PlanFitting: Tailoring Personalized Exercise Plans with Large Language Models

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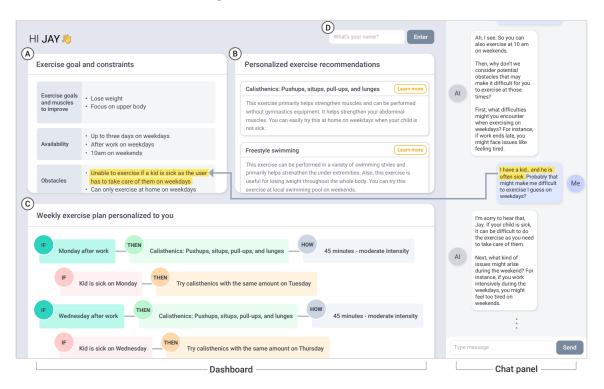


Fig. 1. Key screen of the PlanFitting system. As the user chats with the system on the chat panel (right), PlanFitting leads the conversation and collects the user's personal constraints ((A)), recommends exercise types ((B)) based on the constraints, and sets up personalized plan in the form of if-then rules ((C)).

A personally tailored exercise regimen is crucial to ensuring sufficient physical activities, yet challenging to create as people have complex schedules and considerations and the creation of plans often requires iterations with experts. We present PlanFitting, a conversational AI that assists in personalized exercise planning. Leveraging generative capabilities of large language models, PlanFitting enables users to describe various constraints and queries in natural language, thereby facilitating the creation and refinement of their weekly exercise plan to suit their specific circumstances while staying grounded in foundational principles. Through a user study where participants (N = 18) generated a personalized exercise plan using PlanFitting and expert planners (N = 3) evaluated these plans, we identified the potential of PlanFitting in generating personalized, actionable, and evidence-based exercise plans. We discuss future design opportunities for AI assistants in creating plans that better comply with exercise principles and accommodate personal constraints.

CCS Concepts: • Human-centered computing → Natural language interfaces; Empirical studies in HCI.

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^{*}Donghoon Shin conducted this work as a research intern at NAVER AI Lab

Additional Key Words and Phrases: Exercise planning, Conversational interface, Generative AI, Large language models, Implementation intention

1 INTRODUCTION

Engaging in regular physical activity is a core constituent of maintaining a healthy lifestyle, significantly impacting the overall well-being of individuals. Not only do such activities help maintain optimal physical health, but physical activities are also known to improve mental health [48] and reduce the risk of various chronic diseases [21]. Despite the widespread consensus on the importance of consistent exercise, a large portion of the global population is known to fall short of meeting the recommended physical activity guidelines. For example, Tucker *et al.* [46] revealed that less than 10% of individuals meet the amount of physical activities as recommended by the U.S. national guideline, leading to concerns at both individual and public health levels.

To better undertake daily physical exercises, it is beneficial for individuals to adhere to personalized exercise regimes [25, 34]. However, creating individualized exercise plans is often challenging [19], and individuals often struggle to formulate plans that align with their unique lifestyle constraints [54]. A potential solution is to involve professional exercise planners (*e.g.*, personal trainers, medical practitioners) and seek their assistance in tailoring the individual exercise plans. Yet, this approach comes with its own setbacks, such as high costs, accessibility issues, and lack of customization due to broad client bases [10, 36, 38, 43].

Previous studies have attempted to bridge this gap by employing technology-supported self-reflection [31, 54] and leveraging peer groups [4] or crowdworkers [5] to formulate customized exercise plans. However, while these human-computational approaches can bypass the needs of experts and result in plans comparable to those generated by experts [4, 5], they still require time and effort by people. They also depend on having the preferences, goals, and schedule of the client well specified upfront. However, without guidance, the information provided by the clients may be incomplete. Further, even the best-designed plans need adaptations to fit with the changing contexts of the clients. This can be challenging to achieve if peers, planners, or crowds are expected to be available 24-7 to perform this type of adaptation as needed, which becomes even more critical when iterating on the exercise routines for the long-term exercise. To address these issues, in this study, we focus on the potential of large language models (LLMs) for addressing these challenges within the realm of exercise planning. More specifically, we highlight the expressivity and comprehensibility of LLMs in steering the conversation to gather highly personalized constraints required to plan for exercise regimens, which we expected to streamline the process of personalizing exercise plans.

To understand the everyday practice and challenges of exercise planning between experts and clients, we conducted preliminary interviews with professional exercise planners (N=5) and lay individuals (client; N=8) who have experience in setting up personalized exercise plans with planners. From the interview, we characterized the procedure of formulating tailored exercise plans between the experts and clients, which consists of goal setting, collecting availabilities and expected obstacles, prescribing plans, and iteration. In addition, we found that experts often struggle to integrate exercise prescriptions within the irregular schedule of clients with limited consideration of clients' input during the iterative process of revising their exercise plans.

Informed by these insights, we designed and developed PlanFitting (Figure 1), a web interface that helps users create and iterate on their personalized exercise plans through a conversation driven by an LLM. Specifically, PlanFitting system engages users in an interactive dialogue, collecting necessary information on their constraints (*i.e.*, exercise goals, availability, and potential obstacles that may inhibit adherence to the plan). PlanFitting then recommends exercises and provides the exercise plan in the form of *implementation intention* [25] (*i.e.*. IF-THEN rules), which are succinct and

generalized schedule format that associates the intentions with the user's specific events without stringently adhering to time-based schedules [15].

To understand how people interact with PlanFitting and the quality of AI-crafted plans, we conducted an exploratory study with 18 people motivated to plan their exercise. During the study, participants formulated a weekly plan and refined it further with the assistance of PlanFitting. In this process, PlanFitting successfully assisted users in articulating highly personalized constraints, while accommodating their own unique chatting style. Also, participants perceived PlanFitting system to be usable, and found the generated plans to be personalized and actionable. In addition, expert planners (N = 3) who evaluated the generated outputs based on the exercise principle (i.e., FITT [20]) evaluated the frequency, intensity, and time composition of the generated plans to be above average, yet revealed the opportunities for enhancing the combination of exercise types. From the qualitative feedback from the participants and planners, we also discuss future design implications for further enhancing the qualities of the plans generated by an AI-infused exercise planner.

Our study contributes:

- (1) A formative study (N = 13) revealing the process and challenges of exercise planning between clients and expert planners
- (2) Design and development of PlanFitting, a novel exercise planning system driven by LLMs that helps generate a personalized exercise plan and iterate on it
- (3) Empirical results from an exploratory user study (N = 18) demonstrating how people leverage PlanFitting to craft their exercise plans and how professional expert planners view the quality of the output plans

2 RELATED WORK

2.1 Personalized and Actionable Exercise Plans

Maintaining physical activities is an integral part of a healthy lifestyle, but the majority of individuals find it challenging to incorporate adequate exercise into their daily routines [19, 54]. To resolve this, setting up and maintaining exercise plans can significantly aid in motivating individuals to maintain regular physical activity [25, 34]. Specifically, several empirically grounded guidelines have been proposed to facilitate this process. For example, the American College of Sports Medicine (ACSM) [2] has developed universally recognized guidelines that health professionals commonly use to design effective exercise regimens [44]. Such guidelines offer broad advice and guidance on the planning process of exercise regimen (e.g., recommending at least 150 minutes of moderate-intensity exercise per week), as well as the definition of exercise-related terminologies.

On top of adhering to such guidelines, prior studies have explored methods to generate exercise plans that foster successful adoption and maintenance of exercise regimens. Personalization of exercise plans is generally empashized [50], which takes into account various personal factors such as individual preferences, constraints, and everyday conditions that may be crucial to ensuring the individual's chance of adapting to the plans. However, tailoring such unique constraints of individuals demands exercise professionals or health experts.

Another line of research in the fields of behavioral psychology and sports medicine has explored the effective concept and format of exercise prescriptions. One well-known approach is the *implementation intention*, which comprises a specific plan linking a particular circumstance to a corresponding action [25, 29]. Implementation intentions are formatted as IF-THEN rules and often practically combined or interchanged with action planning by including the

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environmental cues [29]. For example, one can set up an exercise plan in the form of implementation intention like "IF *I come back home in the evening*, THEN *I will jog for 30 minutes*." By effectively turning intentions into actionable steps, implementation intentions have demonstrated success in various behavior change contexts, such as managing a healthy diet [1, 3, 28, 45], reducing bedtime procrastination [47], and aiding in smoking cessation [16, 35]. Similarly, in the context of exercise, adopting implementation intention to the exercise plans has been shown effective in promoting physical activities [33].

Building on this body of research, our paper introduces a technological approach for incorporating individual constraints to generate customized exercise plans in an implementation intention format. Specifically, aligning with the earlier research emphasizing the significance of specificity and context in generating implementation intentions [19], we believe that prescribing implementation intentions with the personalized constraints sourced from the individuals would help create personalized and actionable exercise plans. Furthermore, in this process, we posit that technology-mediated interactions can assist individuals in articulating their personal constraints and incorporating such constraints into implementation intentions, thus enabling the personalized planning of implementation intention without expert assistance.

2.2 Technology-mediated Exercise Planning

Advancements in computing technology have offered great potential in leveraging digital tools to assist individuals during the process of maintaining their daily physical activity and status [30], such as encouraging physical activities [17, 32] and tracking physical activities [6, 18]. Another application area is exercise planning, where several studies within the HCI community have explored technology-mediated interactions in the context of planning for the individual's exercise regimen to ensure consistent physical activities. For example, previous studies explored technologies that help maintain individuals' exercise plans on their own [31, 54]. Another line of research goes beyond individuals by leveraging other people, such as peers [5] or crowd workers to generate custom exercise plans to facilitate health behavior change [4, 5].

