# Prescribing 10,000 Steps like Aspirin: Designing a Novel Interface for Data-Driven Medical Consultation

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## ABSTRACT
Due to the prevalence of personal health tracking, cases of self-logged data being utilized in the clinic are gradually increasing. However, obstacles to clinicians' ability to further adopt such data-driven medical consultations in the existing workflow remain, such as lack of time and poor interoperability. In this paper, we conducted a workshop to design a clinician interface supporting the integration of data-driven consultation into the existing workflow and investigate the role of the interface in situ. After implementing the clinician interface designed based on the workshop results, we observed 32 cases of actual use within the clinical context. We found that our interface, *DataMD*, helped the clinician construct a new workflow, enhanced the clinician's counseling skills, and facilitated more in-depth conversation. This paper contributes to empirically identifying the role of a clinician interface through a user-centered design approach.

## Author Keywords
Data-driven medical consultation; patient-generated data; self-logged data; clinician interface; design workshop.

## ACM Classification Keywords
H.5.2. Information interfaces and presentation: User Interfaces; User-centered Design.

## INTRODUCTION
It is difficult for clinicians to acquire a thorough understanding of their patients in the medical office. To understand patients, clinicians collect evidence by reviewing various kinds of lab data, such as vital signs and specific test results [18, 51]. In order to determine the correlation between the lab results and the symptoms patients report, clinicians often ask their patients additional questions. Based on these fragmented pieces of evidence and their prior knowledge, clinicians make medical decisions, such as which medicines to prescribe [47]. They also have to explain the type of medication and any side effects of the treatments to their patients. All these tasks should be done in as little as five to at most 20 minutes [14, 34]. This is a common problem in the hospital, and it is obvious that the doctor's office is a site where clinicians encounter information overload [17, 18, 54], which inhibits clinicians' ability to understand their patients completely.

It is extremely challenging to insert another process into this already dense workflow. It is even more difficult when the new process involves patient-generated data consultations. Previous studies and reports have already pointed out the obstacles of utilizing such patient-generated data within the medical setting [2, 14, 37, 44, 49, 53]. Many issues relate to data capture/access and further situational constraints in medical practices [53]. As mentioned above, situational constraints, such as lack of time [35, 49] and information overload [27, 54], have been pointed out as some of the most challenging and endemic obstacles.

Despite these challenges, major hospitals and healthcare providers are attempting to adopt data-driven consultation [52]. Quickly obtaining information on patients' everyday lives is more critical in specific clinical settings where overweight patients suffering from chronic diseases need regular visits to check their overall health conditions and receive advice from clinicians. It is crucial for clinicians to have a thorough understanding of their patients for precise diagnosis and proper treatment [1, 6, 33], especially in the case of chronic disease patients [8]. In the past, patients mostly provided their daily habits through verbal recall, which was time-consuming and forced doctors to make estimations. On the contrary, data-driven consultation helps clinicians gain a deeper understanding of their patients' behaviors and feelings [14] in a relatively short amount of time. In other words, if the data-driven consultation process is well integrated into the current workflow [38], the doctor–patient relationship can be improved despite the situational constraints [8, 14, 29].

However, it was not until recently that the integration of data-driven consultation, in which clinicians utilize self-logged data in the hospital, began to be researched. Chung et al. identified the feasibility, benefits, and challenges of


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data-driven consultation from the perspective of both healthcare providers [14] and patients [15]. West et al. [53] reviewed prior studies and examined clinicians using vignette-based roleplaying. These studies derived empirical findings by investigating how data-driven consultation aligns with current workflows and work practices. However, little research has been done on the role of actual clinician interfaces and the way in which such interfaces should be designed [8, 38].

Therefore, in this paper, we aim to help doctors understand patients quickly by designing a clinician interface that provides a set of clues for checkup conversations. To do so, we explore how the data-driven consultation interface should be designed and identify its role by in-situ observation. Given these objectives, the research questions are as follows:

- How should a clinician interface for data-driven consultation be designed?
- How does the newly designed clinician interface help the integration of data-driven consultation with the current routine?

In order to answer these questions, we conducted a 15-month-long user-centered design process with 18 stakeholders. Focusing on the first question, we set design goals based on the preliminary study. We found two issues clinicians encountered: (1) difficulty catching any distinctive events that caused dramatic changes in patients' behaviors when clinicians were not monitoring them and (2) difficulty discovering those events quickly and discussing them further with patients. To reflect on these issues, we conducted a design workshop and designed a dashboard interface for supporting conversations in the exam room. Then, we implemented the interface, DataMD, which can be integrated with the current electronic medical records (EMR) system. To answer the second question, we conducted a field study by observing 32 cases of actual use within the clinical context.

This study contributes to the HCI field by (1) providing design guidelines through a user-centered approach, (2) developing an interface that supports data-driven consultation, and (3) identifying the role of the clinician interface using patient-generated data in an actual clinical setting.

## RELATED WORK

We reviewed previous work to understand the opportunities and challenges of data-driven consultation as well as the role of the clinician interface.

### Benefits of Using Patient-Generated Data in Clinical Settings

Triggered by the advent of smartphones and wearable devices, and the *Quantified Self* movement [24], self-tracking has become a common habit [13]. According to [23], 70% of Americans—especially those suffering from chronic diseases—log at least one of their or their spouses' health indicators. Many studies have been carried out to investigate how these data could be useful for health management [16, 31, 32, 43]. While addressing the difficulties of interpreting such data [9], researchers further emphasized the necessity of expert interventions [12].

This led to recent studies on data-driven consultations in which clinicians utilize patient-generated data within the clinical setting [14, 34, 53]. It has been identified that using patient-generated data has many benefits. Chung et al. [14, 15] asserted that patient-generated data could offer supporting evidence for diagnoses and positively influence the doctor–patient relationship. Above all, it could enable clinicians to learn about and motivate their patients [38] and thus provide them with personalized treatment [22].

### Challenges of Integrating Data-Driven Consultation into Existing Workflow

Despite its benefits, the challenges that hinder the integration of data-driven consultation mostly relate to situational constraints within the clinician's office, such as information overload and lack of time. Clinicians are responsible for multiple tasks, both behavioral and cognitive, and therefore need a high mental capacity [54]. Internally, numerous types of reference data are needed to support clinicians' decision making [27, 47]. Externally, some resources are displayed on the EMR, while others are presented in paper form [4, 11, 27]. Several studies report that clinicians encounter difficulty in appreciating the value of data-driven consultation due to such information overload [17, 54]. Furthermore, lack of time has come to the fore [20, 35, 48, 49]. Clearly, the adoption of data-driven consultation is challenging, as the existing workflow is already tight and dense.

The data itself has also been deemed an obstacle. Data gathered by patients is less standardized [30]; therefore, hospitals still have difficulties collecting data from diverse sources [25]. Recently, healthcare service providers released data platforms such as HealthKit [28] and Google Fit [26] to manage personal health data. In the near future, data recorded from individual tools will be supplied from health data platforms, and hospitals will obtain the data by accessing the platforms. In the end, the problem returns to how clinicians can utilize such data efficiently.

