StoryMap: Using Social Modeling and Self-Modeling to Support Physical Activity Among Families of Low-SES Backgrounds

Herman Saksono Harvard University, Cambridge, MA, USA hsaksono@seas.harvard.edu Carmen Castaneda-Sceppa Northeastern University, Boston, MA, USA c.sceppa@northeastern.edu Jessica A. Hoffman Northeastern University, Boston, MA, USA j.hoffman@northeastern.edu

Magy Seif El-Nasr University of California at Santa Cruz, Santa Cruz, CA, USA mseifeln@ucsc.edu Andrea G. Parker School of Interactive Computing, Georgia Institute of Technology, Atlanta, GA, USA andrea@cc.gatech.edu

ABSTRACT

Physical activity (PA) is crucial for reducing the risk of obesity, an epidemic that disproportionately burdens families of lowsocioeconomic status (SES). While fitness tracking tools can increase PA awareness, more work is needed to examine (1) how such tools can help people benefit from their social environment, and (2) how reflections can help enhance PA attitudes. We investigated how fitness tracking tools for families can support social modeling and self-modeling (through reflection), two critical processes in Social Cognitive Theory. We developed StoryMap, a novel fitness tracking app for families aimed at supporting both modes of modeling. Then, we conducted a five-week qualitative study evaluating StoryMap with 16 low-SES families. Our findings contribute an understanding of how social and self-modeling can be implemented in fitness tracking tools and how both modes of modeling can enhance key PA attitudes: self-efficacy and outcome expectations. Finally, we propose design recommendations for social personal informatics tools.

CCS CONCEPTS

Human-centered computing;
Collaborative and social computing;

KEYWORDS

Health, Family, Physical Activity, Social Cognitive Theory, Social Modeling, Self-Modeling, Self-Efficacy, Low-SES

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1 INTRODUCTION

Obesity is an epidemic that disproportionately burdens households of low-socioeconomic status (SES) backgrounds in the United States (U.S.) [55]. This epidemic poses numerous chronic health issues, such as cardiovascular diseases and diabetes [59, 72]. Although obesity can be prevented by regular physical activity (PA) and a healthy diet, low-SES households face many barriers to being active [19, 44]. These barriers include limited time due to burdensome jobs and also limited PA facilities. Therefore, obesity preventions need to be prioritized for households of low-SES backgrounds.

For more than a decade, Human-Computer Interaction (HCI) research has examined how personal informatics tools (e.g., fitness trackers) can support PA. This body of work has examined design strategies that can positively impact PA, such as novel visualizations [16, 47], goal-setting tools [29, 45, 50, 54], reflection support [10, 12, 42], as well as fitness comparison tools [53, 58]. Indeed, these studies give us insights on how to design tools to support PA. However, designing impactful fitness tracking tools also requires an understanding of how such tools can facilitate the development of positive health attitudes [40], such as self-efficacy [34, 71]. For example, although many studies have examined how individuals reflect on their PA experiences (e.g., in Fitbit Plan, Reflection Companion, Visualized Self) [12, 42, 45, 64], more work is needed to advance this field. More specifically, more work is needed to examine the theoretically grounded processes in which reflection can impact health attitudes. Furthermore, even though PA behavior among adults and children is linked to social factors such as family support [34, 71], only a few works have examined how personal informatics tools can help people leverage social influences [53, 58]. In fact, children PA is influenced by parental support [34] via involvement, encouragement, and facilitation [31]. Thus, by targeting caregivers (e.g., parents), fitness trackers can positively support the caregivers as well as their children in being active. In short, we need to examine how personal informatics can be more social and enhance PA attitudes, especially in families.

To this end, we sought to examine how technology can support self-modeling and social modeling for promoting PA attitudes.

These two modes of modeling are important processes in Social-Cognitive Theory (SCT), a well-established theory that explains how human cognition, human behavior, and their social environment reciprocally influence each other [3–7]. Self-modeling is reflecting on one's best performances in the past [3:71, 21] and social modeling is observing similar people's performances [3:47, 7:270]. Furthermore, in SCT, health behavior is induced by two attitudinal factors: self-efficacy and outcome expectations [3:391, 4:22, 5:627]. Self-efficacy is our belief about our ability in completing a task (e.g., being active regularly). Outcome expectations are our beliefs in what happens if we do the task (e.g., tired, injured, becoming healthy).

Guided by SCT, we developed a smartphone app prototype called StoryMap to answer this research question: how can technology be designed to (1) facilitate self-modeling as well as social modeling, and (2) positively impact PA attitudes? To answer this research question, we conducted a five-week field study with 16 families of low-SES backgrounds using data-driven retrospective interviewing (DDRI) [68]. This method uses log data to help participants explain their experiences.

Through our naturalistic study, we provide three key contributions. First, we demonstrate the caregivers' cognitive processes during self- and social modeling in the context of fitness tracking, and personal informatics generally. During these processes, users elicited and exchanged four key pieces of information about PA experiences: information related to one's sense of adequacy, tasks that one can undertake to be active, emotions that arise during PA, and peers' behavioral norms. Such information has the potential to enhance PA self-efficacy and outcome expectations. By understanding these processes, researchers and designers can develop personal health informatics systems that are aligned with the way humans process personal and social information. Second, we demonstrate how DDRI can be used to study participants' cognitive processes in a naturalistic field study. Finally, our findings and design guidelines expand the HCI community's understanding of how SCT constructs can be translated into the design and evaluation of personal informatics systems [33], especially given that many mHealth studies are not theoretically-grounded [70]. Furthermore, through our theoretical contributions, we encourage researchers to further explore how SCT can be used for designing social health technologies and also test our guidelines across different health domains, user characteristics, and sociocultural contexts [33].

2 RELATED WORK

2.1 Social Cognitive Theory (SCT)

Introduced by Albert Bandura, SCT posits that human behavior is an interplay of human cognition and humans' interactions with their environment [3–7]. Thus, humans are not simply passive bodies who are triggered solely by external stimuli, nor fully autonomous beings that completely ignore their social environment. Rather, humans actively observe their surroundings, develop attitudes from these observations, and in effect, these attitudes guide humans' complex patterns of behavior.

As we have stated, according to SCT, human behavior is induced by two attitudinal factors: *self-efficacy* and *outcome expectations* [3:391, 5:627]. Additionally, *impediments* that we face often readily constrain our behavior (e.g., limited time, no PA facilities). The

importance of SCT as a model of human behavior has been demonstrated by review papers on health that show self-efficacy is a key predictor of PA behavior [34, 71]. SCT also argues that self-efficacy and outcome expectations can be enhanced by self-modeling and social modeling. Table 1 shows the key constructs in SCT.

Self-modeling is learning by observing our behavior but specifically focused on our successes at performing a task [3:21, 71]. Traditionally, self-modeling is done by videotaping the performance of a person, editing out the less desirable performances, and then asking the person to review the best performances [21]. However, Dowrick also argues that self-modeling can be reenacted in other ways, for example, by remembering best performances [21]. Therefore, a potential mode of self-modeling is through reflections on past experiences from a positive lens.