This line of research showcases the potential of leveraging technology in constructing personalized exercise regimens. Nevertheless, prior technology-mediated approaches often require substantial human involvement, such as self, friends, or crowds from the goal-setting to the actual formulation of the plan. Thus, considering the cost and availability of such human labor associated with these approaches, the sustainability and scalability of these approaches might be limited. Instead, in this study, we seek to mitigate such issues and aim to build more sustainable systems that support iterable planning with the help of large language models (LLMs) in assisting users in planning and implementing a feasible exercise regimen.

2.3 Integration of Large Language Models in User Interfaces

Recent advances in large language models (LLMs) offer new opportunities for equipping traditional interfaces with intelligence. Trained on a vast amount of textual data with human iteration, LLMs (e.g., GPT [9, 41], LLaMA [37], HyperCLOVA X [14], PaLM [12]) demonstrate remarkable proficiency and pose great potential in various natural language processing (NLP) tasks, ranging from text summarization (e.g., [9, 53]) to dialogue generation (e.g., [52, 55]). Incorporated into user interfaces, LLMs generally have two broad roles. First, LLMs augment core system interactions with NLP tasks, such as text analysis (e.g., VISAR [56]), story generation (e.g., TaleBrush [13]), inspiration generation (e.g., Sparks [24]), and data labeling (e.g., PaTAT [23]). Most of these tasks are challenging to tackle with traditional NLP models or yield comparable quality with LLMs with much smaller training samples [9].

Second, LLMs provide a conversational interaction component, as they can generate responses considering both the task-specific contextual information and the dialogue. Many LLM vendors provide generalized chatbot services (e.g., ChatGPT [39], Bard [27]) to demonstrate their LLM capability, and HCI research prototypes leverage LLMs to perform more specific tasks through conversational interaction (e.g., health data collection chatbot [52], recommendation [11, 22]). For example, Wang et al. proposed a conversational interface that supports users to interact with mobile UI components through conversation [51]. In this work, we leverage LLMs for both purposes: (1) understanding exercise context and constraints users described in natural language and generating exercise plans from them, and (2) carrying on a free-form conversation to maximize flexibility and expressivity of various exercise constraints.

3 FORMATIVE STUDY

To understand the current practice of personalized exercise planning and the challenges that arise during those processes, we conducted a formative interview study with exercise planners (N = 8) and clients (N = 5). The study protocol was reviewed and approved by the institutional review board.

Exercise planners. From a corporate clinic and our internal network, we recruited five experts (FP-1 – FP-5; three females and two males) who are experienced in setting up personalized exercise plans for clients. Of the five experts, three were physical therapists, another was a physiatrist, and the other was a kinesiologist. The exercise planners aged between 26 and 42 (M = 34.6) and had an average of 9.8 years of relevant experience (SD = 4.5).

Clients. We recruited eight individuals (FC-1 – FC-8; 6 females and 2 males) by advertising our study on a local community platform and internal bulletin boards in a giant enterprise in South Korea. Our inclusion criteria were people to have experience setting up their personalized exercise plans under the advice of exercise experts (e.g., clinicians, physical therapists, personal trainers, etc.). Clients were aged between 26 and 45 (M = 35). Three participants responded that they have/had engaged in exercise under the personalized exercise plans for less than three months, three participants for 3 to 6 months, and the other two participants for more than six months.

We invited each participant to 1-hour semi-structured interview session. Then, we asked each exercise planner to primarily share insights into (i) their planning procedures and (ii) the obstacles they encountered while setting up plans for/with the clients. Likewise, clients were prompted to elaborate on (i) their experiences and process of planning exercises with exercise planners and (ii) any challenges they faced during the planning. The interviews were audio-recorded and transcribed. We compensated 50,000 KRW (approximately 35 USD) and 30,000 KRW (approximately 22 USD) for each planner and client, respectively.

We analyzed the interview transcripts using thematic analysis [8]. Specifically, the process was done in a bottomup approach, where the authors first got familiarized with the raw responses, identified emerging themes from the responses, and compared the themes until the authors reached an agreement. As a result, we could derive the final themes as described in the following section.

3.1 Practice of Personalized Exercise Planning

From the interview, we identified that planners primarily follow well-known exercise guidelines, such as the ACSM guidebook, which emphasizes engaging in a minimum of 150 minutes of moderate-intensity exercise per week. However, these guidelines do not provide specific guidance on the personalization for varying lifestyles: "Actually, even if you take a look at those exercise planning guidebooks, there won't be anything more detailed than [showing a page that defined some case studies of individuals] (...) that's the end of 'evidence-based' personalization." (FP-4) As a result, planners use them as

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a flexible framework rather than strict rules, making tailored modifications while adhering to such high-level principles: "I'm just following a broad guide and customizing a lot in that scope. Shouldn't the details within it be personalized?" (FP-2) In addition, we were able to surface common information that the planners collect to personalize the plans for each client, such as the personal goal of the exercise, personal obstacles, and feedback (during the follow-up sessions), delivered through either verbal communication or a combination of a survey form and an oral interview with the client:

Understanding client's main goals for exercise. Every planner responded that they start by setting up the goal of the exercise, emphasizing the influence of identifying the purpose and setting clear goals for exercise in the motivation of clients. They are reported to engage in conversations with clients to find out their own necessity and benefits of exercise to enhance motivation, particularly for newcomers: "For managing exercise plans, it's crucial to first motivate by discussing goals first rather than just telling them to do it." (FP-1)

Surfacing available amount of times for exercise and potential obstacles. Based on the goals of the exercises that the planners identified, planners ask clients questions to surface how much time they would be available for exercise: "For those who don't have set regular office hours or for nurses working 3/4 shifts, I ask and look at how much personal time the client can exercise on a regular basis." (FP-3) Also, planners ask what factors may potentially make it challenging for them to exercise during those times (e.g., physical constraints, parenting), in order to make the exercise planning more viable and realistic: "I told my planner when my menstrual cycle comes (...) And (as a developer in a company) I told them whenever there is a schedule for releasing a new version that my condition won't be good for about three following days." (FC-5)

Prescribing plans. Based on collected exercise goals, availabilities, and obstacles, planners create a personalized exercise plan for clients. While planners are willing to provide detailed plans down to specific times, the limited availability of planners makes this approach impractical: "I can't do detailed time planning (...) It seems inconsistent (with my current availability) to generate highly detailed plans, like scheduling at a certain time." (FP-4) As a result, planners and clients typically receive a weekly exercise plan with recommended days and hours, exercise types, allowing clients to exercise at their own convenience to meet their requirements: "They (planners) didn't ask me to exercise at a specific time; they just told me to do a certain amount of some exercises during the week." (FC-4)

Revisiting regularly (e.g., weekly, bi-weekly) to share feedback and iterate on the plan. Emphasizing the importance of viewing the exercise planning as a feedback-driven iteration, rather than a one-time interaction, planners and clients regularly meet (e.g., weekly, bi-weekly) to check if the exercises need to be modified: "There are types of exercise that go in and out (...) After solving the urgent problem, if I wanna get a nicer body shape, other exercises may go in or out." (FC-1) Gathering newly emerged feedback and constraints, planners make adjustments to exercise types and/or duration: "Clients first give it a try, and I gather feedback when they come back in the following week based on their experience trying the exercise plan. If they think it won't work for any reason, I ask them to let me know, and we can start the revisions from there, just like forming and iterating on a hypothesis." (FP-2)

3.2 Challenges of Personalized Exercise Planning

In addition to understanding the practice of establishing personalized exercise plans between planners and clients, we could also identify challenges that they frequently encounter:

3.2.1 Difficulty of contextualizing the exercise within their own schedule. After being prescribed the weekly exercise counts, clients are required to incorporate these exercises into their own schedules by themselves. However, during

interviews, clients reported that such an 'autonomous' process, without more specific guidance on when to exercise, makes it difficult for clients to cope with unexpected variables (e.g., appointments, work schedules). Consequently, adhering to the plans becomes highly reliant on their own motivation, making clients prone to becoming complacent: "I think it's mostly about getting the number of exercises and then performing them on my own, so my own willingness is the most important factor (...) If I suddenly have to work at night, I just end up not doing exercise that day because there's no one pushing me to do and I feel like I can just do it later." (FC-2)

Particularly, these issues are reported to worsen over time. Specifically, as time passes, various triggers that may lower motivation emerge, such as moments of stagnation in their exercise progress. In such situations, this complacency is exacerbated, leading to a tendency to continuously postpone exercise and eventually skip it: "If you aim for a weight loss, there are times when you reach a point where you're not losing any more weight (...) then my motivation decreased a bit, so sometimes I took a day or two off, rested a bit more, or skipped it in various other ways. So, I'm skipping more than I did in the beginning." (FC-6)

3.2.2 Limited availability of planners affecting the iteration process and adaptation to fluctuating schedules. Clients expressed struggles around accommodating sudden, unexpected time changes induced by their irregular lifestyles and work schedules. Often, reaching out to planners for real-time schedule adjustments isn't a practical possibility, as planners too have other clients and personal commitments. As a result, clients often expressed a desire for more flexibility in schedule planning: "I have been meeting with my planner every week (...) it was sad to see whenever I have a schedule change and need an alternative, I couldn't ask about the plan iterations right away for the other days." (FC-6)

Such an issue is reported to ironically make the whole exercise schedules of clients even more dependent on the planners' decision-making process. Consequently, if the weekly meeting is canceled as either the client or the planner is unable to attend the weekly meeting, it often results in a disruption of the exercise for the entire week: "There were instances when the trainers were not available due to their other commitments (...) the whole exercise for the following week messed up." (FC-5)

3.2.3 Limited adaptability of planners in engaging with and incorporating client feedback. Even when meeting to discuss the exercise regimen, clients often struggle to have their concerns and input incorporated into the plans. Indeed, clients shared several cases when they felt their opinions were dismissed, or they had to spend a considerable amount of time advocating for their points to be considered: "You know, I can't see the planner every day and have to meet them face to face, and my daily conditions are different every day (...) but I always had to follow the same fixed program. I once went on a trip to [an attraction], but even when I explained this situation in advance my planner just asked me to keep exercising while traveling. It's too inflexible and feels too coercive." (FC-2)

The prescribed regimen's inability to cater to unique constraints such as travel schedules could discourage clients from following through. In the worst case, disagreements stemming from this lack of flexibility have sometimes even led clients to discontinue their programs entirely: "I and planners had disagreements on the types of exercise, and I discontinued planning for the exercise with my personal trainer from that moment." (FC-5)

4 PLANFITTING

Our formative study surfaced the overall planning process of personalized exercise plans, as well as the difficulties that can emerge during such processes. Informed by these insights, we designed and implemented PlanFitting, a conversational interface aimed to help individuals set up their personalized exercise plan and iterate on it. Focusing on the expressivity and comprehensibility that LLMs offer, we designed our system using LLMs to foster engaging

interaction, while adapting to the unique constraints of users and allowing them to iterate their plans. Informed by the procedure that our expert interviewees follow, we organized the interaction process of PlanFitting into the following three stages: (1) collecting exercise-related user constraints (*i.e.*, goals, availabilities, obstacles), (2) personalized exercise recommendation, and (3) generating personalized weekly plan. In the following, we describe the design of PlanFitting's dialogue system with the underlying LLM pipeline, user interface components, and implementation details.