### Role of Clinician Interface

A well-designed interface could be helpful for integrating data-driven consultation into the existing workflow [8, 38]. According to Kim et al. [34], showing patient-generated data on a standardized interface can help clinicians better understand their patients. When interpreted using the six activities suggested by West et al. [53], Kim et al.'s study implied that an interface can help clinicians overcome information overload by supporting the stages of discovery, evaluation, and initial hypothesis formation. The study also showed that the clinician interface's summary data allows clinicians to assess patients' status, and the detailed information enables them to discover abnormal points very quickly [34]. It implies that the role of the interface is important in overcoming the problem of insufficient time.

Data-driven consultation mediated by an interface could also affect the doctor–patient relationship. According to previous studies [35, 46], clinicians have difficulties counseling patients in the exam room due to a lack of confidence, information, and time. Taft et al. [50] found that an EHR helped physicians' communication skills in the exam room by assisting them with the reading and writing of medical information. The problem is, according to many studies [4, 11], that clinicians' focus on devices while reviewing medical data could cause exclusive viewing [11]. The same problem could arise during a data-driven consultation [4]. However, the characteristics of patient-generated data distinctively differ from those of medical data, since patients play a significant role in the acquisition of the data [7, 8]. Therefore, patient-generated data is more likely to lead to collaborative viewing [15, 29, 40]. According to Kim et al., patients showed great interest in self-logged data and were highly engaged with their medical treatment when reviewing their data on the interface with clinicians [34]. The studies mentioned above suggest that a well-designed interface might help to both improve clinicians' counseling skills and increase patient interest.

## DESIGN PROCESS

To design the clinician interface, we employed a user-centered approach. The design process lasted 15 months and went through five stages: **preliminary study, design goal, design workshop, implementation,** and **field study**. A total of 18 participants—clinicians (4), healthcare informatics experts (3), healthcare service providers (3), a healthcare service developer (1), an EMR developer (1), a college student (1), and HCI researchers (5)—were involved in the design process. The long-term design process allowed us to explore various issues and more thoroughly develop the design.

In the preliminary study, we identified the current workflow and discovered opportunities to insert data-driven consultation. We conducted in-depth interviews with four clinicians with different specialties from Seoul National University Bundang Hospital: otorhinolaryngology (C1), family medicine (C2), rehabilitation medicine (C3), and urology (C4). The interviews consisted of two parts and took a total of 40 minutes. During the first part, we asked clinicians about their behavioral procedures in the examination room and their interaction points with the EMR system, paper reports, and nurses. During the second part, we investigated clinicians' opinions on how they would integrate data-driven consultation into the existing workflow based on the scenarios they wrote. After the interviews, we combined the journey maps of the existing workflow from each clinician into a unified journey map. Finally, we concluded with the final two journey maps that represented the current (as-is) and desired (to-be) workflows (Figure 1).

Secondly, we refined the requirements by observing actual data-driven consultations and conducting discussion sessions with clinicians. We derived three themes from the requirements, which were gathered from three types of data. The main data were transcripts containing 40 cases of six clinicians using patient-generated data [34], which were re-analyzed considering this paper's research questions. Other data were collected from clinician interviews and survey results. We asked clinicians about their thoughts on data-driven consultation and investigated their perceptions of the usefulness of each type of data through a survey. After extracting and listing several requirements from the data, we conducted a thematic analysis and elicited three themes.

Thirdly, we conducted a design workshop with 18 participants to make sketches of a concrete interface. The objectives of the co-creative design workshop were to (1) make sketches of a concrete interface with clinicians who were aware of the current workflow and (2) consider unexplored issues through the participation of various stakeholders. The participants were divided into four groups with various backgrounds. Every group contained a clinician or healthcare informatics expert.

The design workshop consisted of three sessions (structure, visualization, and paper prototyping), which took a total of five hours. Before the group activities, we explained the current workflow and essential requirements, and printed guides were distributed to each team to serve as reminders for participants. Most of the time was spent on teamwork, but there were presentations after each session. During the first session, we asked everyone to spend 30 minutes selecting an interface structure. The participants were provided with examples (e.g., dashboard, grid view). Afterward, they were asked to make a new structure for a clinician interface. In the second session, participants spent 80 minutes sketching ideas about data visualization. We handed out data samples in Excel-sheet format. In the last session, each group spent 70 minutes making a paper prototype. Finally, each participant had three votes to cast on the paper prototype components. A week after the workshop, we documented the results with a decision-making list. After all the participants attended charrettes, we shared the voting results and reached the final guidelines.

After finishing the design workshop stage, we implemented the interface, Data MD, on the actual EMR system. Then, we conducted a field study to observe the role of our interface. These two stages are described in the respective sections below.

## PRELIMINARY STUDY

Before designing the interface, we investigated the current workflow and identified how data-driven consultation might integrate with it. As a result of the preliminary study, four behavioral tasks were identified: skimming lab data on the EMR system, asking patients follow-up questions, typing in comments on the EMR system, and orally

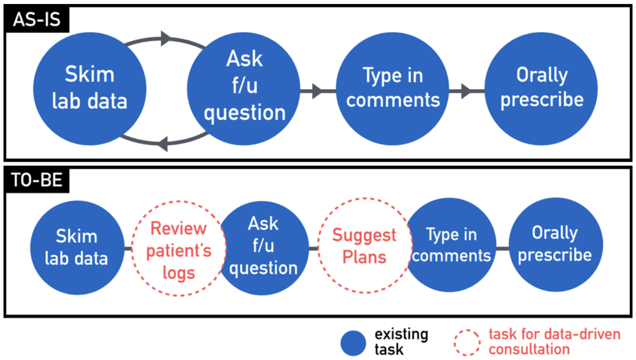


**Figure 1. The two boxes are the current and desired workflows. Each circle represents a task and is ordered by time. The to-be workflow is what the clinicians want/expect in terms of change.**

prescribing and explaining medications. Clinicians emphasized that data-driven consultations can aid in the betterment of the first two tasks, which involve iterative learning about patients through conversations. This provides the clinicians with the prerequisite information and allows them to approach critical questions without wasting time. This provides the clinicians an opportunity to plan behavioral changes with the patient.

Clinicians addressed the necessity of a uniform clinician interface that integrates patient-generated data from various individual tools, supporting the findings in previous studies [3, 8, 29]. Interestingly, clinicians emphasized that the new interface should be designed as a separate window from the existing EMR system. They pointed out that EMR data and patient-generated data differ in terms of reliability, validity, and medical value, as revealed in previous studies [19, 38, 49]. They clarified that patient-generated data has not yet been proven to have a clinical correlation with any diseases and that a separate window would help distinguish patient-generated data from medically verified data. Therefore, we decided to design it such that the patient-generated data was separate from the EMR system.

## DESIGN GOAL

We refined the requirements of clinicians and derived three goals of the clinician interface design.

### Helping Clinicians Skim Data Quickly

We found that the clinician interface should help clinicians skim trends from various types of data quickly so that they can discover distinctive points. Clinicians want to be able to review summarized data to understand patients effectively. C2 commented, *"To put it simply, I want to see my patients' status at a glance; that is, in as little time as it takes them to leave the exam room and enter my office."* Simultaneously, clinicians need to review data in detail to determine abnormalities. For example, clinicians often read the trends of the activity data (steps) and discover an unusual point when the number of steps taken suddenly decreases. They then need to scrutinize the data collected that day. These conflicting requirements imply that both summarized and detailed data are needed.

