Crowdsourcing Exercise Plans Aligned with Expert Guidelines and Everyday Constraints

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ABSTRACT
Exercise plans help people implement behavior change. Crowd workers can help create exercise plans for clients, but their work may result in lower quality plans than produced by experts. We built CrowdFit, a tool that provides feedback about compliance with exercise guidelines and leverages strengths of crowdsourcing to create plans made by non-experts. We evaluated CrowdFit in a comparative study with 46 clients using exercise plans for two weeks. Clients received plans from crowd planners using CrowdFit, crowd planners without CrowdFit, or from expert planners. Compared to crowd planners not using CrowdFit, crowd planners using CrowdFit created plans that are more actionable and more aligned with exercise guidelines. Compared to experts, crowd planners created more actionable plans, and plans that are not significantly different with respect to tailoring, strength and aerobic principles. They struggled, however, to satisfy exercise requirements of amount of exercise. We discuss opportunities for designing technology supporting physical activity planning by non-experts.

Author Keywords
Exercise Plans, Crowdsourcing

ACM Classification Keywords
H5.m. Information interfaces and presentation (e.g., HCI).

INTRODUCTION
As of 2012, half of all adult Americans experience one or more preventable chronic diseases [42] often caused by a lack of exercise [42]. The U.S. Department of Health and Human Services has created a set of national physical activity recommendations to maintain good health and prevent chronic disease [43]. Despite that recommendations exist, only 22% of Americans follow the aerobic and muscle strengthening national guidelines [43], and less than 23% of the world population meets recommended guidelines [45]. To meet the recommended levels of physical activity, people must change their daily practices to incorporate more exercise.

A critical barrier to changing behavior is getting started and fitting the behavior into their life [15] - what can a person do now? how can they adjust their lifestyle to accommodate for exercise in their life? People often turn to exercise experts, such as personal trainers, to create plans for them which meet national guidelines. Personal trainers are educated to tailor these guidelines to abilities and goals of the person [6]. However, personal trainers can be prohibitively costly. On average, in the U.S. one hour with a personal trainer can cost $50 an hour [44].

Because experts are expensive, some people turn to cheap or free mobile apps which provide exercise plans that people can follow weekly, like the 7-minute workout, or couch to 5K. Though these apps can help people make progress on exercise, the apps still offer limited ability to tailor the plans. Some apps allow customization of exercise plans based on goals, age, weight, and gender, but struggle to account for people's schedules, or personal preferences for exercise. Furthermore, the plans included in exercise apps fall short of national physical activity recommendations [16,19,30].

Previous HCI research shows that, with adequate support, crowd workers can help complete tasks normally performed by experts, such as providing mental health support with expert strategies [33] or providing surgery feedback [13]. We apply insights from this prior research to the creation of personalized exercise plans.

We hypothesize that crowd workers can create quality exercise plans if they are provided with means to help them follow expert guidelines. Our system, CrowdFit, helps the crowd worker (i.e., *crowd planner*) make plans *compatible* with the recipient (i.e., *client*) by providing an exercise profile of the client. It also guides the planner towards making recommendations that satisfy national guidelines, with respect to *how much* and *what types* of physical activity is recommended. It does so through providing quantitative feedback during plan creation on calories progress and strength-cardio balance, and by providing a database of activities with exercise properties.

To test whether CrowdFit helps crowd workers create useful plans, we conducted a field deployment with three conditions

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comparing plans created by: (1) crowd workers using CrowdFit, (2) crowd workers without CrowdFit but with links to exercise information, and (3) personal trainers. We recruited 46 participants who wanted to exercise (i.e., *clients*), 122 crowd workers (i.e., *crowd planners*), and 21 personal trainers (i.e., *expert planners*). To create plans, regardless of which study condition, planners used information shared by clients. Clients were randomly assigned a condition, following the generated exercise plans for two weeks.

In this research, we demonstrate techniques for supporting crowd workers in the creation of physical activity plans that balance client preferences and needs with nationally recommended physical activity guidelines. These techniques include feedback on satisfying the guidelines, a rich client profile including historical information about client's exercise, and a collection of physical activities with metadata relevant to guidelines. Our study provides empirical evidence that crowd plans can be a viable alternative to expert-generated exercise plans. CrowdFit plans were more actionable than plans created by experts or crowd workers not using the system. Compared to experts, crowd planners created plans that are not significantly different with respect to tailoring, strength and aerobic principles.

RELATED WORK

Many people want to improve exercise activity, but fail to achieve this goal because they do not know what to do, do not have the skills to exercise, are concerned about injury or cannot make the time to exercise [41].

Behavior planning

Behavior planning is an effective technique for behavior change. Action plans [14] has been found beneficial in domains such as smoking cessation, healthy eating, exercising, and oral hygiene [21,26].

Action plans link behaviors related to goals, to environmental cues, by specifying *when*, *where* and *how* a behavior will occur [14,15], for example "I will go running after I get home from work on the trail near my house". Prior work has tried to understand what aspects of planning are most effective. Providing people with flexibility in what activities they do can help [11]. Plans that include adaptations for potential barriers, e.g., "if it rains, I will go to the gym", are also more successful [21]. While plans can support behavior change, not everybody has sufficient knowledge about the elements of a strong plan or about appropriate goals to write a plan that will work for them.

Further, while many behavior change plans exist in books or online, these are rarely tailored to people's preferences and constraints, making the plans less effective [37]. To receive tailored advice, people turn to personal trainers. Face-to-face coaching helps reduce exercise barriers and better facilitates exercise than individual efforts [31]. When personal trainers create exercise plans they use *tailoring* to help people pursue the plans [29,31] and *exercise science guidelines* to help provide the best health benefits [12].

