

Social Reflections on Fitness Tracking Data: A Study with Families in Low-SES Neighborhoods

Herman Saksono
Northeastern University
Boston, MA, USA
saksono.h@husky.neu.edu

Carmen Castaneda-Sceppa
Northeastern University
Boston, MA, USA
c.sceppa@northeastern.edu

Jessica Hoffman
Northeastern University
Boston, MA, USA
j.hoffman@northeastern.edu

Magy Seif El-Nasr
Northeastern University
Boston, MA, USA
m.seifel-nasr@northeastern.edu

Vivien Morris
Mattapan Food and Fitness Coalition
Boston, MA
vivien.morris@gmail.com

Andrea G. Parker
Northeastern University
Boston, MA, USA
a.parker@northeastern.edu

ABSTRACT

Wearable activity trackers can encourage physical activity (PA)—a behavior critical for preventing obesity and reducing the risks of chronic diseases. However, prior work has rarely explored how these tools can leverage family support or help people think about strategies for being active—two factors necessary for achieving regular PA. In this 2-month qualitative study, we investigated PA tracking practices amongst 14 families living in low-income neighborhoods, where obesity is prevalent. We characterize how social discussions of PA data rarely extended beyond the early stages of experiential learning, thus limiting the utility of PA trackers. Caregivers and children rarely analyzed their experiences to derive insights about the meaning of their PA data for their wellbeing. Those who engaged in these higher-order learning processes were often influenced by parenting beliefs shaped by personal health experiences. We contribute recommendations for how technology can more effectively support family experiential learning using PA tracking data.

CCS CONCEPTS

• **Human-centered computing** → *Empirical studies in ubiquitous and mobile computing.*

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
CHI 2019, May 4–9, 2019, Glasgow, Scotland UK

© 2019 Copyright held by the owner/author(s). Publication rights licensed to ACM.

ACM ISBN 978-1-4503-5970-2/19/05...\$15.00

<https://doi.org/10.1145/3290605.3300543>

KEYWORDS

Fitness tracking data, Family, Children, Low-SES, Wearables, Reflection, Self-monitoring, Physical Activity, Personal health informatics, Experiential Learning

ACM Reference Format:

Herman Saksono, Carmen Castaneda-Sceppa, Jessica Hoffman, Magy Seif El-Nasr, Vivien Morris, and Andrea G. Parker. 2019. Social Reflections on Fitness Tracking Data: A Study with Families in Low-SES Neighborhoods. In *CHI Conference on Human Factors in Computing Systems Proceedings (CHI 2019), May 4–9, 2019, Glasgow, Scotland UK*. ACM, New York, NY, USA, 14 pages. <https://doi.org/10.1145/3290605.3300543>

1 INTRODUCTION

Obesity is a health condition that increases the risk of diabetes and cardiovascular diseases [44, 57]. Obesity often develops at a young age [40] and disproportionately affects adults and children of low-socioeconomic status (SES) backgrounds [1]. Therefore, targeted obesity prevention at an early age is critical for low-SES families.

One approach to reducing the risk of obesity is to promote regular physical activity (PA) [50]. For promoting PA among adults, combining self-monitoring with behavioral support (e.g., supporting intention formation or goal setting) has been shown to be more effective [35]. For children, involving families in PA interventions is needed for lasting behavior change [5, 60]. Wearable health sensors open opportunities for novel PA intervention for adults [9, 31, 38] and children [3, 32, 36, 62]. While these tools are promising, only a notable few have explored the provision of behavioral support [38] or involved families [48, 52]. This trend underscores the need to investigate how PA tracking tools can help families develop support structures to be active regularly. These support structures include factors at the personal (e.g., PA enjoyment), interpersonal (e.g., social support), and environmental levels (e.g., access to PA facilities) [56, 59]. Moreover, as socioeconomic adversity is linked to childhood obesity

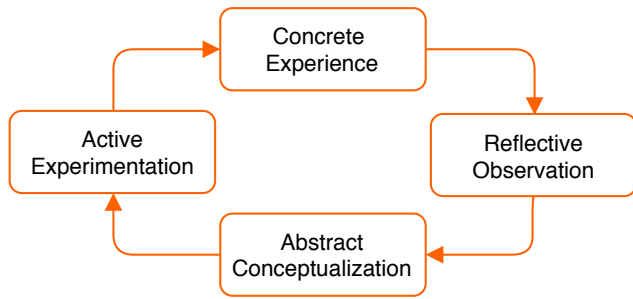


Figure 1: Kolb’s Experiential Learning framework [27]. Learners begin with a *concrete experience* and think about the experience in *reflective observation*. In *abstract conceptualization*, learners interpret the reflected-upon experience, forming insights that can be applied in the future. In *active experimentation*, learners test the insights to form a new concrete experience. Completing this cycle forms a new knowledge.

[6, 21], more work is needed to examine how can technology help low-SES families develop these structures.

To examine how technology can help individuals and families develop PA support structures through engagement with PA tracking data, we used Kolb’s *experiential learning framework* (Figure 1) [27]. In this framework, reflection on past experiences is a key part of learning. While prior work in Human-Computer Interactions (HCI) has studied how technologies can support reflection on past experiences [2, 7, 17, 43], supporting reflection alone does not facilitate learning [27]. Learning takes place through figurative representations of experience in the mind (as result from *reflective observation*), in conjunction with a transformation of that experience through *abstract conceptualizations* and action [27]. In our work, we investigated how PA data can help individuals build *abstract conceptualizations* of their PA (i.e., broader insights that can be applied in the future).

Specifically, we examined how commercial PA trackers can help families identify and develop PA support structures. Furthermore, building upon prior work examining how individuals reflect upon and gain insights from their data [7, 17], we investigated how groups (i.e., families) in a low-SES context interact socially with their PA tracking data.

In summary, we sought to answer the following questions: (1) How do families interact with and reflect on their PA tracking data?; (2) How can such interactions and reflections support positive PA attitudes and behaviors?; and (3) How do aspects of living in a low-SES context impact family interactions with PA tracking data? Answering questions (1) and (2) can help researchers and designers to develop systems that enable individuals and groups to gain more impactful PA data insights. Answering question (3) is critical for guiding the design of technology-based PA interventions

for low-SES populations [53], where obesity is prevalent [1] and resources are limited [10, 29].

To answer these questions, we conducted a two-month qualitative study with 14 families living in low-SES neighborhoods. We contribute to research on personal health informatics, reflective informatics [2], and family informatics [42] by integrating experiential learning, reflection, and self-tracking theories to characterize family interactions around PA tracking data. We discuss how a majority of the families did not go further than the *reflective observation* stage, and illuminate factors that motivated some families to be engaged in *abstract conceptualization*. We suggest that caregivers’ beliefs related to health, crime, and education affect family engagement with PA trackers. Thus, we recommend that PA tracker designs should be aligned with these beliefs. Finally, we present design directions for reflection-driven technology that helps families develop PA support structures.

2 RELATED WORK

Technology-Based Physical Activity Promotion Tools

Prior work in HCI research has shown that technologies can encourage families to be active. For example, PiNiZoRo is a GPS-based app that layers neighborhood maps with virtual treasure maps [52]. Caregivers in this study appreciated that the app encouraged their family to be active together. Another example is Spaceship Launch, a PA tracking exergame for families [48]. This work shows that caregivers’ engagement with health apps is influenced by their desire to bond with their children. In short, these family-centered designs are aligned with prior health research that shows the importance of caregivers’ support in children’s PA [19].

Despite families playing an important role in supporting PA, most HCI research on child PA promotion has focused instead on school settings [3, 32, 36, 62]. This work parallels non-technological PA intervention research with children, which has also been predominantly school-based [60]. While school-based programs have important benefits (e.g., providing an organizational structure for intervention delivery), family support is necessary for sustained behavioral change in children [5, 25, 60]. As families who use health apps often gain support from the in-person interactions that emerge through their use [8, 49], more work is needed to explore how health technologies can be designed to stimulate family interactions that facilitate regular PA.

Self-Tracking Data Reflection

To support PA, health sensors have been used to capture and visualize PA behavior. While PA visualizations can help increase PA behavior awareness (i.e., how a user was previously active), many have raised concerns regarding how well such tools can support long-term PA behavior change

[31, 32, 54, 62]. As individuals' PA behaviors may return to baseline when they stop self-monitoring, Klasnja et al. suggest that individuals can maintain the desired behavior when they develop support structures (i.e., resources that help a user to be active in the future) [26]. This work suggests that increasing PA intensity awareness alone is not sufficient for supporting long-term PA. Technology should also help users develop personal, interpersonal, and environmental resources that help them to be regularly active.

