

Chapter 5

Helping Users Reflect on Their Own Health-Related Behaviors



Rafal Kocielnik, Gary Hsieh and Daniel Avrahami

Abstract In this chapter we discuss the use of external sources of data in designing conversational dialogues. We focus on applications in behavior change around physical activity involving dialogues that help users better understand their self-tracking data and motivate healthy behaviors. We start by introducing the areas of behavior change and personal informatics and discussing the importance of self-tracking data in these areas. We then introduce the role of reflective dialogue-based counseling systems in this domain, discuss specific value that self-tracking data can bring, and how it can be used in creating the dialogues. The core of the chapter focuses on six practical examples of design of dialogues involving self-tracking data that we either tested in our research or propose as future directions based on our experiences. We end the chapter by discussing how the design principles for involving external data in conversations can be applied to broader domains. Our goal for this chapter is to share our experiences, outline design principles, highlight several design opportunities in external data-driven computer-based conversations, and encourage the reader to explore creative ways of involving external sources of data in shaping dialogues-based interactions.

R. Kocielnik (✉) · G. Hsieh
University of Washington, Seattle, WA, USA
e-mail: rkoc@uw.edu

G. Hsieh
e-mail: garyhs@uw.edu

D. Avrahami
FXPAL, Palo Alto, CA, USA
e-mail: daniel@fxpal.com

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5.1 Introduction: Behavior Change, Personal Informatics and Self-tracking Data

In recent years, interest in tracking one's own activities around health and wellbeing has boomed thanks to the availability of wearable tracking devices such as Fitbit, Jawbone, Apple Watch and Microsoft Band to name a few and numerous apps on mobile phones. These wearable wristbands collect measures related to user activity, such as step count, heart-rate, and calories burned. This trend has enabled users to continuously track aspects of their activity with minimal effort. Availability of such devices suddenly allowed users to collect massive amounts of data about themselves and sparked the creation of movements such as Quantified Self, where users share their experiences about self-tracking with others (Rivera-Pelayo et al. 2012), and scientific discipline of personal informatics, which deals with tools for supporting the collection, management and use of data about self (Li et al. 2010).

Conversational agents, and conversation-based interaction in general, stand to play an important role in helping users extract meaning from self-tracked data and supporting them in setting and meeting a range of personal goals. Indeed, for many users, the ultimate purpose of collecting such health and lifestyle related data is to understand and consequently improve their health-related behaviors. Aside from interest in a personal level improvement, the pursuit of improved health and wellness has reached a global scale. In the workplace, employers encourage employees to wear fitness trackers as a way of improving their health and wellbeing. Such efforts are intended to benefit both employees and employers by means of reduced health insurance costs, higher job satisfaction, increased productivity and lower absenteeism (Chung et al. 2017). On a national level, the epidemic of obesity and heart diseases, combined with aging populations has triggered various health behavior-change government-supported programs involving activity trackers (Tanumihardjo et al. 2007).

Naturally, such need for supporting health behavior change and the availability of wearable self-tracking devices sparked the creation of numerous tools for exploring the collected data. Most of these tools rely on visualizations, such as Fish'n'Steps (Lin et al. 2006), UbiFitGarden (Consolvo et al. 2008) for physical activity; Affect Aura (McDuff et al. 2012) for affective states and LifelogExplorer (Kocielnik 2014) for stress. Such approaches assume that people have enough knowledge and motivation to effectively use their data for the purpose of changing their own behavior, which is oftentimes not the case (Fleck and Fitzpatrick 2010; Rivera-Pelayo et al. 2012). Other approaches to changing user behavior rely on reminders and motivational triggers that focus on prescribing actions (Chung et al. 2017; Kocielnik and Hsieh 2017). Such interventions can result in a phenomenon called *reactance*, which is when forceful persuasion causes a person to strengthen a view contrary to what was intended. Furthermore, relying on reminders may not help people formulate long-term commitments and habits well aligned with their own value system (Schueller 2010; Kinnafick et al. 2014); because such commitments do not directly come from users' own motivations, they are more likely to be abandoned with time. Behavior

change research is thus an ongoing effort and technology-based support has a mixed record of success (Consolvo et al. 2008; Bentley et al. 2013).

In this chapter, we draw on our experience in the behavior change, persuasion and conversational domains to discuss how to combine dialogue-based interaction with self-tracking data for behavior change. Our research explored the design of diverse message-based mobile triggers for promoting physical activity (Kocielnik and Hsieh 2017), the use of sensor-based measurements, assessment and coaching based on stress data from teachers at work (Kocielnik et al. 2012, 2013b) as well as the methods of visualizing such data for the purpose of reflection (Kocielnik et al. 2013a). We have also worked on tailoring voice conversations to cultures, albeit not in the behavior change domain (Dhillon et al. 2011) and on exploring the value of voice and text modalities for workspace reflection around activity reporting (Kocielnik et al. 2018a). Finally, we have also worked on supporting reflection through mini-dialogues on self-tracking (Kocielnik et al. 2018b).

We organize the chapter around six detailed design scenarios containing practical dialogic interactions around self-tracking data. The first three scenarios are based on the framework of reflection in learning (Moon 2013) and offer guidance based on self-tracking data to help users better understand their own actions, form interpretations and hypotheses about behaviors, and define future goals. These scenarios are: (1) discovering patterns in self-tracking data, (2) understanding past behaviors, and (3) forming future plans. We also propose three additional scenarios inspired by specific behavior-change techniques and by major challenges in the behavior-change domain that can be addressed thanks to natural strengths of dialogue-based interaction. These scenarios are: (4) relapse handling through negotiation, (5) reflection on goal setting, and (6) coordinating social activity.

5.2 The Value of Human Conversation Around Data in Health Behavior Change

Some of the most effective practices in non-technology-based behavior-change interventions rely on personal counseling (Treatment 1999). Human counselors successfully employ techniques such as motivational interviewing (Rollnick and Miller 1995) and reflection-based dialogues (Lee et al. 2015). Much of the focus of these strategies goes into reflective conversations that help with assessing a client's goals, identifying barriers to successful behavior-change, negotiating around effective methods of overcoming such barriers, readjusting the client's goals and expectations, and management of relapse (Abraham and Michie 2008). The key aspect in such techniques is to support reflection on one's own behaviors exemplified by the self-tracking data and rather than force the client to perform a certain action, to help her come up with the most effective action by herself. Reflection-based conversations around behavior change have a potential to make client commitment to behavior change not "forced", but emerge from the client herself and therefore garner

higher levels of commitment (Rautalinko et al. 2007; Lee et al. 2015). However, a recent review of behavior-change applications (Conroy et al. 2014) identified that very few technology based solutions incorporate such aspects.

In helping people understand their own behavior and work towards effective solutions through thoughtful and constructive reflection (Rollnick and Miller 1995), self-tracking data offers an invaluable source of information. A conversational approach around self-tracking data is arguably one of the most natural ways to trigger reflection and has multiple specific advantages.

Leading to deeper understanding: Skilled human counselors can dynamically act on a client's data and associated responses in the conversation, prompting deeper insights about specific patterns and following up on the client's observations and responses. Such flexibility allows these counselors to dive deeper into a client's specific situation, understand their goals and motivations, and use this knowledge to jointly create personalized plans and maintain motivation through tailored feedback (Lee et al. 2015). What is critical in this process is the very first step in which counselors guide their clients to reflect on her own behavior with the use of her data and articulate what motivates her so that she can orient herself to her underlying needs and goals. Aside from the counselor being able to better understand the client, properly guided dialogue has an ability to trigger valuable insight in the client herself, simply by asking the "right" question at the "right" time. In fact, past research has shown that simply asking reflective questions can help people articulate their underlying needs and goals and increase their engagement. In one study, people who were asked to think about why they eat snacks before making a choice were more likely to choose healthy options (Fujita and Han 2009). Research suggests that asking people their reasons for doing an activity triggers their underlying motivations and leads them to focus on higher-level goals (Lee et al. 2015).

Guidance based on expertise: Second, an experienced counselor is able to bring expertise about what techniques are most likely to work for behavior change, how to successfully set up behavior-change plans and how to set realistic goals based on the client's past performance observed in the self-tracking data. Bringing such expertise to behavior-change efforts can help minimize the risk of setting unrealistic expectation, avoid relapse and eventual dropout. Counselors normally rely on in-depth interviews or the client's journaling to gain the necessarily depth of knowledge to offer constructive guidance (Rautalinko et al. 2007). The use of the client's automatically collected self-tracked data offers an additional, valuable, and more precise source of knowledge.

Building rapport: Third, engaging in conversation enables a counselor to build rapport with the client, allowing them to express empathy towards her struggles while trying to help her change behavior. Such qualities are essential as behavior change is a long-term endeavor in which social emotional support plays an important role. Indeed, past research has indicated that a crucial aspect of positively affecting health outcomes in most counseling techniques involves the counselor's ability to establish rapport and to express empathy (Miller and Rollnick 2009). The achieved rapport also contributes to the feeling of commitment and accountability, for both counselor

and the client. Conversation-based interaction has a unique ability to support such aspects.

