

Fine-Grained Sharing of Sensed Physical Activity: A Value Sensitive Approach

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ABSTRACT

Personal informatics applications in a variety of domains are increasingly enabled by low-cost personal sensing. Although applications capture fine-grained activity for self-reflection, sharing is generally limited to high-level summaries. There are potential advantages to fine-grained sharing, but also potential harms. To help investigate this complex design space, we employ Value Sensitive Design to consider whether and how to share fine-grained step activity. We identify key values and value tensions, and we develop scenarios to highlight these. We then design a set of data transformations that seek to maximize the benefits while minimizing the harms of detailed sharing. These include a novel approach to interactive modification of fine-grained step data, allowing people to remove private data and using motif discovery to generate realistic replacement data. Finally, we conduct semi-structured interviews with 12 participants examining these scenarios and transformations. We distill results into a set of design considerations for fine-grained physical activity sharing.

Author Keywords

Personal Informatics, Value Sensitive Design, physical activity sensing, social sharing.

ACM Classification Keywords

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

INTRODUCTION

The rise of personal informatics has been enabled in part by the increasing ubiquity of personal sensing [25]. Sensing takes many forms, from simple pedometers [6,10,19] to location and other information sensed by mobile phones [2,13,18] to sophisticated disaggregation of home utility usage [14,15]. Prior work examines how such sensing can support a variety of goals, including increasing physical activity [30,37], adopting more environmentally sustainable behaviors [13,28], and improving sleep quality [5,20].

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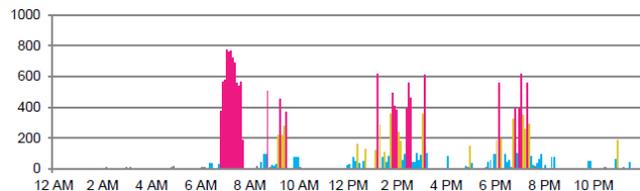


Figure 1. A fine-grained view of daily step activity. Five-minute intervals are colored by activity level.

Many applications highlight social sharing in personal informatics and behavior change. Sharing sensed data with family and friends can be effective for gaining social support [22,25,28]. Prior work emphasizes goal sharing around high-level summaries, such as walking 70,000 steps per week or remembering to turn off lights [6,28,30]. Commercial applications also share high-level summaries, such as daily step totals in FitBit [10] and Jawbone UP [19] or weight-loss progress in MyFitnessPal [31].

We are interested in the additional opportunities and concerns presented by sharing fine-grained personal activity data. For example, Figure 1 presents a detailed view of a day’s step activity displayed in five-minute intervals [10]. Detailed sharing can enable new forms of social interaction around sensed activity data. Instead of only seeing that a person did not reach a weekly step goal, family and friends could praise morning walks visible in the detailed data. Family and friends might also use detailed data to discover effective strategies, such as adding a morning walk to their own routine or noticing a person is generally idle during lunch and suggesting they walk together.

Although detailed sharing presents new opportunities, it also presents complex design considerations. One concern is over-sharing. For example, Munson and Consolvo found people worried about sharing a trivial accomplishment and thus opted not to share at all [30]. Other concerns arise around privacy. A person who chooses to share fine-grained data expects to give visibility into associated activities, but may object to how that data might be used to infer apparently unrelated information. Current approaches generally provide only a simple binary choice of “share” or “do not share”, thus limiting how people can take advantage of these opportunities while managing concerns.

To help address the complex value considerations that arise in fine-grained sharing, we turn to Value Sensitive Design

(VSD), an established method for addressing human values and value tensions in a design process [11]. VSD uses three types of investigations: conceptual investigations of stakeholders, values, benefits, and harms; technical investigations of features and infrastructure; and empirical investigations involving stakeholders and potential contexts of a design. These are applied iteratively and integratively.

The focus of our technical investigations is on methods for transforming fine-grained activity data prior to sharing. We consider designs based on unmodified data, a high-level summary, and deleting data prior to sharing. Finally, we develop a new approach to interactively transforming data that attempts to explicitly preserve benefits of sharing while giving people greater control over what they share. We also focus our current exploration on fine-grained step activity as captured by the FitBit pedometer [10]. Step activity is important to fitness applications and is appropriate for these initial explorations. Our discussion considers how our work might be extended to other types of activity data.

The specific contributions of this work include:

- Identification of a range of values and value tensions arising in sharing of fine-grained physical activity data.
- Exploration of a set of transformations of fine-grained activity data, including how designs might preserve the benefits of sharing while minimizing potential harms.
- Development of a new approach to interactively transforming fine-grained physical activity data, allowing people to remove private data and using motif discovery to generate replacement data, implemented for step data.
- Results of value-oriented semi-structured interviews with people who use pedometers, based on scenarios that highlight potential benefits and harms of social sharing.
- Design considerations for future applications that include social sharing of fine-grained physical activity data.

RELATED WORK

Prior research has examined sharing in ubiquitous computing, including some work from a VSD perspective.

Value Sensitive Design

VSD is an established approach to addressing human values throughout a design process [11]. An early application of VSD in Ubiquitous Computing investigated a privacy addendum for open-source licenses [12]. Camp and Connelly discuss many aspects of privacy in Ubiquitous Computing, including opportunities for Value Sensitive Design as an approach to understanding privacy and data sharing in Ubiquitous Computing [4]. Our focus on social sharing means the revelation of information is inherent and intentional. But there are still important value questions and value tensions around potential designs.

Czeskis et al. used VSD to investigate personal safety applications for use by teens and their parents [9]. Although sharing in the parent / child relationship differs from social sharing among peers, that work explored a number of key

issues that also arise in this work, such as unwittingly revealing personal information about indirect stakeholders.