Exercise guidelines

The U.S. Department of Health and Human Services and the American College of Sports Medicine (ACSM) have identified a set of guidelines for effective exercising based on evidence from physical activity studies to date [12,43]. Both organizations are consistent in their recommendations, but ACSM targets exercise experts and thus contains more guidelines for creating effective exercise recommendations. We selected five exercise guidelines that incorporate the main recommendations in the current National Exercise Guidelines [43] and ACSM recommendations [12] . Several other ACSM guidelines exist, but we will focus on the primary principles articulated by both institutions. In this work, we define them as follows:

Amount (*how much* activity to perform): People should perform 75 minutes of vigorous or 150 of moderate physical activity weekly [43], or a range of calories [12] (e.g., a person of 170lb and 5.6ft should burn at least 1270 calories).

Progression (*how much* to increase activity): Based on the client's level of activity, the plan should start with a few days of activity a week and increase gradually. To be realistic, recommendations should consider the person's level of activity, and ability, and increase exercise duration, frequency and intensity gradually [12].

Balance (*what types* of activity to perform): The plan should have a similar amount of strength and aerobic activity. Healthy adults should perform both types of exercise [12], because of the different physiological benefits they provide.

Pattern (*when* to perform activity): The plan should include rest days. If consecutive days contain physical activity, they should include different types of activities to allow muscle recovery time and prevent injury [12].

Compatibility (*what activities* to perform): the plan should match the client's lifestyle, schedule, preferences, constraints, goals, and experiences, to increase likelihood it is followed.

We focus on how these guidelines can be represented in an exercise planning tool to help people create quality plans.

Technology to Personalize Physical Activity Plans

Extensive prior research in HCI has worked to help people set and achieve physical activity goals. Systems like UbiFit [8], GoalPost [34], and Fish'N'Steps [25] enable people to set goals and track progress toward them. These systems commonly encourage people to set a goal as a daily step count (e.g., 10,000 steps per day as an ongoing goal) or a set of exercises for a week. Other systems encourage people to consider what is achievable over each day of a week. CommitToSteps prompted users to set a step goal as both a minimum number of steps and the minimum number of days per week they would achieve it (e.g., "I will walk at least 8,000 steps per day on 3 or more days this week.") [35]. It also supported the concept of *progression* by automatically setting the new daily goal as an increase over the previous week. Lee et al.'s Fitbit plan presented people with step goals for each day of the week [24]. Allowing people to personalize these step plans increases their physical activity compared to automatically generated plans.

Other systems are designed to help people surface insights and opportunities for change in their everyday life, supporting *compatibility* with their everyday routines. Both Health Mashups [4] and Cuts present people with patterns, routines, or anomalies in their behavior to help them identify behaviors they would like to continue or that they would like to alter. MyBehavior goes one step further and learns an individual's physical activity and dietary patterns to generate behavioral recommendations based on context and past behavior [36,37].

When compared to the characteristics of a strong exercise plan, these systems do not support important planning work. Setting a goal, whether it is for a day or for a week, is less effective than planning when one will do the activities that make up that goal [14]. Identifying insights or opportunities for change, or receiving suggestions about what to do, does not necessarily lead to a *balanced* set of activities, to an appropriate *progression* or *pattern* of activity, or *compatibility* with one's long term aspirations.

While it may be possible to encode some of these principles in recommender systems, in goal setting tools, and in planning algorithms, we believe that another promising approach is to connect people who need plans (clients) with people who can help create plans (planners). Previous research demonstrates that plans generated through this process can fit people's preferences, constraints and routines in planning behavior change [1], but it also identified opportunities to better support the planning process.

In this research, we draw on insights from technologies to support planning and from crowd work techniques to support crowd workers in creating actionable physical activity plans that fit with client lives while adhering to principles in exercise guidelines. Many of the techniques we develop in this work may also help individuals create plans for themselves. In this work, though, we focus on crowd worker planners, as they may be more able to see beyond barriers that people perceive to their own change.

Technology supported planning for behavior change
Technology interventions have explored techniques for developing behavior plans and found benefits like increased following of user personalized step plans over sytem personalized ones [24], or effectiveness of tutorials to create sleep plans [23]. Crowd workers can contribute to planning [1,20,40]. For example, crowds can create tailored behavior change plans for others [1]. In another study of various types of goals, people who received plans from the crowd were more likely to achieve plans than those who did not receive crowd plans [20]. In this research, we use inspiration from action planning to crowdsource exercise plans.

Supporting crowds to perform expert tasks
Crowdsourcing systems enable crowd worker to accomplish expert tasks by breaking down the complex tasks. Some systems decompose tasks to a level anyone can do: writing articles [18], local news reporting [2]. Other systems assign tasks either to crowds or to experts depending on system complexity, e.g. meeting scheduling [9]. Sometimes crowds exhibit strengths over experts. For example design feedback from the crowd can be perceived as more helpful than expert feedback [27]. Crowds can provide feedback on topics traditionally done by experts, e.g. providing feedback on surgery technique [13]. Crowds can also provide feedback that produces similar benefits as expert feedback, e.g. nutrition information [5,28]. This indicates crowds can provide feedback with similar or higher benefits than experts.

Crowds can offer specific benefits for providing personal support: they can create tailored behavior plans when provided enough information about a person [1], create effective motivational exercise messages for exercise [39], effective smoking cessation messages [7], provide support to people with autism [17] . But none of this work has tried to improve the crowd capabilities so they provide higher quality support. Few systems exist that elevated crowd support to expert quality help in personal health. Panoply [32,33] shows that expert principles of cognitive behavioral therapy principles can guide the crowd to provide useful mental health support to others.

We seek inspiration in crowdsourcing to break down the task of exercise planning into tasks that are achievable by crowd workers, and to guide them through the task.

RESEARCH QUESTIONS
We seek to demonstrate techniques to help non-experts create exercise plans for others which are as good or better than expert-generated plans. This leads to our research questions:

RQ1. Can a system scaffold creation of expert-quality exercise plans by crowd workers? How and on which criteria are crowd workers able to match or exceed expert plans?

RQ2. With the software support provided, what facilitated and prevented planners from creating high quality plans?