Unfortunately, human counselors are not available to everyone at all times. Qualified health coaches are expensive and may not always be available at the right time, when the crucial moments in behavior change take place. As a result, efforts have been made to reproduce some of the unique advantages of conversation-based behavior-change counseling through technology by employing persuasion (Fogg 2009), tailoring (Lewis et al. 2013), offering recommendations (Skurnik et al. 2005), reflecting on goals formulation (Lee et al. 2015), and even by building embodied counseling agents (Novielli et al. 2010).

5.3 Computer-Based Conversational Approaches in Self-tracking

The paradigm of computers as social actors (Schueller 2010) argues that people will apply social rules to a computer. This suggests that successful human counseling techniques might also work effectively in computer-based delivery. Unfortunately, despite recent progress in dialogue-based interaction, relatively little has been done to bring these conversational capabilities to the self-tracking domain (Götzmann 2015).

There have been recent attempts at building commercial conversational behavior change assistants in self-tracking domain, such as Lark,¹ HealthyBot,² and CountIt³ to name a few. Unfortunately, these solutions still leverage dialogue-based interaction to support user tasks that could already be done quite well, if not better, with non-conversational interaction. For example, HealthyBot and CountIt, mainly provide activity triggers along with motivational content through Slack. This is no different from regular one-sided text-based behavior-change triggers sent through SMS or email (Kocielnik and Hsieh 2017); input typed by the user is used to query information, as a replacement for clicking a button. Lark—arguably the most advanced of these conversational behavior-change assistants—actually provides some interesting use cases. It actively interviews the user to gather basic profile information and weaves in reports of user activity into the chat; however, user input is limited mostly to provided and fixed responses.

In the research community, a comprehensive review by Bickmore and Giorgino on work in health education and behavior change dialogue systems (Bickmore and Giorgino 2006) has revealed application domains spanning exercise, diet, smoking cessation, medication adherence and chronic disease management. Specifically for physical activity, most common approaches relied on building persuasive dialogues, oftentimes based on fixed dialogue structures (Bickmore et al. 2010). For these

¹<http://www.web.lark.com/>.

²<https://healthybot.io/>.

³<https://beta.countit.com/>.

studies, reflection on self-tracking data was not the main focus, although as we pointed out in the previous section, it is one of the core principles of human-based counseling and would benefit greatly from the use of self-tracking data.

There are several reasons why such strategies have remained largely unsupported. First, the proper “understanding” of very personal, dynamic and contextual user barriers and motives expressed in natural language is difficult for an algorithmic approach. Thanks, however, to recent advances in machine learning (ML) and natural language processing (NLP), conversational assistants such as Amazon’s Alexa, Apple’s Siri and Microsoft’s Cortana are now robust enough to be in wide practical use. Conversational agents are now able to understand user input in natural form and generate appropriate responses in natural language. This opens opportunities for behavior change systems to engage users in new ways.

5.4 Methods for Incorporating Self-tracking Data into Computer-Generated Dialogues

In this section, we focus on how self-tracking data could be incorporated into agent utterances and how it can shape the dialogic structure from a technical perspective of selecting and shaping conversational agent utterances. We present several methods that have been explored in past work and used in our own research.

5.4.1 *Communicating Summary Data Statistics*

Arguably the most straightforward way of incorporating activity data into conversations is by using template utterances that are filled in with relevant key statistics summarizing the data when the agent communicates with the user. Such template-based utterances can inform the user about simple aspects of her data: “*So far today you have walked 9836 steps, keep on going!*” Template-based utterances can also communicate goal accomplishment status: “*You have accomplished 87% of your daily step goal. Only 2.3 k steps to go.*” Finally, they can communicate relevant changes to the user: “*You have increased your step count by 20% this week*”. Such presentation of self-tracking data allows the user to quickly grasp important metrics or attract the user’s attention to specific aspects of the data the agent wants to emphasize, e.g. the fact that step count has increased. Template-based utterances are easy and fast for users to process, but offer less context or room for interpretation or reflection (Tollmar et al. 2012). In presenting the data in such ways, especially when the agent reports the status of goal completion, positive and encouraging framing of

the presentation might be important (Bentley et al. 2013). Indeed, such manner of presenting the external data to the user can be especially useful as evidence for helping the user in defining attainable goals or to inform the agent’s negotiation tactics meant to encourage the user to be more active.

5.4.2 *Communicating Patterns Found in the Data*

A more sophisticated variation of presenting key statistics to the user is for the agent to communicate statistical patterns discovered in the data: “*You walk 20% more on weekends than weekdays*”, “*Your sleep quality usually increases by the end of the week*” Appropriate utterances for communicating patterns can be selected from a set of templates or generated on the fly based on grammatical structure. By communicating such patterns the agent can attract the user’s attention to particular relations found in the data and shape the conversation around guiding the user to think more about the reasons for these patterns or how the knowledge from such patterns can be used to improve behavior in the future. While past research shows that such presentation is useful for simplifying the task of understanding the data and can help focus user attention on specific patterns that the agent may want to emphasize, it can also take away some of the user’s ability to learn directly from the data. This was the case in the HealthMashups study in which users expressed a desire to see the visualizations of raw sensor data (Bentley et al. 2013).

5.4.3 *Embedding Visual Data Representations as Conversation Artifacts*

A different way of shaping the agent’s and user’s conversation around data is to inject visual data representations directly into the dialogue. This can be done when the conversation takes place over a visual medium, such as a smartphone. For example, a simple daily steps graph such as the one presented in Fig. 5.1 can be used along with a conversational prompt. A conversational agent can then ask the user specific questions around such data graph in an open manner: “*Can you observe anything about your behavior during the week?*” or guide the user to focus on specific aspects of the data: “*Can you see any particular day when you walked much more?*” Such conversation around the graphed data can involve several questions exploring different aspects of the visualization. Also, the conversation can relate to the automatically-detected statistical patterns, to further guide the user’s attention or directly switch the conversation to thinking about the reasons behind the existence of such patterns: “*It seems you were gradually increasing your steps throughout the week, what helped you?*” The visual representation further adds the ability for the user to make open interpretation and is likely to trigger open thinking about their

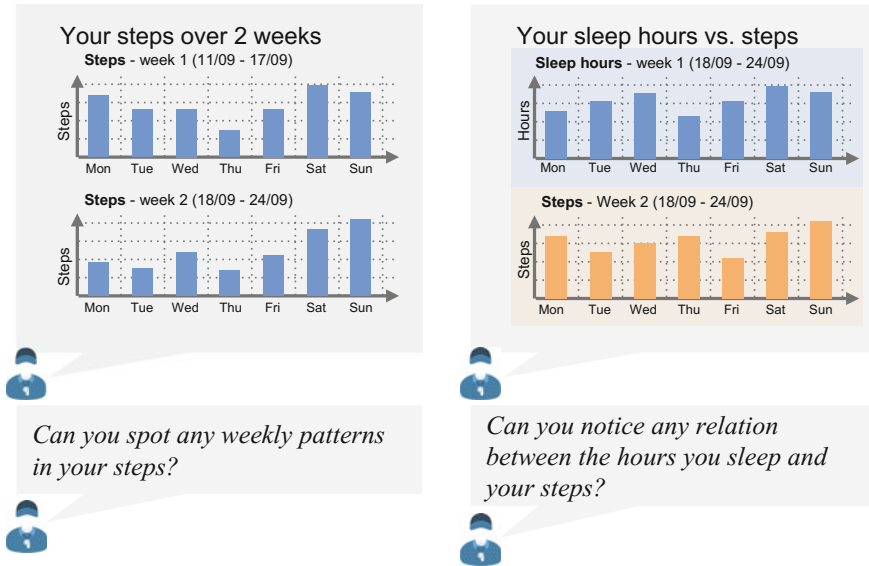


Fig. 5.1 Example visualizations of the activity data along with related conversational prompts

behavior. Past research indicates that visual aids have an ability to increase user engagement and provide a quick overview of recent progress in line with theories from information visualization research (Tuft 1991) and health visualizations in particular (Consolvo et al. 2008; Kocielnik and Sidorova 2015).

Indeed, incorporating data and visual representations of data into conversations can be particularly useful for users to gain insights about long-term behavior patterns, to understand the context of activities, and can potentially also be used as a social evidence of the level of one’s activity.

5.4.4 *Shaping the Flow of the Dialogues Based on Data*

External self-tracking data may also shape the dialogue on a structural level, where different conversational paths may be followed depending on the evidence from the activity data. For example, if the user met the daily activity goal, the dialogue can alert her to the success, ask her what helped her achieve this success and how to increase the likelihood of meeting the goal consistently in the future. If the goal was unmet, the dialogue can follow a path that tries to help the user understand the barriers to reaching the goal and think about how to avoid similar situations in the future. An example of a dialogue shaped by the data in such a fashion is presented in Fig. 5.2.