Sharing Applications

Sharing For Social Support

Online communities have been studied for how they promote social support, including studies of communities emphasizing weight loss and cancer care [17,34]. Tang et al. differentiate social sharing from purpose sharing in the context of location sharing [36]. In our work, we are mostly considering social sharing of physical activity, but can imagine purpose-driven scenarios. For example, sharing with a personal trainer or doctor would be purpose-oriented.

Some prior research employs deception to address privacy concerns. Iachello et al. implement a location-requesting application in which a person can provide incorrect or time-shifted responses [18]. They found a low amount of deception in their field study, and suggested this may have been in part due to an expectation of trust. Page et al. interviewed people who use location-sharing services, finding they mislead friends about their location and worry the services could expose the discrepancy [33]. However, many participants believed deception would go undetected.

Sharing In Activity Applications

Consolvo et al. consider the design of technology to encourage physical activity [6]. Their Houston system shared participant daily step activity with friends. Participants reported receiving social support and pressure through the system, and also reported interest in sharing more information than total step count. Klasnja et al. examine privacy concerns in personal sensing applications [21]. They report participants react differently to the potential recording and sharing of different types of sensor data: they felt comfortable disclosing accelerometer data, but were concerned about revealing location or raw audio.

Fish'n'Steps varied the size of fish in a bowl as a metaphor for physical activity, as sensed using pedometers [27]. Fish'n'Steps included cooperative and competitive sharing of physical activity: participants shared a fishbowl with other participants, and the fishbowl of the most active group was displayed on a public screen. The system allowed people to send words of encouragement to other people in the same bowl, but participants rarely used this feature as they seemed unwilling to interact with people they did not know outside the context of the study. Toscos et al. sought to increase physical activity among adolescent girls using a step count sharing application that allowed the teenagers to send motivating text messages to one another [37]. When social support dropped off, activity levels were lower.

Location Sharing

Location sharing has been extensively explored in prior work. In early work, Barkhuus and Dey found a desire for location-based services [2]. Consolvo et al. built a location service that allows selecting a granularity of sharing [7]. Participants generally felt comfortable disclosing their most detailed location (address or place name), except when it

would not be beneficial to the recipient (as when a recipient is not knowledgeable of the area where a sharer is located).

Systems have also explored always-on location sharing. These often take a policy-based approach, allowing people to define when and with whom to share their location [8,23]. People generally have complex privacy settings and are not very good at defining rules or understanding their consequences. Cornwell et al. found the rules people define accurately classify 59% of location disclosures, which can be improved by having people modify their rules or by applying machine learning techniques [8].

Krumm proposes obfuscation as a method of injecting privacy into location-sharing applications [24]. He suggests degrading data prior to sharing, such as by adding noise to obscure a person's exact location. Another approach is K-anonymity, which selectively does not disclose information that could be used to narrow the identity of a person to a set smaller than K [35]. K-anonymity does not support sharing for social purposes, as the identity of the sharer is already known and privacy concerns instead focus on what sharing reveals about a person's activities.

Varying Sharing Granularity

Munson and Consolvo developed GoalPost, which included sharing a vague physical activity view that linked to a more detailed view [30]. Participants in their study generally found this additional privacy protection unnecessary. Consolvo et al.'s study of location sharing at multiple levels of granularity found identity of the recipient to be the biggest factor in deciding what to share [7]. Tang et al. found people sometimes share location information that requires 'insider knowledge' to fully decode (e.g. 'at the Giant Eagle') [36]. They also believe that people resist providing a very general location (e.g. 'Pennsylvania') because they feared coming off as intentionally vague.

CONCEPTUAL INVESTIGATIONS

Per our VSD approach, we examine sharing of fine-grained personal activity data through a lens of stakeholders, benefits and harms, values, and value tensions.

VSD emphasizes considering perspectives of both people who directly interact with technology and others who might be impacted by it [11]. In our domain, direct stakeholders are both the *sharers* (i.e., the people sharing activity data) and *recipients* (i.e., those who view activity data). Indirect stakeholders include anybody whose activity correlates with a *sharer* (e.g., people who live or walk together). Because their activity correlates, a *sharer* gives *recipients* indirect insight into activities of these additional stakeholders.

Fine-grained sharing offers many potential benefits. As motivated in our introduction, family and friends might give concrete praise for activities visible in shared data, might discover or share exercise strategies, or might identify opportunities to exercise together. These and other interactions around fine-grained data can help people achieve fitness goals [7]. Other opportunities include

supporting closeness for couples [1] or peace of mind in formal and informal caregiver relationships [32].

There are also potential harms to sharing fine-grained data. Sharers might be concerned about a loss of privacy, as data may reveal activity they are not comfortable sharing. Transformations can help mitigate privacy concerns, but introduce their own potential harms, including undermining the trust of recipients. For example, Page et al. found recipients of location-sharing updates reported ignoring sharers who regularly lied about their locations [33]. Transforming data prior to sharing can also impact the quality of interaction sharers might have around that data, as sharers may not know whether they can trust advice given based on incomplete or modified activity data.

Key Values and Value Tensions

In our conceptual investigations, we identified two values motivating fine-grained sharing: *support* from family and friends who can use shared data to help sharers accomplish their goals, and support for sharer *accountability* to others for achieving their goals. Additionally, recipients expect *honesty* from the sharer, and in turn develop *trust* in the sharer. Finally, sharers want to preserve certain forms of *privacy*. Friedman et al. [11] present working definitions of these values, which have also appeared in value-oriented work in related domains [4,9].

In designing sharing applications, there is a tension between *privacy* and the other values. Sharers must find a balance between how data sharing impacts their *privacy* while also enabling *support* and *accountability*. Some transformations may preserve *privacy* at the expense of *honesty*, potentially undermining recipient *trust*. The remainder of this work motivates and discusses designs in terms of these values.