SYSTEM DESIGN
CrowdFit is a system that scaffolds principles of exercise science to support non-experts in creating actionable exercise plans. First, CrowdFit solicits information from clients to build a client profile for planners. CrowdFit scaffolds weekly exercise planning: the planner does tasks of scheduling and exercise selection, while CrowdFit provides feedback on progress, and global constraints based on national guidelines and client needs. Clients receive the plans created and can adjust the time of the activities.

Information Clients Contribute to CrowdFit
To create actionable and personalized plans towards behavior change, we need to include client's needs and goals [1,29]. CrowdFit collected: short- and long-term goals, constraints and access, physical activity preferences

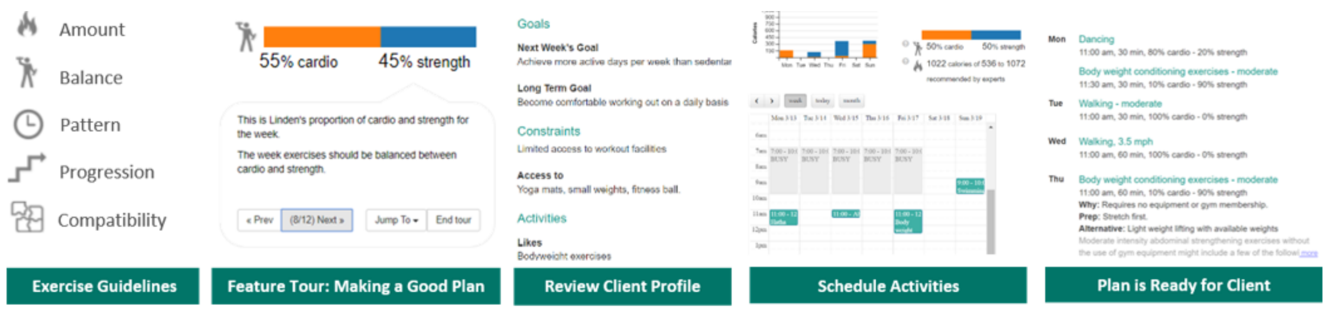

Figure 1. In CrowdFit, planners schedule exercise activities following expert guidelines. Planners are first given a tour of the interactive system and presented with the guidelines, then review the client's profile, and schedule activities which fit within the client's schedule and match their preferences.

(likes, dislikes, interests and reasons for their activity preferences), schedule, gender, age, weight and occupation. This information helps create plans that align with the client's goals and connect with the client's experience.

Scaffolding the Exercise Planning for Crowd Workers

Once CrowdFit received the client's information, the client is assigned a planner. CrowdFit scaffolds the plan creation process in smaller steps (Fig 1). First, CrowdFit provides an overview of the five dimensions of exercise science (amount, progression, balance, compatibility, and pattern). Then, CrowdFit walks the planner through a tutorial which maps the principles of actionable planning and exercise science onto CrowdFit's features. After the tutorial is completed, planners are presented with the client's profile and are given tools to create plans.

Creating plans through CrowdFit

Figure 2 shows how planners create the plans. The right panel shows the client's profile (e.g., preferences and goals). The left panel contains the principles of exercise science to match (top-left, Fig 2B-D) and a calendar for scheduling activity (Fig 2E). The calendar helps planners meet the *when* component of actionable planning by including times the client has other responsibilities or events to schedule exercise around. The planner schedules physical activities directly onto the calendar. When a time slot is selected on the calendar, a pop up allows the planner to choose *what* activity to recommend to the client.

To facilitate planning, the system provides the planner with a list of 112 common exercise activities curated by an exercise expert. The list contains information relevant to the exercise guidelines emphasized by the system: number of calories burned per minute, distribution of strength and cardio, and a description of the activity. The description includes exercise routines or links to videos when appropriate (e.g. several circuit training routines). Once an activity is selected, the planner is given text fields to provide clients with a justification of *why* the activity is a good fit for them and suggestions of *what* they can do to ensure they perform the activity. The justifications aim to motivate clients to follow the plan by helping understand why this exercise was recommended to them. To help clients overcome barriers to completing the plan, CrowdFit also has planners suggest exercise alternatives [38].

As exercises are added to the calendar, the weekly calorie breakdown (Fig 2C) and balance (Fig 2B) update in real time. The calorie breakdown translates the **Amount** guideline of exercise science. The balance chart visualizes how the activities recommended are **Balanced** with respect to cardio and strength. The **Pattern** is integrated through the calendar view (Fig 2E) and the spread of activities across the week (Fig 2D). Providing the planner with a client's preferences encourages **Compatibility** (Fig 2A). **Progression** is represented by providing information on what plan the client received last week (Fig 2F), what the client did, and why (Fig 2G). After the planner finishes scheduling physical activities, they get an overview of the plan and can provide holistic comments to the client.

Clients receive plans created through CrowdFit

Once planners create a week-long plan through CrowdFit, the link to the plan is sent to the client. The client's view also centers around a calendar which includes their schedule for the week, and the planner created exercise plan (clients' calendar is the same as planners' calendar view in Fig 2E).

The calendar view helped integrate actionable planning principles. Aside from showing *when* and how *long* the activity should be performed, the plan also included: (1) a description of the activity, created by an exercise expert, (2) an explanation of why the activity is a good match for the person created by the planner, (3) a description of how to prepare for the activity also created by the planner.

FIELD STUDY

We conducted a study to assess if CrowdFit helps crowd workers create quality exercise plans. We ran a between subject experiment with three conditions: baseline (crowd using Google docs), expert (using Google docs), and CrowdFit (crowd using CrowdFit). The baseline condition allowed us to examine the benefits of using CrowdFit for crowd workers. The expert condition allowed us to examine whether the system can result in plans comparable to those generated by experts.