Fig. 5.2 Example of how the activity data affects the conversational paths

Such use of the data in shaping the conversations can be particularly useful for guiding the user to dig deeper into understanding activity context and reflecting on the important factors that could have contributed to successes or failures in particular situations.

5.5 Practical Examples of Design for Data-Driven Conversational Dialogues

In this section, we dive deeper into concrete examples of conversations around behavior change involving external sources of data. Some of these techniques have been used in our research, while others are based on the studies of others or our knowledge and expectations around useful strategies. For each scenario, we describe its goal and the support for it from the perspective of behavior-change theories. We also provide mock-ups of conversational exchanges and discuss the challenges involved in applying the design in practice which the designers should consider.

Our main design principle in shaping these interaction scenarios was to provide guidance following motivational interviewing approaches (Treatment 1999). Conceptually, guidance is positioned between just passively observing and informing the user on their activity (e.g. tracking) and forcefully prescribing actions (e.g. persuading). In our work, we defined six “guidance” scenarios in which reflective dialogues make use of self-tracking data and other sources of data to help users better understand their own actions, form interpretations and hypotheses about behaviors, and define future goals and activities. An example of a chat interface that can be used for our scenarios is presented in Fig. 5.3.

The first three scenarios are based on a reflection process that involves several consecutive steps: from helping the user identify relevant patterns in the activity data (Scenario 1), through prompting the user to understand these patterns (Scenario 2), to formulating effective future actions (Scenario 3). This structure is based on reflection in learning framework (Moon 2013) and the scenarios can be used consecutively over

Fig. 5.3 Example interaction for identifying patterns in self-tracking data presented in the context of chatting application. It is assumed here, that the agent has access to an activity tracker from a phone or external device (e.g. FitBit)



a period of time. Scenario 4, on the other hand, is based on the goals-setting theory (Locke and Latham 2006), which suggests decomposing larger, vaguely defined behavior change goals into a series of small, well-defined, attainable and timed goals. In this scenario, the agent tries to guide the user to refine their initial goals to make them achievable, precise and measurable. Scenario 5 explores the potential for a conversational agent to prevent relapse, that is a situation when skipping one planned activity may lead to discouragement and abandonment of the entire activity goal. In this scenario, the agent tries to negotiate with the user at least a partial completion of an activity or proposes more attainable alternatives. Finally, Scenario 6 tries to leverage the powerful social support aspect of behavior change (Colusso et al. 2016), by facilitating several users to perform physical activities together.

5.5.1 Sample Implementation

Realization of the above scenarios requires technical architecture that can deal well with integrating data elements into dialogue. Specifically, the architecture needs to be able to use external data to shape and inform the agent’s utterances, and also be able to translate free-text user responses into a structured representation of the data interpretable by the agent. In this section, we describe our implementation of a sample system used in our research. Readers focused on design aspects not concerned with implementation details may skip ahead to the description of the first scenario in Sect. 5.6.

Our system implementation employs a modular architecture in which multiple data management modules exchange information with a main Conversation Module (Fig. 5.4). The Conversation Module keeps track of current user dialogue status and is responsible for extracting intents and entities from free-text user responses. It is also responsible for creating natural agent utterances from the data received by any of the data modules. The exchange of the information between the data modules and the Conversation Module is done using structured representation of the data (encoded in JSON format).

From structured data to agent utterance: An important aspect of our system is the incorporation of external data into the dialogue. Here we describe more details of how we approach this task through an example of interaction between the Conversation Module and the Activity Data Module (Fig. 5.5). One of the functions of the Activity Data Module is to provide structured representation of patterns identified in user activity data (e.g. user had 30% more steps on weekend than on week

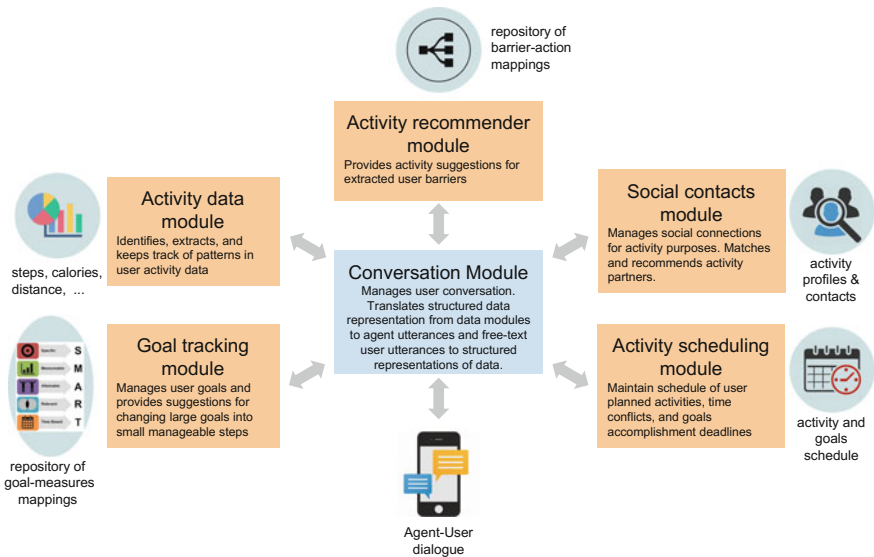


Fig. 5.4 Overview of the technical architecture

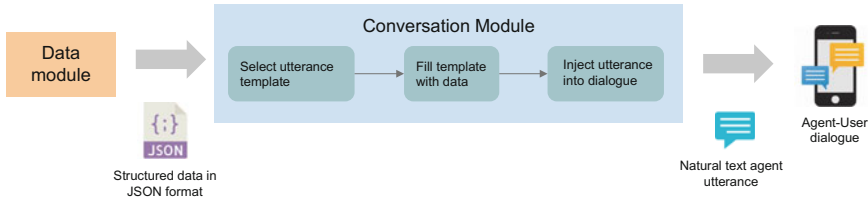


Fig. 5.5 Overview of the process involved in translating the structured representation of the data module into an agent utterance

days). After extracting such data pattern using statistical methods, the module sends it, upon request, to the conversation module in a structured JSON format, where the data pattern is described by its type: “time association” in this case, magnitude: “30% increase”, type of activity data it describes: “steps”, reference time: “weekdays” and target time: “weekends”. Each such data pattern has its own specific data fields.

The conversation module then takes such structured representation and finds an appropriate sentence template that fits the type of the pattern and the data provided along with the pattern. For naturalness and diversification of the conversation we have supplied multiple sentence templates that can fit the same data pattern. The template is then selected at random and filled-in with appropriate values as shown on the example of activity data patterns in Fig. 5.6.

As a result of this process, the agent utterance presented to the user may look something like: “Hey John, I have noticed you walked much more on weekend than on week days this past few weeks, do you have any idea why that could be the case?”

From free-text user response to structured data: Similarly, in the other direction a free-text user response needs to be analyzed and structured information needs to be extracted from it. We use intent detection and entity extraction/resolution to convert

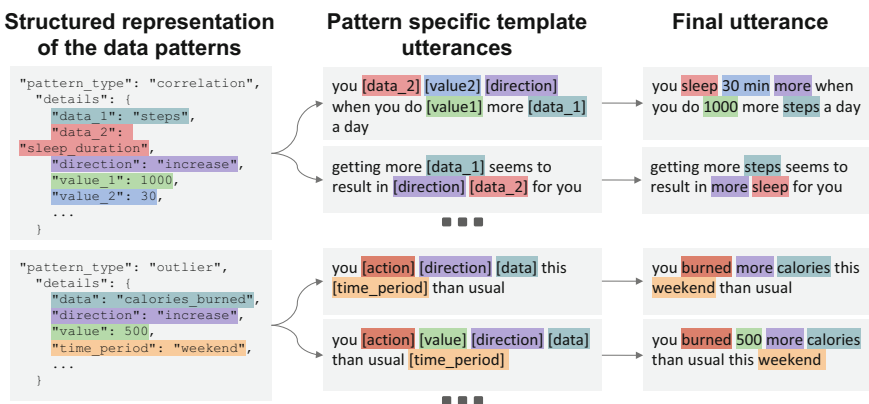


Fig. 5.6 Example of translating the structured representation of the identified data patterns into natural utterances used by the agent in the dialogue with the user

the free-text user responses into a machine-readable meaning representation (Wang et al. 2005; Tur and De Mori 2011). In personal assistant dialog systems, intent-models are classifiers that identify the category of user reply, e.g. “*add meeting to calendar*” or “*play a song*”. Entities are utterance substrings that contain specific information such as “today” or “noon”. The entity resolution maps those substrings to canonical forms such as 2014-09-11 or 12:00:00Z-08:00:00 (Williams et al. 2015). In our case, intents are categories such as “*user suggested an activity*” or “*user recognized a pattern*” and entities are types of activity data, such as “*steps*”, “*calories burned*” or barriers to activity shared by the user, such as “*time*”, “*motivation*”. Using these tools, the free-text user response is processed following several steps as shown in Fig. 5.7. First the raw response is preprocessed to split long multi-sentence responses into individual fragments. This step is quite specific to the domain of reflection where users are likely to provide long and extensive responses. In the second step the intents are detected and entities are extracted from each individual fragment. Collected information is then structured into a JSON representation ready to be exchanged with the Activity Data Module. Given a structured representation, the module can perform several operations on this information such as verifying the accuracy of the observation or finding similar activity patterns.