### Supporting Collaboration of Clinicians and Patients

It is important for clinicians to read the data collaboratively and discuss them with their patients. Clinicians think they can answer critical questions quickly using patient-generated data and that discussing cases with patients can increase the quality of care. While patient-generated data is produced by the patients, lab data is generated at hospitals. Patients are interested in and knowledgeable of their data [7, 15]. Thus, an interface should be designed to facilitate doctor–patient collaboration and discussion [4, 11, 14].

### Creating Procedures to Enable Clinicians to Have an Impact on their Patients

Clinicians highlighted that data-driven consultation was useful only when it included specific plans that could affect patients in the real world. This implies that not just reviewing data but actually setting goals creates therapeutic value [22], especially by motivating patients to modify their behaviors [15, 34]. Despite such importance, little research has been conducted on setting goals with patient-generated data. We observed that clinicians easily forget patients' unrecorded data. Since clinicians orally set goals, patients and clinicians cannot remember them with exactitude. To prevent goals from being lost, a clinician interface should be designed to record them and influence patients' lives.

## DESIGN WORKSHOP

We explored how the three design goals can be reflected in the clinician interface through a design workshop.

### All-in-one Interface with a Hierarchical Structure

The first design guideline was related to a desirable structure. The results showed that the information should be organized hierarchically on a single-page screen.

#### *All-in-one Interface is More Efficient*

Interestingly, all the groups proposed new types of structures in which all data were displayed on a single page. We expected that navigating separate pages would allow clinicians to read data faster, but the results indicated the opposite. Clinicians and health informatics experts argued that a single page is better for a holistic review. *"Clicking wastes time, so one screen is better for speed"* (C2). A single view was also beneficial for cross-referencing various types of data. One team's developer and designer preferred to distribute information across a few pages, but they changed their minds after hearing the clinician's opinion. Another group reported similar processes.

The legacy system, the existing EMR system, influenced clinicians' preferences for combining all the data in a single page. Clinicians were accustomed to the current EMR system, which runs on a 21-inch monitor. As they were used to reviewing heterogeneous data on a single-page view, it was natural for them to design the new interface in a similar way. *"I'd rather not design it too differently from the (current) EMR"* (C1). Two other clinicians (C2, C3) and an EMR developer made similar points.

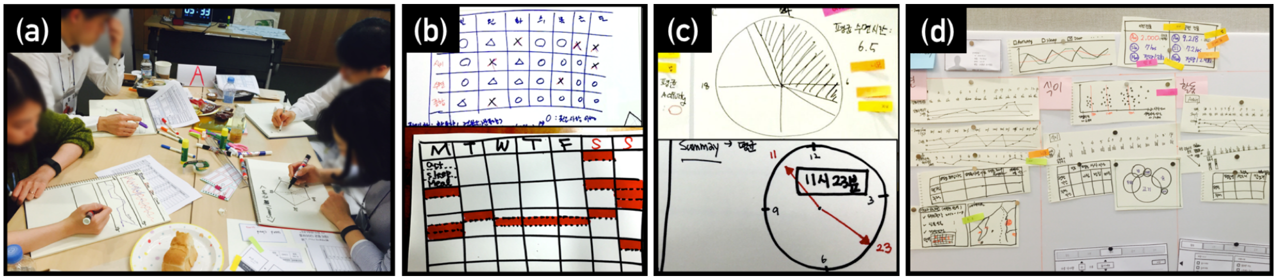


**Figure 2. (a) is a scene of sketching ideas in the second stage of the workshop. (b) shows sketches of a calendar-style grid with O/X marks. (c) presents ideas that borrowed a schedule pie chart to represent wakeup time, bedtime, and sleep duration. (d) is an example of a paper prototype.**

*Hierarchical Structure for Skimming Data Quickly*

Most groups discussed the issue of information overload caused by listing the data on a single page, and two groups proposed a hierarchical information structure to solve this issue. During this process, there was a discussion on the importance and characteristics of each data type. Clinicians suggested that each type should be distinguished, as they categorize weight, blood pressure, and stress as outcome data in their practices. The activity, food, and sleep data were considered primary data that affect the outcome data.

They suggested a three-level data summarization process involving a holistic summary, individual data summary, and detailed individual data. This could be connected to interpretation levels. For example, if a holistic summary were to represent the average quantity of activity, meals, and sleep, a clinician could think, “This patient did not exercise but ate a lot. No problem with sleeping.” After that, the clinician might decide to review the individual data summary of activities and get a new interpretation: “S/he is usually active but only has inactive days on particular weekends.” If needed, the clinician could look into the detailed individual data. This step-by-step sequence might improve effectiveness, because some information might not be necessary but could be selectively interpreted.

All the groups mainly dealt with a holistic summary, since it is essential to deciding the level of interpretation required. The two highest ranked components were a different type of representation of a holistic summary. One was a table with numeric values (e.g., averages) to help clinicians quickly comprehend each value. The other was a multi-line graph where the multiple lines overlapped to enable clinicians to compare various data trends. Clinicians supported its usefulness, stating that the current vital signs are visualized in the same way. For this reason, we agreed to adopt the overlay graph and test it in the field despite several issues with axis synchronization and its complexity of interpretation.

## Line Graphs for Trends and Heat Maps for Distinctive Points

In this section, we mainly describe the result of the drawing session where participants discussed data visualization.

*Easiest Visualization for Representing Trends*

Participants agreed that an individual data summary could help clinicians scan trends effortlessly. That is, an individual data summary shows a span of data, while a holistic summary provides a snapshot of data. As for the voting results, the most popular individual summary visualization was the time-series line graph. There are two merits to using a line graph. Because line graphs are common, clinicians can quickly catch trends from them, and some values are displayed on line graphs. In addition, it is possible to visualize any time-series data with ease, whereas other new visualizations depend on the data type.

One of the groups argued the necessity of customized visualization techniques based on the different traits of each data type. Activity data could be represented on a calendar-style grid view with O/X marks, because whether patients achieve their goals is important (Figure 2-b). It would allow clinicians to check at a glance if their patients are exercising continuously. In the case of sleep, some borrowed a schedule pie chart to represent wakeup time, bedtime, and sleep duration (Figure 2-c). However, many participants were concerned that those visualizations required additional interpretation and did not show trends well.

After discussion, all participants agreed on the common formats, such as the line and bar graph formats, due to their familiarity. It reflects the conflicts between the needs and costs of using patient-generated data in the exam room. Clinicians were confident that using the data would be useful, but they had trouble anticipating the difficulties associated with the data. The cost, including misinterpretation of the data and learning system, influenced their preference for familiarity. Since clinicians did not want to take risks or have uncertainties, they were inclined toward common visualizations and various options (e.g., summary & details, reference values).

*Heat Maps for Looking into Distinctive Points in Depth*

Heat maps were chosen to express detailed individual data for the primary data (i.e., activity, food, and sleep). When clinicians discover a distinctive point, such as a sudden decrease in a line graph, they form initial hypotheses and want to verify them [53]. They want to know exactly what happened at that point. Many participants tried to represent the details of each data type by dividing a day into three


**Figure 3. The view of the clinician interface is named *DataMD*. A clinician, the intended user, can: (1) skim patient-generated data via the numerical summary and graph with multiple trend lines (2) review a trend line for each data component, and discover abnormal points (3) if needed, look at the heat map to check for details (4) adjust the goal with his/her patient.**

sections: morning, afternoon, and evening. It reflected the requirements that clinicians wanted to examine in-depth dimensions beyond daily quantities. It was also expected to promote communication between clinicians and patients. As the visualization was similar to the mental model of a daily routine—morning, afternoon, and evening—patients could talk about their status and feelings without difficulty.