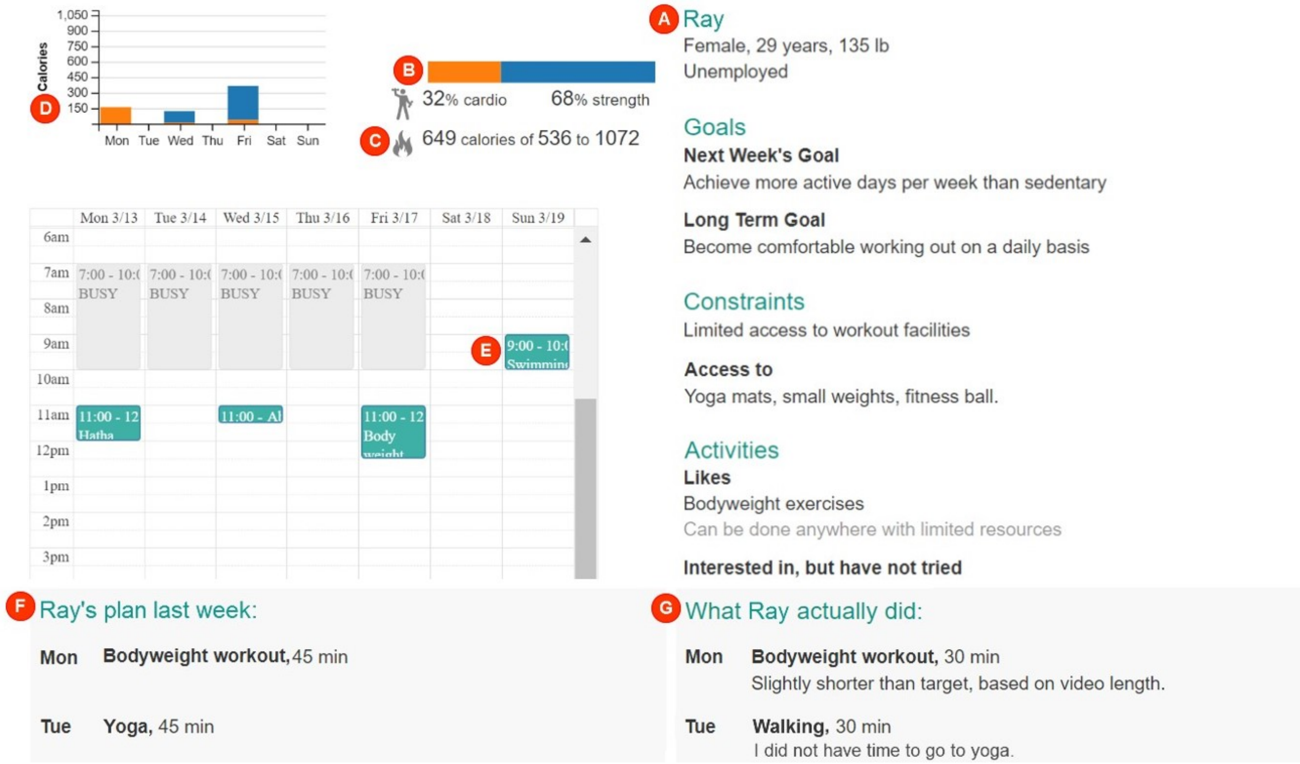

Figure 2. (A) profile of client, (B) distribution of cardio and strength over the week, (C) calories burnt if following the plan on the calendar, (D) distribution of calories and strength-cardio per day, (E) client calendar with scheduled physical activities in green, (F) overview of last week's plan and (G) plysical activity the client performed.

We gave the baseline and the expert condition a Google doc to provide a basic means of communicating and sharing a plan. The Google doc included instructions to create an exercise plan and the client's profile (Appendix 2). To give the planner flexibility to decide how to structure the plans they create, we left instructions for plan creation open ended in both the baseline and expert condition. In the baseline condition, planners were also provided with links to common and popular websites containing exercise guidelines (e.g. webmd, reddit), to simulate resources people can commonly access online. At recruitment, *crowd planners* are assigned randomly to either the baseline or the CrowdFit condition. *Expert planners* are always assigned to the expert condition.

Clients were assigned at recruitment to one of the three conditions. They were asked to fill in a profile and received plans created according to their study condition each week, for two weeks. Clients were asked to complete a post survey at the end of the two weeks. Aside from feedback about the plans they received, we also shared with them all the generated plans (from the other two conditions), in a random order. This allows us to capture clients' perceptions of each of the four plans (one created for each week of the study, plus the other two conditions), and discuss them in a follow up interview. A total of 184 plans were created in the study.

Clients

Forty-six clients (32 female, 12 male, and 2 self-identified as other) participated in the study. We recruited through email lists and neighborhood social media groups. All participating clients were randomly assigned to the three conditions: baseline crowd (15), CrowdFit (15), expert (16). Our inclusion criteria were that clients needed to: (1) be between 18 and 35 years old, a commonly used bracket in exercise for young adults (M=28); (2) self-identify as not regular exercisers (e.g., exercised regularly less than two weeks in the last month); and (3) be motivated to exercise regularly for the next 30 days. For our analysis, we excluded 9 additional clients that dropped out during the first week of the study, three from each condition.

Clients had diverse occupations: half were students, others worked in medical or media fields (Appendix 1). Clients were interested in healthy goals and good exercise habits. Half of clients mentioned barriers of time, school work, long work hours, travel, taking care of family, or balancing work and social life. Eleven clients (1 in baseline, 5 in CrowdFit, 5 in expert condition) listed in their constraints a range of physical limitations, including having a cold, being postpartum, or having a sore back. Injuries were not assessed during the study. Two participants did not have access to a gym. Clients were compensated $50 for participating in the two-week study, and $15 for an end of study interview.

