differed content and goals from posts made using the RunKeeper app.

Removing all tweets with these characteristics reduced our sample to 4,771 tweets, and our remaining analysis considers only these tweets.

Statistical methods in the CT study

We used regression analyses to characterize the correlations between different tweet attributes and responses. We used a Poisson model for the number favorites and retweets because each favorite or retweet came from one unique user. For replies, however, 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 users or quickly went off topic, and so additional replies rarely offered further support. In all models, we used log(followers) as an offset (exposure) variable, because one's follower count limited their potential for replies.

To differentiate between excess zeros caused by attributes of the user's account and zeros caused by attributes of the tweet, we used zero inflated model in all three analyses, due to the fact that 4,362 of the 4,771 tweets (91.4%) did not receive any response from Twitter users. We used the presence of the default image and the log of the user's tweet frequency to predict the excess zeros.

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.

Descriptive findings of the CT study

From our analysis of these tweets, a few common trends emerged. Most (74.0%) of the tweets included only system-

Figure 1. Tweets generated for the GT study varied on several dimensions, allowing us to separately evaluate the role of each of these features.

generated content. Of the tweets that included user-generated text, 22.0% contained positive or negative emotion. We also observed tweets containing descriptions of the weather, asking for advice or support, and additional information such as heart rate or run intervals. 299 runners added pictures in their tweets, which were typically landscapes, pictures of their shoes, or selfies.

Prior work has studied the sharer perspective for generating such posts [11,38,42,56]. Because sharers in prior work and in our survey of goals and desired responses emphasize the importance of audience responses for feeling that they have achieved their posting goals, we focus on audience reactions and opinions. We analyzed these tweets for audience response, including replies, favorites, and retweets.

Analysis of tweets in this study, however, only takes into account the observable responses. It cannot measure unobservable actions or audience members' opinions and reactions that did not result in a favorite, reply, or retweet. That is, from the CT study we can learn *what* tweets get replies, favorites, or retweets by not *why* or any other ways in which people may have reacted.

Generated Tweets (GT) study

With the limitations of the CT study in mind, we conducted a second study to better understand how a post about physical activity to a SAS would be interpreted by potential consumers or readers. We used the descriptive findings from the CT study to generate parameters for a system to randomly generate tweets similar to those we coded in the CT study. Three tweets generated by our system appear in Figure 1.

We varied nine parameters when generating tweets. Tweets could contain a milestone event (half marathon, return from surgery, or a long-term goal), one of four types of requests to the audience (asking for a recommendation, support, accountability, or an activity partner), or details about the sharer's run. The details about the run included 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 random between 2 and 15 miles, and could be either live or have already taken place. Finally, the post could include a photo of either a runner's shoes or a landscape depicting the run's location. For the posts that did not include a photo, RunKeeper's default Twitter card was displayed with statistics about pace (an 8:30 per mile pace regardless of distance) and calorie consumption (calculated using the American College of Sports Medicine metabolic consumption rate formula [1] for a person weighing 150 pounds).

Some parameters affected what we displayed for other parameters. For example, if the tweet communicated poor weather and a picture was to be shown, the picture changed to a rainy park or wet shoes. We 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. We 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 all of these parameters resulted in 102 possible styles of tweets, plus additional variation in exact wording, content ordering, and run distance. We used a factorial study design to obtain responses to these tweets, surveying 97 respondents recruited from Twitter, Facebook, and University mailing lists; respondents were entered into a raffle for one $50 or two $25 Amazon gift cards. Each respondent saw five tweets. Each tweet contained a randomly-ordered gender-neutral name (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 our responses, and we exclude them from further analysis.

The five tweets that each respondent saw were selected to overlap on four or fewer parameters to avoid the feeling that respondents were seeing the same tweets multiple times. Finally, our survey enforced that no two tweets among the five generated for an individual contained the same picture. As a result, tweets containing RunKeeper Twitter cards were oversampled in our analysis.

a) Tweet received replies (Negative Binomial)

	Count Model Coefficients		
Variable	Estimate	Std. Error	p
(Intercept)	-8.789	1.092	<0.001***
Default text	0.063	1.073	0.953
User text	1.147	0.248	<0.001***
User picture	-0.533	0.407	0.190
Positive	-0.116	0.409	0.777
Negative	0.326	0.604	0.590
Tweet is live	-13.851	671.103	0.984
@mentions	0.070	0.600	0.907
0:00	-0.346	0.629	0.582
	Zero-inflation model coefficients		
Variable	Estimate	Std. Error	p
(Intercept)	-0.011	0.392	0.979
Egg image	13.456	877.604	0.988
log(tweet frequency)	0.440	0.114	<0.001***

b) Favorites (Poisson)