Indeed, HCI researchers have investigated how technologies can support reflections on past experiences. For example, Echo, MAHI, Pensieve, and Visualized Self [12, 36, 48, 56]. The evaluations of these prototypes show that remembering memories of the past can help people gain insights about their PA [12], enhance well-being [36], and improve diabetes self-management [48]. Furthermore, Baumer has theorized the dimensions of reflection (i.e., breakdown, inquiry, transformation) [9]. As these findings and model provide insights into the dimensions and the positive effect of reflections, an important next step is to investigate the process of reflections and how it impacts health behavior attitudes. By doing so, we can design technology-mediated reflections that match the way humans process their experiences and make the technology more impactful. Here, we argue that self-modeling is a form of reflection that is focused on positive experiences aimed at enhancing behavioral attitudes.

Social modeling is learning by observing the behavior of other people performing a task [3:47, 7:270]. This modeling can be performed directly by observing people's actions, or indirectly through symbols (e.g., stories, imageries).

A few HCI studies have also investigated how health technologies can help people benefit from their social environment, for example, Citisenze Maker, EatWell, and StepStream [30, 53, 58]. These studies show that learning other people's behavior can help people pick reasonable goals [58], gain a feeling of social support [53], and get motivated to engage in healthy behavior [30]. However, designing more impactful systems requires an understanding of the processes that could impact key health attitudes [40], such as self-efficacy and outcome expectations. Thus, more work is needed to examine the process of social modeling in health technologies.

Moreover, given the myriad of events that happen in our social environment, supporting social modeling requires supporting the human's attentional process to focus on relevant observations [3:51, 7:272]. More specifically, social modeling is more effective by observing people similar to us [3:302,403]. However, there remains a question of what constitutes as similar. The notion similarity can be from material observations (e.g., similar gender or similar physical appearances) [28, 51]. But similarity can also be interpretative (e.g., perceived model's ability) [11]. Therefore, a potential mode of social modeling is enhancing people's attentional process to focus on PA success stories from similar people, either through a material or interpretative similarity.

Table 1: Key constructs in Social Cognitive Theory [3-7]

Construct	Definition
Self-efficacy	A person's belief about their ability in completing a task appropriately. A task is the steps taken to complete the behavior of interest
Outcome expectations	A person's beliefs in what happens after they perform the task.
Impediments	Personal or external challenges that limit a person's ability to do the task.
Self-modeling	Learning by observing own behavior but focused on the successes at performing the task.
Social modeling	Learning by observing how other people performs a task.
Internal Standards	A person's beliefs about the value of a behavior.
Social Standards	A person's beliefs about how other people value a behavior.
Adequacy	A person's belief about what constitutes as sufficient behavior.

In short, prior work has examined how technologies can support reflection and social comparison. However, Klasnja et al. argued that research on novel health technologies needs to examine in what ways such technologies can impact people [40]. Thus, to advance research in this field, we argue for the need of examining the processes that facilitate self- and social modeling. Furthermore, given that social modeling is more impactful if the observer perceived that they share similar characteristics with the model, we also need to investigate how to convey model similarity in health technologies.

2.2 Physical Activity Technologies

The field of personal informatics [46] has examined how fitness tracking data can be enhanced with novel design elements. *Metaphorical visualizations* are design elements that help users feel more connected with their data (i.e., using a fish tank, flower garden, and spaceship fuel metaphors to visualize PA data [16, 47, 67]). *Goal-setting tools* are design elements that help people pick and manage their fitness goals (e.g., Bounce, Fitbit Plan, GoalPost, Habito [29, 45, 50, 54]). *Reflection support* is a design element aimed at helping people gain insights about their behavior (e.g., VisualizedSelf, Health Mashups, Reflection Companion [10, 12, 42]). *Social comparison* is a design element that helps people gain behavioral insights from their peers (e.g., Citisenze Maker, StepStream [53, 58]).

Findings from these studies revealed open questions that can be investigated to make personal informatics more impactful. First, although novel metaphorical visualizations can enhance behavioral awareness [16, 47], they need to provide behavioral support to help users maintain the desired behavior [40], for example through goal setting [15, 54]. Furthermore, consistent with SCT, people are more committed to their fitness goals if the goals are linked to their aspirations [45, 64]. Second, personal data reflections indeed help people to gain deeper insights into their behavior [10, 12]. But, observation solely on past behavior has limited value [29] because, from SCT's standpoint, observing past behavior does not guide people towards immediate action [3:338]. People tend to value observations that guide them to make near-term changes. Finally, studies on social comparison designs show that information about a person's social circle's behavior can help them make sense of their behavior and also enhance the feeling of social support [53, 58].

Although these findings informed us on how to design impactful fitness tracking tools, there remain research gaps that need to be investigated. First, many of these tools are designed for individual use, although prior studies overwhelmingly show that interpersonal relationships, such as those in families, are important sources of PA support [34, 71]. Second, while there is a wealth of studies on the kind of insights that people gained when they are reflecting on their PA experiences [10, 12, 64], more work is needed to understand how reflection can facilitate the development of positive PA attitudes (e.g., self-efficacy). Finally, while social environment shapes health behavior, only a few works on fitness tracking examined how people benefit from an increased awareness of their peers' PA behavior [53, 58]. Still, these important studies have not fully explained in what ways social influences are beneficial for health promotion.

In conclusion, we highlight the potential of self-modeling and social modeling in enhancing PA self-efficacy and outcome expectations. We also argue for the need to investigate how fitness trackers can support the processes of self-modeling (i.e., reflection) and social modeling towards the development of positive PA attitudes in a family setting, especially in low-SES contexts where PA resources are limited.

3 METHOD

We developed the StoryMap prototype to examine how technology can facilitate self-modeling and social modeling and support health attitudes, more specifically self-efficacy and outcome expectations. We then conducted a five-week qualitative study to examine the cognitive processes when caregivers used a self- and social modeling technology in a naturalistic setting. That is, how caregivers used such technologies amid barriers related to low-SES and COVID-19 pandemic. To do so, we used the Data-Driven Retrospective Interviewing (DDRI) method [68].

This study was conducted from April to July 2020, which was the beginning of the COVID-19 pandemic in the U.S. To maintain social distancing, we conducted our study over the phone. Our university's ethics board approved the study protocol. In this section, we will discuss StoryMap's design rationale followed by the study design.