During the charrette, the heat map was considered an appropriate format to visualize amounts in each time section. Adding an additional time section, night, was suggested to review problematic points. For example, many patients take a late-night meal impulsively, which would be dealt with separately from supper. In addition, a stacked bar graph was selected for sleep data due to the different structure of sleep quality data.

### Multiple Numeric Input Fields for Prescribing Measurable Goals

The requirement of creating preset procedures to prescribe goals and therefore impact patients was emphasized. Clinicians desired to set goals as they would prescribe medication on the EMR system. One group suggested the idea of setting goals by entering exact numbers. The idea was popular with participants, especially clinicians. This simple interaction was expected to help clinicians compress a discussion with patients and integrate it into the workflow. An additional opinion that the history of the prescribed goals should be shown was also reflected.

To adjust and set specific goals, appropriate criteria were required. Clinicians noted that reference values are needed to make immediate decisions. Among many candidates, two values were selected: the average of an individual patient's data during the total logging period and the average during the interval between the last visit and the current visit. During the workshop, some participants commented that a similar group's average could be helpful. However, it was not reflected in the interface, because there would not be enough data to calculate in the early stage. The discussion of reference values changed frequently. Participants could not decide which reference values would assist clinicians' decision making. This implied that a field study should be conducted to identify the final reference value choices.

## IMPLEMENTATION

We implemented the clinician interface, named DataMD, enabling clinicians to utilize patient-generated data based on the design guidelines. After developing the first prototype, we modified it five times based on the feedback from the workshop participants. We revised the graph scale, certain kinds of reference values, and the color of the graph and background. Considering the legacy system, we made a small button on the bottom right of the original EMR page to access the interface for patient-generated data. In response to the clinicians' request, we also chose a dark theme to maintain consistency with the existing system.

We confirmed the six types of data, which can be classified into two categories (primary and outcome data), as discussed in the section above. The primary data area includes activity, food, and sleep data, and the outcome data area includes stress, weight, and blood pressure data. Every data type has a unique color to prevent confusion (Figure 3). There had been save buttons placed on each goal, but we reduced it to just one button, reflecting clinicians' comments that it was too confusing.

### Holistic Summary Area

The holistic summary area is located at the top left, which is expected to help clinicians skim data quickly and choose the level of interpretation.

- ***The profile*** is provided as a bar at the top. It contains patients' basic information, such as name, sex, age, disease, and body mass index (BMI).
- ***The numerical summary*** consists of six boxes, which represent the average or the latest value of each data type. For the primary data, average values are displayed to catch a snapshot of a patient: average number of steps, food portion size and eating frequency, and sleeping duration. All the data boxes include the last goal number in a small font.
- ***The graph with multiple trend lines*** represents the relative trends of each data type. Due to the axis synchronization issue, the axes are not displayed. Instead, we define the lowest data point as zero and the highest as 100. This component helps clinicians cross-reference and compare the six types of data so that they can discover correlations between them.

### Primary Data Area
The primary data area contains three data components. Each data component has four elements, including an individual data summary, detailed individual graph, reference values, and numeric input fields for goal setting.

- In ***the activity data*** component, there is a trend line graph for grasping the total daily number of steps. The heat map in the activity data component represents the intensity of exercise during four predefined time sections: morning, afternoon, evening, and night. Two input fields are provided to insert a goal number for the daily step count and a required duration of a high-level exercise per day.
- In ***the food data*** component, there is a bar graph representing the average portion size per day. The heat map represents the portion size for each time section. Additionally, the frequency of snack intake is provided with another tab for the trend line graph. There are four input fields to input frequency of meals, portion size per meal, time of eating, and frequency of snack intake.
- ***The sleep data*** component is different from the other primary data. The total sleep duration and wakeup/bedtime are represented with a unique type of trend graph with a bar element. A stacked bar graph is used to visualize the quality of sleep based on the duration of light sleep, deep sleep, and awakening. There are three input fields to set the bedtime, wakeup time, and total sleep duration.

### Outcome Data Area
The outcome data are different from the primary data. There is only a summary of each data type, because these data do not have qualitative dimensions. They are usually cross-referenced with the primary data, so we chose different graph forms.

- ***Stress data*** is represented in the heat map to emphasize a remarkable change. Since individuals cannot control stress levels, there is no input field to set a goal.
- ***Weight data*** is visualized as a line graph with a reference line of the previous goal weight. There is a numeric input field to set a goal weight.
- ***Blood pressure data*** is visualized in a line graph, similar to weight data. There are two lines, the highest and lowest values, with dotted reference lines.

## FIELD STUDY
We investigated in situ how DataMD helps the integration of data-driven consultation into the existing workflow.

***Case study.*** In the field study, we aimed to trace how clinicians interact with DataMD and how it encourages clinicians to change over time. We employed the case study method, since we focused on tracking the variations between each patient, as well as the internal change in the clinician, over experience. A total of 32 medical checkups were observed within a month.

***Recruitment.*** Due to the strict consent policies of certain departments, only one clinician (C1, otorhinolaryngology) participated in the field study. The clinician recruited patients interested in weight management. Most of them were suffering from chronic diseases, such as hypertension, hyperlipidemia, and sleep apnea. After deciding to participate in the study at the clinician's office, patients were informed about the overall process outside the office. The patients were provided with Misfit devices to log their steps and sleep data and a logger app to collect food, stress, weight, and blood pressure data for a month. They were asked to visit every two weeks to check their status and receive advice from clinicians. We funded their blood tests and three consultation visits. They were also rewarded with a $15 coffee card.

Among the recruited patients, we observed 26 checkups of 18 patients with their consent. Among the patients, eight of them visited twice in a month. Therefore, we could identify the change in the clinician's use of the interface with the same patient. In addition, we examined six cases without using our interface to compare and therefore identify the distinct role of the clinician interface, DataMD.

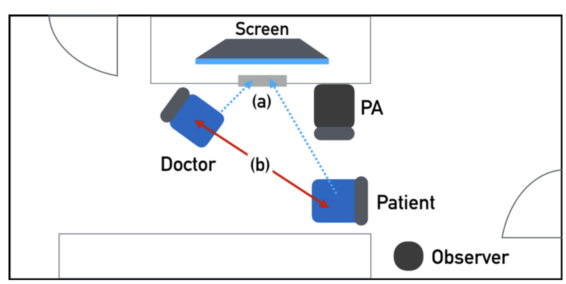


**Figure 4. Layout of the observation site. The blue arrows (a) indicate line-of-sight if both patient and clinician want to. (b) infers an eye contact between patient and clinician.**

***Environment.*** The office was equipped with several medical machines. Patients sat on the prepared chair (Figure 4). A clinician and physician assistant (PA) were present in all cases. Researchers voice-recorded the conversations and counted the number of times the clinician and patient made eye contact, the clinician's interactions with the interface, and other nonverbal events.