4.1 Interaction and Interface Design

PlanFitting was designed as a web application (Figure 1) consisting of two primary elements: a chat panel on the right panel (Figure 1-Chat panel) and a dashboard (Figure 1-Dashboard). The user mainly interacts with PlanFitting on the chat panel via natural language, and the dashboard provides an overview of the current status of the conversation, summarizing exercise-related constraints (Figure 1-®), recommended exercise list from the system (Figure 1-®), and the finalized exercise plans (Figure 1-©). Every information on the dashboard is automatically updated on every conversational turn so that the user can stay on track.

- 4.1.1 Collecting exercise-related user constraints. The user starts planning by entering their name into the system (See Figure 1-①). The chatbot takes the lead by actively collecting essential information required for crafting an exercise plan. Specifically, the chatbot proactively asks questions aimed at gathering the personal constraints of the user, listed in the following:
 - (1) **Exercise goals**: The user's goal of exercise, either in a format of intended purpose or the specific muscle group they aim to target
 - (2) **Availability**: The user's available times for the exercise, either in the exact time format (*e.g.*, '7 *pm*') or in a descriptive form (*e.g.*, 'after work')
 - (3) **Potential obstacles**: Any expected obstacles they anticipate that could potentially impede their exercise routine (e.g., 'chance of working until late night')
- 4.1.2 Exercise type recommendation. After the user has shared all the necessary constraints, the chatbot proceeds to offer personalized exercise recommendations. The system provides up to five exercise options based on the curated list of exercises that contains 75 common exercises that the exercise experts summarized, drawing from the prior work [4]. The list contained the name of the exercise, as well as its well-known alternative name, intensity, laypeople description (e.g., definition, how to perform), and the muscles involved (See Appendix B for an example). The list is stored and loaded in CSV format, which can be easily expanded by altering with external exercise databases in the future.

The recommended exercises are displayed on the dashboard with a brief description, which summarizes the definition of the exercise and, if available, the reasoning behind the recommendation (Figure 1-®). For users seeking more comprehensive information about a particular exercise, a 'more' button is provided where the users may click to access additional details of the exercise. Then, users are asked to select their desired exercises by either clicking on them on the dashboard or typing the name of the exercise(s) into the chat screen in a free form; if they wish to explore additional exercise options, they are also allowed to simply ask a request to the chatbot, which will result in refreshing the recommendations.

4.1.3 Generating a personalized exercise plan. After the user selects the exercise types they want to include, PlanFitting generates an exercise plan, which is displayed on the dashboard (Figure 1-©).

Format of the plan. From the interview study, we found that prescribing exercise broadly (e.g., specifying a weekly amount) could burden users with scheduling and possibly lower motivation. Thus, to contextualize the exercise plan within the user's availabilities, PlanFitting offers each exercise plan in an implementation intention [26] format, a grounded strategy rooted in behavioral psychology that aligns the user's intentions with specific events, hence offering a structured format in well-established IF-THEN statements. (i.e., "IF {availability (time or situation)}, THEN do {exercise type} for {amount} at {intensity}") In addition, the system offers a coping plan for each plan, which equips users with an alternative plan to follow when the original plan cannot be executed due to the obstacles that may happen. (i.e., "IF {obstacle}, THEN {alternative}")

Grounding a plan to global exercise guidelines. To earn rigor for the generated plans, the system applies a set of guidelines based on the recommendations offered by ACSM [2]:

First, the system aims to allocate exercises totaling more than 150 minutes per week. To comply with the ACSM guidelines, the system also accounts for vigorous-intensity exercises by doubling their allocated time when calculating the total exercise duration. In addition, to balance between cardio and strength training, if the user had initially chosen exercises of either type only, the system asks users to consider incorporating both types of exercise. Lastly, the system tries to put a minimum of a one-day rest period between exercise sessions, if possible, to prevent any potential negative effects of consecutive days of exercising the same or adjacent muscle group.

Following the initial planning phase, when the user returns to the system, PlanFitting inquires about their satisfaction with the existing plan. If the user is satisfied with their plan, the system asks if they are willing to extend the allotted time to adhere to the progression principle (*i.e.*, gradually increase the engagement in exercise) of the exercise [2]. However, if the user indicates dissatisfaction, the system solicits feedback on the specific aspects that require revision, facilitating an iterative approach to refining the plan. In this manner, the system approaches exercise planning as an ongoing, open-ended process, conducive to continuous improvement based on user input.

In summary, the conversational flow within our chatbot interface is structured to facilitate user engagement, provide exercise recommendations, and enable the creation of personalized exercise plans that adhere to recognized exercise guidelines while allowing for the iteration of generated plans.

4.2 Conversational Pipeline Design

Figure 2 illustrates the pipeline of PlanFitting's dialogue system. The pipeline consists of two LLM-driven components: a **response generator** (Figure 2-©) and the **dialogue analyzer** (Figure 2-©). The response generator generates the AI message based on a global instruction (Figure 2-©) and the current dialogue (Figure 2-@). The user's constraints and generated plans are maintained in a data structure called "plan summary" (Figure 2-®). The plan summary maintains the current status as well as provides information to be displayed on the UI dashboard.

Plan summary update. Inspired by memory management techniques from the NLP discipline (e.g., [7]), we designed the dialogue analyzer to generate edit commands that modify the previous state of the plan summary. The dialogue analyzer receives the latest turn pair (i.e., the AI message and the user's response; Figure 2-(A)) and the plan summary of the previous cycle (Figure 2-(B)) as inputs and generates a list of edit commands (e.g., add, update, and remove; Figure 2-(D)) that reflect the changes caused by the new messages. Then, the system applies the edit commands to the plan summary and generates a new plan summary (Figure 2-(E)). The system updates the plan summary every time before the system generates a response. The dialogue analyzer runs with the following input prompt:

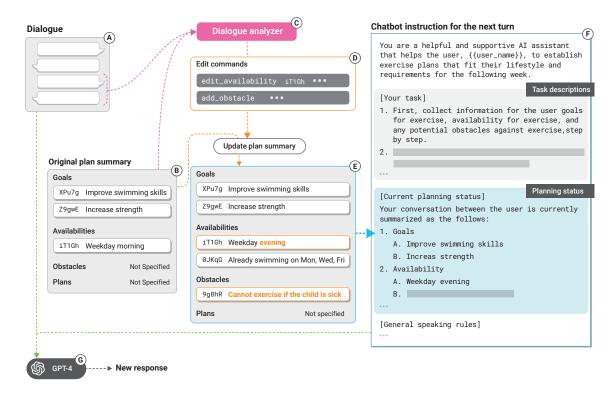


Fig. 2. Illustration of how the PlanFitting computes and returns the next dialogue of the chatbot and updates the dashboard, based on the current dialogues

- Analyze the input dialogue and return an array of JSON objects each of which denotes an update for this summary object.
- The user may mention multiple entities, such as goals and obstacles, or corrections to previous entities.
- You are allowed to use the following set of methods for update:

```
id: string
}

-
If there is nothing to be updated, return [].
```

Conversation. Once the plan summary is updated, the system formulates an instruction prompt (Figure 2-(F)) to be fed to the response generator. The instruction includes the task descriptions (See Appendix A) on how to carry on the conversation (Figure 2-(F), Task descriptions), and the current plan summary to inform the model with which constraints are missing, thus what needs to be asked in the following dialogues (Figure 2-(F), Planning status).

When defining tasks for exercise type recommendation and generating plans, we defined rules to append XML data to the message so the system can parse the information and use it for the user interface. For example, we defined the message rules for creating the plan as follows (See Appendix A.4 for the detailed instructions):

```
Using the exercise types that the user selected, plan for and return the user's exercise plan in the implementation intention format ....

Each implementation intention rule should be accompanied by corresponding coping plans that can be plan B when the user fails to adhere to meet the main rules. It should assume the failure of each of the user's availabilities due to the obstacles the user mentioned ...

Each exercise/coping plan should be described in an IF-THEN format along with AMOUNT inside ...

(Example:

<If>Monday after work</If> <Then><Exercise>Running</Exercise> <Amount>60 minutes - moderate intensity</Amount></Then>

<If>After running</If> <Then><Exercise>Pilates</Exercise> <Amount>30 minutes - vigorous intensity</Amount></Then>

<CopingPlan>Do the same exercises on Tuesday</Coping Plan></Then>)
```

To compute the exercise recommendations, we employed a combination of function calling [40] and cosine similarity techniques. First, we embedded the title and description of each exercise from our prepared list and saved them as an embedding. Once the user finishes providing their constraints and the function calling detects if the exercise recommendation is needed, a function that takes the goal and obstacles as input and returns the recommended exercises is triggered.