Planners

We recruited 122 non-expert crowd planners by posting HITs on Mechanical Turk. Half (61) of the non-experts

Measures of plan quality based on ACSM principles
Amount, *Progression*, *Pattern, Balance:* single item concepts
Compatibility: match with client's preferences, constraints, schedule, goals, balance preferences, exercise level
Aerobic: occurrence of variety of exercises, appropriateness of intensity and duration of exercise
Resistance training: occurrence of variety of exercises, intensity of exercises, appropriateness of repetitions and sets, progression through single and multi-joint exercises, rest periods, rest time between days of exercise
Transition exercises: occurrence of warmup and cooldown
Flexibility: occurrence of flexibility exercises
Measures related to plan actionability
Specificity: explicit exercise names, how to exercise, reasoning for recommendations
Alternatives, Encouragement, Vocabulary: single item concepts
Accuracy: mistakes and irrelevant information

Table 1. Criteria used for expert evaluation

were randomly assigned to the baseline condition and the other half (61) were randomly assigned to the CrowdFit condition. Crowd planners were only allowed to participate once and thus, only created one plan for the study. Crowd planners were given two hours to complete a plan. An additional 16 crowd planners submitted tasks but were rejected due to incomplete submissions of the task. Crowd planners were compensated $7 for creating the plan. We added $2 if the researchers considered the plan above average. Crowd planners that were interviewed were given an additional $15. Two crowd planners reported having an exercise degree. Of the non-expert planners, only 10 had taken some exercise class before, although the majority (112) exercised or read about exercise regularly.

We recruited 21 expert planners through snowball recruitment from a local exercise sciences program, local gyms, and Craigslist. To qualify, experts needed to have a national personal trainer certification or a degree in exercise science (one expert had a course in exercise physiology). Each expert created up to 4 plans throughout the study, for different clients. Experts were compensated $15 per plan.

Client and Planner Surveys and Interviews

Whenever a client received a plan, they were asked to complete a short survey (week 1 plan, week 2 plan, at the end of study for the 2 plans from the conditions the planner was not assigned to). A total of 184 plans were evaluated by clients (4 plans each for the 46 clients). This survey allowed us to gather clients' perceptions of the plan. The survey included client's self-reported likelihood to follow the plan and how the plan fits with their life. Clients estimated their level of physical activity prior to the study by describing the exercise they had done the week before. During the study, clients reported daily activity and the intensity of exercise.

We interviewed 17 clients across all conditions: baseline (5), CrowdFit (7), expert (5), until we reached data saturation. Clients reported on their experience following the plans for two weeks and their impression of the two plans they were given at the end of the study.

At the end of creating the plan, planners provided feedback on their experience creating the plan. We interviewed 13 crowd planners across conditions (Appendix 1): baseline crowd (5), CrowdFit (8) until we reached data saturation. We did not interview experts as the process of experts creating plans is documented [6]. We interviewed non-experts because we wanted to understand their process for creating plans on their own (e.g., baseline) or through CrowdFit.

We adopted a mix of inductive and deductive approaches to analyze the data. First, four researchers each open coded a different transcript and discussed the emergent codes, organizing the codes via affinity diagramming and creating a code book based on our original research questions. We then re-coded the same transcript using the code book, augmenting with codes that emerged through the process. After discussion, the code book was updated with the emerging codes and used to code the remaining transcripts.

Expert Evaluation of the Plans

We recruited a team of expert judges to evaluate the quality of the generated plans. The expert judges consisted of: a co-author (professor in exercise science) and two personal trainers with national certifications. One trainer created 4 plans in our study, but did not rate any of their own plans in the evaluation.

To evaluate the plans against the ACSM principles (Table 1), expert judges adapted an ACSM evaluation rubric (Appendix 3) [16] to capture the national guidelines and aerobic, resistance, flexibility and transition exercise principles. The plans were evaluated on: (1) how well they matched ACSM exercise principles, including exercise principles incorporated in the system, (2) how actionable the plans were, and (3) how well they were tailored to the client's needs. Table 1 contains the evaluation metrics. To ensure expert judges evaluated all plans the same way, they started by coding the same 9 plans individually, after which they added items, changed items, and resolved differences in interpretation of the items. They then rated the rest of the plans.

OVERVIEW OF PLANS CREATED

The plans created by crowd workers and experts varied by structure and information included in them. The plans created with CrowdFit were structured based on the system workflow: schedule, justifications of the recommendation, preparation and alternatives. Crowd planners using Google docs had no special support on how to structure the plan: they often followed a bullet point structure or open paragraphs, whereas expert planners often incorporated tables in their documents and were more likely to use photos and provide explanations on how to perform exercises. Clients valued the structured plans and images. Plans across conditions included reasoning of decisions made in the plan: *"I have provided a plan each day to* *ensure we achieve your goal 3 times per week"* (P_{CF}41). Some plans included words of encouragement for the client: *"Halfway through the week! You can do this!"* (P_B01). Many plans created with Google docs contained days of the week when exercise should be performed, but few contained times to schedule the exercise.

QUALITY OF PLANS CREATED

We report on the quality of the plans based on the criteria used by the expert judges (Table 1), and the client's perception of the plans. We build several linear mixed effect models to understand how plan quality was different in the expert analysis. For these models, the evaluation criteria are used as the dependent variables. The analysis models the plan type (CrowdFit, baseline, expert), and the week in the study (week 1, week 2) as fixed effects. Participant id is used as the random effect. Figure 3 shows expert ratings.

Client evaluation of plans

We find that across conditions, there is no statistical difference between conditions in how good of a fit the plans were, or how likely the clients were to follow them. Clients reported they were likely to follow the plan with minor modifications (M=4.05, sd=0.14 on a 5 point scale), and that the fit of the plan with their lifestyle was positive (M=3.6, sd=0.2). Among the 46 clients, 14 were already satisfying the exercise amount guidelines before the study. During the study, 28 of 46 clients reported satisfying the amount of exercise required nationally, and 33 participants reported an increase in physical activity during the study than before.

Similar capabilities of crowds and experts

We find that there is no statistical difference between crowd workers and experts in terms of incorporating exercise principles of pattern (M=4.35, sd=1.01), compatibility (M=3.96, sd=0.54), balance (M=3.67, sd=1.24), and aerobic (M=3.58, sd=0.67). Both pattern and compatibility were rated as good across conditions (average above 4 on a 5 point scale), whereas balance and aerobic were positive-leaning (average around 3.5 out of 5).