Following this general architecture, our Conversation Module communicates with various Data Modules in a similar fashion. Each Data Module is responsible for managing different types of data about the user, such as activity data, user goals and barriers, user annotations for activity patterns, social contacts, activity recommendations and others. For each of these Data Modules, the Conversation Module follows the described transformation of data from structured representation to agent utterances using sentence templates and from free-text user responses to structured representations, using intent identification and entity extraction/resolution. We provide concrete examples of the data formats and sentence templates in the following few sections discussing exact scenarios in practice.

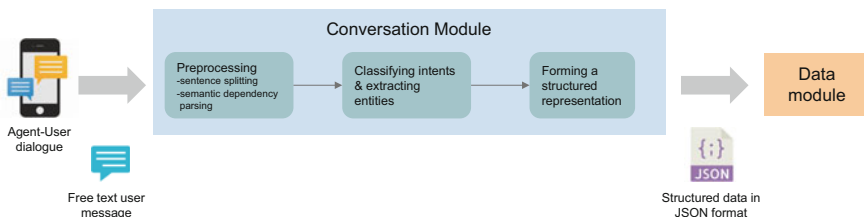


Fig. 5.7 Processing free-text user response into a structured representation for data module use

5.5.2 Handling Unrecognized User Utterances

Our system aspires to support user reflection, which requires that users have freedom of expression. However unconstrained user utterances are challenging to process automatically using existing tools. Lack of recognition of all or parts of user utterances are a common occurrence.

In dealing with the imperfections of automated recognition, we take advantage of three intentionally-designed aspects of our dialogues: (1) they are not task-oriented and they do not have a specific precise action they need to accomplish, but are meant to trigger thinking/reflecting; (2) they do not have to follow a predictable, repeatable steps of interaction, they should in fact, be novel and diverse to keep the user engaged; (3) because reflection needs to be triggered and encouraged, agent initiative in shaping the dialogues is both acceptable and desired.

Using these aspects, we employed three design strategies to mitigate the likelihood and impact of misrecognitions in processing free-text user responses.

Agent initiative: By having the agent initiate and largely guide the direction of the conversation we were able to limit the scope of expected user responses. For most interactions users are given specific question so they will stay “on topic” in their responses. Additionally, such agent-initiated interaction, given proper diversity and novelty of the dialogues, serves to help the user think about novel aspects of her data and activities.

Gracefully shortening the exchange: In an ideal case, once the agent asks about barriers that the user encountered when trying to accomplish an activity goal, the user would respond with some barrier, such as a lack of time. The agent would recognize such a response and suggest specific strategies to consider, such as scheduling things ahead in the calendar. However, if the response is not recognized, the agent will be unable to tailor follow-up exchanges. Task-oriented agents, requiring such information to proceed, would follow-up with a clarification request such as “*I’m sorry I did not understand, could you repeat please?*” Such request for clarification can break the conversation flow, especially if encountered frequently. In case of a reflection system, however, the recognition of a particular user barrier for activity is a useful piece of information, but not crucial for continuation of the conversation. In fact, retaining user engagement is far more important. Therefore to deal with such scenarios, the agent would offer a *generic* follow-up reflection question asking the user to e.g. think about the value of realizing one’s barriers for physical activity.

Utilizing partial information: We have found that often the automated entity extraction would only be successful in extracting parts of the information shared by the user. For example when the user describes an activity pattern, “*I had quite a few more steps on weekend than in the beginning of the week.*” The agent may recognize that the user talks about “*steps*” and “*weekend*”, but not that she describes an increase or compares the steps between two time periods. Such partial information is still very useful for designing dialogues. Instead of defaulting to a *generic* follow-up as described in the previous paragraph, the agent can acknowledge recognition of partial information by saying, “*So, regarding the weekends and the steps, what do*

you think you could do to improve that in the future?” Acknowledging such partial information lets the user know that the agent is actively considering user responses and building upon them. In practice, for each dialogue we have designed a number of conversation follow-up patterns that incorporate various combinations of partial information extracted from the user utterance.

After the interaction a system designer can process such unrecognized user reply and update a set of recognized intents and entities or add a new example utterance for one of the known intents. This will help enhance system capabilities in future interactions. In the following sections, we describe six concrete scenarios that can be supported by a reflection agent and discuss each one in detail.

5.6 Scenario 1: Identifying Patterns in the Data

Our first scenario is meant to help users take a good look at their self-tracking data and help them identify meaningful patterns in their own activities.

Goal of the scenario: Various theories of behavior change and personal informatics posit numerous scenarios in which data can play a crucial role. The stage-based model of personal informatics (Li et al. 2010) describes the initial stages of data collection in which the data is either logged or automatically collected; this is eventually meant to lead the user to self-reflection with the help of the collected data and to motivate action. For such data to be useful, however, the user’s attention needs to be directed towards potentially informative and revealing aspects and patterns in this data.

Automated self-tracking offers objective information that can help users discover unknown behaviors, check their progress and help form realistic future goals. All these benefits, however, are only possible if the user can notice and understand relevant data patterns. From a reflection framework perspective, such initial step is called **noticing** in which the user needs to notice, purely perceptually, the learning material in order for any further steps of self-learning to occur (Moon 2013).

Dialogue design: Exchange 1.1 below illustrates a dialogue for guiding a user through *identifying* relevant patterns in their own self-tracking data (Exchange 1.1).

(1.1) Identifying Patterns-Agent Recognition

```
01 A: Can you see anything of interest in your recent data?
02 U: Yes, I think I sleep much better when I walk more
03     during the day
04 A: Great observation! Indeed your sleep quality improves
05     by 10% when you do 1,000 more steps a day.
06 A: Were you able to observe anything else?
07 U: I think that’s it, no?
08 A: Well, I also noticed you walked more this weekend than
09     usual. Is this something relevant for you?
10 U: Interesting, can you give me more details?
11 A: Sure, it seems you did 3,550 more steps than usual:
```

12 ((step chart))
 13 A: Would you like me to keep track of this pattern?
 14 U: Yes, sure :)

Users are prompted first to actively think about patterns in their activity data (line 01), and only in case it is needed, are offered support to guide them through such discovery. Hence instead of starting with: “*You walked 20% more this Friday than last Friday*”, the dialogue begins with “*Can you see anything of interest in your recent data?*” (line 01). There are two reasons for this: First, when users identify patterns on their own, these patterns are more likely to be remembered (Kim and Hullman 2015). Second, automated techniques can identify thousands of irrelevant patterns (Tollmar et al. 2012), hence human cooperation helps keep track of the interesting ones. Once the user observations have been identified, the system can match them against the patterns identified in the data and offer more details on the pattern observed (lines 04–05). When the system identifies some other strong pattern similar to the one the user is interested in tracking, it can share such pattern with the user (lines 08–09, 11–12). The agent can offer to track activity patterns for the user (line 13), thus creating a tailored set of conversation starters for the future. Such dialogues can be further enhanced by integrated visualizations or coupled with a visualization dashboard. We note that in order to prevent user tedium with having to recognize patterns each time, the system can begin with soft guidance by replacing the opening prompt in line 01 with more focused suggestions, as presented in Table 5.1. Abstract prompts require more work from the user, but can be beneficial for remembering whereas directing prompts point closer to the pattern and lower user effort—different dialogue openings should be designed to offer guidance at different levels, as needed.

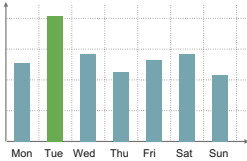
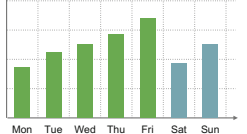
Handling misrecognitions: The example interaction in Exchange 1.1 represents an ideal exchange in which user intents and associated entities are fully recognized. As the agent deals with open-ended user input, it is possible that parts or entire user replies will not be recognized at all. Exchange 1.2 presents an interaction in which the initial user response was not recognized at all.

(1.2) Identifying Patterns-Agent Misrecognition

01 A: Can you see anything of interest in your recent data?
 02 U: Not walking enough :)
 03 A: That sounds interesting. What do you think patterns in your
 04 data can tell you?
 05 U: They can probably tell me about what motivates me and how my
 06 trends change based on what my goal was that day
 07 A: Thanks for sharing.