***Analysis.*** After transcribing all the voice-recording files and collecting field notes, we conducted a thematic analysis [10] using a supporting tool named Reframer [43]. We aimed to explore the roles of the interface based on the initial perspective. Thereby, the transcription and field notes were coded according to the three essential requirements.

### Helping Clinicians Make a New Workflow Suitable for Data-driven Consultation

To our surprise, we observed that the physician created a new workflow around the interface. Three phases were identified: (1) skimming data, (2) asking questions, setting goals, and providing explanations, and (3) inputting goals.

The first step, skimming data, naturally integrated into the workflow. When the patient stepped into the medical office, the clinician engaged the patient in small talk and started using the interface to review self-logged data. When necessary, the clinician viewed lab reports or paper reports and briefly explained the results to the patient.

> ***Doctor:*** *Did you do a good job?*
> ***Patient:*** *I tried, but I was on vacation, so I couldn't take a lot of walks.*
> ***Doctor:*** *(while looking at the EMR) Your cholesterol levels were high, but the numbers are even higher than usual. (switches windows, looks at the numerical summary on DataMD) I see you wore the device every day; that's good. You don't exercise, you eat two meals on an average day, and you sleep pretty well. You have to look after your weight; it is excessive. Mainly, you need to walk more.*
>
> **— Case no. 1 (sex: male, age: 43, visit 2, duration: 09:12)**

The second phase was unique, because the clinician repeatedly asked questions, set goals, and provided explanations. After skimming information, the clinician asked for context, such as abnormal points or feelings. By doing so, the clinician set goals with the patient.

> ***Doctor:*** *(while looking at the line graph on the meal component) Your meal patterns aren't dramatic. I mean the pattern hasn't really changed from before. (clicks on the snack tab) Oh, I see that you've been munching a lot. (looks at patient)*
> ***Patient:*** *Snacks… Yeah, I feel a bit guilty. Well, I ate a lot of snacks during vacation.*
> ***Doctor:*** *Oh, I see, during vacation. But besides that, you're doing good. (looks at the heat map in the meal component) What about keeping our goal as before? Or maybe we can cut down on the snacks a bit? (looks at patient)*
> ***Patient:*** *Good, I'll cut my snacks in half.*
>
> **— Case no. 14 (sex: male, age: 37, visit 3, duration: 02:21)**

This process was repeated for each data type. However, goals were only set when the clinician decided that the patient needed behavior modification. By selectively setting goals, the clinician made effective use of the limited time.

During the third phase, the clinician did not type in the goals right away but waited until the end of the consultation and typed in all the goals at once, perhaps because typing during consultations would have hindered conversations with patients. This all-at-once behavior was possible, since the goals were simple numbers. The PA occasionally typed in comments in the EMR for the clinician. However, as for DataMD, the clinician took charge of setting goals and typing comments.

As a result, data reading and explaining integrated into the workflow as expected; however, goal setting did not. This conflict between DataMD and the existing EMR will be elaborated upon in the discussion section.

### Improving Clinicians' Counseling Skills with Data

The clinician showed selective behavior with more experience with DataMD, which resulted in looking at the data he deemed important. This means that the clinician formed strategic approaches to read the data efficiently within a short period of time.

As the clinician's data-driven counseling skills improved, his overall strategy of using DataMD also changed. At first, he read the interface as intended by the designers. However, as time passed, he reduced the time spent on reading data and started to compare primary data and outcome data to interpret interrelations. The results of such interpretations were reflected in the goal setting.

> ***Doctor:*** *(while looking at the line graph in the activity component) Your activity graph drops significantly (looking at the line graph in the food component), but your food intake is high. Not just the food intake, but I think you should start working out. That's why you're not losing weight. I think you should walk about 10,000 steps a day… (looks at the patient)*
>
> **— Case no. 23 (sex: male, age: 39, visit 3, duration: 03:04)**

In addition, the data deemed important differed across patients. In the following case, the clinician interpreted high stress levels, along with changes in sleeping patterns, and recommended a medical test.

> ***Doctor:*** *Are you going through a lot of stress lately?*
> ***Patient:*** *Yes, the company isn't going well these days.*
> ***Doctor:*** *I see that your sleep satisfaction scores are lower than before. Is it because of the stress?*
> ***Patient:*** *I can't sleep these days, because of the pressure. I'm too tense.*
> ***Doctor:*** *First of all... I think you should find a way to lower the stress. Maybe you can take some walks… (while looking at the snack graph in the meal component) But you have to stop eating at night. Let's wait and see how the polysomnography goes.*
>
> **— Case no. 13 (sex: male, age: 35, visit 3, duration: 02:37)**

Data that was difficult to interpret, or which needed further experience, tended to be excluded. For instance, the trend summary was a relatively harder component to interpret. Therefore, the first two or three times, the clinician tried to read the trend summary graph as shown. However, after gaining experience, he excluded the trend summary graph and focused on interpreting other data. It implies that the clinician became skillful enough to manage his counseling time and select data content.

### Facilitating In-depth Conversation

The DataMD interface supported and promoted doctor–patient communication within the medical office. The conversation naturally kicked off with the clinician asking the patient if they were logging data consistently. When the interface showed that the patient had diligently gathered data, the clinician would make eye contact with the patient and compliment them; otherwise, he would encourage them to do so.

> ***Doctor:*** *(looking at the whole screen) Overall, you're doing a great job on collecting data. You've been doing especially great on logging your meals (makes eye contact with patient). Great, this is amazing. (looks back at the screen) But I can see a few days are empty.*
>
> ***Patient:*** *Oh, I was a bit busy during the weekend. It's difficult to log everything.*
>
> **— Case no. 5 (sex: male, age: 39, visit 3, duration: 03:06)**

The DataMD interface became the center of attention, leading to the collaborative viewing of clinician and patient. Since the interface was on a fixed monitor screen, and the patient was sitting at a 45-degree angle (Figure 4), the interface was constantly viewable. The patients showed high interest in the fact that the doctor had reviewed the data that they had collected and actively asked questions.

> ***Doctor:*** *You're the best patient I've seen so far. (looking at the heat map in the meal component) You started to deliberately eat less at night compared to before you came to the hospital, right?*
>
> ***Patient:*** *Yes, yes. How did you know? (looks at the DataMD screen) Can you tell?*
>
> ***Doctor:*** *Yes, can you see? The colors are different. (looks at the patient) We can see it at a glance, because the color fades. You did a great job at eating less.*
>
> **— Case no. 3 (sex: male, age: 37, visit 2, duration: 04:40)**

The interesting point was that despite an additional screen (DataMD was used on top of the EMR), more eye contact was observed while using both systems compared to when the clinician only used the EMR. The clinician recursively asked patients questions, searched for new evidence, and tried to relate that to the medical values that appeared on the EMR. This shows that the use of an interface does not directly lead to less eye contact or human interaction. On the contrary, shorter appointments and less eye contact were observed in the existing workflow without DataMD. We also found that patients' responses were mostly short, such as yes/no, in the existing workflow. Therefore, it took longer to obtain the same context information (e.g., on vacations, lifestyle patterns). This result suggests that when appropriate data is shown, the doctor–patient relationship is enriched through increased eye contact and depth of conversation.