Furthermore, individuals are often driven by aspirations beyond health goals when they use self-tracking tools [13, 39, 45]. Rooksby et al. show that self-trackers are driven by their needs and desires in the context of their social lives [45]. Similarly, work by Niess et al. shows that individuals set PA tracking goals to satisfy their needs for enjoyment as well as their need for a meaningful and authentic life [39].

Collectively, this work highlights two important ideas related to PA promotion. First, it is important to help individuals develop the support structures necessary to achieve and maintain regular PA. Second, health behavior change is often supported by people's desires to achieve goals that go beyond health, including seeking enjoyment and meaningful life, all within the backdrop of one's social context. This suggests that PA trackers can be made more effective by supporting social reflections focused on how PA can help one achieve regular PA as well as broader life goals.

Within HCI research, an emerging line of work called reflective informatics has shown that digital tools can help individuals examine their data, identify discrepancies between the data and their beliefs, and act upon or change those discrepancies [2]. In the context of self-tracking, Choe et al. identified several types of insights that individuals acquired while reflecting on their data [7]. However, individuals were less likely to engage in deeper reflections, such as determining the value and the meaning to their data. This presents a challenge because deeper reflection is believed to facilitate behavior change [7]. Fleck argues that reflecting socially with another person can help individuals to engage in deeper reflection [17]. Although Fleck's work was in the context of picture-based reflection, it suggests that perhaps deeper PA data reflection is better supported by reflecting in a social setting. As prior work found that caregivers seek qualitative insights from their family's data [42], investigating how technologies can support family PA data reflection is particularly important.

In summary, research is needed to inform the design of PA trackers that help families develop support structures for facilitating regular PA and achieving their broader life goals.

3 METHOD

We conducted a two-month qualitative study to understand how caregivers and children interact with their PA trackers'

data in a naturalistic low-SES context. We selected the Fitbit Alta for adults and the UNICEF KidPower for children, after reviewing consumer PA trackers in terms of their accuracy ease-of-use, comfort, on-band display, battery life, and the presence of features designed for adults and children [14, 20]. This study was conducted in collaboration with three community organizations. One of the authors is a community leader who was involved in the study design, data collection, and analysis [58]. The study was conducted in May-August 2017 and December 2017-February 2018.

Study Design

We recruited participants from family-focused community organizations in the Northeast United States. At the beginning of the study, we acquired consent from the caregivers and the children. We then asked caregivers to complete a survey on PA frequency [34], children's PA [33], PA support [33], and demography. Then we loaned the trackers to the adults and children for two months. We trained them on the basics of using the trackers and asked them to review the trackers and the companion mobile app at least 10 minutes/week, but we did not guide them to reflect on their data.

We then conducted semi-structured interviews with caregivers and children at three points in time: at the beginning of the study, and one month and two months after the initial meeting. Interviews were conducted at participants' homes (10 families), community centers (5), or both (1). Caregivers were interviewed before or after the children. At the end of the study, we gave a US\$100 gift card to each caregiver. The Institutional Review Board at our university approved the study protocol.

Data Collection and Analysis

In the first interview, we asked about caregivers' and children's baseline PA attitudes and beliefs. In the subsequent interviews, we asked about participants' interactions with the trackers as well as PA data conversations that they had in the context of their SES. Example questions include "*What do you think about your family's PA?*", "*What conversations did you have with your children about the numbers on the trackers, if any?*", and "*What motivated you to have that conversation?*" For participants who recalled PA data conversations, we asked them if they remembered additional conversations. These probes helped us to gain a more comprehensive picture of their experiences, as people are more likely to first recall events that were at emotional peaks [55]. We also asked participants about PA barriers that they face to probe whether low-SES contexts (e.g., crime, education values) can impact PA tracking. We audio-recorded and transcribed the interviews. The authors reviewed the transcripts and identified preliminary themes. We refined the interview guides

to probe these themes further in the subsequent interviews. The median duration of the first, second, and final interviews was 30, 43, and 46 minutes, respectively.

We qualitatively analyzed the transcripts using the general inductive approach [55]. The first author performed open coding on the transcripts and clustered the codes to develop the themes. Next, we linked higher-level themes to theorize their relationships. Throughout the analysis process, the authors met regularly to refine the analysis.

Participant Overview

We recruited 16 caregivers and 15 children from 14 families. Caregivers' median age was 36 years ($IQR=16.5$), 10 were female. Child participants' median age was 7 years ($IQR=3$), 13 were female. Fourteen caregivers were African-American and three were Hispanic. 13 caregivers were single. The median family size was 3.5 with a median 2 children. The median household income was US \$21,979 per year or less. Most families qualified for the state's need-based health insurance program ($n=12$). Most caregivers' highest educational level was some college or vocational training ($n=7$). Participants lived in low-income neighborhoods ($n=9$) or government-subsidized housing ($n=5$).

The recommended level of PA for adults is 150 minutes of moderate intensity PA or 75 minutes of vigorous intensity PA per week; and 60 minutes of PA a day for children [50]. At baseline, participants' median PA levels were lower than these recommendations. Caregivers reported a median of three 30-minute PA bouts in the last week. For children, the median was six days with 60+ minutes of PA in the last week. This trend is consistent with prior work showing younger children are often physically active; however, they become less active between 6 and 14 years of age [61]. At the end of the study, caregivers reported an increase to a median of four PA bouts in the last week; there was no change in PA bouts among the children. The caregivers' PA support was moderate ($Median=0.70$ out of 1.0, $IQR=0.17$).

4 FINDINGS

Family participants described a range of interactions while using the PA trackers. Their accounts reflect moments with the trackers that were particularly memorable for them. As we analyzed their interviews inductively, we found that their experiences aligned with Fleck's reflection levels [17] and Choe et al.'s insight types [7]. We then developed a framework that integrates concepts from these works with Kolb's experiential learning stages [27] to help organize our findings. This approach allows us to bridge the general concepts in Kolb's framework with concepts specific to reflections and fitness tracking. Additionally, Fleck's and Choe et al.'s work describe the attributes of reflections; and Choe et al.'s work is focused at the level of the individuals. We extend their

work by characterizing the mechanics that drive reflections in a social setting, i.e., families.

Experience-Reflection-Insight Integrative Framework

Figure 2 shows our preliminary framework that integrates experiential learning stages [27], reflection levels [17], and insight types [7]. The top-level categories are Kolb's experiential learning stages [27] that directly involve cognition focused on prior experience: *reflective observation* (thinking about the experience) and *abstract conceptualization* (interpreting the reflected-upon experience).

Within these stages are Fleck's reflection levels [17]. Levels within reflective observation are **R0** (*non-reflective description*—describing data without elaboration) as well as **R1** (*descriptive reflection*—describing data with elaboration). R0 and R1 are under reflective observation because past experiences were discussed without analyzing the experience further. Within abstract conceptualization is **R2** (*dialogic reflection*—identifying relationships between data sources and/or between data and external knowledge). R2 is characterized by seeing experiences from a new perspective. We added **R-none** to describe participants with limited interactions with their PA data. This preliminary framework does not include R3 (transformative reflection) nor R4 (critical reflection) because our participants did not report experiences beyond R2.

Under R0, R1, and R2 we added Choe et al.'s insight types [7]. Categorized under R0 is *detail* insight (i.e., discussing the face value of PA data). Categorized under R1 are *recall* (i.e., discussing external information that explains the PA data) and *comparison* (i.e., comparing PA data with external data). Under R2, we introduced *causal* insight where users discussed the health implications of the observed PA data. We put comparison insights under R1 because they involved simple descriptions of data, without elaboration on the relationships between them.

Figure 2 shows that the majority of the families did not report going beyond the *reflective observation* stage. Only three families described *abstract conceptualization*, namely *causal insights* when they discussed the relationships between their PA data and its health implications (e.g., a healthier weight).

For the remainder of this section, we organize our participants' experiences using their reflection levels (R0, R1, R2, R-none) and we characterize their reflection experiences within each level. Because *abstract conceptualization* is an important step towards knowledge formation, we will theorize why few caregivers were engaged at level R2 and why others were engaged at R-none (i.e., how low-SES context and caregiving aspirations influenced reflections depth). Our findings will help future work to refine the design of PA trackers that meet the needs of adults and children.