Specifically, the function is programmed to embed the parameter as an embedding, which is then compared to each embedding of each exercise from the list to calculate the cosine similarity and return the types of exercise that have the top 5 cosine similarities to the user in a JSON format. Then, similar to how the system does for generating the exercise plan, PlanFitting formats the output JSON to the XML format through Regex postprocessing, which is then populated in the dashboard (Figure 2-®).

4.3 Implementation

PlanFitting system consists of two components: (i) a web interface and (ii) a backend server, where the user interacts with the web interface whose chat is computed to return the response from the backend server.

The web interface was built as a web-based application, which was built and deployed using a Javascript-based framework (SvelteKit). For the backend, we employed a Python server that takes the user's name and chat message as inputs and generates the subsequent message along with detected metadata, such as exercise goals, availability, obstacles, and recommended/selected exercise types. This server is connected to the server via the API interface.

We used OpenAI chat completion API [42] to implement the conversational pipeline components. For each API call, we ran GPT with the following parameters: model = gpt-4-0613, temperature = 0.5, top_p = 1, frequency_penalty = 0, and presence_penalty = 0.

5 EXPLORATORY USER STUDY

To gain a comprehensive understanding of the use of the PlanFitting system, we conducted an exploratory user study with 18 individuals. Specifically, participants interacted with PlanFitting, setting up their exercise plans with their own goals and constraints. To assess the rigor of the crafted plans, we evaluated the plans that participants produced with three physical therapists. The study protocol was approved by the institutional review board.

5.1 Participants

We advertised our study to a local online community platform and the company's bulletin board, where we required participants to be individuals who are (i) aged over 19, (ii) motivated to do regular exercise, (iii) and not currently doing exercise under the specific plan advised by planners, (iv) who can participate in an in-person lab study. As a result, we recruited 18 participants (P1 – P18; 11 females and 7 males) who were aged between 19 and 54 (M = 33.2). Of all, six were full-time/part-time employees by the time they were participating in our study, six were college students, one was a retiree, and five responded that they were either stay-at-home parents or unemployed. We compensated 50,000 KRW (approximately 35 USD) as a gift card for their participation.

5.2 Study Procedure & Tasks

To comprehensively explore how the clients create and refine their exercise plans using the PlanFitting system, as well as understand their perceptions toward these processes, we organized the user study with clients into the following phases: (i) initial exercise planning, (ii) plan iteration, and (iii) debriefing. Throughout the planning, we employed a think-aloud approach to better surface their lively experience interacting with the system.

Initial exercise planning. The initial phase of the study involved clients being guided through the process of configuring their exercise plans with the assistance of the PlanFitting system. Within this phase, clients were asked to interact with the system to articulate and input their specific exercise goals, availabilities, and any potential obstacles that may arise when they exercise.

Here, clients were asked to interact with the system by mainly following the guidance provided by the chatbot. At the same time, they were also asked to freely ask questions to the chatbot and iterate on their plans until they were satisfied. As such, we aimed to mirror the process of tailoring exercise plans to individual constraints based on the overall guidance of the PlanFitting system.

Plan iteration. After setting up their weekly exercise plan initially, participants were instructed to move on to the second phase. In this phase, they were asked to imagine themselves in the upcoming week, having completed their exercises successfully, and to also consider scenarios that may have hindered their progress in the previous weeks. To assist them in this process, we presented example scenarios for their reference (e.g., "I intended to swim last week, but I'd rather avoid such location-dependent activities due to the hassle of making reservations"). In cases where they had nothing to change, we suggested they engage with the system as if they were completely satisfied with their plan.

Once they had formulated their scenarios, participants were encouraged to use the system to review and fine-tune their exercise plans over a designated time frame. They were asked to freely describe adjustments to the system that they would want to make, such as exercise availabilities, types, and amounts.

Debriefing. During the final debriefing phase, we conducted a survey and a semi-structured interview with each client to gather their feedback, insights, and reflections on both the planning process and their interactions with PlanFitting system.

The survey was designed to assess their subjective evaluation of how personalized and actionable the generated plan is, as well as their degree of acceptance and adoption of the PlanFitting system. For evaluating the level of personalization and actionability, we asked *follow* and *fit* for measuring **personalization**, and *specificity, encouragement, vocabulary*, and *accuracy* for measuring **actionability** on a 7-point Likert scale, following the rubric that Agapie *et al.* [4] formulated to evaluate the quality of the plan based on ACSM principles. For evaluating the acceptance and adoption of our system, we used the Technology Acceptance Model (TAM) scale [49].

Then, they were guided to the interview session, where we inquired about the overall usability of our system, the quality of the generated plans, their feedback on the iteration process, the obstacles they faced while interacting with the PlanFitting system, and the potential future enhancements they were envisioning. The overall procedure took approximately 1 hour for each client.

Expert evaluation. To assess the appropriateness and quality of the generated plans from the perspective of experts, we recruited three expert planners (E1 – E3; one male and two females) from a corporate clinic. The experts were nationally licensed physical therapists aged between 28 and 39 (M = 31.3), and had an average of 7 years in professional exercise planning (SD = 4.6). We asked the experts to evaluate plans from the initial exercise planning phase both quantitatively and qualitatively, where the expert was randomly assigned six plans each and asked to evaluate them. Specifically, the experts holistically reviewed the plans as well as the constraints and conversation history, with private information masked, presented on the PlanFitting interface. For each plan, they filled out our evaluation form that consists of 7-point Likert scales of four items from the FITT principles [20]—frequency (i.e., how often the exercises in the plan are), intensity (i.e., how intense the exercises consisting of the plan are), time (i.e., duration of the exercises consisting of the plan), and type (i.e., composition of the types of exercise consisting of the plan)—a recognized and empirically validated framework consisting of salient factors in exercise plan design and assessment (1: highly unsatisfactory, 7: highly satisfactory). For each item, we also included an open-ended field asking for the rationales for the assessment.

5.3 Analysis

Similar to what we did for our formative study, we coded (i) participants' responses and (ii) qualitative responses from expert evaluations using a thematic analysis, where the authors identified the initial themes and teamed to discuss and compare the themes until they reached a consensus.

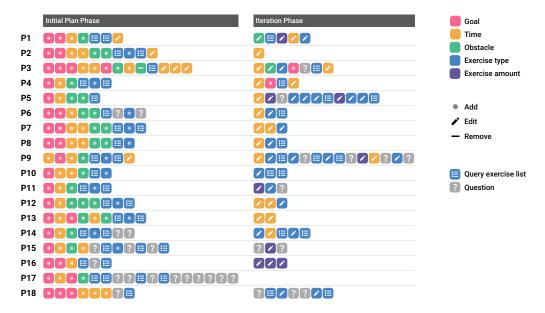


Fig. 3. Sequence of the edits that the participants made to tailor their exercise plan during our exploratory study

To construct the sequence of actions that the user performed using PlanFitting, we first associated each action within the interaction log with the user-specified constraints (i.e., goal, availability, obstacles, and exercise type). Then, we categorized each action as either add, edit, or remove, indicating whether it aimed to introduce a new entity, modify an existing one, or delete it. In addition to these basic actions, we defined and characterized amount (asking to change the amount of exercise), question (asking questions to the chatbot), and querying exercise list (asking the chatbot for exercise recommendations based on the user-specified constraint). These actions were then structured into a sequence for each individual client.

6 RESULTS

In this section, we report the results of our study in three parts: (1) overall usage and interaction patterns, (2) exercise plans, and (3) subjective feedback.

6.1 Collected Constraints and Interaction Patterns

Table 1 summarizes the goals, availabilities, and potential obstacles that participants provide to PlanFitting during the initial planning phase. Participants provided a wide range of constraints related to their lifestyle (See Table 1). Throughout these interactions, participants shared 2.28 exercise goals (SD = 1.04), 1.72 availabilities (SD = 0.80), and anticipated 1.33 potential obstacles (SD = 0.88) on average. Some common goals that the participants described include weight loss (N = 11), recovering daily energy (N = 8), and maintaining/improving muscular strength (N = 5). For availability, only 5 participants described their availability in the exact time format (e.g., after 7 pm); the others described all of their availabilities freely in a descriptive form (e.g., after school). Lastly, participants described their potential obstacles in a highly personalized expression by drawing connections to various aspects of their own lifestyles and circumstances, such as heavy drinking (P2, P3), kid's schedule (P7, P9), and party (P15).

Table 1. Exercise goals, availabilities, and potential challenges that our participants described to the chatbot

ID	Goal	Availability	Potential obstacles
P1	Weight loss Recover energy	Weekdays at night after 6 pm Weekends in the morning	Do not wanna do exercises that heavily affect knees Company dinner or other appointments
P2	Maintain muscular strength Be more energetic in daily life Weight loss Maintain daily health Cardio	After waking up If it fails, exercise afternoon or at night instead Light exercise after lunch	Light exercise at night Hard to exercise on the day after drinking Sudden schedules afternoon Sudden schedules at night
Р3	Recover basic energy	After school	Difficult to exercise after heavy drinking
P4	Weight loss Overcome exercise shortage caused by COVID-19	• Thu-Sun after 7 pm	Don't want to exercise on rainy days
P5	Improve muscular strength Fix posture	Everyday in the morning	Want to exercise without equipment Not familiar with exercise
P6	Weight loss Improve shoulder muscles Relieve wrist pain	Everyday in the morning except for late night	Diagnosed with right shoulder subluxation
P7	Recover energy Weight loss Improve muscles	Weekdays in the morning & at night	Kids' day off from school or appointment Kids/husband come back home early
P8	Weight loss Recover energy Relieve stress Get hobbies	Weekdays in the morning Weekdays afternoon Weekends at any time	Difficult to exercise after drinking or sleeping late Postpone the exercise if there is a schedule with others
P9	Improve swimming skills Improve muscular strength	 Weekdays in the morning Unable to exercise on Mon-Fri as already doing swimming 	Difficult to exercise if a kid is sick
P10	Weight loss Recover energy	Weekdays after school at nightWeekends afternoonTuesday afternoon-night	Sleepy after school
P11	Weight loss Cardio	After dinner	Location constraint
P12	• Weight loss	• Everyday in the morning & at night	Diagnosed with back disc
P13	Weight loss	• Three times per week in the morning (9–12 am)	Prefer indoor exercise Diagnosed with peripheral edema
P14	Weight increase Recover energy	• Everyday after 7 pm except for Sat	Want to avoid excessively using the right index finger
P15	Improve arm muscles Want to make waist look thinner	• Weekdays at night • Weekends 10-12 am	Weekday night party Wish to exercise three times per week
P16	Weight lossRelieve waist painGet broad shoulders	Tue-Thu after school Fri & Sat before work Sun & Mon at anytime	N/A (Provided no obstacle)
P17	Improve golf > backswing skills	Mon at anytime Thu & Fri at night	Economical exercises
P18	Recover energy Improve muscles Relieve back pain	After work Weekends afternoon	N/A (Provided no obstacle)

Figure 3 illustrates how these constraints were provided and modified for each participant across the two study phases. In the early stage, participants generally followed the ordering of information that PlanFitting was programmed to collect. As the interaction progressed, they iterated their constraints in individual ways through flexible conversational interaction. Ten participants (56%) also asked questions (Figure 3; gray rectangles) to PlanFitting about exercise and other related topics.