	Count Model Coefficients		
Variable	Estimate	Std. Error	p
(Intercept)	-7.811	0.801	<0.001***
Default text	0.098	0.788	0.901
User text	0.806	0.154	<0.001***
User picture	-0.170	0.208	0.413
Positive	-0.153	0.200	0.442
Negative	0.496	0.375	0.187
Tweet is live	-0.093	0.466	0.841
@mentions	-0.403	0.289	0.163
0:00	-1.483	0.787	0.060
	Zero-inflation model coefficients		
Variable	Estimate	Std. Error	p
(Intercept)	-0.351	0.205	0.088
Egg image	-2.095	9.624	0.828
log(tweet frequency)	0.473	0.076	<0.001***

c) Retweets (Poisson)

	Count Model Coefficients		
Variable	Estimate	Std. Error	p
(Intercept)	-6.860	0.828	<0.001***
Default text	-2.056	0.787	0.009**
User text	0.283	0.543	0.601
User picture	-0.053	0.641	0.934
Positive	0.833	0.650	0.200
Negative	-13.250	895.397	0.988
Tweet is live	0.383	1.163	0.742
@mentions	1.586	0.832	0.057
0:00	0.440	1.180	0.709
	Zero-inflation model coefficients		
Variable	Estimate	Std. Error	p
(Intercept)	1.552	0.581	0.008***
Egg image	-14.428	434.771	0.974
log(tweet frequency)	0.141	0.135	0.294

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

Table 3. Results from regression models on a) whether a Tweet received replies, b) the number of favorites received, and c) the number of retweets received.

For each tweet, we asked respondents to select from a list of reasons why they believed the poster shared. This list was motivated by prior work [44,55]. Reasons included 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 agreed with being happy or annoyed that their friend made the post and whether they found the post interesting or boring. Finally, they were asked whether they would reply to the post, and to describe how they would reply or why they would not reply using an open-ended text box.

97 people responded to at least one tweet in the survey; 83 responded to all five they were presented (mean: 4.58, stdev: 1.06), resulting in 444 total responses to the tweets. Sixty-two respondents identified as female, thirty-four male, and one did not provide a response. Respondent average age was 28.49 (stdev: 7.79, median: 26, min: 18, max: 63). 45 stated they ran regularly, and 14 of these respondents regularly posted their runs to social media. 18 respondents had used RunKeeper to track their runs before, and 56 used Twitter.

Seven researchers used affinity diagramming to categorize respondent reactions and reply descriptions into similar themes. Two researchers further refined these initial groups, and the qualitative results from this refinement are presented in the results section.

Statistical methods in the GT study

We used similar regression analyses to the CT study to characterize the correlations between different tweet attributes and audience reactions. We used Ordinal Logistic Regression on responses to the 5-item Likert questions about whether respondents found the tweet interesting or boring, or whether they would be happy or annoyed if a friend made the tweet. We perform multilevel modeling by respondent to control for intrinsic respondent opinions.

Limitations

Even with two studies, there remain some limitations in our analysis. Because we only analyzed tweets that were publically available in mid-May 2014 in the CT study, we did not analyze any that a sharer removed after receiving no response or a negative response, an impression management strategy identified in prior work [53]. We additionally did not collect any replies, favorites, or retweets occurring after that point, though we anticipate that there were very few, as all tweets had been shared for at least 30 days before we collected the reply data. Since followers can change at any time, the audience count we use may differ somewhat from their count at the time they shared. We also noticed some of the tweeters had been followed, favorited, and/or retweeted by bots, and these are included in our analysis even though they may not result in the same feelings of support as reactions from real people.

The tweets in the GT study were all hypothetical, so respondents' actual behavior may differ from what they described in the survey and respondents may or may not actually respond to the tweets posed if they were presented in context. Given the frank nature of the responses, we believe respondent reactions to tweets seen in the study were authentic. As discussed later, many respondents indicated their response would depend on their relationship with the tweeter. Neither our study of actual tweets nor our survey measured the influence of these factors.

RESULTS

We triangulate the results from CT and GT studies to create a more complete understanding of how people post and respond to posts from RunKeeper to Twitter. Results from the regressions analyses of the CT and GT study data appear in tables 3 and 4, respectively.