3.1 StoryMap Prototype Design

We developed StoryMap (Figure 1) on top of an existing opensourced Android app called Storywell [63, 65]. We extended Storywell design by adding the community story map in which caregivers can record and share PA stories and listen to other

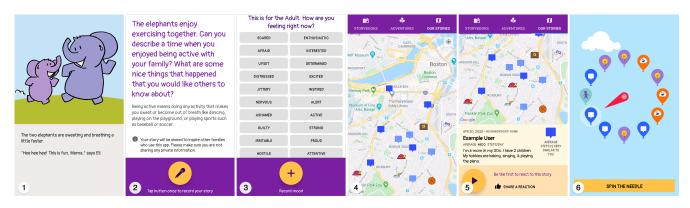


Figure 1: StoryMap Screenshots. (1) A family begins with reading a storybook, then (2) the caregiver shared a community story. After that, (3) the caregiver logs their emotions which we will use for the interviews. (4) Families can see other families' community stories on the story map, and (5) listen to the stories. If a family missed their goal, (6) they can spin the magic needle and get the *listen to a community story* balloon. Doing so will unlock the story. Note: this figure does not show the actual locations of community stories.

families' stories as well. Next, we will discuss the user scenario and the design rationale of StoryMap.

3.1.1 User Scenario. In StoryMap, families begin by reading a PAthemed storybook (Figure 1.1). At the end of each chapter, StoryMap asks the family to do one of these activities: (1) record answers to a set of reflection questions, or (2) record and share a community story — a personal story that other families can listen to (Figure 1.2). By default, a community story is accompanied by metadata about the caregiver who shared the story. The metadata includes caregivers' neighborhood, approximate age, number of children, hobby, and average seven-day steps. After sharing a story, StoryMap will ask the caregiver to log their emotion at that moment (Figure 1.3). The emotion logs were used to drive the interviews, which we will discuss in section 3.2.

We made the following designs to protect the family's privacy and provide more autonomy. First, StoryMap added a random 3 miles offset when placing community story marker on the map. Caregivers also have the option to change the marker location to a nearby landmark. Second, caregivers have the option to select which metadata to disclose when they share a story. Finally, to protect children's privacy, StoryMap only invites caregivers to share community stories

Next, similar to Storywell, to continue reading the next chapter, the caregiver and the child must choose a one-day step count goal. StoryMap uses MiBand 2 (we provided the bands) to track step counts because of their accuracy, long battery life, and low cost [46]. If the family members completed their goals, they can unlock the next chapter.

If the family misses their goal, they may continue using the app by spinning the magic needle to randomly get one of the exit balloons (Figure 1.6). In addition to Storywell's three exit balloons (i.e., bypass, fitness tip, and pick another challenge balloons), we also added the *listen to a community story* balloon. This balloon asks the family to listen to other families' stories in the community story map to unlock the next chapter.

The community story map shows other families' community stories as markers on the city's map (Figure 1.4). When a user taps

on a marker, StoryMap will show the player sheet for listening to the story (Figure 1.5). It also shows the metadata of the caregiver who shared the story. To ensure the story content is appropriate and does not contain personal information, the research staff reviewed the community stories before they were made available to other users.

3.1.2 Design Rationale. The purpose of the storybooks in StoryMap is to provide families with social rewards [63], and to prime families for discussing PA as a means of self- and social modeling. We developed eight storybooks [61] through workshops with health and HCI researchers. Then, a community organization focused on children's literacy reviewed the storybooks and provided feedback on the stories that we used to further iterate on them. The goal of this process was to ensure that the story themes, health messages, and language complexity are appropriate.

We implemented *self-modeling* as reflection questions and community story prompts. The questions were designed for children and caregivers to remember their past positive experiences in being active [66]. Each set of reflection questions consists of a broad experience question, a focusing question, and a closing statement. For example, families begin with reflecting on their physical activity experiences broadly, then focus on the specific aspect of their experiences (e.g., self-efficacy, enjoyment, supportive people, comfortable places). The closing statement is aimed at helping caregivers and children conceptualize meanings in their PA experiences [43, 64]. Below is an example of a three-part reflection question:

- Can you tell a time when you tried a new physical activity that was hard at first?
- How did that activity become easier when you tried it again?
- Being active does not happen overnight. Starting with small activities and repeating them often can make physical activity easier to do.

The community story prompts (for the caregivers) have a similar structure. The only difference is the broad experience question and the focusing question is merged into one question. The aim is to simplify the story sharing process. Below is an example of a community story prompt:

"Can you describe a time when you enjoyed being active with your family?

What are some nice things that happened that you would like others to know about?"

We implemented *social modeling* as the community story map (Figure 1.4). StoryMap sought to facilitate social modeling by enabling families to listen to other families' success stories. This is symbolic social modeling because the behavior is indirectly observed through symbols (i.e., stories). We also placed the stories on a neighborhood map because social interactions in neighborhood places can help people develop a sense of connectedness [62].

Additionally, social modeling is more impactful when individuals feel the model is similar to them [11, 28, 51]. Therefore, to better facilitate modeling, health informatics tools should provide features that highlight salient aspects of the model and thus capture users' attentional process. But aspects of the model's similarities that capture users' attention remains unexplored in the field of personal informatics, as well as how users understand these similarities [35]. Therefore, to examine how to support social modeling by similarity, we designed the story viewer (Figure 1.5) to display metadata about the caregiver who shared the story. To support identifying similarity from objectively measured ability information, StoryMap shows the caregivers' step count. This design is guided by Braaksma et al.'s work that shows ability information is important for observational learning [11]. To support similarity based on subjectively constructed ability information, StoryMap shows the caregiver's approximate age, the number of children, and their neighborhood. These pieces of information are subjective because they do not directly show PA ability, but act as a proxy that could determine PA behavior. Additionally, neighborhood information also acts as a proxy indicator of SES, which is also a PA correlate [71]. Collectively, showing these pieces of information enabled us to examine how such information affects the feeling of similarity.

3.2 Study Design

We recruited families from family-focused community organizations in a Northeast U.S. city. Families were eligible to participate if: (1) they had at least one child aged 3-8 years, (2) owned an Android phone, and (3) met the low-SES criteria (i.e., eligible for the state-based health insurance program for low-income families or lived in low-SES neighborhoods). We conducted the study from April to July 2020 when the COVID-19 pandemic began in the U.S. One month before the interview with the first participant, the governor ordered schools to close and issued a stay-at-home advisory. Thus, to ensure the safety of the family participants and the research staff, all of the participant's interactions were conducted over the phone and the Mi Band 2s were mailed to the participants. Participants can keep the bands after the study.

This five-week study consisted of one week for baseline data collection and four weeks for the intervention. We conducted the three interviews during the first meeting, then three and five weeks after the first meeting.

Each family can receive up to \$160 in gift cards for their study participation. At the end of every interview, each caregiver received a \$40 gift card. Caregivers who completed the study also received an extra \$40 gift card. The \$40 compensation is about 2.5 times

the city's hourly living wage. This is to compensate caregivers' time in participating in the interview during the difficult COVID-19 pandemic and also for using StoryMap throughout the study.

3.2.1 Data Collection and Analysis. In the first session, we asked the caregiver to fill out an online survey which includes the caregiver's 7-day PA [37], and the caregivers' perception of their children's PA [132]. After that, we helped them to set up StoryMap and the fitness bands on their phone. We asked them to wear the bands daily and to check StoryMap at least once a week. Then, we informed the caregiver that they can start choosing fitness challenges in one week. This is to allow StoryMap to collect baseline fitness data for determining fitness challenges. Finally, we conducted the first interview with the caregiver. After two and five weeks, we conducted the second and final interviews, respectively.