In case the system is unable to extract a pattern from the user response (line 02), the system falls back to a generic follow-up (lines 03–04) that does not rely on any information shared by the user, but still could retain user engagement. The dialogue designer can benefit here from the domain of reflection for which the dialogues are applied. Such reflection dialogues do not have a strict functionality they need to support (contrary to e.g. flight booking system), but their function is to trigger user

Table 5.1 Example data patterns and associated abstract and directing prompts

Data patterns	Pattern specific prompts
<p data-bbox="147 234 362 261">One time outlier</p>  <p>The chart shows walking activity from Monday to Sunday. The y-axis represents activity level. Tuesday's bar is the tallest, indicating a one-time outlier. The other bars are of similar, lower heights.</p>	<p data-bbox="482 322 1026 349">Abstract: “Was there a day when you walked much more?”</p> <p data-bbox="482 349 1026 402">Directing: “Can you see anything specific about your behavior on Tuesday?”</p>
<p data-bbox="147 451 405 478">Continuous change</p>  <p>The chart shows walking activity from Monday to Sunday. The bars for Monday through Friday show a steady increase in height, while the bars for Saturday and Sunday are significantly shorter, indicating a continuous change in behavior.</p>	<p data-bbox="482 525 1026 578">Abstract: “Was there anything specific about your walking throughout the week?”</p> <p data-bbox="482 578 1026 631">Directing: “Can you see any change in your walking from Monday to Friday?”</p>

thinking about health behaviors. While the interaction presented in Exchange 1.1 is more tailored and potentially more beneficial for the user, the interaction in Exchange 1.2 still can accomplish the basic goal of supporting reflection.

Design insights: When deploying similar dialogues for encouraging users to notice patterns in their behavior in the field it is important to ask the user to notice aspects that are non-trivial, e.g. “Can you spot any patterns in your walking throughout the week?” or “Were there any changes in your sleep throughout the week?” rather than asking relatively simple straightforward questions such as “Which day did you walk the most?” The latter can sometimes be considered too trivial to respond to and feel a bit like a quiz that could be automatically identified by the system. This could result in user frustration over time.

5.7 Scenario 2: Understanding Past Behaviors

The following scenario guides the user towards understanding the reasons and mechanisms behind the patterns observed in their own activity data.

Goal of the scenario: Even successfully identifying patterns in the data does not necessarily lead to meaningful interpretation and actionable decisions (Li et al. 2011). An important step of making sense of the data, described in the reflective framework as **making meaning** (Moon 2013), is needed. This is when a person revisits the past with an attempt to understand and form an explanation of the behavior. This step is important as it helps the user make connections between actions and health outcomes and think about ways in which past decisions could have been changed. There are at least two challenges here: The person may not be able to recall the situation because the information needed for explaining the behavior may not be captured by

self-tracking (e.g. the system “knows” the user did not sleep well, but not that she was studying and drinking a lot of coffee the night before). Additionally, even if the user is able to recall the information needed, they may be unaware of important links between the context and outcome (e.g. not realizing the links between sleep, studying late and consuming lots of caffeine).

Dialogue design: Exchange 2.1 illustrates a dialogue for guiding a user through an *understanding* process and explanation of her behavior patterns.

(2.1) Past Behaviors-Agent Recognition

01 A: About the *decrease in steps last weekend* we identified last
02 time, what happened there?
03 U: I don't really recall anything specific.
04 A: I actually found a similar pattern 4 weeks ago.
05 ((steps chart))
06 Back then you said "*I worked late on Friday and felt tired to*
07 *do anything on the weekend.*" Maybe a similar thing happened?
08 U: No, not really, but it made me think what I did this Friday.
09 We went for a birthday party and I had too much to drink.
10 A: Would you like me to make a note of that and attach it to
11 this pattern?
12 U: Sure.

The agent first recalls a pattern identified in user-activity data and asks the user to think about the explanation of this pattern (01–02). Such patterns have been identified earlier by the user in the noticing step (Scenario 1) or can also have been identified automatically by the system. The ability to think about the context behind the data and causal relationship enabled by the trigger may itself lead the person to a successful reflection. In case of difficulty recalling, as in this case (line 03), the agent can offer assistance by providing examples of similar patterns identified in the past along with user reflections on these patterns (lines 04–07). Another way in which an agent could jog the user's memory is through guidance in retracing the steps of an activity. In case this approach is successful in helping the user understand the reason behind the activity pattern as in 08–09, the agent prompts the user to attach the provided explanation to the pattern for future reference (lines 10–11).

Handling misrecognitions: Exchange 2.1 presented an ideal scenario for system recognition whereas Exchange 2.2 presents an exchange in this scenario where the agent failed to identify the user response in line 03.

(2.2) Past Behaviors-Agent Misrecognition

01 A: About the *decrease in steps last weekend* we identified last
02 time, what happened there?
03 U: In transition and off this week, it's been unorthodox.
04 A: I see, do you find it valuable to go back and understand
05 what happened when you see patterns in your data?
06 U: Generally yes, but in some cases there is nothing I can do
07 with this knowledge.
08 A: OK, thanks a lot for sharing!

In this case, following our design pattern, the agent will proceed to offer a generic follow-up question (lines 04–05) to trigger further thinking from the user and then end the exchange (line 08).

Design insights: The challenge in supporting user understanding lies in focusing the user’s attention on meaningful and actionable patterns. This becomes challenging especially when the activity patterns are identified automatically. Such patterns may not be meaningful for the user and discussing them may lower user engagement. A challenging technical aspect in this scenario also lies in automated extraction of the explanation provided by the user. While entity extraction can be trained to identify meaningful parts of the user’s response, the extracted parts usually do not cover the full explanation; the extracted parts are also not always in the linguistic form acceptable for direct use in future dialogues. Finally, the user explanations might be long and may need summarizing before being used further.

5.8 Scenario 3: Thinking About Future Actions

This scenario focuses on helping the user formulate concrete actions to take based on identified patterns in past behavior and an understanding of the mechanisms behind them. It builds upon the dialogues described in the previous scenarios.

Goal of the scenario: After identifying interesting behavior patterns and working through the causal relations between the activity data and the context of activities, it is valuable for the user to take the lessons learned and translate them into actionable future plans. A crucial step in behavior change is indeed helping people set concrete action plans for achieving their desired behaviors (Locke and Latham 2006). This can be paralleled with the **transformative learning** step in the reflective framework (Moon 2013). The power of the reflective approach here is that by working together with the user, the action plans can be formulated by the users themselves. Such approach to formulating plans can offer a stronger fit and more motivational support than when an action plan is formulated without active user involvement (Schueller 2010; Lee et al. 2015). Dialogue-based interaction lends itself well to supporting such scenario since arriving at meaningful and feasible plans is oftentimes an iterative process (Bovend’Eerd et al. 2009).

Dialogue design: Exchange 3.1 illustrates a dialogue for providing guidance towards formulating future actions.

(3.1) Future Actions-Agent Recognition

01 A: Regarding the *missing running sessions on Thursday evenings*,
 02 you mentioned this was due to *working late and not having*
 03 *enough energy*
 04 A: What do you think you could do about it?
 05 U: I am not sure, I have to do my work and some Thursdays are
 06 very busy for me?
 07 A: Indeed you’re not alone in having this problem. Do you think

08 it would be possible to try moving your running sessions
 09 earlier in the day?
 10 U: Hmm, not sure. I guess I could try one day and see how that
 11 works out.
 12 A: Great! Shall I move the workout on Thursday to 8:30am?
 15 U: Sounds good!

The agent first recalls the past behavior pattern along with the user provided explanation of the reason for this pattern (01–04). This information is assumed to have been obtained in Scenarios 1 and 2 discussed earlier. Then, the agent essentially prompts the user to think about what could be done differently in the future (04). Depending on the user’s reply, the agent tries to guide her towards formulating goals or explores the barriers she has for trying to introduce a change in the future. In the example given in Exchange 3.1, the user communicates an inability to improve on the behavior along with some reasoning for it (05–06). The agent tries to extract such reason and suggest appropriate action the user could consider, in this case rescheduling the running session (07–09). Based on user approval and, in this case, consultation with the user’s calendar, the agent proposes a rescheduling time (12–14) and updates the user’s schedule.

Handling misrecognitions: As with the previous dialogues, in this scenario a number of fallback strategies can be introduced to handle failures in automated recognition. Exchange 3.2 gives an example where the user response in line 04 is not recognized.

(3.2) Future Actions-Agent Misrecognition

01 A: Regarding the *missing running sessions on Thursday evenings*,
 02 you mentioned this was due to *working late and not having*
 03 *enough energy*
 04 A: What do you think you could do about it?
 05 U: This will be resolved soon and I am changing my job.
 06 A: In general, do you try to think creatively about making your
 07 days more active?
 08 U: Yes, for sure. I have a sitting job, so any piece of activity
 09 I can squeeze in is extremely valuable.
 10 A: Ok, great! Thanks for taking the time to think about it.

In Exchange 3.2, the agent follows up with a more generic prompt as in lines 06–07 and proceeds to close the exchange (line 10). While this exchange does not accomplish nearly as much as Exchange 3.1, it still serves the basic goal of triggering the user to think about future actions.