System-generated content

Analysis of tweets from our CT study shows that tweets with user-generated text receive more replies ($Z = 4.63$, $p < 0.001$, 95% CI: 1.94-5.12 more replies) and how many favorites a

	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

Table 4. Results from regression model on how tweet characteristics impacted respondent opinions.

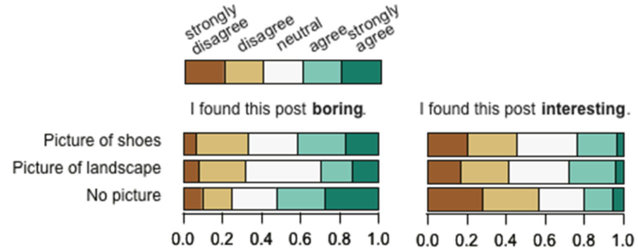

Figure 2. Respondents agreed that both posts lacking pictures and posts with pictures of shoes were more boring than pictures of landscapes.

tweet receives (Z = 5.25, $p < 0.001$, 95% CI: 0.51-1.11 more favorites), while tweets containing any system-generated text receive fewer retweets (Z = -2.61, $p < 0.01$, 95% CI: 0.51-3.60 fewer retweets) than those that do not. 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 GT study resulted in only 13 respondents viewing a tweet containing only system-generated content. Three of these respondents said such tweets 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.*"

Even when a tweet contained user-generated content, some GT 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 part of a canned tweet. Even if they really mean it, I don't believe they do.*"

We conducted a secondary analysis on the 27 tweets in the CT study made with the RunKeeper hashtag not containing any system-generated text, which were previously excluded. 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.

Details about activity are well-received

Many tweeters in the CT 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 biometrics or how they were training 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 the 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 GT study respondents explicitly reacted to the distance of a run. Most were impressed by the tweeter, 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 GT study respondents' opinions of the tweet. When a post included a specific reason for the run, respondents found the post less annoying ($F_{1,363}$ = 15.84, $p < 0.001$), less boring ($F_{1,365}$ = 10.35, $p < 0.01$), and 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 [42,44], when a post contains a request of the audience, 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, $p < 0.05$).

Pictures in posts are seen as valuable

In the CT study, we did not find a significant effect of 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 GT 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 2. While a picture may not trigger more feedback, the tweet audience still values posts with photos more.

The content of the picture also affected audience responses. We used a Wilcoxon signed rank test to compare the impressions of the 54 audience respondents who saw both a landscape and a shoe picture. Shoe pictures were more boring (Z = 2.36, $p < 0.01$, 95% CI: 0.25-4 on a 5-item Likert scale) than pictures of landscapes. However, there was no difference in how interesting participants found these two types of pictures (Z = -0.49, *n.s.*). Both received primarily positive reactions from the audience, with respondents reacting to the "*nice shoes*" (GT50; sentiment shared by GT57, 64, 76), "*liking the setting that is pictured*" (GT14; shared by GT5, 41, 50, 56, 57, 64, 65, 74, 88), 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).

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 CT set received replies. Eight of the ninety-four GT study respondents who saw a live tweet stated they would follow the link to watch their friend run live. Seven others did not see value in watching someone else run, such as GT96: "*I have better things to do than watch someone's run online*".

Positive outcomes from sharing

Both the CT and GT study found positive experiences that could result from sharing, for both the tweeter and the audience.

Positive impressions of the tweeter

GT study respondents were "*happy for*" the tweeter (GT8, 9, 10, 14, 32, 79). GT66 elaborated more on this sentiment, being "*glad that my friend is making a commitment to be active.*" Providing context for a run tended to support these feelings: "*Good to see them back on their feet*" (GT62, a sentiment shared by GT24, 45) 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*"). While these respondents may not reply or interact with the tweeter within the social network, these positive impressions indicate a potential for in-person conversations about running that might not have occurred without the share. We do not evaluate impressions generated from the CT set, as this would not be feasible.

Favoriting

Favoriting a tweet requires little effort from followers but provides an easy way to provide emotional support or motivate the poster without taking as much effort as a reply. Six GT 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.*"

User-generated text in a tweet seemed to give followers more to respond to. This could be a positive sentiment: CT4204 received four favorites for stating a run was "*Easy Peasy Lemon Squeezy*", a negative sentiment: one favorite for adding "*#dying #turtlesrunfaster*" (CT4678), or simply what the runner was thinking: one favorite for "*Push it to the limits*" (CT508).