To better examine caregivers' cognitive processes when using StoryMap in a naturalistic setting, we used DDRI [68], which is an approach for conducting an in-depth examination of users' experience. The DDRI approach was applied in this study as follows. After a family responded to a reflection question or shared a story, StoryMap prompted the caregiver to log their emotion (Figure 1.3). The list of emotions was taken from a Positive and Negative Affect Schedule (PANAS) questionnaire [161]. StoryMap also kept a log of users' interactions within the app. We used the combination of emotion and interaction log to help caregivers remember their experiences during the interviews. Figure 2 shows an example of a DDRI log. The complete example log is included in the Supplementary Material.

The semi-structured interviews were organized as follows. In the first session, we interviewed the caregivers to understand their attitudes and perceptions on PA as well as barriers that they may face in being active. We focused on the caregivers in these interviews

Family 07's Moments

Wed, May 13, 2020 - Tue, May 19, 2020

Tue, May 19, 2020 Caregiver: 3792 steps, child: 7164 steps 8:08 PM Completed family fitness challenge. 8:08 PM Unlocked a story chapter in: Have You Ever Seen a Unicorn?. 8:08 PM Read a storybook: Have You Ever Seen a Unicorn? 8:11 PM Caregiver 7 shared a community story Question: Discovering a unicorn is new for Edith. Tell a story about when you tried a new physical activity. Did you face any challenges? How did you deal with those challenges? "I remember when I face the challenge [in being active]. It was Zumba. It was a lot of work, it was active, it was going, it was fun, But, a lot of work, How did I deal with it? Just kept trying. Practice make perfect. Keep trying, and trying, and trying. Until I had fun with it." 8:12 PM Child 7 logged this emotion: Happy, Laugh. 8:12 PM Caregiver 7 logged this emotion: Excited, Active, Strong, Proud. 8:13 PM Picked a fitness challenge. Caregiver: 3880 steps, child 7030 steps.

Figure 2: An example DDRI log that we used in the interviews

because of the challenge of engaging young children in phone interviews. Understanding caregivers' perspectives is our first step in designing family health apps. In the second, and third sessions, we investigated caregivers' experiences with StoryMap. We began by first emailing the caregivers their DDRI logs. Then, we reviewed the log with the participants to help them remember and explain their experiences, specifically their experiences in using the reflection, the story sharing, and the community story map feature. I also investigated the challenges they faced, especially how the COVID-19 pandemic might have affected their ability to use the fitness app optimally. Throughout the study, we continuously refine the interview guide to capture the concepts we identified in our analysis. The final interview guide is included in the Supplementary Material.

The median duration of the first, second, and third interviews was 25, 28, and 41 minutes, respectively. In total, we conducted over 26 hours of interviews across the three sessions and accumulated a total of 672 pages of transcripts.

We analyzed the interview data using the *constant comparative method* [17]. The steps are as follows. (1) We conducted open coding on the interview transcripts. While we were informed by SCT constructs during the analysis, we did not deductively look for those concepts during the open coding stage. (2) We wrote memos to capture the preliminary analysis (*n*=38 pages). (3) Using the initial concepts that we identified from the initial coding, we conducted theoretical sampling by probing and comparing the concepts in the subsequent interviews. (4) We grouped the concepts to develop higher-level categories. While initially we distanced ourselves from SCT constructs to avoid interpreting the data prematurely, at this point, we began using SCT constructs to further explain the findings. (5) We linked the categories and subcategories to identify their relationships.

3.2.2 Participants Overview. We recruited 16 caregivers and 16 children from 16 families. The caregivers' median age was 34 (IQR=10) and the children's median age was 6 (IQR=2). All of the caregivers were women; 10 children were girls and 6 were boys. Twelve caregivers self-identified as Black and four self-identified as White. Three caregivers self-identified as Hispanic. Nine families were single-caregiver households and seven were dual-caregiver households. The median household size was four and the median number of children was two. Most of the caregivers' highest educational level was some college or vocational training (n=6) or college (n=5). The median income group was US\$ 23,017 or less (n=8). As a comparison, the city's median income was US\$65,883. More detailed information about the participants is included in the Supplementary Material.

Caregivers' median self-reported PA frequency was 1-2 bouts of PA in the previous week, which is below the recommended PA level [57]. Caregivers also reported that their children's median PA frequency in the previous week was five bouts of 60+ minutes of PA, which is also slightly below the recommended PA level for children [57].

4 FINDINGS

Throughout the four-week intervention, caregivers shared a total of 86 community stories (*mean*=6 stories, *SD*=6). On average, families opened the StoryMap app 17 times (*SD*=12). Our qualitative

analysis characterized how reflection and storytelling can enhance PA attitudes, namely self-efficacy and outcome expectations. In this section, we will discuss the characteristics of self-modeling (Section 4.1) and social modeling (Section 4.2). Finally, we will discuss findings about the impediments that families face in being physically active, which limit the impact of health technologies (Section 4.3).

4.1 Reflection as Self-Modeling

For the caregivers, reflecting on family PA experiences evoked exercise memories from the past, and such evocations helped caregivers relive the emotions they felt in those past experiences (n=11). We also found that such emotions can reinforce outcome expectations for being active. For example, P7 logged the inspired emotion after reflecting on her experience of doing sit-ups with her son. She explained that she reached those emotions after the reflection because being active as a family was valuable for her:

P7: When we were doing our sit-ups, it felt good just to watch him [, my son,] do it too. If I'm active or I'm doing something active or doing a different activity, then he likes to do it as well. And so that's really why [I experienced positive emotion remembering it].

Similar to P7's experience above, the positive effect of remembering was also discussed by P4 when she was proud that she supported her daughter to learn how to ride a bike. She explained how remembering can lead her to bring past events to the present, and doing so will evoke the emotions of those events:

P4: When I think about things I used to do with the kids, and what made them happy, laughing, have fun... it brings it from the past, and it brings it back to the present. And it puts me back in that moment because it's a memory I have that I'll never lose. And it was a happy, joyful time for me and something that I cherish.

In short, these accounts show that reflections of positive experiences can lead to remembering that evoked positive emotions. However, the effects of reflection go much further. Reflections can help people (1) identify their abilities and emotional outcomes of the task and also (2) identify discrepancies in their behavior.

4.1.1 Reflections Identify Abilities and Emotional Outcomes. As a result of reflections, some caregivers expressed (1) enhanced perceptions of their abilities and also (2) the desire to repeat the activities. The effect of reflections on **enhancing ability perceptions** (n=3) is exemplified by P9's quote:

P9: [Reflection] just makes us realize. Before, we weren't thinking about how active we were.