Design insights: As the main principle of the dialogues is guidance, one of the significant challenges of this scenario lies in balancing the elicitation of user’s own action suggestions and the suggestions given by the agent. Repeated suggestions that do not match the user’s context and abilities can easily diminish the trust in the agent. On the other hand, lack of any suggestions may leave the user stuck on the problem and unable to come up with any out-of-box approaches. In practice designers should balance the automated suggestions and user’s own explorations, by leading the user

to explore initially and if that fails, suggest possible actions to consider. The agent could also make use of the record of past data patterns and past successful actions user has taken to intelligently suggest similar approaches. Finally, it is also possible that some of the identified negative patterns in user's data do not have clear actions that could address them. In such cases, rather than having the user think about the same unsolvable pattern repeatedly, the agent should move on to discussing other patterns that may show more promise.

5.9 Dialogue 4: Formulating SMART Goals

The following scenario focuses on helping the user arrive at a precise and measurable definition of the goal she wants to accomplish.

Goal of the scenario: Specifically, on aspects of future actions and plans, the setting of measurable and attainable future goals for behavior change is an important pre-requisite for long-term success. The dialogue's guided process of reflection on formulating future goals can help the user refine these goals so they are achievable, yet ambitious enough and, while doing so, also increase user commitment to such refined goals (Lee et al. 2015). People are oftentimes overly ambitious with their goals and this may lead to disappointment and eventual drop-out if the goals are not met. According to goals-setting theory (Locke and Latham 2006), an aspirational long-term goal and a set of so-called S.M.A.R.T (specific, measurable, attainable, relevant and timely) short-term goals are an ideal combination for maximizing the success of behavior change. Formulating such goals, however, is challenging. Conversational interaction has the potential to guide and support users through this challenging process.

Dialogue design: An approach in behavior change called "motivation interviewing" uses concepts of reflection to help guide people to realize their own behavior-change goals (Rollnick and Miller 1995). Following the S.M.A.R.T. goals principle from goals-setting theory, the conversational approach could try to identify if current user goals have the desired properties and if not, help the user in refining such initial goals. Exchange 4.1 illustrates how such guidance could be accomplished.

(4.1) Measurable Goals-Agent Recognition

01 A: How would you like to measure your success in achieving the
 02 "becoming more fit" goal?
 03 U: I think, I should walk a lot.
 04 A: Perhaps think about a specific number of steps you would like
 05 to achieve (e.g. 10,000/day)?
 06 U: Sounds good, but not sure if 10,000 is realistic for me.
 07 A: We can start with fewer, but 10,000 is the average for a
 08 healthy person your age. See <this article> for more.
 09 U: OK, let's go with that then :)
 10 A: Great! I added this goal for you.

In line 01, the agent refers to one of the goals previously shared by the user and asks for a clear measurement of success related to such a goal. The user response provided in line 03 is analyzed to extract the specific measurement suggested by the user. If such measurement is not provided, the agent suggests a specific measurement suitable for this goal (lines 04–05). In response to such suggestions the user may express agreement or disagree with the suggestion as in line 06. If the user disagrees, the agent tries to extract the reason for such disagreement and provide an appropriate follow-up response as in lines 07–08. The dialogue concludes when the user and the agent agree on a certain measurable threshold for goal accomplishment as in lines 09–10.

Handling misrecognitions: Exchange 4.2 illustrates a situation where the agent is unable to recognize the intent of the initial user response in line 03. In such a case, no entities can be extracted and the agent provides a generic follow-up question to maintain a natural conversation and avoid breakdown (lines 04–05). After the user response, the agent proceeds to conclude the dialogue as in line 07.

(4.2) Measurable Goals-Agent Misrecognition

01 A: How would you like to measure your success in achieving the
02 "becoming more fit" goal?
03 U: Just how I feel, I guess.
04 A: It is important to make sure your goals are measureable and
05 achievable. Do you think that's the case for you?
06 U: Yes, I think so.
07 A: Great! You can always edit your goals on <website>!

As illustrated in Exchange 4.2, even when an agent is unable to guide the user to set a concrete measurable goal, it can still trigger relevant reflection. Ultimately it is up to the user to make their goals measurable, but an agent can still offer valuable guidance.

Design insights: In practice, there are different levels of goals that users might have; some goals might be long-term, ongoing, or purely motivational in their nature. The conversation should try to help the user refine her goals to be measurable, but also, if the user expresses a desire to keep certain goal abstract the agent should try to recognize that and ultimately let the user keep the preferred goal formulation. It might also be that the user has a number of goals at the same time, some abstract and some already fitting the definition of SMART goals. In such case the dialogue should have access to the user's other goals and perhaps ask the user if one of the SMART goals is already associated with an abstract goal the user wants to keep. The main principle is guiding, but not pushing or constraining the user, hence the ultimate decision should be left to the user. Finally, not every goal, even measurable ones can be captured by measurement devices, hence goals such as "increasing one's happiness" ultimately relies on the user's own perception and self-reporting.

5.10 Scenario 5: Negotiation Around Relapse

The following dialogue demonstrates how to encourage a user to perform at least part of a scheduled activity in case of a relapse. This is accomplished through negotiation of activity performance between the agent and the user.

Goal of the scenario: Relapse takes place when the user stops following activity plans and reverts back to previous patterns of behavior or inactivity. Relapse is one of the hardest aspects to handle due to its, often unpredictable, appearance and various causes, as well as the difficulty of reestablishing rapport with the user to get back on track (Bouton 2014). Occasional decreases in motivation, disappointment with progress, unexpected schedule changes, lack of energy, and forgetting can all form dynamic, unexpected barriers contributing to relapse (Myers and Roth 1997). Once the user skips a planned activity, abandoning the entire plan altogether is more likely. Such a scenario is sadly common, with average dropout rates for physical-activity and diet/weight-loss interventions at 50% and 60% respectively (Kinnafick et al. 2014).

Dialogue design: In this example, the agent follows-up on user non-adherence with negotiation tactics. Exchange 5.1 demonstrates an ideal exchange in this scenario.

(5.1) Negotiation-Agent Recognition

```
01 A: It is time to do your 10 lunges now. Please confirm when
02   you're done.
03   (after 20 minutes without confirmation)
04 A: Did you manage to complete lunges? If not, what happened?
05 U: No, I don't have time at the moment.
06 A: OK, I will get back to you in an hour.
07   (after 1 hour)
08 A: Hi, I hope you have some time now to do your 10 lunges.
09 U: I feel a bit tired!
10 A: Well, doing even 5 lunges is better than none :)
11 U: OK.
```

The agent first prompts the user to perform a scheduled activity (lines 01–02). This is a simple reminder function based on the user's activity schedule. After some time, in case the user does not complete the scheduled activity, which can be determined based on sensors or user explicit confirmation, the agent prompts the user to share the reason for non-adherence at the moment (04) and adjust the next action in a way that would increase the chance of the user doing at least part of the activity. In this exchange as the user shared "bad timing" as a reason for non-adherence, the agent will wait one hour to prompt again (06–08) and in case the user shares a new barrier, the agent will adjust the strategy again, for example to lower the number of exercise repetitions (09–10). The main idea here is that it is better for the user to complete at least part of the activity. Expressing interest in the user's barriers may further lead to higher perception of empathy expressed by the agent.

Handling misrecognitions: Illustrated in Exchange 5.2, is a scenario in which the reason for non-adherence shared by the user is not successfully categorized (04). Following our design pattern, the agent offers a generic follow-up that is likely to trigger the user to think further and does not break the conversation (05–06).

(5.2) Negotiation-Agent Misrecognition

01 A: It is time to do your 10 lunges now. Please confirm when
 02 you're done.
 03 *(after 20 minutes without confirmation)*
 04 U: I don't want to do this right now.
 05 A: I'll leave you to it then. Just remember that being
 06 consistent in your exercising is the key to success!

Design insights: Getting users to spend time explaining non-adherence to the agent can be challenging. As one solution, the system could offer quick shortcuts to the most common reasons for non-adherence. Unfortunately, this might reduce the feeling of conversation and degrade the reflective aspect of the exchange. Worse yet, it can remove the details of the actual reasons and make users gravitate towards suggested responses (e.g. the user actually feels lack of motivation, but gives a “lack of time” shortcut reason). Care must be taken when attempting this approach. Regarding the reporting of activity completion, Exchange 5.1 assumes the user self-reports it. Alternatively certain activities could be measured automatically and hence the user could skip the reporting step. While such solution would lower user effort, it may also suffer from occasional misrecognitions (e.g., system managed to automatically identify only 9 lunges out of 10 the user actually performed). In such cases, the dialogue should gently ask the user about it instead of behaving in the same way as if the user did not perform any activity. Following principles from (Treatment 1999) the agent should avoid explicitly arguing with the user. The ultimate goal the designer should have in mind is keeping the user engaged, even at the risk of occasionally allowing the user to “cheat”. A number of different and tailored negotiation tactics could also be employed in this scenario. One such negotiation tactic could even explicitly involve the use of cheat-points, which has been shown to actually lead to higher levels of adherence (Agapie et al. 2016).

5.11 Scenario 6: Coordinating Social Activity Performance

The following scenario demonstrates how an agent can be employed as an intermediary that helps coordinate physical activity performance between two or more connected users.