Replying

Twenty-seven GT study respondents indicated they would reply to at least one of the tweets that they saw. These replies fell into three general categories. Congratulating the runner was a common type of support with "*good job!*" (GT1, 8, 10, 31, 42, 67, 85, 97; replies to CT1221, 1661, 2311, 3570, 4419), "*congrats!*" (GT15, 81, replies to CT2160, 3755), "*great work!*" (replies to CT563, 1607, 4170, 4454, 4533, 4832) or simply "*yay!*" (GT11, reply to CT4382) or "*wow!*" (replies to CT1128, T4423, T4907). Others encouraged the runner, with "*come on!*" (GT1, 10), "*you can do it!*" (reply to CT1121) or "*keep at it!*" (GT8, 85). Finally, GT study respondents responded expressing care for the runner: "*be careful*" (GT1, 59 in response to runners who were injured or recovering for injury).

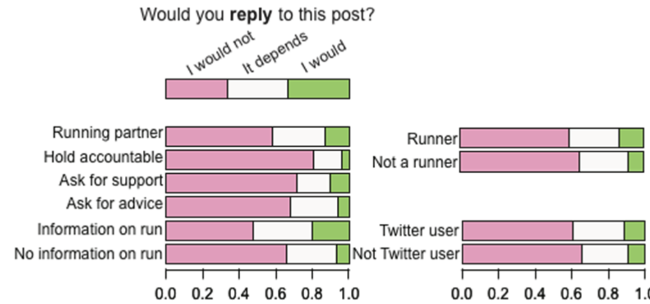

Figure 3. Respondents indicated that they were more likely to respond to posts that included information about a run, a request for a running partner, a request for support, or if they were a runner or a Twitter user.

Forty-three tweets in our CT set received more than two replies. These posts show conversations occurring over Twitter as a result of the post. These 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). GT study respondents similarly replied with questions for the tweeter, 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.

GT study respondents said they would offer or solicit advice in response to several hypothetical tweets. GT8, 35, and 71 offered recommendations on routes, with GT35 saying, "*I might think of my favorite running routes and suggest one to them*", and GT7 indicated they might reply "*if I wanted advice on getting a better time*". The original tweeter 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 3 presents how characteristics of the tweet and of the respondent vary GT study respondents' likelihood of 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.

Responding beyond Twitter

Nine GT study respondents indicated that they would want to run with the tweeter in the future, some in direct response to a request for a running buddy "*Let me join next time?*" (GT45, similar replies by GT1, 35, 47, 77), 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 tweeter then offered encouragement back to the replier.

Connecting with the tweeter

When tweets made an audience member think of their own experiences, the audience member felt more connected with the tweeter 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!*", and indicated she would want to reply with saying "*I empathize with this situation and I'd want to encourage this person to keep working toward their goal.*"

Other GT study respondents discussed relating to or commiserating with the tweeter. GT19 commented "*Seeing as I have knee pain from time to time, I'd be pretty sympathetic to this individual.*" GT92 similarly related to the runner, commenting, "*I would commiserate, as I also rarely look forward to runs.*"

The CT set also contained several examples of shared experiences between tweeters 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 the momentum.*" Some tweeters added text to indicate who they were with, e.g., "*With Dave & Matty*" (CT123) and "*Walking with Vinny*" (CT3922) or @mentioning the others, including: "*Thanks @[removed] for getting me out of bed!!*" (CT4074).

Undesired consequences to sharing

A large portion of GT study respondents reacted negatively to some or all of the tweets they saw. In this section, we describe negative repercussions of sharing and how some audience members react to seeing these posts.

Our CT study analysis is unable to capture many of the potential negative reactions: we were unable to observe reactions such as unfollowing a person, hiding posts from the RunKeeper app, feeling bored, or forming a more negative impression about the sharer. Thus, to characterize potential negative reactions, we use data from the GT study.

Tweets are ignored by the audience

Thirteen out of the ninety-seven GT study respondents indicated they would ignore at least one the tweets, with eight others reacting to a tweet with "*meh.*" Seventy-three of the respondents agreed or strongly agreed with the statement "I found this post boring" for at least one tweet, suggesting 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?*"

Fifty-five respondents agreed or strongly agreed with the statement "I would be annoyed if a friend shared this" to at least one tweet. In the free response section, sixteen respondents described being annoyed by at least one tweet, with eleven 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.*" Four respondents said they would unfollow the poster or try to hide the post.