SCENARIO DEVELOPMENT

We took the findings from the conceptual investigation and developed four concrete scenarios. These scenarios were designed to highlight different stakeholders, potential benefits and harms, and value tensions that we anticipate when sharing fine-grained personal activity data in the real world. We later use these scenarios in our empirical investigation as part of our semi-structured interviews.

Scenario 1: Goal Achievement

Ellen works a desk job, becomes curious about her activity level, and purchases a pedometer. She sets a daily step goal, but has trouble reaching it because her job keeps her sedentary most of the day. One day, she decides to walk around her office multiple times throughout the day, and she achieves her goal. She is very excited by this and wants to share her accomplishment with her friends, many of whom also have desk jobs and want to become more active.

Discussion: The benefit of fine-grained sharing is clear for Ellen. She is proud of achieving her goal by including activity in her work day, and she wants to share how she accomplished her goal. Ellen's friends are similarly motivated and would likely appreciate her accomplishment. Ellen's primary value consideration is *support*.

Scenario 2: Leaving Work Early

One weekday, Hunter decides to go for an afternoon run around a nearby lake. He goes to work early, completes his responsibilities, and leaves to run in the afternoon. Hunter finishes his run in record time and wants to share on a running website. He is conflicted, however, because some of his friends on the site are co-workers who work standard hours. He is concerned that highlighting his afternoon absence will reflect poorly on his work performance.

Discussion: Hunter wishes to share detailed activity to gain social *support* and challenge his friends. However, he is concerned for *privacy* because sharing will highlight he was not at work that afternoon. Flexible hours may be acceptable and Hunter may not have reason to be concerned, but he still may not want the event recorded. Even if not currently cause for concern, the run may be found and interpreted out of context when Hunter is being reviewed for a future promotion by a different manager.

Scenario 3: Late Night Activity

Whitney regularly wears a pedometer to track her physical activity. She has configured her privacy settings so her fine-grained data is visible to close friends, including her boyfriend Chris. One day, she tells Chris she will be studying in the evening. She later receives a text from a friend she has not seen recently, suggesting they meet at a local bar. Whitney meets the friend and returns home at 3:00am. A few days later, Chris is comparing his activity levels to Whitney's to find ideas for how they can be more active. He notices late night activity and wonders if Whitney is intentionally not disclosing something to him.

Discussion: This scenario motivates transformations, as Whitney did not intend to share her late night activity but did not have an option to transform it. Whitney must now manage a discrepancy between her activity data and what she told Chris. This is a tension between *privacy* and *trust*. Depending on their relationship, it may not be an issue. Neither was malicious: Whitney did not intend to deceive, and Chris was not intentionally snooping. This scenario is therefore fairly tame, but more worrisome variants could include accusations of infidelity or even stalking.

Scenario 4: Finding a Running Buddy

Gloria recently began running a route near her home. She is now bored with the route and decides to post it to a running website for suggestions. She is messaged by a member of the website who lives nearby. The two run together once, have a good experience, and it becomes a regular event.

Discussion: Gloria was motivated to share her detailed route because she wanted *support*. Although Gloria's experience was positive, there were potential harms. Specifically, Gloria undermined her own *privacy* (and in the worst case, potentially her safety) by disclosing where she lives (i.e., the start and end of her running route).

TECHNICAL INVESTIGATIONS

We began this research with an investigation of an interface for interactively transforming fine-grained activity data, but

later realized there were important value considerations and the design space was more complex than we first thought. We then adopted a VSD approach and conducted our conceptual investigation, including developing scenarios to highlight value tensions. Based on our identified values and value tensions, we returned to our technical investigation and considered five transformations. These transformations were created to surface an array of value tensions, with each transformation supporting certain values while raising concerns about others. We now present these, discussing each in terms of both our FitBit pedometer data and how an analogous transformation might be applied to different types of data. Our final transformation requires significant novel implementation, which we also present.

Detailed Single-Day View

This view makes fine-grained data captured for self-reflection directly available for sharing (i.e., directly shares the detailed data presented in Figure 1). A person can decide whether to share a day's activity, but cannot modify the data. This is analogous to existing applications that limit sharers to "share" or "do not share" (e.g., running or biking applications that allow a person to share a detailed map of their just-completed route).

Value Tensions: This design's transparency emphasizes *support*, *accountability*, and *honesty*. It also raises concerns for *privacy*, as choosing to share reveals all of a day's activity. The design can also raise concerns for *trust*. If a recipient becomes accustomed to daily activity shares, but a sharer chooses not to share a particular day, the recipient may wonder what activity prevented sharing.

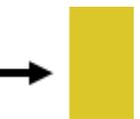
Longitudinal View

This view aggregates step data into daily step counts, shared automatically at the end of every day. These step counts appear in a chart with step totals for the prior week. This is analogous to existing applications that automatically share high-level summaries. Here the summarization is simply a summation of step count data, but will vary in other applications (e.g., using the total length of a run, thus removing location details).

Value Tensions: Of the five views we consider here, this gives the least insight into sharer activities. It thus maximizes *privacy* at the expense of minimizing *support* and *accountability*. Concerns around *honesty* or *trust* are also minimized by the completely automated approach.

Limited Hours View

This view presents the same detailed information as the single-day view, but limits sharing to a range of "daytime" hours specified by a sharer. Activity outside this range is not shared, under an assumption it may be more private (e.g., sleep patterns, staying out late with friends, or other nighttime activity spikes a person may not want disclosed). As with the detailed view, a sharer can decide whether to share this limited view of a day's activity. Total activity, as



reported elsewhere in the application, also reflects only steps from shared “daytime” hours. This was motivated by prior work on location sharing, in which participants refuse sharing before 8:00am or after 6:00pm to avoid revealing non-work locations [8]. Analogous approaches might also be based on different types of contextual filters (e.g., only sharing data sensed within sharer-approved locations).