Goal of the scenario: Social support relates to the use of social relations to encourage performing a behavior by leveraging competition or cooperation between people. Such support is valuable and known to increase motivation and adherence (Maher et al. 2014). Most major models of behavior change involve a social aspect as a key contributor of behavior motivation (Ajzen 1991). Although social support has been shown to be effective, there is still considerable effort and social anxiety involved

in asking others to join an activity even in the same office (Hunter et al. 2018). These potential barriers can prevent the person from making an activity social and make her miss out on an opportunity for an additional motivation boost. Although social coordination can be done in multiple different ways, a social agent is a natural solution for closed work groups and co-located environments, where users communicate through chat regularly. An agent could lower the barrier of setting up a social activity by taking care of the coordination tasks.

Dialogue design: In this example, a conversational agent serves as a facilitator and coordinator of social performance of an activity (Exchange 6). The dialogue is meant to lower the barrier of performing an activity socially and boost motivations to do so by connecting users directly.

(6) Social Activity-Agent Recognition

(conversation with Mike)

01 A: Hey Mike, today it's time for your 30 minute jog, would you
02 like to make it social?
03 M: Sure, why not

(conversation with Kate)

04 A: Hey Kate, maybe you would be interested in a short jog with
05 Mike?
06 K: Yep, sounds good.
07 A: Great, these times are possible for both of you: 11:30am,
08 1pm, 3pm. Which one works best for you?
09 K: 1pm works for me

(conversation with Mike)

10 A: It's time for your jog in 15 min! Kate and Alex will join
11 you.
12 M: Great, let's do it!

The agent starts a conversation with one of the users proposing to make one of the scheduled activities social (lines 01–02). In this case Mike approves (line 03) and the agent consequently contacts other connected users that are interested in similar activities and have time available in their schedules. In this example, Kate is informed that Mike is planning a jog and is invited to join him (lines 04–05). If she agrees, as in this case (line 06), the agent facilitates a negotiation of available times based on access to users' schedules (lines 07–08). Kate can then select one of the available times (line 09). The agent may also contact other users with similar interests and available times. When the time to perform the activity comes, the agent informs the originator of the activity—Mike, about who will be joining him (line 10). This dialogue has a very strict structure and misrecognitions are rare. In case they do happen, as this dialogue is task oriented, the agent needs to obtain precise information to be able to proceed and consequently it defaults to asking the user to repeat the answer.

Design insights: Simple agent coordinated time arrangements for meeting scheduling have already been demonstrated feasible in commercial products (Cranshaw et al. 2017), but the agent could go beyond that. An agent could access data about user preferences regarding the activities as well as past patterns of interaction between people to actively find and suggest the most likely activity partners. Another interesting aspect here relates to the initiator of the activity. In the presented scenario the agent leverages the fact that one of the users already planned an activity. An alternative approach could rely on the agent initiating an activity from the start. In such approach, success depends on the ability of an agent to successfully match people and on careful design of agent interruptions to prevent the perception of an agent being annoying and actively disruptive. This is especially important in work environments.

5.12 Discussion

In closing this chapter, we wish to summarize some of the main considerations of designing dialogues around health related self-tracking data and also discuss some of the technical challenges involved in realizing some of the dialogues we propose. Finally, we discuss some of the design principles from our process in general.

5.12.1 *Specific Considerations When Designing Dialogues for Personal Informatics*

One specific aspect of dialogue design on self-tracking health data relates to the important fact that such dialogues need to be designed for long-term use. Self-tracking is a continuous, longitudinal process and behavior change can take a long time to fulfill. A successful conversational agent must be designed with this in mind. Such long-term focus introduces the challenge of making conversations novel and diverse each time—a big practical challenge. For example, in the study of FitTrack (Bickmore and Picard 2005), several subjects mentioned that repetitiveness in the system’s dialog content was responsible for them losing motivation to continue working with the system and following its recommendations.

Knowledge about a user’s motivations and barriers to activity, as well as health-related data can be sensitive. Agent and dialogue designers must take this information sensitivity into account. In our experience, designing dialogues to be neutral or slightly positive can go a long way. Dialogues with negative framing can be risky and should be used sparingly if at all. General encouragements and expressions of appreciation for user performance and accomplishments are almost always a positive addition.

In the dialogues illustrated in this chapter, the user is guided to come up with their own plans and goals and to discover their own motivations. It is key when designing an agent for behavior change for it not to be perceived as judgmental or prescriptive. Still, the designers must keep in mind that users will sometimes need the agent's help in suggesting what could or should be done. Otherwise, a user who is unable to e.g., formulate attainable action plans, will be left frustrated.

5.12.2 Technical Challenges

Several of our design recommendations presented in this chapter rely on the use of machine learning, natural language processing, or crowd-sourced approaches for recognizing free-text user responses. We wanted to allow users to enter free-form responses by design, especially in self-reflection where unconstrained expression is valuable. Handling user inputs this way, however, can be error prone and may lead to misunderstandings. From our experience, in personal informatics around physical activity and other well-being applications, with proper design agent mistakes can often be tolerated.

In contrast, in some domains such as medication adherence or hospital-based applications, agent mistakes can have dire consequences (e.g. see Bickmore et al. this volume). In such domains, given the current state of technology, constraining the format of user responses to avoid misrecognitions is advisable.

The proposed scenarios heavily rely on the use of external sources of information. Different types of data involve different challenges. The user activity data from wearable trackers could be most sensitive and volatile information. Currently in order to connect to such data the user needs to give explicit permissions for the exact types of data being accessed (e.g., user may only allow sharing of step count, but not calories burned). The impact of such restrictions of access could be incorporated into conversations by e.g., not engaging in dialogues around sources of data the agent can not access. Alternatively, the agent could also try to rely on user self-reporting for such information (e.g., asking the user about change in weight). It is possible, that the user may be willing to give more access to automatically tracked data if a trust relationship with the agent is established over time. Finally the tracked data may also suffer from occasional gaps and mistakes due the sensing imperfections, user forgetfulness, or delayed synchronization. The agent could actively address some of these challenges by e.g., reminding the user to synchronize or making the user aware of the gaps in the data. Regarding the mistakes in automated sensing, we briefly touched upon when discussing one of the scenarios, the agent should in the end trust the user if a discrepancy between the user report and automated sensing arises. The agent should avoid arguing, as long-term user engagement is most important.

Other sources of data used in the scenarios, such as schedule information, social contacts, and goal tracking are highly personal, but less likely to suffer from lack of availability. In dealing with such information the agent should transparently communicate to the user what information is shared and at what level of detail. Sharing

schedule information is quite common and the privacy aspects there are addressed by allowing the user to choose the level of details shared, e.g., sharing only busy/free time information, sharing the names of the calendar events, or sharing all the details of events. Similar approaches could be used for other data sources.

Finally, to establish a trust relationship, the agent should enable the user to query the information it possesses about her. Dedicated dialogues could be used to let the user query such information e.g., the user could ask: “*What do you know about my schedule this week?*” and the agent should disclose any information and also allow the user to change/remove it. Some information may be too complex and detailed to be used directly in the dialogues, e.g., raw sensor data. In such cases the agent could point the user to a graphical dashboard. Giving the user an ability to actively scrutinize the information in possession of any AI system is a general design recommendation that is, unfortunately, often not followed.

5.13 Conclusion

In this chapter, we discussed the value of integrating external sources of data into conversational interactions and techniques for designing conversations that help users learn and reflect on their data. We focused specifically on the domain of health behavior change and the process of reflection and learning from collected self-tracking activity data. Such data are readily available thanks to wearable fitness devices such as Fitbit and Apple Watch. At the same time, conversational agents such as Siri and Google Assistant are available on mobile devices. Integrating agents and personal data is a valuable and necessary direction to explore. We described a practical technical architecture for integrating external sources of data into conversations and discussed design strategies for mitigating effects of possible imperfections in automated recognition of free-text user responses. Finally, we provided blueprints for six unique conversational scenarios in the domain of health behavior change, as a guide for designers and implementers.

The current use of conversational agents is still centered mostly on transactional interactions, such as “booking a restaurant” or “asking for the weather”. We believe that the future of conversational interaction will increasingly involve context-aware agents that will have access to meaningful data about the user and beyond. Such external data will allow conversational agents to provide more personalized interaction and transform them from being mere replacement for graphical user interfaces to true personal assistants. The health behavior-change domain we explored here offers an early glimpse into the likely future where conversational agents will be integrated with various IoT devices. Awareness of the environment, user preferences and activities will allow future agents to provide a natural and highly personalized interaction environment. Therefore, exploration of early design principles, challenges and use cases provides an important step towards such a future.