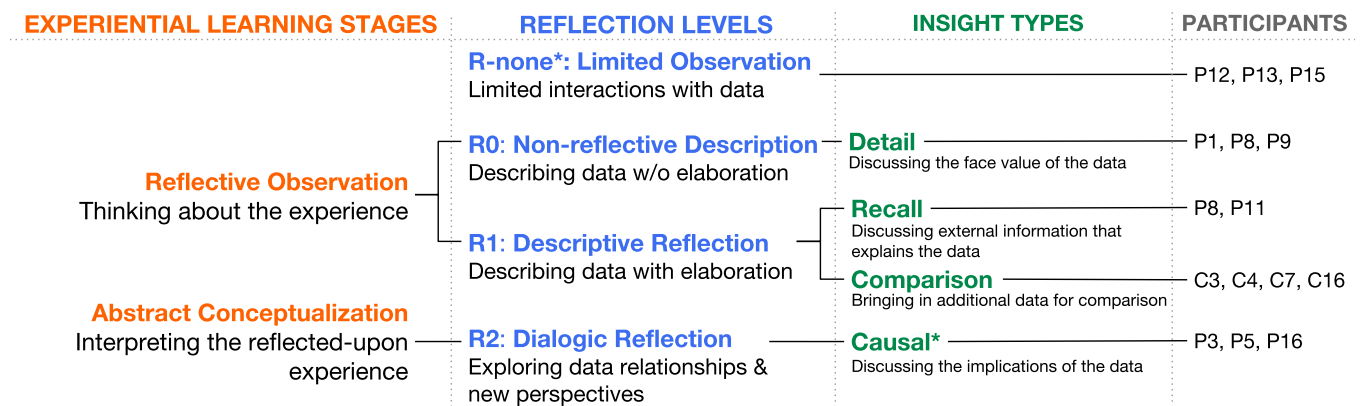


Figure 2: Experience-Reflection-Insight integrative framework. This framework links Kolb's **Experiential Learning Stages** [27], Fleck's **Reflection Levels** [17], and Choe et al.'s **Insight Types** [7], as well as participants who reported the insights. *R-none and Causal Insight are new concepts introduced in this work.

Level R0: Non-reflective Description

At level R0, participants discussed their data as is (i.e., detail insight [7]). Their conversations focused solely on numbers as measured by the PA trackers (e.g., P1, P8, P9). For example, P8 described when she went for a walk with her child and they only talked about the numbers:

P8: I'm like, "What does your Fitbit say?" You know. "What's going on with you? How many steps did you do?" You know, and then she's like, "Let's see. Oh, I did [this number of steps]."

Later in the interview, P8 said that she actively took her niece (9 y.o.) for a walk because she was concerned with her niece's weight ("What really motivates me [to be active with her] is because I see her growing and she's getting round"). She further described how she has to be a model for her niece to be healthy ("I have to motivate her. I have to be a mentor. You know what I mean? I have to show her. I have to eat right. I have to exercise."). However, while P8 values PA, she did not describe accompanying her detail insights with a discussion of how walking can support a healthy weight.

Similarly, P1—a gym coach—told us about a time when he talked about the PA tracking data when he was active with his daughter (7 y.o.). He said that he and his daughter only looked at the numbers and then continued with their activity:

P1: We just look at them [...] I mean, it's pretty much like just look at the, see what the numbers say. Um, and it's, I leave it.

While these limited discussions may be related to P1's personality or values, P1 also described that he did not want his child to pick up habits that are counter to an active life:

P1: She's beginning to pick up some habits where they like to stand in front of a fan instead of running [at the gym, ...] I know it was hot and whatever. But she never went and stood in front of the fan until yesterday. And I'm like, "No, this is gonna change."

P8 (who was an athlete in high-school and college) also discussed a challenge in supporting her niece to be active:

P8: I wanted to just do, um, some aerobics just to get her heart pumping. You know what I mean? Just, um, you know, just to move [...] She did not want to do it.

In summary, P1 and P8 were concerned about and tried to support their children's PA. However, they did not appear to use their PA data to drive the deeper discussions about PA with their children that can support experiential learning processes.

Level R1: Descriptive Reflection

At level R1, participants discussed their PA data along with some additional information, but without further analysis (e.g., P3, P4, P7, P8, P11, P16's families). Two types of insights emerge at this level: *recall* and *comparison* [7].

Recall Insights. These insights occurred when participants (e.g., P8, P11) discussed external information not captured by the trackers [7]. For example, P11's dinnertime conversation about PA data spurred discussions about the activities done to achieve that data:

P11: At night they, you know, we always [talk about], "Oh, how many steps did you do?" [...] Basically [we begin with] whatever you talk about at night is, "How was your day?" You know,

and this [conversation about trackers] comes up, "Well, yeah, we were running [...]" They talk about what they've done.

It appears that this family's detail insights (discussions about step counts) led to recall insights as the family added additional context [7].

Similarly, although P8 described a time where non-descriptive reflection took place (discussed in the previous section), she also described one moment where her family found her data surprising. She told us about a conversation with her sister, in which they discussed taking more steps than they had imagined:

P8: We went all the way to Dunkin Donuts. That's all the way down and around past the highway. It was a good walk there and back. [...] At times we can't believe how many steps we've taken.

P8's account shows how families can gain recall insights when they discover surprising new knowledge (i.e., PA data challenged existing beliefs [7]). In summary, in-person interactions and surprising discovery led some families to discuss recall insights.

Comparison Insights Facilitate Family Competition. Another form of descriptive reflections were *comparison insights*, where participants (e.g., C3, C4, C7, C16) considered external data (e.g., family members' data) in light of their own data [7]. Such comparisons often led the child to bring the caregiver into a family PA competition. As the comparisons are centered on the tracked PA data without further analysis, we categorized these comparisons as reflective descriptions (R1).

For example, P7 described how her daughter (C7, 9 y.o.) initiated the comparisons ("[My daughter said], 'let's see, let's see who walked more? Who had the highest numbers?'"). While P7 did not appear to see that the comparison is a serious matter ("I just laughed"), her daughter described that the comparison was more like a competition with a bet. She also described how she appreciated the feeling of winning during the competition:

C7 (9 y.o.): I'm happy [when I beat my mother and my aunt] because they're not getting money, because like sometimes we bet. Whoever gets the most for steps and miles. [...] I did [come up with the idea]. I got 5 dollars.

The experience is strikingly similar to P4's family where P4 initiated a competition that evolved into a competition with a prize. P4 further described how her daughter (11 y.o.) became very involved with the competition—although she herself found the competition to be silly:

P4: At first, we were doing let's see who gets more. So, she be doing crazy stuff in the house

just to see who can get more. [...] I will do, like, I'll be doing movements. A lot of like moving around and doing stuff. And then she's like, "Oh, no, no, no. You trying to get more than me." So, then she tried to get up and do stuff and we're racing so. It's silly, but.

Furthermore, P4's daughter appeared annoyed that she did not get the prize even if she beat P4 in the competition.

C4: I said, "Whoever gets the, whoever gets to 10,000 steps in the week, the first person gets to go to a restaurant that they want to go to." And then which was that was for me. And I said, "If I lose you get to punish me for whatever." And I won, but you [the mother] didn't take me to the restaurant.

Finding that children sought competition is not surprising as it is likely that children enjoyed games with their family and friends. This enjoyment was evident when we asked P3's daughter why she liked the KidPower smartphone game:

C3 (9 y.o.): I give [the KidPower app a] 10 [out of 10] because like I love walking. And like I love, love to walk and it gives you missions. And points, which I really love points.

Similarly, C16 (9 y.o.) also described the excitement of family competition, especially the experience of beating his father in a steps competition.

C16 (9 y.o.): I feel happy [when I beat my father]. Once I get in the car I'll be like, "Dad, how much do you have?" Then you go like that and then I'll be like boom. Then you see like 10 numbers on my screen or four. It's amazing to beat him.

Author 1: Why is it amazing to beat your father?

C16: Because I don't really beat him a lot.

C16's account shows that, for some children, competition with parents is a source of motivation in itself. This was further explained during our interview with the father, in which P16 said that his son viewed him as a role model.

P16: I'm his role model. If you ask him who's your role model, he'll be like my dad. I know I have to stay a certain way. He told me, "I don't want you big ever again. I don't want to see you like that because I know you get sick." I have to stay active for him. He really looks up to me.

P11 shared a similar story:

P11: [My children] like the fact that they beat their parents in the goal, stuff like that. That's basically the big conversation, that big sense of accomplishment of beating your parents.