These results indicate crowd workers might be familiar with these principles and can apply them even without any technology support. While not trained, these concepts may be fairly easy to grasp and implement given the information provided: *"I gave her cardio, strength"* (P_B39) or *"I tried to stagger them out as far apart from each other, so it wasn't too intense so her muscles had time to rest"* (P_{CF}57).

When crowds are better than experts

We found that plans created with CrowdFit were significantly more understandable (M=4.25, sd=0.08) than expert plans (M=3.56, sd=1.24, p<0.01), with no significant difference between CrowdFit and baseline plans. We attribute this to the experts using more specialized language than crowds. *"I didn't do clean and jerk, because I still have no idea what those are. I looked it up and I tried to do it and I'm like, 'I'm just not going to bother'"* (C38).

CrowdFit improves quality of plans

We find that plans created with CrowdFit were reviewed more positively compared to the baseline along several criteria: progression, resistance training, specific details of activities, alternatives, and trends in improving amount of exercise. Some of these criteria even received comparable ratings to expert-created plans. The design of CrowdFit successfully supported these exercise principles.

We find that amount of exercise in all crowd plans was more than the minimum recommended amount of exercise in the national guidelines. The planned amount was the most in the baseline condition (M=1.03, sd=1.09), which was marginally higher than the planned amount in CrowdFit plans (M=0.5, sd=1.1). Experts' planned amount was generally less than the recommended amount (M=-0.22, sd=1.1). When we analyze the 61 CrowdFit created plans, 59% of the plans (36) were within the range of

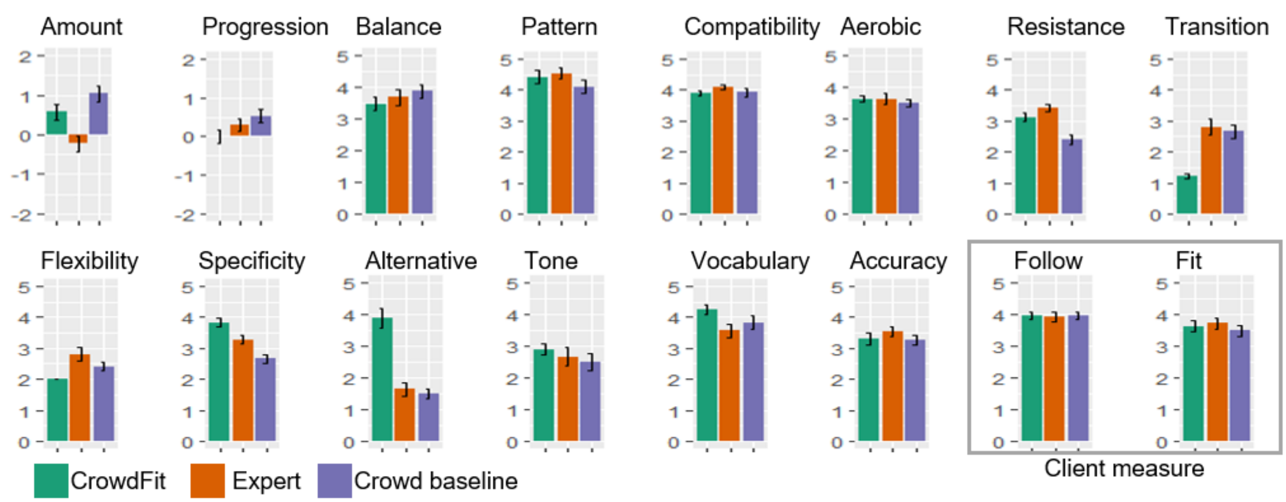

Figure 3. Expert evaluation of plans based on ACSM and actionability criteria from Table 1. Follow and Fit are client measures of quality of plans. Measurements are from 0 (lowest quality) to 5 (highest quality). Amount and progression are measured from (-2 too little exercise) to 2 (too much exercise)

recommended calories, and 38% (23) were above, while only 3% (2) were below the recommended minimum range. This suggests that crowds generally over-prescribe, but CrowdFit was able to compensate slightly by getting planners to prescribe less exercise, perhaps because of the real-time calories feedback.

Both CrowdFit plans and expert plans received great ratings for the progression metric (M=0.0 and 0.29 respectively). CrowdFit plans were rated better than baseline (M=0.5, sd=0.8, p=0.05) (Fig 3). While CrowdFit had more exercise amount than recommended, the progression was optimal.

The resistance training was rated significantly better for CrowdFit plans (M=3.12, sd=06) than baseline plans (M=2.4, sd=0.84, p<0.01). The specificity level of the CrowdFit plans (M=3.82, sd=0.73), was rated significantly higher than baseline plans (M=2.65, sd=0.69, p<0.01), as well as expert plans (M=3.28, sd=0.86, p=0.01).

Alternatives were also more frequently occurring in the CrowdFit plans (M=3.88, sd=1.47) than in the expert plans (M=1.16, sd=1.12, p<0.01) or baseline plans (M=1.48, sd=0.82, p<0.01). We believe that CrowdFit supported planners along these criteria through including the database of exercises with detailed descriptions, and requiring alternatives for all activities. Even so, the database we used could be improved. We found through interviews that clients much preferred detailed routines that included names for all the exercises than a generic routine titled “strengthening exercises” (C19, C28).

When CrowdFit does not improve quality

Compared to expert plans, we find that CrowdFit plans included lower amount of flexibility (M=2.0, sd=0.0) exercises than expert plans (M=2.8, sd-0.86, p=0.02). CrowdFit plans also included lower amounts of transition exercises (M=1.2, sd=0.4) than baseline plans (M=2.6, sd=1.2, p<0.01). This is likely due to our database not including this information. The design of CrowdFit did not explicitly encourage this type of exercise even though these exercises should accompany each activity.