References

- Abraham C, Michie S (2008) A taxonomy of behavior change techniques used in interventions. *Health Psychol* 27:379
- Agapie E, Avrahami D, Marlow J (2016) Staying the course: system-driven lapse management for supporting behavior change. In: Proceedings of the 2016 CHI conference on human factors in computing systems. ACM, pp 1072–1083
- Ajzen I (1991) The theory of planned behavior. *Organ Behav Hum Decis Process* 50:179–211
- Bentley F, Tollmar K, Stephenson P et al (2013) Health mashups: presenting statistical patterns between wellbeing data and context in natural language to promote behavior change
- Bickmore T, Giorgino T (2006) Health dialog systems for patients and consumers. *J Biomed Inform* 39:556–571
- Bickmore TW, Picard RW (2005) Establishing and maintaining long-term human-computer relationships. *ACM Trans Comput-Hum Interact TOCHI* 12:293–327
- Bickmore T, Schulman D, Yin L (2010) Maintaining engagement in long-term interventions with relational agents. *Appl Artif Intell* 24:648–666. <https://doi.org/10.1080/08839514.2010.492259>
- Bouton ME (2014) Why behavior change is difficult to sustain. *Prev Med* 68:29–36
- Bovend'Eerd T, Botell RE, Wade DT (2009) Writing SMART rehabilitation goals and achieving goal attainment scaling: a practical guide. *Clin Rehabil* 23:352–361
- Chung C-F, Jensen N, Shklovski IA, Munson S (2017) Finding the right fit: understanding health tracking in workplace wellness programs. In: Proceedings of the 2017 CHI conference on human factors in computing systems. ACM, pp 4875–4886
- Colusso L, Hsieh G, Munson SA (2016) Designing Closeness to Increase Gamers' Performance. In: Proceedings of the 2016 CHI conference on human factors in computing systems. ACM, New York, NY, USA, pp 3020–3024
- Conroy DE, Yang C-H, Maher JP (2014) Behavior change techniques in top-ranked mobile apps for physical activity. *Am J Prev Med* 46:649–652
- Consolvo S, Klasnja P, McDonald DW, et al (2008) Flowers or a robot army?: encouraging awareness & activity with personal, mobile displays. In: Proceedings of the 10th international conference on Ubiquitous computing. ACM, pp 54–63
- Cranshaw J, Elwany E, Newman T et al (2017) Calendar. help: designing a workflow-based scheduling agent with humans in the loop. In: Proceedings of the 2017 CHI conference on human factors in computing systems. ACM, pp 2382–2393
- Dhillon B, Kocielnik R, Politis I et al (2011) Culture and facial expressions: a case study with a speech interface. IFIP conference on human-computer interaction. Springer, Berlin Heidelberg, pp 392–404
- Fleck R, Fitzpatrick G (2010) Reflecting on reflection: framing a design landscape. In: Proceedings of the 22nd conference of the computer-human interaction special interest group of Australia on computer-human interaction. ACM, pp 216–223
- Fogg B (2009) A Behavior Model for Persuasive Design. In: Proceedings of the 4th International Conference on Persuasive Technology. ACM, New York, NY, USA, pp 40:1–40:7
- Fujita K, Han HA (2009) Moving beyond deliberative control of impulses: The effect of construal levels on evaluative associations in self-control conflicts. *Psychol Sci* 20:799–804
- Götzmann V (2015) Towards a persuasive dialog system supporting personal health management. National Research Center
- Hunter RF, Ball K, Sarmiento OL (2018) Socially awkward: how can we better promote walking as a social behaviour? BMJ Publishing Group Ltd and British Association of Sport and Exercise Medicine
- Kim Y-S, Hullman J (2015) User-driven expectation visualization: opportunities for personalized feedback
- Kinnafick F-E, Thøgersen-Ntoumani C, Duda JL (2014) Physical activity adoption to adherence, lapse, and dropout a self-determination theory perspective. *Qual Health Res* 24:706–718

- Kocielnik RD (2014) LifelogExplorer: a tool for visual exploration of ambulatory skin conductance measurements in context. In: *Proceedings of measuring behavior*
- Kocielnik R, Hsieh G (2017) Send me a different message: utilizing message cognitive space to create engaging message triggers. In: *CSCW*. pp 2193–2207
- Kocielnik R, Sidorova N (2015) Personalized stress management: enabling stress monitoring with lifelogexplorer. *KI-Künstl Intell* 29:115–122
- Kocielnik R, Pechenizkiy M, Sidorova N (2012) Stress analytics in education. In: *Educational data mining 2012*
- Kocielnik R, Maggi FM, Sidorova N (2013a) Enabling self-reflection with LifelogExplorer: generating simple views from complex data. In: *Pervasive computing technologies for healthcare (PervasiveHealth), 2013 7th international conference on*. IEEE, pp 184–191
- Kocielnik R, Sidorova N, Maggi FM, et al (2013b) Smart technologies for long-term stress monitoring at work. In: *Computer-based medical systems (CBMS), 2013 IEEE 26th international symposium on*. IEEE, pp 53–58
- Kocielnik R, Avrahami D, Marlow J et al (2018a) Designing for workplace reflection: a chat and voice-based conversational agent. In: *Proceedings of the 2018 designing interactive systems conference*. <https://doi.org/10.1145/3196709.3196784>
- Kocielnik R, Xiao Lillian, Avrahami D, Hsieh G (2018b) Reflection companion: a conversational system for engaging users in reflection on physical activity. *IMWUT* 2:26
- Lee MK, Kim J, Forlizzi J, Kiesler S (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*. ACM, pp 743–754
- Lewis MA, Uhrig JD, Bann CM et al (2013) Tailored text messaging intervention for HIV adherence: a proof-of-concept study. *Health Psychol* 32:248
- Li I, Dey A, Forlizzi J (2010) A stage-based model of personal informatics systems. In: *Proceedings of the SIGCHI conference on human factors in computing systems*. ACM, pp 557–566
- Li I, Dey AK, Forlizzi J (2011) Understanding my data, myself: supporting self-reflection with ubicomp technologies. In: *Proceedings of the 13th international conference on Ubiquitous computing*. ACM, pp 405–414
- Lin J, Mamykina L, Lindtner S, et al (2006) Fish'n'Steps: Encouraging physical activity with an interactive computer game. *UbiComp 2006 Ubiquitous Comput*, 261–278
- Locke EA, Latham GP (2006) New directions in goal-setting theory. *Curr Dir Psychol Sci* 15:265–268. <https://doi.org/10.1111/j.1467-8721.2006.00449.x>
- Maher CA, Lewis LK, Ferrar K et al (2014) Are health behavior change interventions that use online social networks effective?. A systematic review, *J Med Internet Res*, p 16
- McDuff D, Karlson A, Kapoor A, et al (2012) AffectAura: an intelligent system for emotional memory. In: *Proceedings of the SIGCHI conference on human factors in computing systems*. ACM, pp 849–858
- Miller WR, Rollnick S (2009) Ten things that motivational interviewing is not. *Behav Cogn Psychother* 37:129–140
- Moon JA (2013) *Reflection in learning and professional development: theory and practice*. Routledge, Abingdon
- Myers RS, Roth DL (1997) Perceived benefits of and barriers to exercise and stage of exercise adoption in young adults. *Health Psychol* 16:277
- Novielli N, de Rosis F, Mazzotta I (2010) User attitude towards an embodied conversational agent: effects of the interaction mode. *J Pragmat* 42:2385–2397
- Rautalinko E, Lisper H-O, Ekehammar B (2007) Reflective listening in counseling: effects of training time and evaluator social skills. *Am J Psychother* NY 61:191–209
- Rivera-Pelayo V, Zacharias V, Müller L, Braun S (2012) Applying quantified self approaches to support reflective learning. In: *Proceedings of the 2nd international conference on learning analytics and knowledge*. ACM, pp 111–114

- Rollnick S, Miller WR (1995) What is motivational interviewing? *Behav Cogn Psychother* 23:325–334
- Schueller SM (2010) Preferences for positive psychology exercises. *J Posit Psychol* 5:192–203
- Skurnik I, Yoon C, Park DC, Schwarz N (2005) How warnings about false claims become recommendations. *J Consum Res* 31:713–724. <https://doi.org/10.1086/426605>
- Tanumihardjo SA, Anderson C, Kaufer-Horwitz M et al (2007) Poverty, obesity, and malnutrition: an international perspective recognizing the paradox. *J Am Diet Assoc* 107:1966–1972
- Tollmar K, Bentley F, Viedma C (2012) Mobile health mashups: making sense of multiple streams of wellbeing and contextual data for presentation on a mobile device. In: 2012 6th International conference on pervasive computing technologies for healthcare (PervasiveHealth) and workshops. IEEE, pp 65–72
- Treatment C for SA (1999) Chapter 3—Motivational interviewing as a counseling style. Substance Abuse and Mental Health Services Administration (US)
- Tufte ER (1991) Envisioning information. *Optom Vis Sci* 68:322–324
- Tur G, De Mori R (2011) Spoken language understanding: Systems for extracting semantic information from speech. Wiley, Hoboken
- Wang Y-Y, Deng L, Acero A (2005) Spoken language understanding. *IEEE Signal Process Mag* 22:16–31
- Williams JD, Niraula NB, Dasigi P et al (2015) Rapidly scaling dialog systems with interactive learning. In: Natural language dialog systems and intelligent assistants. Springer, Berlin, pp 1–13