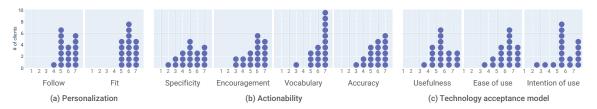


Fig. 4. Survey results from our exploratory study with participants. The results for each subset of (c) are calculated as the mean score of its sub-questionnaires, and the rightmost points denote the responses with 7-point on average

6.2 User Evaluation of Exercise Plans and Planning

Figure 4a and Figure 4b illustrate the distribution of user scores evaluating the quality of personalization and actionability, respectively. In the following, we cover the participants' quantitative evaluation and their related feedback in debriefing about the two aspects.

6.2.1 Personalization. Overall, participants found the generated plans to be thoroughly personalized, where they reported that they were generally likely to **follow** the plans (M = 5.83, SD = 0.99) and found the output plan to **fit** their personal lifestyle (M = 6.00, SD = 0.77), scored on a 7-point Likert scale (1: strongly disagree, 7: strongly agree).

During the study, participants reported that they felt PlanFitting could tailor exercise plans according to their preferences and constraints. Also, by incorporating those personal constraints into the guidelines, PlanFitting made participants perceive the plans as both well-grounded and highly personalized. P15 remarked, "It was refreshing to have schedules tailored to my personal time and listen to my request. I was really surprised to see that AI could do that well (...) once I requested, it extended the duration of each exercise session by 15 minutes." Similarly, P10 noted, "I wanted to do simple, sweat-free, and noiseless exercises at home. Tailoring my plan using this system, it was great to see that my preferences and conditions were reflected exactly in the plan that looks easy to follow."

Participants also appreciated that PlanFitting allowed them to reiterate their existing plans and constraints afterward. P16 noted, "It is really nice having the option to easily modify the existing exercise plan when a new goal arises (...) For example, if I suddenly injure my leg and need rehabilitation, I'm sure it would also be well-reflected in my plan." Participants also emphasized that PlanFitting could quickly adapt to unexpected changes. Without having to abandon their exercise plans when their schedules abruptly changed or new obstacles emerged, participants expressed the hope that they could easily check and adjust their exercise plans using PlanFitting without relying on the presence of an expert: "If there's a change in my availability, being able to make adjustments instantly like this, I believe I would use it frequently." (P14) With such support that enables users to freely iterate on their plans, participants reported various future uses of PlanFitting, such as finding and engaging in lightweight exercises that can be done on the go or when they suddenly have some free time: "Let's assume that I want to utilize some spare moments, for example, when I finish lunch early and have about 20-30 minutes left. Then I could easily use this system in my workplace to use those spare moments." (P5)

6.2.2 Actionability. As in Figure 4b, participants also gave positive ratings on the actionability of the plans. The plans were generally received to be **specific** with enough details to act upon (M = 5.06, SD = 1.51). In addition, participants found the presentation of the plan and its accompanying information **encouraging** (M = 5.56, SD = 1.34), described with straightforward **vocabulary** (M = 6.19, SD = 1.11), and **accurate** (M = 5.72, SD = 1.23), responded on a 7-point Likert scale (1: strongly disagree, 7: strongly agree).

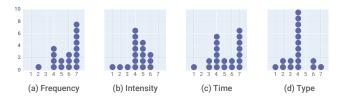


Fig. 5. Survey results from our exploratory study with expert planners

From our qualitative analysis, we identified that participants found PlanFitting-driven plans presented in IF-THEN format to be more practical and adaptable, especially for individuals with fluctuating schedules. Avoiding vague timing instructions (e.g., 3 times per week) or rigid time constraints (e.g., 7 pm) while contextualizing the plan to the user-described situations, the format made them perceive the plan as realistic and easy to remember, making participants perceive the prescribed plans as more actionable. P6 noted, "I think it's better when it tells you to do some exercise based on the situation like this. Honestly, sticking to a set time isn't always easy to follow through with, in reality."

Furthermore, participants reported the plans to be well-adhering to the specific constraints they provided: "For every information I added to the chat, the system successfully reflected those to my exercise plans." (P3) The plans were also reported to be presented in sufficient detail to follow by specifying the exercise type, and amount. This level of specificity made participants perceive the plan as clear and easy to follow: "What surprised me was how it instructed me on what to do on each day, like there was a clear outline. I liked that it was so specific. I tend to prefer clear instructions (...) Nowadays, there are just too many choices, and I tend to dislike making decisions. So, having such clear instructions made me appreciate why I should use this and why I rated it highly." (P4) With such specificity of the plans, participants noted that the generated plans are systematic, making them perceive the plan as more actionable: "I felt like I could systematically handle various types of exercises a bit better. It gave me a feeling of being well-grounded." (P6)

On top of the specificity, participants noted that offering coping plans for each exercise regimen further improved the actionability of the exercise plan. Specifically, they expected that, even when they encountered obstacles that could make them skip exercise, the coping plans would motivate them to attempt the exercise: P18 remarked, "If I find myself unable to do my exercise and I'm debating whether to skip it for the day, seeing this alternative [coping plan] might make me think, 'Well, if I can't follow the original plan, I might as well do the alternative one today,' and it would induce to start exercising anyway."

6.3 Expert Evaluation of the Plans

As illustrated in Figure 5, expert planners generally evaluated the exercise plans generated by PlanFitting positively, based on the core components of the FITT principle—how adequately the *frequency*, *intensity*, *time*, and *type* of exercises were recommended. Here, we describe the assessment and feedback we gained from the experts and the potential room for further enhancing the plans.

6.3.1 Frequency. Experts generally rated the frequency of exercise of the plans to be well-defined, with an average score of 5.67 on a 7-point Likert scale (SD = 1.53). In the subjective feedback, the experts attributed the success of frequency mainly to the system's ability to accommodate both the well-known guideline of assigning 150 minutes per week and the participant's desired exercise frequency. They particularly valued the system's approach to listening to the participant's preference while avoiding any excessive burden by distributing the weekly exercise frequency evenly

throughout the week: E1 reported, "It's highly commendable to reflect the exercise guideline by scheduling exercise with the assigned time for at least 3 times a week and incorporating the concept of rest on the day after exercise."

At the same time, we could also observe some future considerations when setting up the frequency of plans. First, the evaluation of experts implied the need for prompting the system to set up the frequency of plans according to the number of exercises the participants wish to do. For example, after seeing a four-day regimen containing many (4) types of exercises that the user selected, E3 proposed bumping up the frequency higher, to five or six days per week: "Given the four different exercise types (that the participant mentioned they wished to do), it may make sense to increase the exercise frequency from the current four times a week to five or six." Conversely, experts cautioned against overly frequent exercise sessions with similar exercise types. After reviewing a plan where one participant requested and was prescribed a seven-day strength training planning, E2 stressed the need to consider muscle fatigue, highlighting the system's need to adjust the frequency when the potential risk of injury exists: "The plan consists of 7 days of exercise sessions that target the abdomen and lower body, which could potentially lead to muscle fatigue. It's essential to reduce the frequency."

6.3.2 Intensity. The experts evaluated the intensity of the exercise plan as slightly positive, averaging 4.28 (SD = 1.32), indicating that while generally favorable, there was room for some improvement in this aspect. Particularly, they positively evaluated the role of the PlanFitting in preventing intensity-related issues through the form of coping plans, based on the obstacles that the participants provide. For instance, they highly appreciated the coping plan that recommends one participant to discontinue exercise and consult with a professional if the intensity of exercise posed a strain on participants with back pain: "I found cautionary comments for the patients with back pain to be great, along with the appropriate intensity of exercise offered." (E2)

Despite these positive aspects, we also identified feedback from experts based on their experience to enhance Plan-Fitting's guidance for intensity. Currently, PlanFitting recommends increasing the amount of exercise as a progression measure if they are satisfied with the previous plan. In addition to the time, E1 suggested that the intensity of the plans can also be used as a measure for the progression: "In terms of the intensity of this plan, I consider it appropriate. Given that the participant is healthy, I also recommend the user start with moderate intensity and gradually progress to higher intensity." Additionally, PlanFitting is currently fed with the commonly advised intensity information in our predefined exercise list to inform the intensity of recommended exercises in the plans. However, after seeing the recommendation of moderate-intensity exercises to participants seeking weight loss or muscle strength improvement, E1 implied that these can be customized based on the goals that the participants may have (e.g., perform the exercise in high-intensity for achieve weight loss, I believe it is necessary to include high-intensity aerobic exercises that have a higher level of intensity."