This sentiment did not come through in our CT study, likely because Twitter followers did not want to post negative replies publically. 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 has the same outcome to the tweeter: they do not respond. Given that people generally correlate responses with positive sharing experiences, a large audience ignoring these tweets is counter to people's goals for posting. A lack of response also makes it difficult for the tweeter to learn how to regulate their posting habits. Learning that followers are annoyed by certain posts may lead to changes in tweeting behavior, but this sentiment is rarely publically expressed.

In our CT study analysis, we observed that some tweeters created separate accounts for posting only their physical activity. This can complicates the process of following people on Twitter – how do you learn a Twitter user has a separate physical activity feed – but it also gives audience members more control because they can choose whether to follow such accounts and receive physical activity tweets.

Negative impressions of the tweeter

Some GT study respondents also expressed negative opinions of the tweeter because of the tweet. Some respondents believed that the tweeter was posting to brag about their success. GT48 reacted, "*someone likely wants attention,*" with GT49 stating, "*it looks like he's just showing off.*" GT35 and GT74 thought that the tweeter was "*fishing for compliments*".

DISCUSSION

In our analysis of the CT and GT studies, we identified both successes in sharing and problems with many shares. In this section, we describe some potential causes for the disparity, offer design recommendations, and relate our findings to social sharing in personal informatics more broadly.

System vs. Sharer-generated content

GT study respondents reacted negatively to tweets they believed RunKeeper had automatically generated. GT66 was "*annoyed that they didn't customize their automatic tweets*", with GT22 and GT44 suggesting that the tweet "*looks like an* *advertisement*". Respondents also appeared to fatigue after seeing multiple tweets, reporting later tweets seen as more boring and less interesting. We believe respondents got bored seeing the same or similar content repeatedly, a byproduct of the prevalence of automatically generated content.

GT study respondents desired more information about the importance of the run when deciding whether to reply, and often responded 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 towards 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.*"

We note that posts were better received in the GT study when they contained a request of the audience or the context of why a run was significant. While not every run can be a personal best or major milestone, we believe that describing the importance of a run will lead to more positive responses and support.

Design recommendation: Together, these findings demonstrate the importance of supplementing the details of a run with sharer-generated content or possibly carefully crafted automatically-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 prior to sharing, and including this content in the post. Facebook recently took steps toward this. They noticed that people are more likely to engage with posts shared explicitly rather than automatically from within apps, and encourage application developers to share more personal content [57].

GT study respondents wanted to know the context of a run to determine whether to reply. GT43 reacted, "*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.*" A sharing application could easily prompt the user with, "why did you run today?" as part of the sharing process.

Audience and post frequency

Twitter is broad social network where followers range from close friends to total strangers. We expect that it is difficult to frame a post about physical activity to match the expectations of everyone in this audience.

In the GT study, thirty-three respondents said that their willingness to reply depended on how well they knew them. This ranged from "*If I know the person or not*" (GT14) to "*Only if it's a close friend*" (GT23). On a whole, our audience seemed more willing to respond to posts made by close friends or family members.

Five GT study respondents emphasized the importance of "*how often they post content like this*" (GT62, sentiment shared by GT10). After seeing multiple posts, GT97 notes, "*the sense of novelty is wearing off,*" and was left less enthusiastic about posting support. Audience fatigue may play a role, especially if this genre of posts appears frequently in a Twitter feed. A highly motivated audience, such as one of close friend or one that can relate to the poster's challenges, might suffer from less poster fatigue.

Design recommendation: Despite – or *because* of – the ability to reach a wide audience, Twitter may not be the best venue for regularly sharing everyday physical activity or other personal informatics information. One potentially improved system would enable sharing physical activity with a smaller audience of close friends or family members through lists within a broader social network, though previous work has found that many users do not want to spend the effort to configure such lists [42]. Another approach would be to share only to people interested in running, either through a dedicated social network, lists of a subset of friends or followers, or dedicated accounts.

The responses to our GT study indicate that people are willing to offer support to a close friend even if they are not self-trackers 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 SAS 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 others, changing the interaction from automatically generating tweets to one that recommends tweeting if the content supports this.

Mismatch between sharer goal and audience interpretation

Sharers have a variety of goals for posting their personal informatics data to a social networking site, but 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, sentiment expressed by GT32, 65) and thus elect not to provide any feedback.