Here, P9 explained that remembering being active made her realize that her family has always been active. Similarly, P3 experienced strong emotion after reflecting on the time when she won a sports game:

P3: We came out victorious. We won the tournament. So, we felt strong, I felt motivated. You know, that practice makes perfect. When you come out stronger, you come out better. When you win something, it gives you that empowerment feeling.

Thus, in other words, reflections led caregivers to remember the successes they had while being active. By remembering positive moments, people can solidify their beliefs about their ability to do the behavior of interest, that is, their self-efficacy.

The effect of reflections in *inducing the desire to repeat the activities* (n=8) is best exemplified in P8's account:

P8: One of the questions do trigger certain thoughts about, "Oh yeah. I remember when me and my daughter did this." It kind of reminds, like, "Hey, we could do that again and get involved with that again. Why did we stop doing that? That would be so nice."

Here, P8 said that the reflection questions helped her remember a nice family activity and she wanted to do the activity again. Her account, as well as P4 and P7's accounts earlier, show that reflections can induce the intention to repeat the activity because reflections reinforce the emotional outcome expectations of performing the behavior.

In short, reflection can both reinforce the self-efficacy and the outcome expectations of the task. However, intents that were induced by reflections can be impermanent (n=3). For example, if a family answered the reflection questions in the evening, they might immediately develop the intent to be active on the next day. But, on the next day, circumstances change, and they ended up not doing the activity. This is exemplified by P8's account:

P8: I'm doing this [reflection] in the evening and I'm like, "Oh yeah. You know what? Tomorrow we should try to be a little bit more active and get going." But when I wake up in the morning and I'm like, "Oh, I have a headache and I'm not up to it." That motivation is forgotten about.

P8's experience is echoed by P7 who felt that emotions and feelings change:

P7: It depends on what time you read the book [in the app]. Then they ask that question, you feel that way, yes. That is so true. That after you say, "Okay you're going to go do this." Then the emotion and your feelings then change, that you didn't even complete the task.

The fleetingness of intents-from-emotions suggests that PA reflections should be prompted when being active is the most feasible. Alternatively, reflections can be followed with tools to plan the next actions. The value of prompting a behavior during heightened positive emotional state was supported by P8:

P8: But if it's [prompted on] the right time of day, I might be a little more motivated to do something.

Collectively, these accounts show the potential and limitations of reflections. Reflections can help families remember how they have been active and the emotions associated with being active as a family. Such remembering can enhance self-efficacy and reinforces outcome expectations. As a result, reflections can induce the intent to be active because it recalls the positive emotional outcomes related to the activity. However, such intents are often dissipating over time.

4.1.2 Reflections Identify Discrepancies. While reflections about pleasant past events can lead to positive emotions, reflections that

lead caregivers to think about future actions can lead to the feeling of uneasiness (n=3). This uneasiness seems to stem from the perceived discrepancy between caregivers' aspirations versus their beliefs about their ability to reach their aspirations. For example, P7 indicated that she felt alert when her daughter said she loved soccer when responding to a reflection question:

P7: My daughter was saying something about soccer, and she loves soccer. She loves kicking the ball and stuff like that. But they used to do that with their dad a lot. And so now that he's not around, it's just like, "Okay, I can't do it." [...] I'm not really good at soccer. I'll trip over it.

P7 wanted her daughter to be happy, but, at the same time, she was not proficient in soccer. As a result, P7 became more alert, that is, she became vigilant in finding ways to support her daughter's interest in soccer:

P7: So, I'm like, "Okay, I'm watching, but I'm alert. Watching what's going on to see if you all can continue with your dad."

Similarly, this notion of being vigilant was experienced by P12 when she heard her son respond to the reflection question and describe how much he loved swimming. P12 felt vigilant she did not know how to swim:

P12: My son, he always loves water. Whenever he's in water, he's just always happy. He just wants to learn to swim.

As a result, she felt determined and yet nervous because she felt the urgency to learn how to swim so that she can protect her son:

P12: It was a determination to learn how to swim and you would get anxious, you get kind of nervous and everything else. [...] I think my biggest fear was the fact that he would one day go in the water and it's just me and him. I was like, "If I can't swim, how can I save him?"

In contrast, other parents did not experience discomfort, because they felt they are proficient in the physical activity that the child liked. For example, P8 felt differently when we asked her experience in comparison to P7 and P12's experiences of alertness:

P8: I think it's a little different for me because I did sports when I was younger.

It appeared that for P8, her physical activeness enhanced her self-efficacy so that she believed that she can support the activities that her daughter enjoyed. In other words, these accounts show that inducing caregivers to think about PAs that the child enjoys can lead to the feeling of alertness or discomfort, but only if the caregiver is not sufficiently self-efficacious to support the activity. It should be noted that such feelings are not necessarily negative. Rather, these feelings suggest that supporting their children's PA was aligned with the caregivers' aspirations. Then, as a result, the caregivers sought ways to reduce their discrepancies in achieving their aspirations (i.e., supporting their children's PA). As the interview data suggest, by identifying discrepancies, caregivers started to engage in discrepancy reduction.

4.2 Storytelling as Social Modeling

Listening to other families' community stories is a symbolic modeling process that can enhance caregivers' PA beliefs (*n*=10). The motivational effect of listening to verbal stories is exemplified by P7's account:

P7: Hearing their voice saying, "This is what I do with my kid. This is what makes me happy." [...] Just hearing their voice from another point of view, for me, I was like, "Wow, I should do that with my kids. I didn't think of doing that." [...] Just listening to other people saying this is what they did, and this is what they're doing, gives me the confidence of continuing.

Furthermore, listening to verbal stories from other caregivers appeared to be more impactful because caregivers felt the stories were more relevant to them. For example, P5 said:

P5: I think that listening to other families would be more effective [than reading health advice]. Just real people and having their real advice would be more effective.

Similar to P5 who felt caregivers' stories felt real, P11 felt the verbal stories embody the passions and the happiness of the caregivers. P11 said:

P11: Hearing someone else talk about it, they probably talk with more details of what they were doing. [...] You can feel the passion or the happiness. It's different when you hear something than from when you read it.

By unpacking caregivers' accounts further, we identified several characteristics of information that were exchanged while using StoryMap.

4.2.1 Data and Stories Affect Health Beliefs. By sharing fitness stories along with data (i.e., average step counts), families exchanged several kinds of information, and this information impacted the caregivers' beliefs about tasks, emotions, norms, and adequacy. We will describe these kinds of information in more detail below.

Task information derived from listening to the stories expanded caregivers' beliefs about the courses of action that one can engage in to be active (n=9). More specifically, stories gave caregivers new ideas about how they can be active with their children (i.e., task information). These activity ideas felt resonant because other families were able to do the activity. For example, P11 felt she can do Zumba to exercise with her daughter after she listened to a story from P7:

P11: [P7] mentioned the ways that she did her PA with her children. I didn't think of doing Zumba, but I thought that was a great idea. Because we are actually able to go on YouTube and look at that, [Zumba]. [...] So that did inspire me to, to try that out with [my daughter] as well.