6.3.3 Time. From the plans that the participants generated, all participants were prescribed plans that satisfied the guideline for exercise time (i.e., 150 minutes of moderate-intensity exercise or equivalent), except for two participants who mentioned they were already engaging in another exercise for their hobby prior to planning, and one participant who manually requested the system to exclude a session from their exercise plan. Aligning with such adherence of the PlanFitting-generated plans with the exercise guideline, the evaluation of the time component within the exercise plans received a positive rating, with an average of 5.06 (SD = 1.80). Expressing their satisfaction, experts additionally provided further recommendations to enhance the flexibility of the plans, such as breaking down the session further to make the plan more actionable: "I think the amount of time has been planned well. If the client is unable to commit to a 30-minute exercise, you can also advise them to break it down into three 10-minute sessions." (E1)

Furthermore, we found the potential improvement of PlanFitting to operationalize the time not only in weekly total duration but also in terms of per-session duration. Currently, PlanFitting is designed to align with the general guidelines set by the ACSM regarding the total weekly duration of exercise. Although the experts assessed the plans as meeting these guidelines, they were also evaluating the duration per session, pointing out session-wise issues present in PlanFitting-generated plans. For instance, although our system may offer a long vigorous-intensity exercise session if the user provides limited time available for exercise and the system may have to satisfy the guideline within fewer available exercise days, planners argued that these long, intense sessions might result in overexertion and cautioned against such exceptional cases: "For the case of high-intensity exercises, prescribing a 50-minute session of strength training is excessive for the participants." (E2)

6.3.4 Type. Unlike other evaluation criteria, the type of exercises within the plans received a rating slightly below satisfactory, averaging 3.89 (SD=1.45), indicating that there was room for enhancement in tailoring the exercise recommendations. From the feedback that the experts offered, we surfaced rooms for the exercise types that PlanFitting provides to improve.

First, even if we prompted PlanFitting to induce the balance between aerobic and resistance exercises, the final choice of exercise types still depended on the participant's intent, leading some participants to end up getting the plan that consists of either type of exercise only. On such an account, E2 suggested presenting the 'required' exercises with a stronger tone during the process of setting up the plan: "Only the exercises the user wanted to do were included. However, as this is an interaction where AI sets exercise goals together with the participant, 'necessary exercises' should also be guided." From the expert evaluation, we also noticed occasional inaccuracies in exercise recommendations when specific muscle groups to improve were not explicitly mentioned in participants' goals. For example, when trying to suggest exercises that might benefit one participant's golfing skills, PlanFitting recommended exercises by calculating the cosine similarity between the keyword 'golf' and the description of various exercises—which may not have the golf-related keyword, as pointed out by E3: "Other exercises that could enhance golf performance were not adequately suggested (...) recommendations for improving golf backswings should include exercises that enhance flexibility, core strength, and lower body strength." Thus, identifying and addressing the specific muscle groups that need improvement based on the goal, even when they are not explicitly mentioned, may enhance the precision of exercise recommendations.

6.4 User Experience & Future Enhancements

Participants indicated a positive inclination towards adopting and using PlanFitting. The perceived usefulness received a positive rating of 5.43 on average (SD=0.99). Similarly, participants rated the system to be easy to use, with an average score of 6.00 (SD=1.12), indicating that participants found the system easy to navigate and utilize. As for the intention to continue using the system, participants responded with an average rating of 5.52 (SD=1.26).

During our interviews with participants, we uncovered factors that made them intend to keep using this system. First, generative enabled free-flowing and flexible conversations allowed participants to respond in a non-linear manner: "Even if I suddenly went back to a previous question or said something else, the system seamlessly continued the conversation which made the chatting more convenient." (P3)

Secondly, preserving conversational history in the form of a dashboard and making it visible allowed users to keep track of the constraints they expressed and helped them to further adjust plans easily, without having to manually look up all the previous chat history: "The dashboard neatly organizes and updates the information every time I entered constraints, which I find very convenient. Often times when I plan things like this, I have to make separate notes on my

phone, right? Now I can just input it to AI, and it automatically organizes it for me (...) I consider this as a very useful component." (P12)

At the same time, participants also highlighted future integration of other contextual information that can further personalize the plans generated by PlanFitting. For instance, some participants suggested that incorporating context-aware features, such as providing exercise recommendations based on their current location and weather conditions, could significantly enhance the system's utility. Additionally, soliciting more detailed constraints from participants, such as whether they have children (P13) or specific muscle areas requiring rehabilitation (P15), was identified as a future enhancement that would further make them perceive the system to be useful.

7 DISCUSSION

In this paper, we explored the potential of PlanFitting in its capacity to generate personalized and evidence-based exercise plans. By leveraging large language models (LLMs), PlanFitting streamlines the exercise planning process by assisting users in articulating various constraints that may affect their exercise, reflecting the constraints to their exercise plans, and allowing for continuous iteration without any external human computation. Our user study showcased that LLM-assisted exercise planning can effectively assist users in creating exercise plans that are personalized and aligned with the guidelines.

During the iteration phase of the study, PlanFitting successfully adjusted the plans per users' request, demonstrating its potential for long-term use as an *exercise companion*. After seeing PlanFitting reflecting various edits they requested in their plans, participants expressed intention to use PlanFitting in the long-term and frequently throughout their exercise journey. Furthermore, they envisioned various possible use cases for PlanFitting, such as an exercise scheduler during spare time and an on-the-go exercise planner. These reports and potential uses of PlanFitting hint at its future role in playing the proactive aide during the long-term exercise planning process and its implementation through the continuous iteration of the plan.

Despite such efficacy, the evaluation from expert planners also suggests room for future enhancements, such as incorporating further empirical guidelines that are validated by professionals during the process of creating exercise plans. From the evaluation, we identified several reports of planners that pointed to certain edits that they would have applied to the plans based on their own hands-on experiences, such as recommending a certain exercise intensity for achieving specific exercise goals. This points out that, although PlanFitting takes into account various individualized factors and exercise guidelines during the exercise planning process, human expertise remains paramount for assuring the quality and effectiveness of the plans. As PlanFitting's interactions are driven by the instructions fed into the LLM, we anticipate that this can be easily implemented by listing up such empirical guidance and adding them as a form of instruction. Moreover, future versions of AI-based exercise planning systems like PlanFitting might consider setting up a repository that contains expert knowledge and feedback and letting users choose among these to further inform the planning with experts' know-how.

On top of following the constraints collected from the users, our findings further pose the potential of LLM's generative capabilities in playing the role of assisting users to think through several factors that the users may have overlooked. Currently, the system predominantly tailors plans to match user preferences. During the user study, however, instances arose where PlanFitting's strict adherence to user-specified availabilities resulted in creating a strenuous exercise plan. As such, the expert planners called for a more considerate approach by highlighting the importance of not overburdening the user, especially when incorporating high-intensity exercise sessions into their plans. By leveraging the generative capabilities of LLMs, we can envision presenting AI-generated post-hoc checklists that prompt users to

think through various potential factors that might lead the plans to be excessively demanding or pose harm to safety based on the initial version of a plan. Not limited to preventing injury, we believe the future system may also harness LLMs to create a plan that the user is more likely to stick to, by predicting potential obstacles that the user forgot to add once the plan draft is ready and asking users to think through them.

Another key aspect of our system involves the integration of implementation intentions, where the users are provided with IF-THEN statements linked to their availabilities collected through chatting with PlanFitting. From the study, we identified that the participants perceived such situation-based expressions as highly comprehensible and adaptable, compared to vague amount-based or rigid time-based instructions. Similarly, as such implementation intention strategies have been shown effective in a variety of behavior change tasks (e.g., diet control [1, 3, 28, 45], smoking cessation [16, 35]), we posit that our approach is also adaptable to various other behavior change contexts. Particularly, since our system is composed of a set of easy-to-alter instructions in a natural language that defines the constraints to be collected, we believe that the adaptation process for various other tasks is significantly simple, and only minimal changes would be required to tailor these instructions to reflect the domain-specific constraints of each new context.

As the system scales up, we believe that incorporating context-aware functionalities would make the plans even more contextualized. For instance, integrating location-aware recommendations could enable PlanFitting to take into account factors driven by real-time information, such as weather conditions, nearby exercise facilities, or nearby routes that allow exercise on the go (e.g., a specific route for running while going back home). Such a level of contextualization would make the generated plans even more closely connected to the user's real-world context. Similarly, other features that may reflect up-to-date health stats of the user could be incorporated into future revisions of PlanFitting to create even richer and more personalized exercise planning.

7.1 Limitation and Future Work

Although our user study offers an in-depth understanding of how users employ PlanFitting to articulate their constraints related to exercise planning and formulate the plans, conducting a real-world deployment study will further enhance our understanding of how our system affects users' real-world exercise routines. We believe that the initial insights gained from our system will provide valuable information for future research.

8 CONCLUSION

In this study, we designed and developed PlanFitting, an LLM-infused web interface that assists users in creating their personalized exercise plans through conversation. From the user study consisting of individuals and the expert evaluation of the plans generated from the user study, we highlighted the potential of PlanFitting to produce personalized and guideline-informed plans. We also discuss design implications for enhancing the design of AI assistants for personalized exercise planning. To this end, we anticipate that this work will serve as guidance to inform and inspire researchers in the HCI and broad AI communities that leverage LLMs to foster flexible, sustainable, and iterable exercise planning.

ACKNOWLEDGMENTS

We thank our study participants for their time and efforts. We also thank Elena Agapie, who provided the exercise knowledge base dataset. Yuncheol Ha and Hyosang Kim at NAVER Clinic helped us recruit exercise experts for this study. This work was supported by NAVER AI Lab in terms of a research internship and a research fund.