FACILITATORS AND BARRIERS IN CREATING PLANS

Planning made easy

Planners who created plans through CrowdFit reported that the system made the process easier: *“An exercise plan can be quite involved. The moment I actually started using the tool, it got a lot easier”* (P_{CF}49). Planners felt they could follow the system indicators to schedule activities while receiving feedback on progress: *“I liked that it has different aspects, tells you how many calories you're gonna be burning, it gives you a nice little bar graph, with the two colors that shows you the balance, the schedule is very useful because it's everything right there in front of me.”* (P_{CF}71). Planners found it useful to have a database of activities available. P_{CF}76 felt like having information about how to exercise included in the database was helpful when they might not know the necessary details themselves: *“how many sets and how many reps”*. This allowed him to focus on other details *“it's easier for me to say, ‘Make sure you know how to do the exercises before you go, because that's important to watch the video to make sure you're doing it right’”*.

Feedback about amount and balance guided planners

More than half of the planners reported the calories bar and balance as the most helpful system features in creating plans. Planners found it easy to assess their progress towards a good plan: *“figure out whether or not I was getting close to my target, and if I was creating a somewhat appropriate exercise plan”* (P_{CF}57). Planners found the balance distribution bar helpful to inform whether to add strength and cardio activities to add to the plan: *“I like those icons because I could add an activity and then just really quickly look up there at top and see how I was doing in terms of getting a good balance and helping the person meet their objectives”* (P_{CF}41). Several planners aimed for an equal distribution of cardio and strength (P_B39, P_{CF}49, P_{CF}64, P_{CF}76, P_{CF}80). Even so, planners did not always know exactly how balanced a plan should be *“I assume based on what I know, that 30% cardio, 70% strength is okay, but 20% cardio, 80% strength would not be”* (P_{CF}71).

Planners adjusted the plan based on the calories feedback, as they were constructing it to try to fit within the recommended range: *“I just basically used it [the calorie counter] to gauge how close I was to my objective”* (P_{CF}57). The calories feedback triggered reflection on how to break down the amount of exercise across activities (P_{CF}39, P_{CF}49, P_{CF}57, P_{CF}64, P_{CF}76). P_{CF}76 reflected on how many sessions of exercise would reach the recommended amount, although they never used calories: *“Yeah … that makes sense actually. If you do a bunch of cardio, you're gonna get the total of your calories in three days of working out really easily”* (P_{CF}76).

Although the calorie measure was helpful for planners, some clients felt it did not align with their goals. The calories were perceived by some clients as a weight loss goals, which they were not interested in: *"I'm not in a losing weight mode, I'm in a let's get in better shape and be more all-around fit"* (C_{CF}41). Clients felt like a different metric might be more appropriate for their goals. Some were more interested in the balance of cardio and strength, in keeping track of how they felt after working out, whether they had an intense workout, or just in having fun.

Information use and needs: the client profile

In general, the client profile was useful to tailor the plan for their client. However, planners still needed more detailed information. Here we discuss what was useful and what was missing across the different categories of information.

Physical limitations: Planners needed to know the level of physical ability of the client to decide how much exercise to recommend “*I don't know enough to know how much time to schedule each activity. I'm not really sure what her fitness level is”* (P_{CF}71). Many planners also strived to ensure that their activities aligned with clients' physical abilities or fitness levels (P_B35, P_B39, P_{CF}64, P_{CF}71). A quarter of the clients experienced some form of physical limitation, which lead some planners to assign less strenuous activities to the injured area (P_B35, P_{CF}39, P_B49, P_{CF}49). Planners wanted to know the seriousness of the injury (P_B39, P_{CF}49) to create planners around all client restrictions. Clients commented that they were able to follow many of the recommendations in the plans (C10, C36, C72), but avoided activities that posed risks *"I was avoiding crunches just since I'm recovering postpartum and I didn't want to stress the potential ab separations"* (C35).

Access: Planners wanted to recommend activities for which the client had the necessary resources, equipment and access to gym, and showed concerns when they did not have enough information (P_{CF}57, P_{CF}80, P_{B2}67): *"I don't know what machines are there, or what free weights, other than the treadmill and elliptical stuff"* (P_{CF}80). Poor information about access sometimes lead to recommendations that were not actionable for the client: *"Pure Barre and Aerial Soap class, I am an immigrant rights attorney, I work at a non profit, a lot of student loans … bar classes … are incredibly expensive"* (C41).

Schedule: Planners used the schedule of the client when they had it available. Planners wanted to know more details about time based routines: *is the client a morning or evening person* (P_{CF}49), or transit duration between appointments or locations (P_{CF}76), to decide when in the day and during the week to schedule physical activity. When information was missing, planners made potentially poor decisions about scheduling. They had to use their own preferences instead: *"To me it seems like working out at 8 o'clock in the evening—it's something I wouldn't want to do"* (P_{CF}49). This led some planners to schedule activities even though they knew the client would have a hard time doing them: *"her daytime schedule [is] kinda tight the weekdays... Probably, if she's really dedicated, [it will] fit in between 5 and 6:30"* (P_{CF}80). To create a good schedule, planners also found it useful to have *time* based goals from the client. That helped decide how many times a week and for what duration to schedule exercise (P_B39), and it was detrimental when missing: *"I would like to know how long she wants to workout everyday ... I had no idea"* (P_{CF}71).

Although planners tried to incorporate client preferences, when it came to clients following the plans, some clients realized that their original preferences were not aligning with their experience following the plan. Some clients realized that they had different preferred schedules or activities: "*I said in my initial survey that I wanted to work on my flexibility and I thought that I would want to do yoga, but it turns out I really don't like yoga*" (C2).

Information use and needs: the exercise database

The planners used the database of exercises to search for ideas. They used the information about what was the distribution of cardio and strength, sometimes to find creative ideas of how to satisfy strength requirements: *"bowling is something a lot of people do just for fun and relaxation. So I thought that might be a nice way to add a little bit of strength to her exercise plan in a way that wouldn't make her necessarily feel like she was doing strength training"* (P_{CF}64). However, the planners wanted to integrate activities based on other type of criteria as well: fun activities for the client (P_{CF}71), activities close to the client's location (P_{CF}41), or activities that fit the planner's resources (P_{CF}39, P_{CF}41, P_{CF}57).