Overall, these accounts suggest a gap in the way children and the caregivers see competition. Children were excited

about the gameful competition whereas caregivers expressed a somewhat milder enthusiasm. In the Discussion, we will examine the implications of this gap.

Level R2: Dialogic Reflection

At level R2, families discussed the relationships between their data and their prior knowledge. Only three families (P3, P5, P16) reported interactions at this level. More specifically, these three families described *causal insights* (discussing the implications of their numeric behavioral data as captured by the trackers). Causal insights may seem related to Choe et al.'s value judgment insights (i.e., conveying the negative or positive meaning of the data) [7]. However, it is important to note that P3, P5, and P16's causal insights went beyond simply discussing whether their behavioral data was good or bad. They also detailed the causal implications of their behavior. For example, P5 frequently encouraged his daughter (6 y.o.) to be more active and told her the meaning of the data (i.e., that higher numbers would make her stronger)—implying the health benefits of PA:

P5: I always explain to her like, "*You know, this is what we did today*". Um, you know, "*Maybe tomorrow we can do a little more too*." And I explain it to her as, you know, "*We're getting stronger if we do more, like [if] we did this number*."

As we asked P5 about his motivation to convey the causal insight, P5 said that he wanted his daughter to learn that being active will impact her health:

P5: It's to help her be mindful and start being aware of, you know, again, the more we do the better it is just for us and our bodies. Um, she won't learn unless I'm teaching her.

Similarly, P16 also told his son (9 y.o.) about the implications of the numbers on the trackers:

P16: [Using the tracker] I can show him physically, not just explain to him—but where he can see physically—where if you do a certain amount of steps or if you don't work out, if you don't eat healthy, you'll get big. He's getting big.

P16 appreciated the PA trackers because rather than speak abstractly, he can show his son a more concrete relationship between the observed PA data and his son's fitness. At the end of the study, P16's son seemed to be able to see the relationship between being active and his body weight:

P16: When we was coming over here, he was like, "*You're kinda right, my pants didn't wanna fit on me because I'm not doing so much steps*."

These accounts from P5 and P16 show that some families started to engage their children in the higher order of reflection (R2) by identifying the relationships between the

observed data and health implications. In the next section, we will explore the motivations that facilitated reflection level R2.

Personal Health Experiences Influence Reflection Depth. We learned that P5 conveyed causal insight to his daughter because P5's personal health experience led him to be more focused on his daughter's health. P5 was born prematurely and his family made decisions that were later detrimental to his weight status:

P5: I was premature [...] Growing up, you know, because I was a small child [my family] thought, "*Let me just feed him, feed him, feed him, feed him, because he needs to be strong and he needs to grow and he needs to*." And so, it kind of was too much. There wasn't a limit.

The personal health experience encouraged P5 to be more involved in his daughter's health:

P5: I really haven't grown with real much physical problems or physical, you know, like health problems because of overweight. No diabetes, nothing myself. But, in general, since with that understanding that's a concern in life and just for humanity, that's what I want to prevent for my daughter. Um, and that's why I do my best to make sure we all, we're both active.

This desire to be involved in his daughter's health manifested when P5 conveyed a causal insight to his daughter.

P5: I want her to understand that the more active we are, the better we're going to feel.

Similarly, P16 also indicated that his health-related experiences led him to talk about the causal implications of the PA tracking data with his son. He then described the health condition that he had:

P16: I was 260 [lbs.] last January. I did a gastric bypass and [now] I weigh 175 [lbs.]. I don't even have diabetes. My diabetes was perfect. I have no pressures going on. My cholesterol is gone. Plus, my kids want to see me like this. They want to see me fit. [...] I don't want to ever be big again.

The concern that P16 felt from his children also led P16 to value PA and health. This concern further explained P16's decision to convey causal insight.

However, one caregiver did discuss causal insights with her child even though she did not indicate a personal health experience. This causal insight emerged when she discussed the relationship between the PA data and healthy eating:

P3: We talk about how long, how many miles we went around. We went around the park twice or we went up and down eight times with riding the

bikes or we'll say, "Huh." Oh, we do say, "What we gonna eat? We shouldn't mess up. We should eat less fattening because we'll mess up how many steps we took." You know, once you walk and you eat a big meal afterwards it doesn't make any sense.

P3 did have a concern about her daughter's weight. However, unlike P5 and P15, who had relevant personal health experiences, P3's concern over her daughter's weight is strictly based on her observation ("I love her the way she is, but you know, [...] she can still like lose a couple of pounds to me."). Furthermore, what differentiated P3 with P5 and P16's causal insights was how clearly they discussed the data-health relationships. P3's discussion with her daughter centered on how having a big meal after a long walk "will mess up" their exercise. In contrast, P5 and P16 explained concrete health implications of their actions (e.g., exercise will make their children's body stronger).

The accounts from P5 and P16 suggest that personal health challenges encouraged them to take a more proactive role in educating their children about health (e.g., conveying causal insights—which is under R2). Their attention to health is reflected in their parental PA support survey data. Out of the maximum score of 1.0, P5 and P16 scored 0.88 and 0.96, higher than the overall median 0.70 ($IQR=0.17$). Notably, P5 and P16's accounts stand out because the majority of the participants did not discuss personal health challenges nor convey causal insights.

Collectively, these accounts underscore factors that influence caregivers to engage their children in deeper reflection. While we saw some caregivers value PA, the commonality between P5 and P16 is their personal health experiences and their belief that their children are susceptible to similar health issues. In the Discussion, we will reflect upon the design implications of this finding.

Level R-none: Limited Observation

At level R-none, participants' discussions did not include meaningful PA data reflections (e.g., P12, P13, P15). For example, in the final interview, P15 said that he did not have any conversations about the PA trackers with his daughter (6 y.o.), except when he explained the features:

P15: I just told her basically it was going to keep track to see how much she exercise and walks during the day. Not a real conversation. But you know, just letting her know what it was and what it was for. That's it.

In the second interview, P12 said that his daughters (6 and 7 y.o.) were not interested in his explanations of how the trackers work. As a result, P12 believed that while his

daughters understood the mechanics of the trackers, they did not understand the PA goal game in the companion app:

P12: I've told them, but they be so into their the world. [...] They just be like brushing me off. [...] They're used to walking around, and moving and activities. [...] They don't know that they're completing the things on the challenges [in the KidPower app].

During the second interview, we also learned that P13 told her daughter how the numbers in the PA trackers will increase if they are more active. However, she did not recount times when they talk specifically about the PA data:

P13: I was telling her the numbers, they add up to what she did. What was she doing in the activity, right?

Author 1: Did you have any other conversation with her?

P13: No.

Collectively, their experiences show how their conversations about PA data were very limited. These caregivers also did not express concerns about their children's weight. For example, P15 said that his daughter's weight (6 y.o.) is ideal and she is currently active:

P15: I feel she's the perfect weight for her height and stuff like that, and as she gets older, I feel like, you know, she going to be into swimming. She has too many cousins that's into stuff for her to just, I feel like, sit on the sidelines, you know? [...] There's always something to go to, so I don't see [daughter's name] cheerleading. I don't see her just wanting to sit around.

Here P15 believed that her daughter will stay active when they reach adulthood. This belief was also shared by P12 and P13. For example, P12 said:

P12: My kids are showing me that [they will be active when they reach adulthood]. My daughter wants to do gymnastics. The other one wants to dance. So, they gotta be active for that stuff.

While P12, P13, and P15 believed that their children will not be less active in the future, prior work shows that children's PA levels decline greatly between age 6 to 19 [61]. Furthermore, more children (especially those of low-SES families) reach obesity status as they begin entering school-age (6 y.o.) [1]. Therefore, preventing obesity at an early age is critical to reducing the prevalence of obesity. With this in mind, we further investigate why engagements with PA tracking data were more limited in some families.

Differing Priorities Influence PA Reflection Depth. Our data suggests that for some caregivers, their children's education was a higher priority than PA and weight status. For example,

while P15 believed that his daughter's health is important, he saw health as a means for his daughter to achieve higher education ("I want her to be healthy. Grade A. Ready to go to college."). We then asked whether the PA trackers can support P15's aspirations in any way. P15 said that the trackers are not critical for his daughter's education:

P15: Nah, a Fitbit can't do that. That's all on me. That's all on me being a dad. Like, the Fitbit is going to take part of it. I figure it'll help me teach her a little bit about physical activity, but it ain't got nothing to do with me getting her to college. Nah.

P13 described the importance of her child getting a college education as well. She also said that PA is not critical to achieve that goal:

Author 1: So it doesn't really matter if she is active or not active, because she will go to college anyway?