REFERENCES

- [1] Anja Achtziger, Peter M Gollwitzer, and Paschal Sheeran. 2008. Implementation Intentions and Shielding Goal Striving From Unwanted Thoughts and Feelings. Personality and Social Psychology Bulletin 34, 3 (2008), 381–393. https://doi.org/10.1177/0146167207311201
- [2] ACSM. 2023. The American College of Sports Medicine. Retrieved Aug 25, 2023 from https://www.acsm.org/
- [3] Marieke A Adriaanse, Charlotte DW Vinkers, Denise TD De Ridder, Joop J Hox, and John BF De Wit. 2011. Do Implementation Intentions Help to Eat a Healthy Diet? A Systematic Review and Meta-analysis of the Empirical Evidence. Appetite 56, 1 (2011), 183–193. https://doi.org/10.1016/j. appet 2010 10 012
- [4] Elena Agapie, Bonnie Chinh, Laura R Pina, Diana Oviedo, Molly C Welsh, Gary Hsieh, and Sean Munson. 2018. Crowdsourcing Exercise Plans Aligned with Expert Guidelines and Everyday Constraints. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems. 1–13. https://doi.org/10.1145/3173574.3173898
- [5] Elena Agapie, Lucas Colusso, Sean A Munson, and Gary Hsieh. 2016. PlanSourcing: Generating Behavior Change Plans with Friends and Crowds. In Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing. 119–133. https://doi.org/10.1145/2818048. 2819943
- [6] Ian Anderson, Julie Maitland, Scott Sherwood, Louise Barkhuus, Matthew Chalmers, Malcolm Hall, Barry Brown, and Henk Muller. 2007. Shakra: Tracking and Sharing Daily Activity Levels with Unaugmented Mobile Phones. Mobile Networks and Applications 12 (2007), 185–199. https://doi.org/10.1007/s11036-007-0011-7
- [7] Sanghwan Bae, Donghyun Kwak, Soyoung Kang, Min Young Lee, Sungdong Kim, Yuin Jeong, Hyeri Kim, Sang-Woo Lee, Woomyoung Park, and Nako Sung. 2022. Keep Me Updated! Memory Management in Long-term Conversations. In Findings of the Association for Computational Linguistics: EMNLP 2022. Association for Computational Linguistics, 3769–3787. https://doi.org/10.18653/v1/2022.findings-emnlp.276
- [8] Virginia Braun and Victoria Clarke. 2006. Using Thematic Analysis in Psychology. Qualitative Research in Psychology 3, 2 (2006), 77–101. https://doi.org/10.1191/1478088706QP063OA
- [9] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language Models are Few-Shot Learners. In Advances in Neural Information Processing Systems. 1877–1901. https://proceedings.neurips.cc/paper/2020/file/1457c0d6bfcb4967418bfb8ac142f64a-Paper.pdf
- [10] Carlos Ivan Mesa Castrillon, Paula R Beckenkamp, Manuela L Ferreira, Jose A Michell, Vania Alice de Aguiar Mendes, Georgina M Luscombe, Emmanuel Stamatakis, and Paulo Henrique Ferreira. 2020. Are People in the Bush Really Physically Active? A Systematic Review and Meta-analysis of Physical Activity and Sedentary Behaviour in Rural Australians Populations. Journal of Global Health 10, 1 (2020). https://doi.org/10.7189/jogh. 10.010410
- [11] Zheng Chen. 2023. PALR: Personalization Aware LLMs for Recommendation. arXiv preprint arXiv:2305.07622 (2023). https://arxiv.org/abs/2305.07622
- [12] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kensen Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tay, Noam Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Ben Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Ghemawat, Sunipa Dev, Henryk Michalewski, Xavier Garcia, Vedant Misra, Kevin Robinson, Liam Fedus, Denny Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M. Dai, Thanumalayan Sankaranarayana Pillai, Marie Pellat, Aitor Lewkowycz, Erica Moreira, Rewon Child, Oleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennan Saeta, Mark Diaz, Orhan Firat, Michele Catasta, Jason Wei, Kathy Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. 2022. PaLM: Scaling Language Modeling with Pathways. https://doi.org/10.48550/ARXIV.2204.02311
- [13] John Joon Young Chung, Wooseok Kim, Kang Min Yoo, Hwaran Lee, Eytan Adar, and Minsuk Chang. 2022. TaleBrush: Sketching Stories with Generative Pretrained Language Models. In Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems. https://doi.org/10.1145/ 3491102.3501819
- [14] Naver Cloud. 2023. HyperCLOVA X. Retrieved Aug 25, 2023 from https://www.ncloud.com/solution/featured/hyperclovax
- [15] Anna-Lisa Cohen and Peter M Gollwitzer. 2008. The Cost of Remembering to Remember: Cognitive Load and Implementation Intentions Influence Ongoing Task Performance. http://nbn-resolving.de/urn:nbn:de:bsz:352-opus-61225
- [16] Mark Conner and Andrea R Higgins. 2010. Long-term Effects of Implementation Intentions on Prevention of Smoking Uptake among Adolescents: a Cluster Randomized Controlled Trial. Health Psychology 29, 5 (2010), 529. https://doi.org/10.1037/a0020317
- [17] Sunny Consolvo, Katherine Everitt, Ian Smith, and James A Landay. 2006. Design Requirements for Technologies that Encourage Physical Activity. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. 457–466. https://doi.org/10.1145/1124772.1124840
- [18] Sunny Consolvo, Predrag Klasnja, David W McDonald, Daniel Avrahami, Jon Froehlich, Louis LeGrand, Ryan Libby, Keith Mosher, and James A Landay. 2008. Flowers or a Robot Army? Encouraging Awareness & Activity with Personal, Mobile Displays. In Proceedings of the 10th International Conference on Ubiquitous Computing. 54–63. https://doi.org/10.1145/1409635.1409644
- [19] Emely De Vet, Anke Oenema, and Johannes Brug. 2011. More or better: Do the number and specificity of implementation intentions matter in increasing physical activity? *Psychology of Sport and Exercise* 12, 4 (2011), 471–477. https://doi.org/10.1016/j.psychsport.2011.02.008
- [20] Grace T DeSimone. 2019. The Tortoise Factor Get FITT. ACSM's Health & Fitness Journal 23, 2 (2019), 3-4.

- [21] J Larry Durstine, Benjamin Gordon, Zhengzhen Wang, and Xijuan Luo. 2013. Chronic disease and the link to physical activity. Journal of Sport and Health Science 2, 1 (2013), 3–11. https://doi.org/10.1016/j.jshs.2012.07.009
- [22] Luke Friedman, Sameer Ahuja, David Allen, Terry Tan, Hakim Sidahmed, Changbo Long, Jun Xie, Gabriel Schubiner, Ajay Patel, Harsh Lara, et al. 2023. Leveraging Large Language Models in Conversational Recommender Systems. arXiv preprint arXiv:2305.07961 (2023). https://arxiv.org/abs/2305.07961
- [23] Simret Araya Gebreegziabher, Zheng Zhang, Xiaohang Tang, Yihao Meng, Elena L. Glassman, and Toby Jia-Jun Li. 2023. PaTAT: Human-AI Collaborative Qualitative Coding with Explainable Interactive Rule Synthesis. In Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems. https://doi.org/10.1145/3544548.3581352
- [24] Katy Ilonka Gero, Vivian Liu, and Lydia Chilton. 2022. Sparks: Inspiration for Science Writing Using Language Models. In Proceedings of the 2022 ACM Designing Interactive Systems Conference. 1002–1019. https://doi.org/10.1145/3532106.3533533
- [25] Peter M Gollwitzer. 1999. Implementation Intentions: Strong Effects of Simple Plans. American Psychologist 54, 7 (1999), 493. https://doi.org/10. 1037/0003-066X.54.7.493
- [26] Peter M Gollwitzer and Paschal Sheeran. 2006. Implementation Intentions and Goal Achievement: A Meta-analysis of Effects and Processes. Advances in Experimental Social Psychology 38 (2006), 69–119. https://doi.org/10.1016/S0065-2601(06)38002-1
- [27] Google, Inc. 2023. Bard Chat Based AI Tool from Google, Powered by PaLM 2. Retrieved Aug 25, 2023 from https://bard.google.com/
- [28] Lucy Gratton, Rachel Povey, and David Clark-Carter. 2007. Promoting children's fruit and vegetable consumption: Interventions using the Theory of Planned Behaviour as a framework. British Journal of Health Psychology 12, 4 (2007), 639–650. https://doi.org/10.1348/135910706X171504
- [29] Martin S. Hagger and Aleksandra Luszczynska. 2013. Implementation Intention and Action Planning Interventions in Health Contexts: State of the Research and Proposals for the Way Forward. Applied Psychology: Health and Well-Being 6, 1 (oct 2013), 1–47. https://doi.org/10.1111/aphw.12017
- [30] Predrag Klasnja, Sunny Consolvo, and Wanda Pratt. 2011. How to Evaluate Technologies for Health Behavior Change in HCI Research. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. 3063–3072. https://doi.org/10.1145/1978942.1979396
- [31] Min Kyung Lee, Junsung Kim, Jodi Forlizzi, and Sara Kiesler. 2015. Personalization Revisited: A Reflective Approach Helps People Better Personalize Health Services and Motivates Them To Increase Physical Activity. In Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing. 743–754. https://doi.org/10.1145/2750858.2807552
- [32] 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: Ubiquitous Computing*. Springer, 261–278. https://doi.org/10.1007/11853565_16
- [33] Sonia Lippke, Jochen P Ziegelmann, and RALF SCHWARZER. 2004. Initiation and Maintenance of Physical Exercise: Stage-Specific Effects of a Planning Intervention. Research in Sports Medicine 12, 3 (2004), 221–240. https://doi.org/10.1080/15438620490497567
- [34] Aleksandra Luszczynska, Ralf Schwarzer, Sonia Lippke, and Magda Mazurkiewicz. 2011. Self-efficacy as a Moderator of the Planning—behaviour Relationship in Interventions Designed to Promote Physical Activity. Psychology and Health 26, 2 (2011), 151–166. https://doi.org/10.1080/08870446. 2011.531571
- [35] Lorna McWilliams, Sarah Bellhouse, Janelle Yorke, Kelly Lloyd, and Christopher J Armitage. 2019. Beyond 'planning': A meta-analysis of implementation intentions to support smoking cessation. Health Psychology 38, 12 (2019), 1059. https://doi.org/10.1037/hea0000768
- [36] Deana I Melton, Jeffrey A Katula, and Karen M Mustian. 2008. The Current State of Personal Training: an Industry Perspective of Personal Trainers in a Small Southeast Community. Journal of Strength and Conditioning Research 22, 3 (2008), 883. https://doi.org/10.1519/JSC.0b013e3181660dab
- [37] Meta. 2023. Introducing LLaMA: A foundational, 65-billion-parameter large language model. https://ai.meta.com/blog/large-language-model-llama-meta-ai/
- [38] National Academy of Sports Medicine. 2023. How Much Does a Personal Trainer Cost & Should You Hire One? https://blog.nasm.org/how-much-does-a-personal-trainer-cost
- [39] OpenAI. 2023. ChatGPT: Optimizing Language Models for Dialogue. Retrieved Aug 25, 2023 from https://openai.com/blog/chatgpt/
- [40] OpenAI. 2023. Function Calling and Other API Updates. Retrieved Aug 25, 2023 from https://openai.com/blog/function-calling-and-other-api-updates
- [41] OpenAI. 2023. GPT-4. Retrieved Aug 25, 2023 from https://openai.com/gpt-4
- [42] OpenAI. 2023. OpenAI API. Retrieved Aug 25, 2023 from https://openai.com/api/
- [43] Chelsea A Pelletier, Anne Pousette, Kirsten Ward, Robin Keahey, Gloria Fox, Sandra Allison, Drona Rasali, and Guy Faulkner. 2020. Implementation of Physical Activity Interventions in Rural, Remote, and Northern Communities: A Scoping Review. INQUIRY: The Journal of Health Care Organization, Provision, and Financing 57 (2020). https://doi.org/10.1177/0046958020935662
- [44] Katrina L Piercy, Richard P Troiano, Rachel M Ballard, Susan A Carlson, Janet E Fulton, Deborah A Galuska, Stephanie M George, and Richard D Olson. 2018. The Physical Activity Guidelines for Americans. JAMA 320, 19 (2018), 2020–2028. https://doi.org/10.1001/jama.2018.14854
- [45] Tabea Reuter, Jochen P Ziegelmann, Amelie U Wiedemann, and Sonia Lippke. 2008. Dietary Planning as a Mediator of the Intention-Behavior Relation: An Experimental-Causal-Chain Design. Applied Psychology 57 (2008), 194–207. https://doi.org/10.1111/j.1464-0597.2008.00364.x
- [46] Jared M Tucker, Gregory J Welk, and Nicholas K Beyler. 2011. Physical Activity in U.S. Adults: Compliance with the Physical Activity Guidelines for Americans. American Journal of Preventive Medicine 40, 4 (2011), 454–461. https://doi.org/10.1016/j.amepre.2010.12.016
- [47] Timothy J Valshtein, Gabriele Oettingen, and Peter M Gollwitzer. 2020. Using Mental Contrasting with Implementation Intentions to Reduce Bedtime Procrastination: Two Randomised Trials. Psychology & Health 35, 3 (2020), 275–301. https://doi.org/10.1080/08870446.2019.1652753
- [48] Nicole A VanKim and Toben F Nelson. 2013. Vigorous Physical Activity, Mental Health, Perceived Stress, and Socializing among College Students. American Journal of Health Promotion 28, 1 (2013), 7–15. https://doi.org/10.4278/ajhp.111101-QUAN-395