## DISCUSSION

We now summarize and discuss the lessons learned from our design process.

### Tensions Surrounding Data-driven Consultation

Our main objective was to design and explore the role of a comprehensive interface that connects data-driven consultation to existing workflows. In the process, we discovered that tensions surrounding workflow integration still remain. Even though a time-crunched clinician unfamiliar with patient-generated data was able to review many patients' data easily via the uniform interface, we found conflict between the new and old systems. We could not completely prevent the new interface from clashing with the existing system. For example, entering comments into the EMR and setting goals are similar tasks, yet they were separated in our implementation due to the differences in the reliability and completeness of lab data and patient-generated data. There has not been a proven correlation between patient-logged data and diseases, which makes patient-generated data less reliable [5, 19, 38]. In addition, clinicians chose not to view the two data types in the same window for the same reasons. In these circumstances, presenting patient-generated data with medically proven lab data may cause confusion among clinicians.

In short, this issue cannot be solved solely by designing an interface; rather, it requires collaboration among experts in both the medical and HCI fields. HCI researchers and medical experts can investigate whether patients' health could be improved by using patient-generated data.

### DataMD as a Doctor–Patient Translator

The DataMD interface served to connect patients and clinicians like a translator. Specifically, the numeric input fields for setting goals promoted communication between patients and doctors. While setting goals, clinicians acquired a deeper understanding of their patients' behaviors and thoughts. We observed that adjusting and setting goals affected both clinicians and patients. Patients explained their status and expressed their opinions to adjust the goals, which motivated patients to achieve them [2, 33, 36, 41]. Further studies are needed on the patient side, as we were unable to conduct a deep inquiry into the patients.

We believe this observation provides several ideas for further research. First, the way in which patients are influenced by exam-room goal adjustments should be investigated. A one-sided order process, as in a conventional medical practice, can make patients too dependent on clinicians' instructions [34, 40]. Patients should be experts on their data and be able to adjust goals and change their habits independently [40]. Increasing goal type flexibility is strongly recommended to encourage patients to actively express their preferences and interest in their data. For example, the current goal of activity is only represented by steps, so patients cannot reflect their preferences, such as for swimming or cycling. It reduces not only patient interest but also their effort to adjust goals. Therefore, HCI researchers have to support both clinicians and patients by designing flexible clinician interfaces and self-tracking tools that promote in-depth conversations [29].

Second, it is necessary to consider how the adjusted goal in the exam room would be delivered to patients. We designed DataMD, where clinicians can simply enter numbers to set goals without wasting time. Conveying goals via numbers is much more precise and reliable, whereas natural language is much more expressive and easier to understand [9]. Both methods have trade-offs. Thus, patients' perceptions of, and preference for, the interaction type should be examined.

### Potential Risks of Using Patient-Generated Data in Clinical Settings

In this paper, the clinician could understand patients' status and provide advice to them through our interface, DataMD. However, there are several ethical issues that cannot be ignored. The typical problem is the risk of data misinterpretation, which can cause clinicians to endanger patients unwittingly. No correlations have been identified between certain diseases or symptoms and patient-generated data. It means that although clinicians carefully analyze and interpret patient-generated data, there is always a risk of making an erroneous decision. Therefore, both the technology and hospital policies should provide a safety net to lower that risk. For example, on the technology side, inventing algorithms to avoid mistakes could be a solution. On the hospital policy side, hiring experts on analyzing patient-generated data or educating nurses and PAs could prevent clinicians from making mistakes.

Another problem is the side effects of managing health via data. Patients might focus on just collecting data even if they continue to engage in unhealthy behaviors, because clinicians judge patients' status based on the data alone. For example, some patients could skip meals for convenience rather than eating healthy food. Clinicians should consider this kind of risk and encourage patients to talk about their difficulties with changing behaviors. Providing personalized recommendations also encourages patients to engage in healthy behaviors. Further research needs to investigate possible factors affecting patients' attitudes, such as clinicians' usage of data and changes in prognosis.

### Disparity between Expectations and Actual Use

We found that consistent visualizations improved the clinician's counseling skills. This still leaves some points on ways of visualizing the data open to discussion.

The graph with multiple trend lines, which was strongly suggested by clinicians, gradually became less used over consultations, because it required time and effort to read and interpret the data. It was explained that a similar graph containing many vital signs, such as blood pressure and body temperature, was currently in use, so reading a graph with six lines would not be a problem. This was, however, the least-used component. The gap between their expectations and actual use was caused by the unfamiliarity of patient-generated data [1, 2]. Clinicians have learned enough about vital signs in medical school and the hospital to be able to read patterns and discover unusual points without effort. In addition, vital signs do not fluctuate much from one individual to another, making them easy to identify. On the other hand, clinicians do not have enough knowledge of patterns represented in patient-generated data. Patient-generated data change dynamically, unlike vital signs, which increases the confusion in interpretation [9]. In short, this implies that the unique characteristics of patient-generated data should be identified through further study.

## CONCLUSION AND FUTURE WORK

Although many studies have identified the benefits of using patient-generated data in clinical settings, obstacles to adopting data-driven consultation remain. In this paper, we aimed to design a clinician interface to support data-driven consultation and investigate the role of the interface in situ. However, there are several limitations of this study. Further research is to be conducted, as we found that data-driven consultation influenced both clinicians and patients. Because we focused on the clinician's perspective in this paper, we decided to exclude 15 patients' interview data. Future work will cover the patient's side. In addition, we did not observe various clinicians due to the lack of consent. Although the case study of one clinician with 32 cases provided several insights, it should be refined and enriched by other cases.

Despite these limitations, we expect that our findings will offer insights for healthcare providers, designers, and HCI researchers to design a clinician interface. For future work, we plan to investigate both patients and clinicians under data-driven consultation to broaden our perspective and enrich our findings.

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## REFERENCES

1. Manal Almalki, Kathleen Gray, and Fernando Martin Sanchez. The use of self-quantification systems for personal health information: big data management activities and prospects. *Health information science and systems* 3, 1 (2015): 1. DOI=http://dx.doi.org/10.1186/2047-2501-3-S1-S1