P13: My baby is going to college, I already know. I already know, that's not even a question to ask. I already know my baby's going, she's going. [...]

Author 1: It seems that PA is not critical to achieve that?

P13: No it's not.

It should come as no surprise that families prioritize education. However, since obesity often develops at a young age [42], we further investigated how education received more attention than health. In the interviews, caregivers said that education is critical for their children's future because it is a way to achieve a better life. For example, P15 discussed the importance of prioritizing education:

P15: I just really want her to be like into wanting to go to college at that age. I still want her to really be into school and to understand that you really need an education out here, especially before you have children.

Similarly, P13 believed that education will allow her daughter to have a better life:

P13: Education is very important because I want my daughter to go to college. She is very smart, very smart. So I know she is going to make it in this world. And I want to be there to see that, you know? I want to be there to see that. It's crazy out here, people killing other people over stupid shit, you know what I'm saying? I just want my daughter to make it so I can move her out of here.

P13's account above also shows that getting a higher education is not simply a path to achieve a better career, but also a way to have a safer life. In P13's words, her priority for

her daughter's education is influenced by her desire to leave their neighborhood where "*people are killing other people*". This concern over safety was also raised by P15. He recalled when his daughter's mother was killed by stray bullets:

P15: In the same project that I grew up in, my daughter's mom was murdered on Halloween. It was just a random shootout and one of the bullets went through her car and hit her and she passed away. [...] Even though I was older and I thought I was away from that because of my age, ultimately that same shit affected my household and is affecting my daughter to this day.

Here P15 indicated that living in his neighborhood can pose fatal consequences that even for those who are not involved in criminal activities. P10 also expressed concern over the consequences of living in an unsafe neighborhood. She explained that she would not let her children (7 and 4 y.o.) be active outside because she did not want them exposed to the criminal activities in her neighborhood:

P10: My sons are not gonna be out here with these boys [on the streets], and my daughter's not gonna be running around behind these boys. No. Get your education, and you can do whatever you want with your own life. Life is what you make it.

Similar to P15, P10's account above explained why she believed that education is critical for her children to achieve what they want in life, away from their current distressing living situation.

Collectively, the accounts from P10, P13, and P15 suggest that wellness-related goals are sometimes less prioritized as compared to education goals. This resonates with prior work that shows low-income ethnic minority caregivers have higher educational aspirations for their children [51]. P13 and P15 also appear to prioritize education goals because of their belief that higher education will allow their children to live in a safer environment. This may explain why their engagement with their PA tracking data was relatively limited.

Health concerns can be a higher priority if a caregiver feels their children are more susceptible to health issues. For P10, although her younger son was too young to participate in the study, she felt that the tracker will be more beneficial for the younger son because she saw him as being overweight:

P10: [My younger son,] he's overweight. So I figured if I get him one [PA tracker], they [my children] can kind of like compete too. Who takes the most steps. And he might want to be more active.

In summary, our findings suggest that limited engagement with PA trackers are related to caregivers' beliefs that their

children are not susceptible to obesity. Because obesity was not a primary concern, caregivers focused their attention on supporting their children’s education. For them, education was seen as a path to achieve a safer life. Indeed, crime concerns in low-SES context can act as a barrier to children’s PA [37] and self-tracking [46]. In the next section, we explore the design implications of this finding.

5 DISCUSSION

We discussed in the Related Work that PA trackers can help users increase PA behavior awareness (i.e., how a user *was active in the past*) and also help develop support structures to achieve regular PA (i.e., how a user *can be active in the future*) [19, 26, 56]. Prior work has explored how technology can help users think about how to be active, either by providing health information [8] or computer-tailored PA recommendations [11, 28]. However, the efficacy of these tools is often limited [28]. Users often did not use the features [8] or reject the recommendations [11]. Informed by experiential learning theories, we argue that learning how to be active is a negotiation between prior and new knowledge about *ways to be active* [27]. Therefore, feeding users with information on how they can be active may lead to conflicts with their prior knowledge. The utility of PA trackers is that they provide experience-grounded data that helps users bridge and integrate new knowledge with prior knowledge.

Furthermore, the integration of new and prior knowledge is influenced by the context of a person’s life [4, 16]. Although social influences are not included in Kolb’s framework, subsequent experiential learning theorists have emphasized that learning is intertwined with the learner’s social context [4, 16]. Therefore, we must not overlook how social context affects how users learn about how they were active and how they can be active. Rooksby et al. and Niess et al. show that self-trackers were motivated by life goals that were influenced by their social context [39, 45]. Lin et al. and Puussaar et al. show that PA tracker users sought other users’ data to make sense of their own data [31, 43]. These works show that social environments shaped the way individuals learned the meaning of their PA data.

We build upon this work by discussing the social mechanics that help families learn from their PA data. In the next section, we use Kolb’s experiential learning framework [27] to show what encouraged families to interpret PA data towards a more complete conceptualization of their PA. As families in our study did not discuss how to be active in the future, we also discuss design ideas to support such insights.

Caregivers’ Beliefs Shaped Family Data Reflection

Figure 2 shows the range of interactions that the families reported while using PA trackers. Most of the insights were under R-none, R0, and R1. In other words, the majority of

families did not go beyond Kolb’s *reflective observations* stage. Since commercial PA trackers often present PA data as is and implicitly assume that people will engage in deeper data reflection, we show that such assumptions may not be well-founded. Our data shows that family interactions around PA tracking data were limited and PA trackers did not sufficiently help families derive further value from their data—e.g., engaging their children in discussions that reveal deeper insights of their health; or discussions that springboard opportunities to teach life lessons.

However, a few caregivers (P3, P5, P16) were engaged in Kolb’s *abstract conceptualizations* stage when discussing *causal insights* (i.e., the health effect of the actions represented by the PA data). *Abstract conceptualization* (along with *active experimentation*) helps move people to a more complete conceptualization of their behavior and thus can better facilitate regular PA. With this in mind, we sought to understand the mechanics that influenced caregivers to synthesize the meaning of their data.

Our data shows that personal health experiences led P5 and P16 to discuss causal insights with their children. This suggests that caregivers’ health experiences shaped a belief about their children’s susceptibility to weight-related issues. A belief is an idea that a person holds true, and it influences a person’s values, attitudes, and behaviors. Our data shows that caregivers’ *illness-susceptibility* beliefs encouraged deeper reflections on PA data.

Perceived susceptibility to illness is a construct within the Health Belief Model [22]. While prior work has examined the tie between this construct and an individual’s PA [56], our work shows how illness-susceptibility beliefs also influenced caregivers to use PA data to instill PA values in their children.

While a few families reflected on the relationships between PA data and health, other families discussed their aspirations for their children, namely their beliefs that education will offer their children safer adulthood (e.g., to live away from criminal activities). As these parents appeared more focused on their children’s education we suggest that caregivers’ *education beliefs* were more central to those families.

Illness-susceptibility beliefs and *education beliefs* revealed caregivers’ basic needs: the desire for their children’s health and personal safety. We suggest that caregivers’ beliefs shaped the focus of their support. For some caregivers, the acuteness of their *illness-susceptibility* beliefs was aligned with the features offered by the PA trackers. As a result of this alignment, some caregivers engaged their children in deeper discussions of their PA data, namely by discussing causal insights from their PA data. This underscores the need to align health apps with the beliefs that users hold.

More concretely, we suggest that health promotion apps should be designed as a means to achieve goals beyond health. For example, family health apps can be designed as apps for

helping families achieve education goals as well. These apps should highlight the benefits of PA for children, such as increased school performance in math and reading [12, 15]. Furthermore, as caregivers are driven by their desire to support their children’s health and education, we suggest that family apps should be explicitly described as apps for helping caregivers teach their children life-lessons. For example, *vivofit jr.* (a children’s PA tracking app from Garmin) allows caregivers to give virtual points when kids are doing chores. Designing beyond health goals was also suggested by Brown et al. in their review of non-technology PA interventions for children [5]. Brown et al. suggest that future work explore interventions focused “*on something other than PA for health or weight loss*” [5].

In summary, our findings corroborate prior work that shows self-tracking practices are influenced by people’s social environment, such as family, friends, neighbors [13, 45, 46]. We extend upon this prior work by showing how individuals’ beliefs shaped the way they interpreted PA tracking data; and how social influences (e.g., caregivers’ aspirations for their children) shaped these beliefs.