Value Tensions: This view offers greater *privacy* than the detailed view, as it automatically hides a part of the day likely to be more sensitive and still gives control over whether to share. It might also improve *support* and *accountability* if automatic removal of evening activity encourages greater sharing of daily activity. There are minor concerns for *honesty* and *accountability*, because total activity level is not accurate if people have any activity outside their approved “daytime” hours. Concerns for *trust* are similar to the detailed view, as a recipient may wonder why a person limited sharing to certain hours or chose not to share activity for a particular day.

Relatively minor modifications can significantly change the value tradeoffs. Displaying total activity for the complete day instead of only “daytime” hours would improve *honesty* and *accountability*, but would come at the expense of *privacy*, as the discrepancy could reveal the presence of large activity spikes outside “daytime” hours.

Interactive Deletion

This view allows a sharer to interactively highlight and delete data prior to sharing. As an example motivation from our scenarios, Whitney might delete the activity from her night out with a friend and then be comfortable sharing the remainder of her activity. Zero values are common in step data, so deletion is not obviously recognizable. Deletion may require greater care for other types of activity data, perhaps drawing upon the methods we develop for our interactive transformation interface discussed next.

Value Tensions: The primary tension is between *privacy* and *honesty*, *trust*, and *accountability*. Deletion allows sharers to preserve *privacy* by removing activity they do not want to share, but *accountability* is impacted because total activity level is incorrect. A more challenging scenario arises if a recipient loses *trust* after observing inconsistency resulting from a deletion. For example, Whitney might excitedly post her high step count for the day, but later share a detailed view that contains fewer steps after deleting her walk home from the bar in the early morning.

Interactive Transformation

Our final interface explores a novel approach to fine-grained activity sharing: we support interactive modification of fine-grained data to mitigate privacy concerns while working to ensure resulting data preserves the original benefits of sharing. For step activity data, we define this as preserving the daily step count and the typical activity patterns. A sharer can interactively highlight and

modify interval step count (e.g., increasing or decreasing activity in a highlighted interval). In response, the system automatically generates an offset elsewhere in the day (i.e., decreasing or increasing activity to maintain the total step count for the day). As we detail in the next section, our implementation analyzes a person’s activity history to automatically generate realistic offset transformations.

Although we focus on step activity, the idea of interactively modifying fine-grained data while preserving the benefits of sharing can be more broadly applied. From a technical perspective, the goal is to modify data while preserving key invariants. For example, when Gloria seeks feedback on a running route, she might adjust the beginning and end of a sensed route to be in a park through which she runs (i.e., changing the order of points, but not the shape of the route).

Value Tensions: As with deletion, transformation supports *privacy* by allowing a sharer to remove sensitive data. The tensions are again with *honesty*, *trust*, and *accountability*, but the design attempts to mitigate these concerns. Preserving the original reason for sharing by maintaining the day’s overall step count helps support *accountability* and preserve *trust*. A focus on generating realistic transformations is also intended to preserve *trust*, but ultimate responsibility remains with the sharer. A sharer who moves a midday run to the middle of the night may succeed in conveying their overall level of activity, but will probably introduce concerns for *honesty* and *trust*.

ENABLING INTERACTIVE TRANSFORMATION

Interactive transformation is based upon a visualization of 5-minute activity intervals, as in Figure 1. Transformations are therefore defined in terms of a histogram, where the index in the histogram corresponds to time-of-day and the value at a bucket to a step count for that interval. A *region* is a contiguous set of histogram buckets. A sharer can *add* activity to a highlighted region, *remove* activity from a highlighted region, or *shift* an activity region in time. We implement these actions using three lower-level operators:

Set: Given a list of step values and a region of the same size, overwrite the region with the provided step values.

Modify: Given a target step count and a region, overwrite the region with realistic data containing a total number of steps approximately equal to the target.

Offset: Given a full day of activity data, overwrite one or more unmodified regions with realistic data that restores the total step count to its original value.

These operators are sufficient for our higher-level actions and could support additional interface functionality. We currently implement *add* as a relative action:

- (1) compute current step count in the selected region,
- (2) compute a target by applying a fixed difference,
- (3) *modify* the region to the target value, and
- (4) *offset* to restore the original total step count.

We implement *remove* similarly, but using a fixed target of zero. We implement *shift* using three operations:

- (1) *set* the source region into the destination region,
- (2) *modify* the source region to zero, and
- (3) *offset* to restore the original total step count.

We chose these actions and operators to give control without requiring that sharers manage details of realistic histogram manipulation. Realistic transformations therefore depend upon the *modify* and *offset* operations. In our examinations of collected FitBit data, these operations are difficult because activity patterns are highly variable and simple techniques like uniform scaling often appear unrealistic. Instead of attempting to model step activity, we take inspiration from methods developed for image completion [16]. We consider the region to be modified as a *gap* in activity data, search the sharer’s activity history for data that might be a good fit, and fill the gap with historical data. The next two subsections detail our implementation.

Modify Implementation

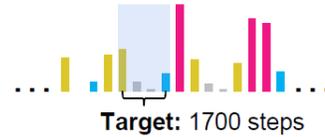
Figure 2 illustrates the workflow of our *modify* operation. The sharer first specifies a region and a target activity level (in this case, a region of size 4 with a target of 1700 steps).

The system obtains a portion of a person’s activity history within which to search. We currently use the past week of activity. This was selected to be large enough to provide data variety and capture day-related patterns (e.g., running Wednesday morning), while small enough to promote recent data, remain responsive to changes, and to ensure interactive performance. Step activity is next discretized, a standard pre-processing step for motif discovery algorithms we employ later in this workflow [26]. We designate a symbol for zero activity (the most common value), then uniformly distribute non-zero activity over eight symbols.