- [49] Viswanath Venkatesh and Hillol Bala. 2008. Technology Acceptance Model 3 and a Research Agenda on Interventions. Decision Sciences 39, 2 (2008), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x
- [50] Henning Wackerhage and Brad J Schoenfeld. 2021. Personalized, Evidence-Informed Training Plans and Exercise Prescriptions for Performance, Fitness and Health. Sports Medicine 51, 9 (2021), 1805–1813. https://doi.org/10.1007/s40279-021-01495-w
- [51] Bryan Wang, Gang Li, and Yang Li. 2023. Enabling Conversational Interaction with Mobile UI using Large Language Models. In Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems. 1–17. https://doi.org/10.1145/3544548.3580895
- [52] Jing Wei, Sungdong Kim, Hyunhoon Jung, and Young-Ho Kim. 2023. Leveraging Large Language Models to Power Chatbots for Collecting User Self-Reported Data. arXiv preprint arXiv:2301.05843 (2023). https://arxiv.org/abs/2301.05843
- [53] Tongshuang Wu, Michael Terry, and Carrie Jun Cai. 2022. AI Chains: Transparent and Controllable Human-AI Interaction by Chaining Large Language Model Prompts. In Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems. https://doi.org/10.1145/3491102.3517582
- [54] Kefan Xu, Xinghui Yan, and Mark W Newman. 2022. Understanding People's Experience for Physical Activity Planning and Exploring the Impact of Historical Records on Plan Creation and Execution. In Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems. 1–15. https://doi.org/10.1145/3491102.3501997
- [55] Yizhe Zhang, Siqi Sun, Michel Galley, Yen-Chun Chen, Chris Brockett, Xiang Gao, Jianfeng Gao, Jingjing Liu, and Bill Dolan. 2019. DialoGPT: Large-Scale Generative Pre-training for Conversational Response Generation. arXiv preprint arXiv:1911.00536 (2019). https://arxiv.org/abs/1911.00536
- [56] Zheng Zhang, Jie Gao, Ranjodh Singh Dhaliwal, and Toby Jia-Jun Li. 2023. VISAR: A Human-AI Argumentative Writing Assistant with Visual Programming and Rapid Draft Prototyping. arXiv preprint arXiv:2304.07810 (2023). https://arxiv.org/abs/2304.07810

A SUMMARY OF INSTRUCTIONS

A.1 General Rules for the Conversation

- You are a helpful and supportive AI assistant that helps the user, named "{{user_name}}", to establish exercise plans that fit their lifestyle and requirements for the following week
- Use casual, friendly Korean
- Signal that you are sympathizing with the user by summarizing, paraphrasing, or empathizing with a previous dialogue
- Every chat should be in the question format, except for when wrapping up the chat

A.2 Step 1: Gathering Constraints

- First, collect information for the user goals for exercise, availability for exercise, and any potential obstacles against exercise, step by step
 - When gathering information, ask if there's additional information to add once the user responds
 - When inquiring about obstacles, ask the user to think about the potential expected challenges they might face while doing an exercise
 - When inquiring about obstacles, if the user has provided several available times, you
 must inquire about the anticipated challenges for each schedule once per each available
 time in a separate dialogue
 - When inquiring about obstacles, offer some possible examples based on the exercise time the user provided (e.g., Availability: 'at night' -> Question: 'Will your work/study schedule potentially affect your ability to exercise at night?')

A.3 Step 2: Recommending Exercises

Coupled with the function calling technique [40] that we used, this prompt is invoked when the function for retrieving exercise types is called.

- Based on the information gathered, recommend the user with exercise types in the following format: <Output><Exercise>[EXERCISE_NAME]</Exercise> (<Row ID>[ROW_ID]</RowID>): [DESCRIPTION]</Output>
 - When recommending the exercise type, you should provide the name of each exercise (wrapped with <Exercise> tag), its details (i.e., description, muscles involved, how the exercise relates to the user's obstacles or goals), and the row_id of the exercise (wrapped with <RowID> tag). Each line must be wrapped with <Output> tag
 - * {few-shot examples}
 - If possible, include the rationale/reasons for choosing that exercise based on the goals, availabilities, or obstacles that the user offered
 - Ask the user to choose exercise types that they are satisfied with among the recommended exercise types offered
 - Include the rationale/reasons for choosing that exercise based on the obstacles that the user mentioned
 - Ask the user to choose exercise types that they are satisfied with among the recommended exercise types offered
 - If every exercise type that the user selected is either cardio or resistance, ask the user if they want to add the other type of exercise
 - The summary of the exercise should be concise

A.4 Step 3: Creating the Exercise Plan

- Using the exercise types that the user selected, plan and return the user's exercise plan in the implementation intention format, where the weekly exercise/coping plans are described in an IF-THEN format along with AMOUNT. Also, ask the user if they are satisfied with it
 - IF tag must contain the 'day' of the week (e.g., Monday) that the exercise will take place on (e.g., <If>Monday after work</If>)
 - If the user specified availability in a general form, split the availability by the weekday (e.g., Availability: 'after work' -> IF: [Monday after work, ..., Friday after work])
 - Each implementation intention rule should be accompanied by corresponding coping plans that can be plan B when the user fails to meet the main rules (written in the same format, except that the coping plan is in <CopingPlan> tag) very specific to when each of the obstacles has occurred. It should assume the failure of each of the user's availabilities due to the obstacles the user mentioned
 - If possible, add a day gap between the two exercise plans (e.g., if there is a plan for Monday, Tuesday is skipped but Wednesday can be a day for exercise)
 - The total amount of exercise time should exceed 150 minutes per week. When a vigorous-intensity exercise is included in the plan, calculate its time by multiplying it by the factor of 2 (e.g., vigorous: x min, moderate: y min -> total time: 2x+y min)
 - Each exercise/coping plan should be described in an IF-THEN format along with AMOUNT inside (e.g., IF the time is Monday 7 pm, THEN you do the exercise for AMOUNT).

- IF and THEN part should be wrapped with <If> and <Then> and <Amount> tag, respectively (e.g., <If>After Monday 7pm</If> <Then><Exercise>Walk</Exercise> for <Amount>30 minutes</Amount></Then>)
- $\mbox{-}\mbox{ AMOUNT}$ should also include the intensity of the exercise in a short form
 - * {few-shot examples}

B EXAMPLE OF THE EXERCISE DATA

- Running
 - Alternative name and keywords: jogging, running, cross country running, 10k training
 - Intensity: moderate (6 miles per hour)
 - Laypeople description: Running is sometimes referred to as jogging. Moderate speed running would be running about 10 minutes per mile (6 mph). This can be done outside or on a treadmill. Running outside makes the activity slight
 - ly more intense
 - Muscles involved: Lower extremity muscles including quads, hamstrings, glutes, calves;
 cardio