Designing for Reflection Towards Action

Our data shows that some caregivers who were driven by *illness-susceptibility belief* were more encouraged to engage their children in deeper reflection. While this reflection allows them to think about how they were active (i.e., that they were active towards a healthy weight), none of the caregivers discussed how they can achieve regular PA. Indeed, this finding is not surprising because, as is common with commercial trackers, the PA trackers we used did not provide support for such reflection. However, our findings reveal the need for future PA trackers to support individuals in thinking about ways to be active. Furthermore, support for reflection is especially needed in low-SES contexts, because socioeconomic hardship during early childhood has been associated with lower cognitive ability [30, 63] for reflection.

In this section, we will discuss how to help individuals arrive at an abstract conceptualization of ways to be active in the future, by reflecting on factors that influence regular exercise [41, 47]. Such reflections should be tailored to the user’s readiness to change their behavior [47] and aimed at conceptualizing ways to be active. We provide examples of tailored reflection themes in Table 1.

Future work is needed to explore how tailored PA data reflection can support *abstract conceptualization*. Guided by experiential learning theories [16], we provide a design example for a family who is not yet considering to be active, thus requiring support to connect PA and positive feelings.

The system could start by presenting the family’s PA data, and then ask them to think about enjoyable activities they can do to increase their step counts for a goal period.

Table 1: Reflection themes tailored to readiness to change.

| User’s Readiness | Themes for reflection |
|---|---|
| Not yet considering to be active | Positive feelings when physically active |
| Have considered being active but not yet regularly active | <ul style="list-style-type: none"> • Enjoyable activities • Time and places to be active • Supportive friends and family |
| Regularly active | How to maintain regular PA |

Throughout the goal period, the system can ask the family to log their mood collectively as a family. At the end of the goal period, the system could invite family members to attend to their emotions and help them acknowledge any negative feelings, especially if they missed their goal. Then, the system should invite the family to compare any differences in their fitness before and after the goal period. This comparison should be aimed at highlighting positive physical or emotional feelings that arise. Finally, the system could ask the family to set a PA goal and think about how they can achieve the goal. The goal should be framed as a way to identify the positive physical or emotional changes that will help the family achieve their collective goal.

In summary, the outcomes of the *abstract conceptualization* should go beyond learning how the PA data will affect health, and towards a greater understanding of the relationship of PA data with factors that support regular PA.

Needs Gap Between Children and Caregivers

As we discussed how caregivers’ beliefs about their children affect their PA tracker engagement, in this section, we will discuss engagement in the context of the caregiver-children relationship. Our data shows that in-person family PA competition emerged in several families. However, we also found that caregivers and children perceived competition differently. Caregivers appreciated the PA trackers because of their desire to support their family’s health, whereas children appear to enjoy the playful family competition. Indeed, the need for playful design amongst children has been documented by Khan et al. in their work on a healthy snacking app [23]. Kimani et al. also found that family health portal users asked for playful elements for children [24]. Our findings suggest one way to support playfulness, by helping the children to appreciate the positive feeling of increasingly matching their parents’ physical strength.

This gap of desires between adults and children suggests that family members have different needs while self-tracking. These unique needs may further be reinforced with the separation between consumer adult and children PA trackers. For example, in Fitbit Ace, Garmin’s *vivofit jr.*, and Unicef

KidPower—commercial tools designed specifically for kids—the children’s PA data visualization is completely separated from the caregivers’ data. Families are required to use different apps or switch to different accounts to see other family members’ data. This renders caregivers’ engagement with their child’s PA data an optional feature in family PA tracking interactions.

In contrast, health research shows that caregivers’ involvement in children’s PA is associated with more active children [19]. Furthermore, research in HCI suggests that in-person interactions—rather than in-app interactions—are more common in family health informatics. Work by Schaeffbauer et al., for example, shows that increased awareness of health is largely due to in-person interactions because family members see each other daily [49]. Colineau et al. also found that health tracking apps encourage family members to collaborate and support each other to be healthy [8]. This work underscores how family PA tracking apps should minimize data separation, support in-person caregiver-children engagement with the data, and at the same time satisfy caregiver and their children’s differing needs. In their work evaluating a family PA dashboard, Saksono et al. suggest that caregivers appreciated the in-person family interactions while using the dashboard because such interactions satisfy the need for family connectedness [48]. Therefore, a potential direction is to design gameful health apps that are framed as tools for supporting in-person family interactions that can support playfulness and connectedness.

Inarguably, minimizing data separation can lead to privacy concerns. For instance, caregivers can be concerned if their children saw uncomfortable health data of the family members [18] (e.g., that the caregiver was not active). We reiterated that future work on family health apps should go beyond visualizing a depiction a family’s activity levels—namely by examining gameful tools that help families *think about and test ways how they can be active*. Example design directions include creating a map-based game to help families find places to be active, or a game to identify friends or relatives who can be active together. Such tools could begin to address the needs of caregivers and children, and help them to reflect on how they can be active.

6 CONCLUSION

We investigated family reflection practices on PA tracking data, aiming to understand how can families derive insights about how *they were active in the past* and how *they can be active in the future*. Guided by experiential learning theories, we found that very few families discussed *causal insights* (i.e., the implications of their PA behavior as captured by the trackers), conveying the limited utility of PA trackers. Caregivers who discussed *causal insights* were driven by their *illness-susceptibility beliefs* that were shaped by personal

health experiences. In addition, some caregivers who were not engaged with their PA data seem to prioritize education over PA. We suggest that caregivers’ *education beliefs* were shaped by a desire to help their children have a safer life.

By identifying *illness-susceptibility beliefs* and *education beliefs*, we emphasized the need to align PA tracker designs—and health apps more generally—with users’ beliefs. Furthermore, as none of the families discussed how they can be active, we suggest that future work support PA reflection that helps families identify enjoyable activities, opportunities to be active, supportive relatives and friends, as well as supportive neighbors in their community.

ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation under Grant Number #1618406. We would like to thank our community partners and our colleagues at the Wellness Technology Lab for their support.

REFERENCES

- [1] 2017. *Health, United States, 2016: With Chartbook on Long-term Trends in Health*. Technical Report. National Center for Health Statistics, Hyattsville, MD.
- [2] Eric P S Baumer. 2015. Reflective Informatics: Conceptual Dimensions for Designing Technologies of Reflection. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems - CHI 2015*. ACM, 585–594. <https://doi.org/10.1145/2702123.2702234>
- [3] Shlomo Berkovsky, Mac Coombe, Jill Freyne, Dipak Bhandari, and Nilufar Baghaei. 2010. Physical Activity Motivating Games: Virtual Rewards for Real Activity. In *CHI 2010*. ACM, Atlanta, 243–252.
- [4] David Boud and David Walker. 1991. *Experience and Learning: Reflection at Work. EAE600 Adults Learning in the Workplace: Part A*. Adult and Workplace Education, Faculty of Education, Deakin University, Geelong, Victoria, Australia. 61–82 pages. <https://doi.org/10.1177/074171368103200101>
- [5] H. E. Brown, A. J. Atkin, J. Panter, G. Wong, M. J.M. Chinapaw, and E. M.F. van Sluijs. 2016. Family-based interventions to increase physical activity in children: A systematic review, meta-analysis and realist synthesis. *Obesity Reviews* 17, 4 (2016), 345–360. <https://doi.org/10.1111/obr.12362>
- [6] Nicole R. Bush, Amber L. Allison, Alison L. Miller, Julianna Dearth-dorff, Nancy E. Adler, and W. Thomas Boyce. 2017. Socioeconomic disparities in childhood obesity risk: Association with an oxytocin receptor polymorphism. *JAMA Pediatrics* 171, 1 (2017), 61–67. <https://doi.org/10.1001/jamapediatrics.2016.2332> arXiv:cond-mat/0604212v1
- [7] Eun Kyoungh Choe, Bongshin Lee, Haining Zhu, Nathalie Henry Riche, and Dominikus Baur. 2017. Understanding Self-Reflection: How People Reflect on Personal Data Through Visual Data Exploration. *Proc. EAI International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth '17)* (2017).
- [8] Nathalie Colineau and Cécile Paris. 2010. Motivating reflection about health within the family: the use of goal setting and tailored feedback. *User Modeling and User-Adapted Interaction* 21, 4-5 (12 2010), 341–376. <https://doi.org/10.1007/s11257-010-9089-x>
- [9] Sunny Consolvo, David W McDonald, Tammy Toscos, Mike Y Chen, Jon Froehlich, Beverly Harrison, Predrag Klasnja, Anthony Lamarca, Louis Legrand, Ryan Libby, Ian Smith, and James A Landay. 2008. Activity Sensing in the Wild: A Field Trial of UbiFit Garden. In *Proceedings of*