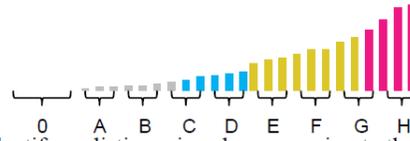
We next identify regions from historical data that would be realistic if inserted in the target gap. Based on the intuition that inserted activity should be consistent with its context, we filter by the data before and after the gap. Figure 2C illustrates this, filtering samples that do not match the gap context. For a gap of size k , we filter based on the $k/2$ entries before and after (referred to as the *gap context*). We use a sliding window to consider all regions of size k , compute Levenshtein distance between our gap context and the context of each region, filtering regions above a threshold. The threshold is initially zero (i.e., an exact match), and is iteratively relaxed if later steps are unable to find a good region for the insertion.

Among regions that match the gap context, we want an example representing typical activity (i.e., that will not be out of place when inserted). We implement this using motif discovery. Motifs are frequently occurring patterns in time-series data [26], previously been used to detect characteristic activities in fine-grained sensor data [3,29]. We apply the 1-motif brute force algorithm described by Lin et al. [26], generalized to find the ten largest motifs among our matching regions of size k . We define our radius using

A: *Modify* receives a gap region and a target step count.



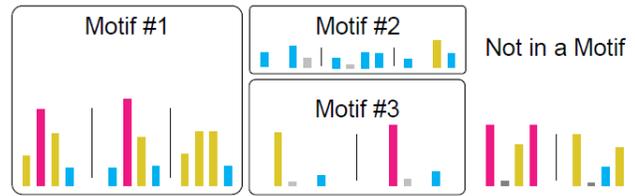
B: Obtain a week of activity and discretize it into nine symbols.



C: Identify realistic regions by comparing to the gap context.



D: Generate motifs from the realistic regions.



E: Select a motif containing regions within 10% of our target, select a random region, and *set* the gap to the sample.



Figure 2. The workflow of the *Modify* operation.

Levenshtein distance, requiring two regions assigned to the same motif have a distance less than $k/4$.

Each motif contains regions that are similar and found at many different locations in an activity history. Regions not assigned to any motif do not occur frequently enough to be good candidates for our gap (i.e., they may seem unusual or out of place). We select a motif containing regions with an average step count within 10% of our target. If no such motif exists, we relax the filter threshold to generate new motifs. We then select a random region from those within the selected motif, and *set* its values to our gap.

Offset Implementation

Figure 3 illustrates the workflow of *offset*. The prior operation implies a number of steps that need to be offset (in this case, 1800 steps were added in a region of size 4 and now need to be offset). We use a sliding window to consider all regions where we might add or remove the offset, using the same k from the prior operation and excluding regions modified by the operation being offset.

As with *modify*, we want a transformation consistent with historical activity. Specifically, we want an offset consistent with daily activity trends. If a sharer walks home daily at 5:00pm, it would be unwise to remove this consistent daily activity. We score each region by the difference between step

A: *Offset* receives the current and target number of steps.

Current: **9822** steps, Target: **8022** steps → Remove **1800**

B: Find all regions where step activity can be offset, and for each calculate the step count that would result if *offset* were applied.



C: For each region, compute the historical step activity at that time.



D: Score regions by the difference in step count between the potential offset and the average step count at that time of day.

Region 1 Score: **13**

Region 3 Score: **248**

Region 2 Score: **1086**

E: *modify* the best-scoring regions until a motif is found, and linearly scale the region to exactly match the target step count.



Figure 3. The workflow of the *Offset* operation.

count that would occur in the region after an offset versus the average step count at that same time of day in the historical data. We sort potential regions by this score and attempt to apply the offset to the region with the best score.

To apply the offset, we use *modify* to search for a motif that matches the region and is within 10% of the desired steps. If no motif is found for the best-scoring region, we try lower-scoring regions. If no motif is found for any region, we recursively apply two offsets of half the desired size (as more regions will be available for a smaller offset). Because the offset must be exact, we linearly scale the results of the *modify*. Note this adjustment is small, as the identified motif is already within 10% of the offset.

Implementation Details and Extensions

Our prototypes are implemented in C#, using the Windows Presentation Framework, accessing step data via the FitBit Intraday API. Based on informal experimentation, our *add* action currently adjusts activity 400 steps at a time.

Although our current implementation is effective and certainly sufficient for our empirical investigation, it could also be extended. Both *modify* and *offset* could consider additional information when transforming activity regions.

EMPIRICAL INVESTIGATION

Continuing our VSD approach, we next conducted an empirical investigation to elicit stakeholder values and concerns and to evaluate the interfaces developed in our technical investigation.

Study Design

Our study employed in-person semi-structured interviews. We first asked participants about their pedometer usage, including their motivation for using a pedometer, average activity level, and their self-reflection and sharing practices. We next asked them to consider our scenarios, first from the perspective of the sharer and then the recipient (a VSD technique first used by Czekis et al. [9]). Finally, we demonstrated each of our five interfaces on the activity data in our scenarios. For each, we again asked participants consider the perspective of the sharer and then the recipient. Interviews averaged 45 minutes (range 30-60).

Participants

We interviewed 12 participants (7 female) who regularly use pedometers. Participants were recruited from university mailing lists, forums for well-known pedometers, and the local Quantified Self forum. Participant averaged 34 years in age (range 23-53), averaged about 9,000 steps per day, and shared high-level activity summaries with an average of 4.33 people (range 0-13). Common recipients included friends (6 participants), co-workers (6 participants), siblings (3 participants), and significant others (3 participants). Primary motivation varied: 4 had a weight loss goal, 3 wanted to be aware of daily activity, and 3 wanted to track activity to look for patterns. For their device, 9 used a FitBit, 2 a Jawbone UP, and 1 a mobile phone application.

RESULTS AND DISCUSSION

We focus on findings that motivate design considerations in fine-grained physical activity sharing applications.

Is Fine-Grained Data Private?