Here, by learning other caregiver's approaches in being active, P11 developed the motivation to be active, watched exercise videos on YouTube, and act on that motivation. Similarly, P1 also felt motivated when learning how other families found ways to be active during social distancing amid COVID-19:

P1: It's very motivating to see that other families are finding ways to continue to be active even through this difficult time when have social distancing.

P1 and P11's experiences were echoed by other caregivers who were pleased to learn different ways to be active with their children, suggesting that their PA self-efficacy was improving. In other words, by learning that there were more feasible means of being active, caregivers enhanced their perception of their PA ability.

Caregivers also derived *emotion information* from the stories they listened to, that is, information regarding the emotional outcomes of being active (n=3) — this information in turn reinforced caregivers' own outcome expectations. In particular, shared stories were evocative because they conveyed the happiness that can come from the feeling of belongingness during family exercise. For example, P9 wanted to be active with her children because she heard other families felt happy when exercising together:

P9: It was nice hearing [those stories], because it makes me, like I said, do more things with my son as well. [...] Just picking up different things that they do and considering how happy they are to do those things.

By listening to stories in which other families felt happy while being active, P9 appeared to gain PA motivation as well. This account also resonated with P7's account at the beginning of section 4.2 where she felt that the family happiness conveyed in the stories gave her the motivation to be active.

These accounts suggest that stories with emotion information can reinforce caregivers' beliefs about the outcome expectations of family PA.

Another type of information that caregivers gleaned was *normative behavioral information*, that is, information regarding what kind of behavior is valued by one's peers (*n*=7). This information was derived from learning about the typical behavioral practices of other families (e.g., from the stories from other caregivers). In turn, when caregivers learned that their internal standards align with the social standards (i.e., what their peers' value), caregivers felt validation of their behavior. According to SCT, individuals judge the expected outcomes of their behaviors using their internal standards [3:340] and behaviors are most optimal when internal standards are compatible with social standards [7:274]. Thus, in short, normative behavioral information can enhance how individuals assess the outcome expectations of their behavior (e.g., a validation). For example, P12 explained why hearing other families' stories felt good:

P12: Just hearing the stories, you were just like, "Oh, okay. So, I'm not the only one." [...] When you sit back and you're like, "Okay, I'm not the only one doing this. I'm not the only one trying to find ways to keep my kids busy and happy." It's good. It works out.

P12's account above shows how stories can validate caregivers' efforts in supporting their children's wellbeing. Furthermore, listening to the stories induced positive emotions because they reduced the feeling of isolation as a caregiver with young children. P12, who was the primary caregiver in a dual-caregiver household, said:

P12: Nobody understands how you're feeling [as a mother], but then when you basically talk to the other

parents, or you, like I said, hearing other parents, you're like, "Oh, okay, so it's not me. It's not just me."

This feeling of isolation was also expressed by other caregivers. Therefore, while listening to a story can guide beliefs about a task and emotion, it can also give validations to caregivers' behavior. Such validations are beneficial in the context of caregiving because caregiving often felt like a socially isolating duty.

The final type of knowledge that caregivers gathered was *adequacy information*. This information refers to knowledge that is gained by observing other caregivers' step count data, and which helps the observer assess their ability to do the behavior of question (*n*=6). Here, data is information that directly shows the behavior of the model (i.e., step count averages). Reflecting on their sense of adequacy helped caregivers to set reasonable goals (*self-improvement*) as well as enhance their perception of self (*self-enhancement*) [73]. Adequacy information is different from normative behavioral information. Adequacy information tells us how many steps are deemed to be *sufficient*, whereas normative behavioral information tells us whether being active (and getting the steps) itself is *valued*.

An example of using an adequacy information for selfimprovement is when P7 felt knowing other caregivers' step averages helped her to set higher goals:

P7: It gives me a challenge because sometimes I be like, "Oh, I beat that person today. Oh my gosh, she was at a thousand. Well, she beat me today. Let me see if I can beat that." And I laughed.

An example of using an adequacy information for selfenhancement was when P5 felt better about herself from knowing that other caregivers' step averages were around her averages:

P5: People [who] were on the same level as you would just give you a lot more motivation. Like, "Okay. I don't need to I kill myself to do a lot more steps. I can try to progress gradually. Because I'm not so far behind."

These accounts exemplified the value of knowing other caregivers' step count averages because such information can inform their sense of adequacy. Their accounts also show that adequacy information can be used to make sense of past behavior (e.g., P5) and also future behavior (e.g., P7).

In short, stories that caregivers shared were impactful and resonant for other caregivers because stories conveyed information that enhanced task, emotion, and normative beliefs. Moreover, the behavioral data that accompanied the story appeared to influence caregivers' adequacy beliefs. The interplay of these beliefs enhances self-efficacy, outcome expectations, and internal standards, which in tandem can support the behavior in question.

4.2.2 Metadata Enhances Data and Stories. Community stories in StoryMap are accompanied by metadata and placed on a neighborhood map. In designing this feature, our goal was to help caregivers assess their similarity with the model, that is, how many characteristics they share with the caregiver who shared the story. We found that this metadata helped caregivers predict how much they can replicate the models' behavior (n=8). By providing context, such metadata goes hand in hand with data and stories. The two types of metadata that were seen as being valuable were the number of children in the family and the family's neighborhood.

The number of children was cited as the most valuable metadata (n=10) because a greater number of children usually inhibited PA, given that caregivers were more occupied with caregiving responsibilities. For example, P2 said:

P2: [The] number of children is important because maybe if you have four kids like I do, and then the other person has two. Maybe, it's easier for that person to be able to get more steps in or have more time to do stuff than it is for me.

Indeed, P2's quote suggests that having more children can limit PA. But P16 disagreed because for her, the number of children should not affect PA:

P16: I think the number of children shouldn't matter. I don't think... Well for me, I don't think it should. And then if the children are keeping us from getting things done, I think the one thing we can do is to get them engaged in it.

That P2 and P16 perceived the effect of the number of children differently show the subjective nature of metadata. Yet, such information is helpful for some caregivers to explain their adequacy.

Neighborhood was also frequently cited metadata because caregivers believed that neighborhoods affect family PA (n=6). Neighborhoods can inhibit PA when they lack places to be active or when those places that are available are lacking in safety. For example, P13 felt caregivers who lived in other neighborhoods may have better resources to be active, thus their step counts could not provide a sense of adequacy because P13 had limited means in being active:

P13: If there's a wooded area that they're doing all these walks on, or a trail, I could be doing the trail and they could be doing hiking or something. It's more of a stretch, versus me doing a trail all on one level.

While P13 felt that neighborhood information can predict PA by signaling the availability of resources, P3 felt that neighborhood information predicts a family's PA ability, specifically due to associated feelings of safety when outside in the neighborhood:

P2: Where you live, it's important to know because maybe they're doing more steps because they're in an area where it's safe, and they can do things.