2. Jessica S. Ancker, Holly O. Witteman, Baria Hafeez, Thierry Provencher, Mary Van de Graaf, and Esther Wei. 2015. "You Get Reminded You're a Sick Person": Personal Data Tracking and Patients With Multiple Chronic Conditions. *Journal of medical Internet research*. 17, 8 (August 2015): e202. DOI=http://dx.doi.org/10.2196/jmir.4209
3. Jessica S Ancker, Holly O. Witteman, Baria Hafeez, Thierry Provencher, Mary Van de Graaf, and Esther Wei. 2015. The invisible work of personal health information management among people with multiple chronic conditions: qualitative interview study among patients and providers. *Journal of medical Internet research* 17, 6 (June 2015):137. DOI=http://dx.doi.org/10.2196/jmir.4381
4. Ole A. Andreas, Anita Das, and Dag Svanæs. 2012. Mobile health IT: The effect of user interface and form factor on doctor–patient communication. *International journal of medical informatics* 81, 1 (January 2012): 12-28. DOI=http://dx.doi.org/10.1016/j.ijmedinf.2011.09.004
5. Jessica S. Ancker, Holly O. Witteman, Baria Hafeez, Thierry Provencher, Mary Van de Graaf, and Esther Wei. 2015. The invisible work of personal health information management among people with multiple chronic conditions: qualitative interview study among patients and providers. *Journal of medical Internet research* 17, 6 (2015). DOI=http://dx.doi.org/10.2196/jmir.4381
6. Geoff Appelboom, Melissa LoPresti, Jean-Yves Reginster, E. Sander Connolly, and Emmanuel PL Dumont. 2014. The quantified patient: a patient participatory culture. *Current medical research and opinion* 30, 12 (December 2014): 2585-2587. DOI=http://dx.doi.org/ 10.1185/03007995.2014.954032
7. Stinne Aaløkke Ballegaard, Thomas Riisgaard Hansen, and Morten Kyng. 2008. Healthcare in everyday life: designing healthcare services for daily life. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI '08). ACM, New York, NY, USA, 1807-1816. DOI=http://dx.doi.org/10.1145/1357054.1357336
8. Stefan Becker, Talya Miron-Shatz, Nikolaus Schumacher, Johann Krocza, Clarissa Diamantidis, and Urs-Vito Albrecht. 2014. mHealth 2.0: experiences, possibilities, and perspectives. *JMIR mHealth and uHealth* 2, 2 (April-June 2014): e24. DOI=http://dx.doi.org/10.2196/mhealth.3328
9. Frank Bentley, Konrad Tollmar, Peter Stephenson, Laura Levy, Brian Jones, and Scott Robertson, Ed Price, Richard Catrambone, and Jeff Wilson. 2013. Health Mashups: Presenting Statistical Patterns between Wellbeing Data and Context in Natural Language to Promote Behavior Change. *ACM Trans. Comput.-Hum. Interact.* 20, 5, Article 30 (November 2013), 27 pages. DOI=http://dx.doi.org/10.1145/2503823
10. Virginia Braun and Victoria Clarke. 2006. Using thematic analysis in psychology. *Qualitative research in psychology* 3, 2 (January 2006): 77-101. DOI=
11. Yunan Chen, Victor Ngo, Sidney Harrison, and Victoria Duong. 2011. Unpacking exam-room computing: negotiating computer-use in patient-physician interactions. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI '11). ACM, New York, NY, USA, 3343-3352. DOI=http://dx.doi.org/10.1145/1978942.1979438
12. Eun Kyoung Choe, Bongshin Lee, Matthew Kay, Wanda Pratt, and Julie A. Kientz. 2015. SleepTight: low-burden, self-monitoring technology for capturing and reflecting on sleep behaviors. *In Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (UbiComp '15). ACM, New York, NY, USA, 121-132. DOI=http://dx.doi.org/10.1145/2750858.2804266
13. Eun Kyoung Choe, Nicole B. Lee, Bongshin Lee, Wanda Pratt, and Julie A. Kientz. 2014. Understanding quantified-selfers' practices in collecting and exploring personal data. In *Proceedings of the 32nd annual ACM conference on Human factors in computing systems* (CHI '14). ACM, New York, NY, USA, 1143-1152. DOI=10.1145/2556288.2557372 http://doi.acm.org/10.1145/2556288.2557372
14. Chia-Fang Chung, Jonathan Cook, Elizabeth Bales, Jasmine Zia, and Sean A. Munson. 2015. More than telemonitoring: Health provider use and nonuse of life-log data in irritable bowel syndrome and weight management. *Journal of medical Internet research* 17, 8 (August 2015): e203. DOI=http://dx.doi.org/ 10.2196/jmir.4364
15. Chia-Fang Chung, Kristin Dew, Allison Cole, Jasmine Zia, James Fogarty, Julie A. Kientz, and Sean A. Munson. 2016. Boundary Negotiating Artifacts in Personal Informatics: Patient-Provider Collaboration with Patient-Generated Data. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing* (CSCW '16). ACM, New York, NY, USA, 770-786. DOI=http://dx.doi.org/10.1145/2818048.2819926
16. Sunny Consolvo, David W. McDonald, Tammy Toscos, Mike Y. Chen, Jon Froehlich, Beverly Harrison, Predrag Klasnja, Anthony LaMarca, Louis LeGrand, Ryan Libby, Ian Smith, and James A. Landay. 2008. Activity sensing in the wild: a field trial of ubifit garden. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*

(CHI '08). ACM, New York, NY, USA, 1797-1806. DOI=http://dx.doi.org/10.1145/1357054.1357335

17. Martin Dawes and Sampson Uchechukwu. 2003. Knowledge management in clinical practice: a systematic review of information seeking behavior in physicians. *International journal of medical informatics* 71, 1 (August 2003): 9-15. DOI= http://dx.doi.org/10.1016/S1386-5056(03)00023-6
18. Neelima Deshpande, Mary Publicover, Harry Gee, and Khalid S. Khan. 2003. Incorporating the views of obstetric clinicians in implementing evidence-supported labour and delivery suite ward rounds: a case study. *Health Information & Libraries Journal* 20, 2 (June 2003): 86-94. DOI=http://dx.doi.org/ 10.1046/j.1471-1842.2003.00422.x
19. Manon L. Dontje, Martijn de Groot, Remko R. Lengton, Cees P. van der Schans, and Wim P. Krijnen. 2015. Measuring steps with the Fitbit activity tracker: an inter-device reliability study. *Journal of medical engineering & technology* 39, no. 5 (2015): 286-290. DOI=http://dx.doi.org/ 10.3109/03091902.2015.1050125
20. Glyn Elwyn, Adrian Edwards, and Paul Kinnersley. 1999. Shared decision-making in primary care: the neglected second half of the consultation. *Br J Gen Pract* 49, 443 (1999): 477-482.
21. Deborah Estrin and Ida Sim. 2010. Open mHealth architecture: an engine for health care innovation. Science 330, 6005 (2010): 759-760. DOI=http://dx.doi.org/ 10.1126/science.1196187
22. Caroline Free, Gemma Phillips, Louise Watson, Leandro Galli, Lambert Felix, Phil Edwards, Vikram Patel, and Andy Haines. 2013. The effectiveness of mobile-health technologies to improve health care service delivery processes: a systematic review and meta-analysis. *PLoS Med* 10, 1 (15 January 2013): e1001363. DOI=http://dx.doi.org/10.1371/journal.pmed.1001363
23. Susannah Fox and Maeve Duggan. Tracking for health. *Pew Research Center's Internet & American Life Project*, 2013.
24. Gary Wolf - The Quantified Self. Video. (June 2010). Retrieved September 22, 2016 from https://www.ted.com/talks/gary_wolf_the_quantified_self?language=en
25. Valerie Gay and Peter Leijdekkers. 2015. Bringing health and fitness data together for connected health care: mobile apps as enablers of interoperability. *Journal of medical Internet research* 17, 11 (November 2015). DOI=http://dx.doi.org/10.2196/jmir.5094
26. Google Fit. Retrieved 2016 form https://www.google.com/fit/
27. Amanda Hall and Graham Walton. 2004. Information overload within the health care system: a literature review. *Health Information & Libraries Journal* 21, 2 (June 2004): 102-108. DOI=http://dx.doi.org/ 10.1111/j.1471-1842.2004.00506.x
28. Healthkit Apple Developer. Retrieved from https://developer.apple.com/healthkit/
29. Alastair van Heerden, Mark Tomlinson, and Leslie Swartz. 2012. Point of care in your pocket: a research agenda for the field of m-health. *Bulletin of the World Health Organization* 90, 5 (2012): 393-394. DOI= http://dx.doi.org/10.2471/BLT.11.099788
30. Institute for Health Technology. Transforming Health Care Through Big Data: Strategies for leveraging big data in the health care industry. *Institute for Health Technology.* 2013
31. Nicholas Huba and Yan Zhang. 2012. Designing patient-centered personal health records (PHRs): health care professionals' perspective on patient-generated data. Journal of medical systems 36, 6 (2012): 3893-3905. DOI=http://dx.doi.org/ 10.1007/s10916-012-9861-z
32. Eun-Young Jung, Jonghun Kim, Kyung-Yong Chung, and Dong Kyun Park. Mobile healthcare application with EMR interoperability for diabetes patients. *Cluster Computing* 17, 3 (November 2014): 871-880. DOI=http://dx.doi.org/ 10.1007/s10586-013-0315-2
33. Sandra K. Joos, David H. Hickam, Geoffrey H. Gordon, and Laurence H. Baker. 1996. Effects of a physician communication intervention on patient care outcomes. Journal of general internal medicine 11, no. 3 (1996): 147-155. DOI=http://dx.doi.org/10.1007/BF02600266
34. Yoojung Kim, Sookyoung Ji, Hyunjeong Lee, Jeong-Whun Kim, Sooyoung Yoo, and Joongseek Lee. 2016. "My Doctor is Keeping an Eye on Me!": Exploring the Clinical Applicability of a Mobile Food Logger. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (CHI '16). ACM, New York, NY, USA, 5620-5631. DOI=http://dx.doi.org/10.1145/2858036.2858145
35. Rober F. Kushner. 1995. Barriers to providing nutrition counseling by physicians: a survey of primary care practitioners. *Preventive medicine* 24, 6 (1995): 546-552. DOI=http://dx.doi.org/10.1006/pmed.1995.1087
36. Ian Li, Anind Dey, and Jodi Forlizzi. 2010. A stage-based model of personal informatics systems. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI '10). ACM, New York, NY, USA, 557-566. DOI=http://dx.doi.org/10.1145/1753326.1753409