Participants held a range of views on whether to share fine-grained data: five wanted to keep it private at all times, three felt comfortable sharing with close friends, and four were willing to open it to anybody interested. Among participants interested in sharing, many found it important to differentiate between social groups. P3 stated, “*I wouldn't mind sharing [my fine-grained activity] with my girlfriend, but I wouldn't want my professor to see it.*”

The transformation presented generally did not influence participant preferences for sharing fine-grained data. The seven participants interested in fine-grained sharing did not object to using the detailed single-day view. Some participants were also interested in the limited hours view, as they believed it was accurate yet kept some activity private. Four participants said their activity outside of typical limited hours is usually minimal or otherwise uninteresting, so not sharing it would be an improvement.

Discussion

We anticipated participants would react positively to the transformations developed to mitigate privacy concerns. However, participants remained concerned about with whom fine-grained data was shared. Because of the wide range of views on sharing fine-grained activity data, it is important any interface allow people to easily select whether to share and with whom to share.

Many participants discussed context as an important factor in how they feel about sharing fine-grained data. Combining data with other information, such as a user's Facebook stream or Twitter feed, raised additional concerns. Situations similar to Hunter not sharing his midday ride become more common when physical activity data can be combined with other context-revealing information, such as check-ins or status updates.

Motivations to Share Fine-Grained Data

Interviews corroborated the motivations for fine-grained sharing of physical activity identified in our conceptual investigation. Current participant practices are consistent with many of these motivations, which suggests they are important motivations for sharing.

For Accountability in Goals

P4 and her co-workers are trying to be more active, so they compete with rewards and good-natured punishments. She uses sharing to increase *accountability*: “*My teammates will know that I haven't met my step goal, so that's looming over my head, 'oh my gosh, gotta get these steps in!'*” She was excited about opportunities for *support*: “*I think the more information out there, the better. If it helps a friend of mine get more motivated and try to keep up with me...*”

Although P6 did not see value in fine-grained data for self-reflection or sharing, he discussed sharing as a motivational tool. He said, “*What I get out of having friends on FitBit... is just creating social pressure by reminding me that other people get more exercise than I do.*”

For Advice

P11 wanted different avenues for giving and receiving advice on activity. Regarding Ellen's scenario: “*If she has other people in her network who are active, they could say something like, 'oh, I see that you walk after dinner. We should just start walking together.'*” When considering giving advice to friends with which he shares, he suggested: “*It'll be like, 'oh, you woke up really early. We should go to the gym tomorrow because we both get up really early.'*” P10 wanted to share detailed activity in a public online community to get feedback. He said, “*That way I can get tips from people I don't know as to like, during this time... you really didn't have that much activity, or at this time you were really hitting that peak, what were you doing?*”

For Closeness

Of three participants who shared with their significant other, none mentioned closeness as a motivation. However, P1 and her sister used FitBits in a competition with the goal of losing weight. This started a trend toward them sharing more of their daily routines with one another. P7 suspected from pedometer activity that a former co-worker with recurring health problems had another incident: “*It would say, like, 'oh, he got 2000 steps average for the week...' oh my gosh, is everything ok?*” Although her friend was not using his pedometer to intentionally track his recovery progress, she deduced his status from his activity level.

Discussion

Participants interested in fine-grained sharing seemed most motivated by advice and detailed feedback, which we characterize as *support* and *accountability* in our conceptual investigation. Although participants described motivations around goal setting and closeness, they did not describe fine-grained sharing as supporting these goals. Fine-grained data may still have value for these motivations, but strong conclusions cannot be drawn until these approaches are deployed and examined *in situ*.

What is Useful to Share?

Two participants emphasized sharing data that recipients might find useful. P11 was willing to share with anybody interested, but focused on sharing noteworthy activity. P2 agreed, stating, “*By default, I wouldn't share anything unless I think it could in some way be useful to someone.*”

P9 was concerned about oversharing, especially in groups not centered on physical activity: “*I am slightly proud of [my activity]... there's always the issue on Facebook of oversharing, TMI, versus not. I wouldn't put everything up, but like, when I got the 4000 flights badge...*” P7 had a firsthand experience with oversharing, and reacted accordingly: “*I used to post [my weekly activity report] to Facebook... in the beginning we were all... giving each other posts and things, and that kind of tapered off.*”

Discussion

Applications should help avoid oversharing. Because frequent posts may overwhelm recipients, it should be easy to select with whom to share. Confining detailed data to a profile view may be a better alternative, while encouraging sharing of major achievements with a larger audience. Interested recipients could still investigate further without the sharer needing to be concerned about oversharing.

Deception

Two participants stated they would use the interfaces that support interactive transformation of their data. However, it can be awkward for participants to state this so directly. We therefore also asked whether *other* people might be interested in having such an interface, to which seven participants agreed. For example, P3 said, “*I can see the benefit of having such a function, but for me, personally, I'll just feel like a liar. I wouldn't use it.*”

P12 liked the idea of the deletion interface, especially in the context of sharing with co-workers: “*If I'm working, and I don't want anyone to know I was up at 2 o'clock. If I'm like, barely making it through the day... I don't want my employer to know that.*” P4 expressed interest in having the data transforming interface: “*I would like that [transformation] is there... Even if it's a bad thing. I would like that it would be there.*” and offered an example use: “*I sleepwalk a lot... if I hide that... it's trying to protect [my fiancé]... it's trying to keep him from worrying about me.*”

In discussing how other people might use interactive transformation, P9 suggested a parent and child relationship as an appropriate use: “*I think that if you were like, FitBit*

friends with your mom... I think doing that might be an interesting way to keep her late-night activity [private]." Three participants discussed sharing with a coach or doctor, but felt transformation was not appropriate for that relationship: *"I wouldn't want to do that either to my doctor or to myself. I want him to see the truth."*

Discussion

Participant concerns for data transformation focused on *honesty*. Although most did not offer examples of when they might use such capability in their own life, they were able to develop other scenarios. Together with the handful of participants who expressed explicit interest, this suggests interactive transformation warrants further examination. Extended *in situ* availability may reveal new use scenarios.