Alignment with everyday physical activities: One participant's job kept her physically active all day. She used the heavy lifting to replace a strength training activity: *"a lot of my job is getting in and out of the truck. It was kind of the heavy lifting part was doing the activities already because just a lot of moving up and down while holding heavy boxes of fruit"* (C72). Our database of exercises did not accommodate for recommending activities like the ones she already did: being active at work.

Tensions between exercise guidelines and client profile

The exercise guidelines came at odds with the client profile and made planners lean towards satisfying the client needs or personal knowledge over the national guidelines.

To align to client goals, some planners choose to make the plan intentionally less balanced: *"If you want to run a marathon, which in this case, she said she did, I was like, okay, I'll give her more cardio training, so she has more endurance"* (P_{CF}49). Other planners leaned towards their personal preferences and did not find it necessary to create a balance: *"I was trying to balance it 50/50 as best I could, but I think I was pretty happy to skew up with a little more cardio if necessary because I think, I mean, you do build some muscle doing cardio too"* (P_{CF}76).

Customization needs in using CrowdFit

CrowdFit's structured features may have also prevented planners from creating plans more customized in format, detail, and other activity suggestions. Planners wanted to be able to customize CrowdFit default activities: *"There's weight lifting, but you can't really fine tune it and pick out specifics for each."* (P_{CF}39).

DISCUSSION

In this research, we demonstrate strategies for helping generate tailored exercise plans created by crowds that follow expert guidelines with respect to tailoring, strength, and aerobic principles. We find that crowd workers benefit from feedback about expert guidelines, but they struggle when trying to satisfy conflicting constraints – within guidelines, within client's needs, or between guidelines and needs. Here we summarize key findings and discuss challenges and opportunities for future work.

CrowdFit facilitated generation of actionable plans consistent with exercise guidelines

Our results showed that CrowdFit was able to support non-expert planners with several key aspects of plan generation.

Planners used the calories feedback, and the balance of cardio and strength to reflect on their choices of exercise that would satisfy the exercise guidelines and to recommend appropriate amounts of exercise. The database of physical activities enabled planners to include information in plans that they otherwise would not know about, such as strengthening routines that combined several exercises, details on how to perform exercises, sets, reps, and durations. The client profile helped planners weigh how to adapt recommendations to fit the many constraints of the clients.

Planners do not have the complex knowledge an expert has about the science behind exercise metrics, but our results show that with sufficient support, they can utilize these metrics to help them produce quality results. Previous systems have escalated parts of tasks that crowds could not accomplish to experts [9]. We instead propose bringing expert-level domain knowledge to crowds, in the interfaces they use to complete the task, and providing guidance about how experts try to satisfy constraints. Doing so, can support crowd workers in accomplishing tasks that they would not be able to perform otherwise.

Creating plans that satisfy competing constraints

We found that planners had to satisfy many competing constraints when creating exercise plans: national exercise guideline requirements, client goals, client resources and abilities, and client preferences. These constraints can be at odds. In our study, it proved challenging for planners to support personal constraints and preferences, and to meet objective guidelines. Intelligent systems show potential in automating recommendations based on user preferences [10], objective expert metrics (e.g. amount of exercise), or successful progressions of exercise based on clients' experiences. Even so, planner's insights to interpret the client constraints and profile might still be needed.

Although crowd workers can make recommendations that satisfy other people's personal constraints [40], we found requesters and crowd workers needed to communicate to resolve and interpret constraints. More work may be needed to understand how to help clients consider and communicate the relative priority of different constraints. Expert guidelines could also incorporate a set of heuristics for how to adjust or relax guidelines to fit client lives.

Facilitating longitudinal interactions with clients

The profiles of clients who are new to developing a routine for a behavior might evolve quickly, as their abilities progress, as they find new activities they enjoy, and as their access to resources changes. Previous work discusses that creating behavior change plans requires iteration and involves reflection on strategies used [23]. Designs of exercise planning systems need to better support the iterative and co-design process between planners and clients (e.g. communication channel for client and planner). Future work could explore mechanisms for interaction and maintaining continuity [22] between different planners to maintain a longitudinal relationship with the client and coherent planning strategies over time.

Activities that account for varied abilities and interests

We found participants had various levels of exercise ability. Over a quarter of participants had existent injuries, pain (unrelated to the exercise plan), or became sick when starting or while enrolled in the study. To support client needs, planners needed to know how to address physical limitations that clients experience. Client profiles should include the physical limitations that a person experiences and their severity. Temporary limitations should be updated as the client abilities change. To help the planner choose appropriate activities, planning apps should incorporate common physical limitations and the physical activities associated with improving or worsening the physical limitation. For people with disabilities, planning tools should use the ACSM guidelines for individuals with disabilities. For example, future databases may include what physical limitations restrict which activities, and how they can be modified to accommodate varied difficulty (e.g., intensity, duration, sets or reps).

The physical activity database was helpful to planners for recommending exercise to others. However, this list did not support the needs of participants who performed physical activity through their job, like being a market manager. The national guidelines encourage people to perform any activity that keeps them active. More occupational and home activities, like "cooking" are becoming available in exercise databases [3]. To give planners a way to account for the physical activity people do in their daily lives, exercise plans can better complement the exercise people already perform, by integrating occupational and everyday activities, and their benefits.

CONCLUSION

Our results demonstrate that crowd workers can create exercise plans that did not significantly differ in quality from expert plans on criteria of tailoring, balance, strength and aerobic guidelines. Feedback about amount and balance helped the crowd follow the relevant guidelines while creating the plan. We find that rich user profiles and exercise databases can facilitate tailoring plans to the needs of clients and requirements of national guidelines. The crowd workers reconciled competing constraints, such as following national recommendations while also satisfying various personal needs that clients have. Techniques used in CrowdFit can successfully enable non-experts to take on tasks that otherwise performed by professional coaches.

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