- the SIGCHI Conference on Human Factors in Computing Systems - CHI 2008. Florence, 1797–1806. <https://doi.org/10.1145/1357054.1357335>
- [10] Kristen Day. 2006. Active Living and Social Justice. *Journal of American Planning Association* 72, 1 (2006).
- [11] Aysegül Dogangün, Michael Schwarz, Katharina Kloppenborg, and Robert Le. 2017. An Approach to Improve Physical Activity by Generating Individual Implementation Intentions. *Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization* (2017), 370–375. <https://doi.org/10.1145/3099023.3099101>
- [12] Joseph E Donnelly, Charles H Hillman, Darla M Castelli, Jennifer L Etner, Sarah Lee, Phillip Tomporowski, Kate Lambourne, and Amanda N Szabo-reed. 2016. *Physical Activity, Fitness, Cognitive Function, and Academic Achievement in Children: A Systematic Review*. Vol. 48. 1197–1222 pages. <https://doi.org/10.1249/MSS.0000000000000901>
- [13] Chris Elsdén, David S Kirk, and Abigail C Durrant. 2015. A Quantified Past: Toward Design for Remembering With Personal Informatics. *Human-Computer Interaction* 0024, June (2015), 1–40. <https://doi.org/10.1080/07370024.2015.1093422>
- [14] Kelly R. Evenson, Michelle M. Goto, and Robert D. Furberg. 2015. Systematic review of the validity and reliability of consumer-wearable activity trackers. *International Journal of Behavioral Nutrition and Physical Activity* 12, 1 (2015), 159. <https://doi.org/10.1186/s12966-015-0314-1>
- [15] Alicia L. Fedewa and Soyeon Ahn. 2011. The Effects of Physical Activity and Physical Fitness on Children’s Achievement and Cognitive Outcomes: A Meta-Analysis. *Research Quarterly for Exercise and Sport* 82, 3 (2011), 521–535. <https://doi.org/10.1080/02701367.2011.10599785>
- [16] Tara J. J. Fenwick. 2001. Experiential Learning: A Theoretical Critique from Five Perspectives. Information Series No. 385. (2001), 76.
- [17] Rowanne Fleck. 2012. Rating reflection on experience: A case study of teachers’ and tutors’ reflection around images. *Interacting with Computers* 24, 6 (2012), 439–449. <https://doi.org/10.1016/j.intcom.2012.07.003>
- [18] Andrea Grimes, Desney Tan, and Dan Morris. 2009. Toward Technologies that Support Family Reflections on Health. In *GROUP ’09*. ACM Press, New York, New York, USA, 311. <https://doi.org/10.1145/1531674.1531721>
- [19] Sabrina L Gustafson and Ryan E Rhodes. 2006. Parental correlates of physical activity in children and early adolescents. *Sports Medicine* 36, 1 (1 2006), 79–97.
- [20] Daniel Harrison, Paul Marshall, Nadia Bianchi-Berthouze, and Jon Bird. 2015. Activity Tracking: Barriers, Workarounds and Customisation. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing - UbiComp ’15*. ACM, Osaka, 617–621. <https://doi.org/10.1145/2750858.2805832>
- [21] Erik Hemmingsson. 2018. Early Childhood Obesity Risk Factors: Socioeconomic Adversity, Family Dysfunction, Offspring Distress, and Junk Food Self-Medication. *Current Obesity Reports* 7, 2 (2018), 204–209. <https://doi.org/10.1007/s13679-018-0310-2>
- [22] K Janz and Marshall H Becker. 1984. The Health Belief Model: A Decade Later. *Health Education Quarterly* (1984), 1–47.
- [23] Danish U. Khan, Swamy Ananthanarayan, An T. Le, Christopher L. Schaeferbauer, and Katie A. Siek. 2012. Designing mobile snack application for low socioeconomic status families. In *2012 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth)*. IEEE, 57–64. <https://doi.org/10.4108/icst.pervasivehealth.2012.248692>
- [24] Stephen Kimani, Nilufar Baghaei, Jill Freyne, Shlomo Berkovsky, Dipak Bhandari, and Greg Smith. 2010. Gender and role differences in family-based healthy living networks. In *International Conference on Human Factors in Computing Systems - CHI EA ’10*. 4219. <https://doi.org/10.1145/1753846.1754129>
- [25] Ruth R. Kipping, Laura D. Howe, Russell Jago, Rona Campbell, Sian Wells, Catherine R. Chittleborough, Julie Mytton, Sian M. Noble, Tim J. Peters, and Debbie A. Lawlor. 2014. Effect of intervention aimed at increasing physical activity, reducing sedentary behaviour, and increasing fruit and vegetable consumption in children: Active for Life Year 5 (AFLY5) school based cluster randomised controlled trial. *BMJ (Online)* 348, 348 (2014). <https://doi.org/10.1136/bmj.g3256>
- [26] Predrag Klasnja, Sunny Consolvo, and Wanda Pratt. 2011. How to evaluate technologies for health behavior change in HCI research. *Proceedings of the 2011 Annual Conference on Human Factors in Computing Systems - CHI ’11* (2011), 3063. <https://doi.org/10.1145/1978942.1979396>
- [27] David A. Kolb. 1984. *Experiential learning: Experience as the source of learning and development*. FT press.
- [28] W Kroeze, A Werkman, and J Brug. 2006. A systematic review of randomized trials on the effectiveness of computer-tailored education on physical activity and dietary behaviors. *Annals of Behavioral Medicine* 31, 3 (2006), 205–223. https://doi.org/10.1207/s15324796abm3103_2
- [29] Shiriki Kumanyika and Sonya Grier. 2006. Targeting interventions for ethnic minority and low-income populations. *The Future of Children / Center for the Future of Children, the David and Lucile Packard Foundation* 16, 1 (1 2006), 187–207. <http://www.ncbi.nlm.nih.gov/pubmed/16532664>
- [30] Gwendolyn M. Lawson, Cayce J. Hook, and Martha J. Farah. 2018. A meta-analysis of the relationship between socioeconomic status and executive function performance among children. *Developmental Science* 21, 2 (2018), 1–22. <https://doi.org/10.1111/desc.12529>
- [31] James J Lin, Lena Mamykina, Silvia Lindtner, Gregory Delajoux, and Henry B Strub. 2006. Fish’n’Steps: Encouraging Physical Activity with an Interactive Computer Game. In *UbiComp 2006*. 261–278. https://doi.org/10.1007/11853565_16
- [32] Andrew Macvean and Judy Robertson. 2012. iFitQuest: A School Based Study of a Mobile Location-Aware Exergame for Adolescents. In *MobileHCI ’12*. San Francisco, 359–368. <https://doi.org/10.1145/2371574.2371630>
- [33] Alison M McMinn, Esther Mf van Sluijs, Nicholas C Harvey, Cyrus Cooper, Hazel M Inskip, Keith M Godfrey, and Simon J Griffin. 2009. Validation of a maternal questionnaire on correlates of physical activity in preschool children. *International Journal of Behavioral Nutrition and Physical Activity* 6 (1 2009), 81. <https://doi.org/10.1186/1479-5868-6-81>
- [34] Rebecca Ann Meriwether, Pamela M McMahon, Nahid Islam, and William C Steinmann. 2006. Physical activity assessment: Validation of a Clinical Assessment Tool. *American Journal of Preventive Medicine* 31, 6 (12 2006), 484–91. <https://doi.org/10.1016/j.amepre.2006.08.021>
- [35] Susan; Michie, Craig; Abraham, Charles; Whittington, John; McAteer, and Sunjai Gupta. 2009. *Effective techniques in healthy eating and physical activity interventions: A meta-regression*. Technical Report 6. 690–701 pages. <https://doi.org/10.1037/a0016136> arXiv:gr-qc/9809069v1
- [36] Andrew D. Miller and Elizabeth D. Mynatt. 2014. StepStream: A School-based Pervasive Social Fitness System for Everyday Adolescent Health. *Proceedings of the 32nd Annual ACM Conference on Human Factors in Computing Systems - CHI ’14* (2014), 2823–2832. <https://doi.org/10.1145/2556288.2557190>
- [37] Beth E Molnar, Steven L Gortmaker, Fiona C Bull, and Stephen L Buka. 2004. Unsafe to Play? Neighborhood Disorder and Lack Among Urban Children and Adolescents. *American Journal of Health Promotion* (2004), 378–387.
- [38] Sean Munson and Sunny Consolvo. 2012. Exploring Goal-setting, Rewards, Self-monitoring, and Sharing to Motivate Physical Activity. *Proceedings of the 6th International Conference on Pervasive Computing Technologies for Healthcare* (2012), 25–32. <https://doi.org/10.4108/icst.pervasivehealth.2012.248691>