Effort Required

Six participants were concerned interactive deletion and transformation required too much effort from the sharer. P1 stated *"People have so much going on in their lives to think, 'oh, someone might look at my FitBit data...' it just seems like too much mental effort."* P8 thought it would be rarely used, but important: *"this kind of feature is nice to have, but I think rarely used... but that one use would be so critical."* Two participants mentioned concerns about remembering what transformations they had made when talking to their friends later. P11 noted: *"That could be useful ... there's a heavier cognitive load. Because then I have to remember that what other people see is not what I see."*

Discussion

We developed the deletion and transformation interfaces to give more control over how data is shared. The effort required to exert that control is a concern that should be explored in future designs. For example, a system might detect anomalous activity (e.g., Whitney's unusual late night activity) and pro-actively suggest transformation. This would reduce required effort, but preserve sharer control.

Current systems generally only support a choice between sharing or not sharing, which we believe is too limiting. Some participants offered additional approaches. P2 and P4 both suggested a view revealing an intermediate amount of information based on typical trends. P2 suggests: *"just your general patterns, 'I'm more of a morning person or an evening person', kind of like sharing a profile"*. P4 says: *"I think that would be awesome! I like seeing how often I'm active and how many steps I've gotten per hour."*

DESIGN CONSIDERATIONS

Through our conceptual, technical, and empirical investigations, we developed a set of considerations for applications that share fine-grained physical activity data.

Mitigate Oversharing

Multiple participants expressed concern about oversharing. We suspect that this can be improved with a more tiered approach. A Facebook-style news feed of the detailed physical activity of friends may be overwhelming, but it may be more appropriate to display major accomplishments or events and allow recipients to seek more detail as desired.

This could place detailed activity where interested recipients could find it, without overwhelming others.

Emphasize Effortless Sharing

Participants felt interactive transformation required too much effort. Some reported that, if concerned about *privacy* in a particular instance, they would perhaps share a higher-level summary. They believed this supports *honesty* while reducing both the time and effort required. But as we have previously noted, unexpectedly not sharing can also present challenges for recipient *trust*. Designs that enable more pro-active or even automatic transformation can be envisioned (e.g., detecting unusual activity and suggesting hiding or transforming it). Designs might also automatically consider other contextual information (e.g., the location of activity). Further research should explore implications of and reactions to such designs.

Support Intermediate Levels of Sharing

Some participants felt 5-minute step intervals infringed *privacy* by allowing inference of too much about a sharer's activity. But participants suggested new intermediate points between this and current high-level summaries. Sharers might configure intermediate intervals (e.g., steps per hour) or share high-level summaries about their activity patterns. Such intermediate representations may help some sharers balance *support* and *accountability* with their *privacy*.

CONCLUSION

We have used Value Sensitive Design to investigate human values and tensions in interfaces for fine-grained sharing of sensed physical activity data. By developing scenarios to highlight value tensions and stakeholders, we captured the results of our conceptual investigations in a more concrete form. Our technical investigations examined how a set of transformations relate to our value tensions and developed a novel approach to interactive transformation that allows removing private data while preserving data invariants important to the benefits of sharing. We then conducted value-oriented semi-structured interviews and learned how people respond to fine-grained sharing. Finally, we enumerate design considerations for future applications.

Further evaluation of this value sensitive approach would strengthen our ability to make prescriptive design recommendations. Future work would extend the empirical investigation to a field deployment, allowing participants to experience real-world reactions to transforming their data. The field deployment would also assess whether the interactive transformation is effective in actual use.

We have explored only fine-grained pedometer data, but other domains may also benefit from fine-grained sharing. For example, the StepGreen and UbiGreen applications explore high-level sharing in environmental applications [13,28]. Disaggregated sensing could enable fine-grained sharing of in-home utility usage [14,15], which may increase *support* and *accountability*. One direction for future work will be investigating values and value tensions in other domains to generalize the insights developed here.