Here P2 suggested that other neighborhoods might be safer, and thus families who lived there can have more PA outside. Therefore, neighborhood information provides important context for how feasible it is for a caregiver to replicate other caregivers' behavior.

In conclusion, data, stories, and metadata can support social modeling by transmitting information about adequacy, task, emotion, and norms. In turn, this information enhances PA self-efficacy and outcome expectations.

4.3 Barriers

Although caregivers received motivating cues from their social peers, there were underlying barriers and temporary barriers that limited families' use of StoryMap and ability to be active (n=12). Underlying barriers included straining caregiving and work responsibilities. Families also faced a temporary barrier, namely social distancing guidelines during the COVID-19 pandemic. For P15, a single mother of two children, these barriers were compounding:

P15: You would think [we can be more active] because [during the pandemic] we're a home that we're able to use [the app more] more. But being home, there's so much more to do, nowhere for [my kids] to go. Even just the energy level and just the amount of work you have to do and get it done. Because right now trying to be a student, a parent, a teacher, everything all at one time just within these 24 hours is a lot.

The account from P15 illustrates how an overlapping set of barriers can compound and further limit PA. These barriers include caregiving and work responsibilities as well as the COVID-19 pandemic, which forced caregivers to take on the role of teacher in supporting their children's education. Furthermore, two mothers were in a residential treatment program aimed at helping women and children who had substance abuse problems. Such a program puts a limit on how often they can go outside. For example, P8 said:

P8: We do have staff here where we're not allowed to get outside on our own free will or on our own time. But the small amount of times we do get to go outside me and my daughter try to find regular activities to do.

Accounts from the majority of the families show that they face barriers to being active. Such barriers are often compounded by the COVID-19 pandemic and also the unavailability of personal spaces for exercising. Only a small set of families in the study reported that they have a backyard (n=4). These families reported that social distancing was not a barrier for them because they can be active within the safe space of their house, which is in contrast to the rest of the families. For example, P11 said:

P11: I'm very grateful that I do have a backyard. I don't have to worry about [social distancing while exercising at the park]. [...] That's very hard with children. I don't like to tell my child "No, you can't touch it. You can't go here. You can't be too close to this person."

In conclusion, a set of barriers limits the families' ability in being active. Underlying barriers include access to the backyard, straining caregiving and work responsibilities, and mandatory health programs. The temporary barrier was the COVID-19 pandemic that caused a myriad of changes in family activities, including limited access to parks and increased caregiving responsibilities.

5 DISCUSSION

Findings from this study show that self-modeling and social modeling can positively influence self-efficacy and outcome expectations, two key attitudes that can induce health behavior. During these modeling processes, families elicited and exchanged four kinds of information embedded in data and stories: task, emotion, behavioral norms, and adequacy. Additionally, our findings show that metadata influence the effectiveness of social modeling, namely by helping users to predict whether they can replicate the models' behavior. However, although self-modeling and social modeling are promising means of health promotion, impediments readily thwart people's ability in achieving healthy behavior. Family participants

faced barriers that limit their PA, which include the underlying barriers and the COVID-19 pandemic.

These findings also highlight the distinction between data and stories. While stories are also data, we need to make a distinction to think conceptually about personal informatics. Data represents the outcomes of interest (e.g., using numbers, texts, visuals) that guide future actions and can be easily compared for informing assessments of adequacy. Stories represent memories that convey processes, progress [23, 27, 60], emotions [39], and values [20, 32, 52] related to the actions. Our findings show that data often supports assessments of adequacy while stories convey information about tasks, emotions, and norms. More importantly, while data sharing is valuable for social modeling, people also benefit from stories that elucidate the steps needed to achieve the modeled behavior and the potential outcomes of that behavior. Building upon Elsden et al.'s work that suggest personal informatics data often lacked important detail [22], we further show how stories can add detail that enhance data and positively impact behavioral attitudes. Guided by SCT, we will discuss how these concepts were in play during social and self-modeling.

5.1 Social Modeling Using Data and Stories

Figure 3 shows a conceptual model of technology-supported social modeling. In this process, individuals shared their data and stories about the behavior of interest (e.g., PA). Data conveys information about peers' behavior, and can inform one's sense of adequacy, while stories provide information about tasks, emotions, and behavioral norms. Adequacy and task information enhance self-efficacy because these two pieces of information can enhance individuals' beliefs about their ability. On the other hand, emotions and norms enhance outcome expectations. More specifically, learning the emotional outcomes of a behavior can reinforce individuals' beliefs about the joy of performing the behavior; while learning that a behavior is compatible with peer norms can enhance one's outcome expectations and make performing the behavior more desirable [7:274]. Collectively, by informing self-efficacy and outcome expectations, data and stories help individuals to further develop the intention in performing the behavior of interest.

Indeed, prior work has begun to demonstrate how social modeling can be facilitated by data, stories, and metadata. In terms of data sharing, prior work shows that sharing of health data can inform adequacy. In Citizense Maker's evaluation, Puussaar et al. found that people appreciated the opportunity to situate their data in comparison with other users [124]. Through our study, we further formalize that people value comparing their data with their peers' data because such comparisons are helpful to give a sense of adequacy.

Relying on peers' performance as the sole metric of adequacy may seem problematic because people could fall into a false sense of adequacy (e.g., feeling complacent). But, from the perspective of SCT, self-efficacious people are naturally inclined towards self-improvements [7:268]. Thus, people are still likely to attain higher goals even if they are surrounded with underperforming peers. However, Wood et al. posited that a false sense of adequacy tends to have negative effects in people who perceived they are surrounded by peers who higher in abilities (i.e., people felt less competent when

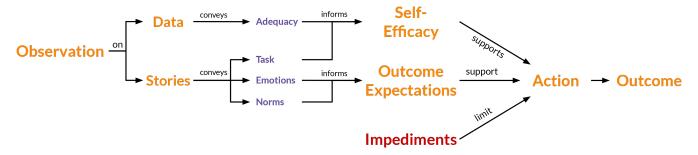


Figure 3: Social Modeling Process

surrounded by higher-performing peers) [73]. Therefore, adequacy information should be tailored to highlight people with similar abilities in tandem with providing prescriptive goals (e.g., aim for x numbers of steps in 3 months) so that people can better manage their fitness goals.

In terms of story sharing, prior work shows that health technologies can transmit task and emotion information in stories. Chung et al.'s study on how Instagram was used to support a healthy diet shows that Instagram allows the exchange of stories that highlight successes or share healthy eating ideas [13]. In EatWell's evaluation, Grimes et al. found that people appreciated the emotive health ideas from people they could identify with [30].

Additionally, prior work also demonstrated how health technologies can convey behavioral norms and validate people's experiences. Physical activity stories can foster norms around being active [53] whereas stories about women's health can challenge false norms [52]. Similarly, the exchange of health support messages [1] and sexual harassment stories [20] can validate people's experiences. Speaking more broadly, stories have been used by people on the margin to genuinely voice their experiences [49, 69] and technology can amplify their voices [49]. Through our study, we confirm these prior findings and begun to formalize the characteristics of impactful stories.