- [39] Jasmin Niess and Pawel W. Wozniak. 2018. Supporting Meaningful Personal Fitness. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems - CHI '18* (2018), 1–12. <https://doi.org/10.1145/3173574.3173745>
- [40] Cynthia L. Ogden, Margaret D. Carroll, Brian K. Kit, and Katherine M. Flegal. 2014. Prevalence of Childhood and Adult Obesity in the United States, 2011–2012. *JAMA: The Journal of the American Medical Association* 311, 8 (2 2014), 806. <https://doi.org/10.1001/jama.2014.732>
- [41] K. Patrick, J. F. Sallis, B. Long, K. J. Calfas, W. Wooten, G. Heath, and M. Pratt. 1994. A new tool for encouraging activity: Project PACE. , 45–46 pages.
- [42] Laura R Pina, Sang-Wha Sien, Teresa Ward, Jason C Yip, Sean A Munson, James Fogarty, and Julie A Kientz. 2017. From Personal Informatics to Family Informatics. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing - CSCW '17*. 2300–2315. <https://doi.org/10.1145/2998181.2998362>
- [43] Aare Puussaar, Adrian K Clear, and Peter Wright. 2017. Enhancing Personal Informatics Through Social Sensemaking. In *CHI '17 Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. <https://doi.org/10.1145/3025453.3025804>
- [44] JJ Reilly and J Kelly. 2011. Long-term impact of overweight and obesity in childhood and adolescence on morbidity and premature mortality in adulthood: systematic review. *International journal of obesity* 35, July 2010 (2011), 891–898. <https://doi.org/10.1038/ijo.2010.222>
- [45] John Rooksby, Mattias Rost, Alistair Morrison, and Matthew Chalmers. 2014. Personal tracking as lived informatics. *Proceedings of the 32nd annual ACM conference on Human factors in computing systems - CHI '14* (2014), 1163–1172. <https://doi.org/10.1145/2556288.2557039>
- [46] Herman Saksono, Carmen Castaneda-sceppa, Jessica Hoffman, Magy Seif El-nasr, Vivien Morris, and Andrea G. Parker. 2018. Family Health Promotion in Low-SES Neighborhoods: A Two-Month Study of Wearable Activity Tracking. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems - CHI '18*. ACM, Montreal, BC, Canada, 1–13. <https://doi.org/10.1145/3173574.3173883>
- [47] Herman Saksono and Andrea Grimes Parker. 2017. Reflective Informatics Through Family Storytelling: Self-discovering Physical Activity Predictors. In *Proceedings of the 2017 ACM Conference on Human Factors in Computing Systems - CHI '17*. ACM, Denver, CO, USA, 5232–5244. <https://doi.org/10.1145/3025453.3025651>
- [48] Herman Saksono, Ashwini Ranade, Geeta Kamarthi, Carmen Castaneda-Sceppa, Jessica A. Hoffman, Cathy Wirth, and Andrea G. Parker. 2015. Spaceship Launch: Designing a Collaborative Exergame for Families. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW '15)*. ACM, Vancouver, BC, Canada, 1776–1787. <https://doi.org/10.1145/2675133.2675159>
- [49] Chris Schaeffbauer, Danish Kahn, Amy Le, Garrett Sczechowski, and Katie Siek. 2015. Snack Buddy: Supporting Healthy Snacking in Low Socioeconomic Status Families. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW '15)*. ACM, New York, New York, USA, 1045–1057. <https://doi.org/10.1145/2675133.2675180>
- [50] US Department of Health Services and Human. 2008. *2008 Physical Activity Guidelines for Americans*. Technical Report. U.S. Department of Health and Human Services. <https://health.gov/PAGuidelines/>
- [51] Christopher Spera, Kathryn R. Wentzel, and Holly C. Matto. 2009. Parental aspirations for their children's educational attainment: Relations to ethnicity, parental education, children's academic performance, and parental perceptions of school climate. *Journal of Youth and Adolescence* 38, 8 (2009), 1140–1152. <https://doi.org/10.1007/s10964-008-9314-7>
- [52] Kevin G Stanley, Ian Livingston, Alan Bandurka, Robert Kapiszka, and Regan L Mandryk. 2010. PiNiZoRo: A GPS-based Exercise Game for Families. In *Futureplay '10 Proceedings of the International Academic Conference on the Future of Game Design and Technology*. ACM, Vancouver, British Columbia, Canada, 243–246. <https://doi.org/10.1145/1920778.1920817>
- [53] Elizabeth Stowell, Mercedes C Lyson, Herman Saksono, René C Wurth, Holly Jimison, Misha Pavel, and Andrea G. Parker. 2018. Designing and Evaluating mHealth Interventions for Vulnerable Populations: A Systematic Review. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. ACM, New York, NY, USA, 1–17. <https://doi.org/10.1145/3173574.3173589>
- [54] Haichun Sun. 2013. Impact of exergames on physical activity and motivation in elementary school students: A follow-up study. *Journal of Sport and Health Science* 2, 3 (9 2013), 138–145. <https://doi.org/10.1016/j.jshs.2013.02.003>
- [55] David R Thomas. 2003. A general inductive approach for qualitative data analysis. *Population English Edition* 27, 2 (2003), 237–246. <https://doi.org/10.1177/1098214005283748>
- [56] Stewart G Trost, Neville Owen, Adrian E Bauman, James F Sallis, and Wendy Brown. 2002. Correlates of adults' participation in physical activity: review and update. *Medicine & Science in Sports & Exercise* 34, 12 (2002), 1996–2001. <https://doi.org/10.1249/01.MSS.0000038974.76900.92>
- [57] Amna Umer, George A Kelley, Lesley E Cottrell, Peter Giacobbi Jr, Kim E Innes, and Christa L Lilly. 2009. Childhood obesity and adult cardiovascular disease risk: a systematic review. *BMC Public Health* 17, 683 (2009), 1–11. <https://doi.org/10.1038/ijo.2009.61>
- [58] Kim M. Unertl, Chris L. Schaeffbauer, Terrance R. Campbell, Charles Senteio, Katie A. Siek, Suzanne Bakken, and Tiffany C. Veinot. 2016. Integrating community-based participatory research and informatics approaches to improve the engagement and health of underserved populations. *Journal of the American Medical Informatics Association* 23, 1 (2016), 60–73. <https://doi.org/10.1093/jamia/ocv094>
- [59] Klazine Van Der Horst, Marijke J.Chin A. Paw, Jos W.R. Twisk, and Willem Van Mechelen. 2007. A brief review on correlates of physical activity and sedentariness in youth. *Medicine and Science in Sports and Exercise* 39, 8 (2007), 1241–1250. <https://doi.org/10.1249/mss.0b013e318059bf35>
- [60] Esther M F Van Sluijs, Alison M McMinn, and Simon J Griffin. 2008. Effectiveness of interventions to promote physical activity in children and adolescents: systematic review of controlled trials. *British journal of sports medicine* 42, 8 (2008), 653–657. <https://doi.org/10.1136/bmj.39320.843947.BE>
- [61] Dana L. Wolff-Hughes, David R. Bassett, and Eugene C. Fitzhugh. 2014. Population-Referenced Percentiles for Waist-Worn Accelerometer-Derived Total Activity Counts in U.S. Youth: 2003 - 2006 NHANES. *PLoS ONE* 9, 12 (2014), e115915. <https://doi.org/10.1371/journal.pone.0115915>
- [62] Yan Xu, Erika Shehan Poole, and Andrew D. Miller. 2012. This is not a one-horse race: understanding player types in multiplayer pervasive health games for youth. In *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work (CSCW '12)*. ACM, Seattle, 843–852. <https://doi.org/10.1145/2145204.2145330>
- [63] Adina Zeki Al Hazzouri, Tali Elfassy, Stephen Sidney, David Jacobs, Eliseo J. Perez Stable, and Kristine Yaffe. 2017. Sustained Economic Hardship and Cognitive Function: The Coronary Artery Risk Development in Young Adults Study. *Am J Prev Med.* 52, 1 (2017), 1–9. <https://doi.org/10.1016/j.jtrsl.2014.08.005>