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REFERENCES

1. Bales, E., Li, K.A., and Griswold, W. CoupleVIBE: Mobile Implicit Communication to Improve Awareness for (Long-Distance) Couples. *CSCW 2011*, 65–74.
2. Barkhuus, L. and Dey, A. Location-Based Services for Mobile Telephony: A Study of Users' Privacy Concerns. *Interact 2003*, 207–212.
3. Berlin, E. and Van Laerhoven, K. Detecting Leisure Activities with Dense Motif Discovery. *UbiComp 2012*, 250–259.
4. Camp, J. and Connelly, K. Beyond Consent: Privacy in Ubiquitous Computing (UbiComp). In *Digital Privacy: Theory, Technologies, and Practices*. Auerbach Publications, New York and London, 2008, 327–343.
5. Choe, E.K., Consolvo, S., Watson, N.F., and Kientz, J.A. Opportunities for Computing Technologies to Support Healthy Sleep Behaviors. *CHI 2011*, 3053–3062.
6. Consolvo, S., Everitt, K., Smith, I., and Landay, J.A. Design Requirements for Technologies that Encourage Physical Activity. *CHI 2006*, 457–466.
7. Consolvo, S., Smith, I.E., Matthews, T., LaMarca, A., and Tabert, J. Location Disclosure to Social Relations: Why, When, & What People Want to Share. *CHI 2005*, 81–90.
8. Cornwell, J., Fette, I., Hsieh, G., Prabaker, M., Rao, J., Tang, K., Vaniea, K., Bauer, L., Cranor, L., Hong, J., McLaren, B., Reiter, M., and Sadeh, N. User-Controllable Security and Privacy for Pervasive Computing. *HotMobile 2007*, 14–19.
9. Czeskis, A., Dermendjieva, I., Yapit, H., Borning, A., Friedman, B., Gill, B., and Kohno, T. Parenting from the Pocket: Value Tensions and Technical Directions for Secure and Private Parent-Teen Mobile Safety. *SOUPS 2010*.
10. FitBit. <http://www.fitbit.com/>.
11. Friedman, B., Kahn, P.H., and Borning, A. Value Sensitive Design and Information Systems. *Human-Computer Interaction and Management Information Systems: Foundations*, (2006), 348–372.
12. Friedman, B., Smith, I., Kahn, P.H., Consolvo, S., and Selawski, J. Development of a Privacy Addendum for Open Source Licenses: Value Sensitive Design in Industry. *UbiComp 2006*, 194–211.
13. Froehlich, J., Dillahunt, T., and Klasnja, P. UbiGreen: Investigating a Mobile Tool for Tracking and Supporting Green Transportation Habits. *CHI 2009*, 1043–1052.
14. Froehlich, J., Larson, E., Campbell, T., Haggerty, C., Fogarty, J., and Patel, S.N. HydroSense: Infrastructure-Mediated Single-Point Sensing of Whole-Home Water Activity. *UbiComp 2009*, 235–244.
15. Gupta, S., Reynolds, M., and Patel, S. ElectriSense: Single-Point Sensing Using EMI for Electrical Event Detection and Classification in the Home. *UbiComp 2010*, 139–148.
16. Hays, J. and Efros, A.A. Scene Completion Using Millions of Photographs. *SIGGRAPH 2007*.
17. Hwang, K.O., Ottenbacher, A.J., Green, A.P., Cannon-Diehl, M.R., Richardson, O., Bernstam, E. V., and Thomas, E.J. Social Support in an Internet Weight Loss Community. *International Journal of Medical Informatics* 79, 1 (2010), 5–13.
18. Iachello, G., Smith, I., Consolvo, S., Abowd, G.D., Howard, J., Potter, F., Scott, J., Sohn, T., Hightower, J., and LaMarca, A. Control, Deception, and Communication: Evaluating the Deployment of a Location-Enhanced Messaging Service. *UbiComp 2005*, 213–231.
19. Jawbone UP. <http://jawbone.com/up>.
20. Kay, M., Choe, E., Shepherd, J., Greenstein, B., Watson, N., Consolvo, S., and Kientz, J.A. Lullaby: A Capture & Access System for Understanding the Sleep Environment. *UbiComp 2012*, 226–234.
21. Klasnja, P., Consolvo, S., Choudhury, T., and Beckwith, R. Exploring Privacy Concerns about Personal Sensing. *Pervasive 2009*, 176–183.
22. Klasnja, P., Consolvo, S., McDonald, D.W., Landay, J.A., and Pratt, W. Using Mobile & Personal Sensing Technologies to Support Health Behavior Change in Everyday Life: Lessons Learned. *AMIA 2009*, 338–342.
23. Kostakos, V., Venkatanathan, J., and Reynold, B. Who's Your Best Friend? Targeted Privacy Attacks In Location-Sharing Social Networks. *UbiComp 2011*, 177–186.
24. Krumm, J. Inference Attacks on Location Tracks. *Pervasive 2007*, 127–143.
25. Li, I., Dey, A., and Forlizzi, J. A Stage-Based Model of Personal Informatics Systems. *CHI 2010*, 557–566.
26. Lin, J., Keogh, E., Lonardi, S., and Patel, P. Finding Motifs in Time Series. *SIGKDD 2002*, 53–68.
27. Lin, J.J., Mamykina, L., Lindtner, S., Delajoux, G., and Strub, H.B. Fish' n' Steps: Encouraging Physical Activity with an Interactive Computer Game. *UbiComp 2006*, 261–278.
28. Mankoff, J., Fussell, S.R., Dillahunt, T., Glaves, R., Grevet, C., Johnson, M., Matthews, D., Matthews, H.S., Mcguire, R., Thompson, R., Shick, A., and Setlock, L. StepGreen.org: Increasing Energy Saving Behaviors via Social Networks. *ICWSM 2010*, 106–113.
29. Minnen, D. and Starner, T. Discovering Characteristic Actions from On-Body Sensor Data. *ISWC 2006*, 11–18.
30. Munson, S.A. and Consolvo, S. Exploring Goal-Setting, Rewards, Self-Monitoring, and Sharing to Motivate Physical Activity. *PervasiveHealth 2012*, 25–32.
31. MyFitnessPal. <http://www.myfitnesspal.com/>.
32. Mynatt, E.D., Rowan, J., Jacobs, A., and Craighill, S. Digital Family Portraits: Supporting Peace of Mind for Extended Family Members. *CHI 2001*, 333–340.
33. Page, X., Knijnenburg, B., and Kobsa, A. What a Tangled Web We Weave: Lying Backfires in Location-Sharing Social Media. *CSCW 2013*, 273–284.
34. Skeels, M.M., Unruh, K.T., Powell, C., and Pratt, W. Catalyzing Social Support for Breast Cancer Patients. *CHI 2010*, 173–182.
35. Sweeney, L. K-Anonymity: A Model for Protecting Privacy. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems* 10, 05 (2002), 557–570.
36. Tang, K.P., Lin, J., Hong, J.I., Siewiorek, D.P., and Sadeh, N. Rethinking Location Sharing: Exploring the Implications of Social-Driven vs. Purpose-Driven Location Sharing. *UbiComp 2010*, 85–94.
37. Toscos, T., Faber, A., Connelly, K., and Upoma, A.M. Encouraging Physical Activity in Teens: Can Technology Help Reduce Barriers to Physical Activity in Adolescent Girls? *PervasiveHealth 2008*, 218–221.