37. John Lynn. 2015. Fitbit Data in the EMR? Retrieved from http://www.emrandehr.com/2015/11/03/fitbit-data-in-the-emr/

38. Maulik D. Majmudar, Lina Avancini Colucci, and Adam B. Landman. The quantified patient of the future: Opportunities and challenges. In *Healthcare* 3, (3): 153-156. Elsevier, 2015.

39. Stephane Meystre. 2005. The current state of telemonitoring: a comment on the literature. *Telemedicine Journal & e-Health* 11, 1 (February 2005): 63-69. DOI= http://dx.doi.org/10.1089/tmj.2005.11.63.

40. Sonali R. Mishra, Shefali Haldar, Ari H. Pollack, Logan Kendall, Andrew D. Miller, Maher Khelifi, and Wanda Pratt. 2016. "Not Just a Receiver": Understanding Patient Behavior in the Hospital Environment. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (CHI '16). ACM, New York, NY, USA, 3103-3114. DOI=http://dx.doi.org/10.1145/2858036.2858167

41. Ira S. Ockene, James R. Hebert, Judith K. Ockene, Gordon M. Saperia, Ed Stanek, Robert Nicolosi, Philip A. Merriam, and Thomas G. Hurley. 1999. Effect of physician-delivered nutrition counseling training and an office-support program on saturated fat intake, weight, and serum lipid measurements in a hyperlipidemic population: Worcester Area Trial for Counseling in Hyperlipidemia (WATCH). *Archives of Internal Medicine* 159, 7 (April 1999): 725-731. DOI=http://dx.doi.org/10.1001/archinte.159.7.725.

42. Bernardine M. Pinto, Henry Lynn, Bess H. Marcus, Judith DePue, and Michael G. Goldstein. 2001. Physician-based activity counseling: intervention effects on mediators of motivational readiness for physical activity. *Annals of Behavioral Medicine* 23, no. 1 (February 2001): 2-10. DOI=http://dx.doi.org/ 10.1207/S15324796ABM2301_2

43. Mashfiqui Rabbi, Min Hane Aung, Mi Zhang, and Tanzeem Choudhury. 2015. MyBehavior: automatic personalized health feedback from user behaviors and preferences using smartphones. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (UbiComp '15). ACM, New York, NY, USA, 707-718. DOI=http://dx.doi.org/10.1145/2750858.2805840

44. Reframer. Retrieved from https://www.optimalworkshop.com/reframer

45. Coline W. Rhodes, 2015. Fitbit data in the EMR? I don't think so! Retrieved November 2 from https://healthcareit.me/2015/11/02/fitbit-data-in-the-emr-i-dont-think-so/

46. Nancy K. Russell and Debra L. Roter. 1993. Health promotion counseling of chronic-disease patients during primary care visits. *American journal of public health* 83, 7 (July 1993): 979-982. DOI=http://dx.doi.org/ 10.2105/AJPH.83.7.979

47. Line Silsand and Gunnar Ellingsen. 2016. Complex Decision-Making in Clinical Practice. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing* (CSCW '16). ACM, New York, NY, USA, 993-1004. DOI=http://dx.doi.org/10.1145/2818048.2819952

48. Moira Stewart, Judith Belle Brown, Heather Boon, Joanne Galajda, Leslie Meredith, and Michelle Sangster. 1999. Evidence on patient-doctor communication. *Cancer* 25 (1999): 30.

49. Mark Sullivan. 2015. Guess what? Doctors don't care about your Fitbit data. Retrieved August 15, 2015 from http://venturebeat.com/2014/08/15/guess-what-doctors-dont-care-about-your-fitbit-data/

50. Teresa Taft, Leslie Lenert, Farrant Sakguchi, Gregory Stoddard, Caroline Milne. 2014. Effects of electronic health record use on the exam room communication skills of resident physicians: a randomized within-subjects study. *Journal of the American Medical Informatics Association*: amiajnl-2014. DOI= http://dx.doi.org/10.1136/amiajnl-2014-002871

51. Athanasios Tsoukalas, Timothy Albertson, and Ilias Tagkopoulos. 2015. From data to optimal decision making: a data-driven, probabilistic machine learning approach to decision support for patients with sepsis. *JMIR medical informatics* 3.1 (2015): e11. DOI=http://dx.doi.org/10.2196/medinform.3445

52. Chris Welch. 2015. Major Los Angeles hospital enables Apple's HealthKit for 80,000 patients. Retrieved April 27, 2015 from http://www.theverge.com/2015/4/27/8502929/apple-healthkit-cedars-sinai-hospital

53. Peter West, Richard Giordano, Max Van Kleek, and Nigel Shadbolt. 2016. The Quantified Patient in the Doctor's Office: Challenges & Opportunities. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (CHI '16). ACM, New York, NY, USA, 3066-3078. DOI=http://dx.doi.org/10.1145/2858036.2858445

54. Nathan Zeldes and Neil Baum. 2011. Information overload in medical practice. *The Journal of medical practice management: MPM*. 26, 5: 314.