GT90 alludes to another problem: even when a poster does not desire specific replies to meet their goal, their post may have harmful side effects, such as causing them to be seen as a braggart, especially when the post is not clear about why 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", (25.3% were perceived as motivated by both goals). This shows two different audience interpretations, which have conflicting sentiments about the tweeter. Bragging might be accepted and even encouraged in peer support communities, which GT21 implies: "*I kind of just ignore [posts] unless on [MyFitnessPal] because it is FOR bragging about exercise ;)*", but less well-received on general-purpose SAS.

Design recommendation: Personal informatics applications should encourage sharers to be more explicit about what feedback they are looking for when they decide to share. Prior to sharing, sharers could be asked to answer "why are you making this post?" Posting this answer along with the original post could give the post audience enough context to provide meaningful feedback for the sharer.

While we focus our analysis on audience reactions in the form of replies, favorites, and retweets, some goals may not be better achieved through 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. People also post physical activity and other goals to social networks to feel more accountable to those goals. If posting alone is sufficient for people to feel more committed to their goal, they may not require feedback from their audience.

Extending beyond RunKeeper and Twitter

We believe that many of the design recommendations we developed for sharing RunKeeper data on Twitter apply for other domains in which people self-track data and for other SAS. For example, GT study respondents felt that that many posts were made to brag or show off. We 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, this might not be true for all domains. Some types of data, such as personal finances or health results, may be seen as more private, but in some cases some members of the audience may have a greater desire to see regular updates, such as when someone has had an ongoing struggle to manage a chronic illness [44]. Future work should more fully explore heterogeneity between different domains of shared data.

Regardless of the data presented, we believe automatic posts from self-tracking applications are likely to receive negative reactions from audience members. While perhaps some types of personal data are less annoying or more interesting in a SAS – something future work should assess – we anticipate that adverse reactions to automatically generated posts will still be common.

Audience reactions to personal informatics posts may correlate to how frequently these posts appear. Current commercial self-tracking applications including Strava, Last.fm, FourSquare and RunKeeper, encourage self-trackers to post to SAS regularly. We believe changes to the design of these applications to encourage fewer, more meaningful posts and descriptions of the post's importance or what sharers hope to gain from posting, will result in better sharing experiences for both sharers and their audiences.

It not always correct to design personal informatics sharing features to maximize post audience. Applications should help sharers route frequent posts to the right audience. These posts should target people who will respond positively to the content and can offer reactions the sharers need, be tolerant or even desiring of seeing it more frequently, and have sufficient context to understand it. For more significant events, they might encourage posters to share more broadly and to provide sufficient context so the audience will understand why they are sharing.

Use of the design dimension framework

In this paper, we describe a framework for evaluating sharing features in personal informatics studies. Use of this framework can help designers consider each design choice they make when creating a sharing feature for a personal informatics application.

We demonstrate the value of our design framework with a relatively simple and constrained sharing problem, varying only a single dimension (shared content) in our experiments. Thorough, empirical evaluation of a range of design options can inform the design of such features. This level of evaluation may not always scale to investigating to less explored, less constrained design questions. In those situations, we believe that our framework and corresponding review of previous literature can guide designers to select and evaluate a smaller number of options.

CONCLUSION

This paper presents a sharing dimension framework that characterizes different design choices for features that support socially sharing personal informatics data. Designers can use this framework determine the impact of a single factor to best share personal informatics data, and researchers can use it to identify unanswered questions and guide future study designs. We characterize prior work into these dimensions and summarize findings made in each dimension. We offer design recommendations for improving sharing of physical activity on Twitter through two studies of RunKeeper, and extend these findings to other domains.

ACKNOWLEDGMENTS

Lindsey Brockish, Danni Hu, Sara Jennings, Chuck Johnston, Rahul Mehan, An Ping, Sreedev Sidharthan, and Melinda Yang contributed to this work through coding tweets, affinity diagramming, and thoughtful discussion. We also thank Felicia Cordeiro, James Fogarty, and Nicole Lee for their feedback throughout this project. We also thank the University of Washington Statistical Consulting Program for advice on the statistical methods. Finally, we thank participants in the CHI 2014 Workshop on Beyond Quantified Self for their feedback on an early version of this project, and Andrew Miller for several helpful suggestions. This work is sponsored in part by the Intel Science and Technology Center for Pervasive Computing, Microsoft, Facebook, and the National Science Foundation under awards OAI-1028195 and SCH-1344613.

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