Finally, in terms of metadata, prior work also begun to show that metadata can help users contextualize health data and stories. Puussaar et al. show that health data would be more impactful if there is more information to contextualize the data [58] and Grimes et al. show that people valued being able to see themselves in the storytellers [30]. Furthermore, Daskalova et al. suggest that being similar is not only about sharing similar characteristics but

also facing similar obstacles [18]. Thus, through this work, we demonstrate that the purpose of metadata is for helping users to predict if they can replicate the model's behavior.

In conclusion, building upon prior study and SCT, we began to formalize the properties of technology-facilitated social modeling (i.e., data, stories, and metadata), the information they convey (e.g., adequacy, task, emotions, and behavioral norms), as well as the health attitudes they impacted (i.e., self-efficacy and outcome expectations).

5.2 Reflection as Self-Modeling

Figure 4 shows a conceptual model of reflections as self-modeling, that is, reflecting on past experiences from a positive lens. This process can help accomplish two outcomes. First, by remembering positive experiences, people experienced positive emotions that reinforce the outcome expectations of the task. Second, by reengaging cognitively on the courses of actions to complete the task effectively, individuals can enhance self-efficacy in a task. Similarly, reflection also helps people to have a greater understanding of their abilities and can enhance self-efficacy [2]. From the perspective of SCT, self-efficacy and outcome expectations can help develop the intention to act on the behavior of interest (e.g., PA) [5].

However, it should be noted that the intention to reproduce the behavior can be transient. Some caregivers said that they lost interest in reproducing the behavior on the next day. There are two potential approaches to mitigate the fleetingness of intentions. First, by prompting reflections when it is most feasible for individuals to do the activity, akin to Epstein et al.'s contextually aware feedback [25]. For example, by using the user's geolocation and calendar

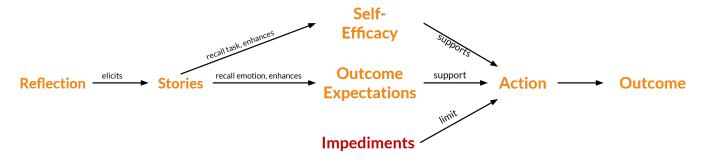


Figure 4: Reflection as Self-Modeling

schedules, a system can prompt users in reflections when they are close to exercise facilities or when they have more time flexibility. Second, is by providing goal setting tools after a user was reflecting. Since intentions are transient, the goals need to be close in time. For example, after a user reflects on their experiences, an app can offer a goal-setting tool to set a PA schedule the next day and specify the type of activity and the people who can provide support to accomplish the activity.

Reflecting socially with loved ones can also help people to experience social connectedness [8] that supports engagement [63] and reduces the risk of technology abandonment [14, 24]. Indeed, Katule et al.'s work shows that family social connections support health app engagement [37] by having children directly help parents to use health apps [37, 38]. Our work contributes to Katule et al.'s work by showing that children can influence parents indirectly. By remembering the joy of exercising with their kids (e.g., P4, P7, P8), parents can be more motivated to exercise as a family.

5.3 Concluding Remarks

Guided by our findings and SCT, we present design recommendations to support self- and social modeling in personal informatics:

- Invite reflections on success stories and invite users to share key information. While prior work has supported more open-ended reflections [12, 30, 42] we suggest that future work should provide prompts that explicitly invite users to share key information about the behavior of interest, such as processes, emotions, progress, and behavioral norms. This key information can enhance self-efficacy and outcome expectations.
- Support the exchange of stories and behavioral data aimed at enhancing self-efficacy and outcome expectations. The data should be behavioral data that users can easily compare and seek to achieve, with the goal of gaining a sense of what is typical behavior and also directing users to set goals towards self-improvement. In contrast to prior goal-setting tools that rely solely on health guidelines [29, 54], we echo prior work in personal informatics [18, 26, 58] by advocating for goal-setting tools that provides cohort data for comparison purposes. Guided by SCT, the aim of showing cohort data is to help make the goals feel achievable because the goals have been done by people who experience similar circumstances.

However, future work should ensure that users choose goals that are not too high nor too low. People with high self-efficacy are likely to set high goals when looking at their peers' data [7:268]. In contrast, people with low self-efficacy are likely to be less motivated if they see they underperformed in comparison to their peers [73]. Therefore, expert insights and health guidelines are still needed to ensure appropriate goals.

• Support users in gaining a sense of similarity with the model by allowing the exchange of information that helps users determine whether they share sufficient characteristics with the model (e.g., metadata). With such information, the user can predict whether they can replicate the actions of the person being observed. However, people define

- "similarity" differently [26]. Thus, we recommend that future work support users in identifying their own cohort of models echoing Daskalova et al. [18]. To encourage users to choose appropriate goals, there should be enough similar people in the pool of models. Additionally, to support users who have low self-efficacy, we recommend showing similar cohorts of models who managed to change their health behaviors gradually over time. This approach will inform users that change is possible when it is done gradually.
- Invite reflections that lead to action by asking users to reflect on when it is most feasible to engage in behavior change. Alternatively, provide action planning tools immediately after reflection when the positive emotions and intentions are still heightened. For example, apps can prompt reflections aimed at helping users to notice higher self-efficacy and positive emotional outcomes when it is the right time and location to exercise [41].
- Amplify community voices using stories. This work and our prior work [63] shows that people often face barriers that are beyond their control. Therefore, future research can examine how personal informatics can be used for advocacy to counter health disparities. Storytelling technologies are powerful means of advocacy [20, 52] because stories can help communities to empower themselves, challenge faulty societal beliefs, develop a sense of collective action, and refocus on their strengths [69]. Technology can amplify community voices and in so doing, provide benefits that transcend primary health outcomes [49]. Therefore, stories from self- and social modeling can be amplified and repurposed as means for communities to express their aspirations.

These guidelines show that the elicitation and the exchange of data, stories, and metadata are the important steps in the social and self-modeling processes. Furthermore, such elicitations and exchanges can positively support self-efficacy and outcome expectations, two key attitudinal concepts in SCT that can induce the behavior of interest. [18]

6 CONCLUSION

Social modeling and self-modeling (i.e., reflections on positive experiences) are promising processes to enhance the impact of personal informatics tools, especially for promoting family physical activity. Through a five-week evaluation of StoryMap, we characterized that social and self-modeling in personal health informatics involves the elicitation and the exchange of four key information, namely adequacy, task, emotion, and norms. Such information can enhance self-efficacy and outcome expectations, two attitudinal factors can induce health behavior.

Therefore, behavioral data sharing is a promising means of social modeling, but it can more impactful if the data is accompanied with stories (that explains how to achieve the modeled behavior and the positive outcomes of the behavior) and metadata (that helps to predict how much the modeled behavior can be replicated). However, families also faced external impediments in being healthy. As such, impactful health technology needs to help people to enhance self-efficacy and outcome expectations and at the same time mitigate the impediments to living a healthy life.

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