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The Design and Evaluation of a Mobile Handheld Intervention for Providing Context-Sensitive Medication Reminders

by

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Submitted to the Program in Media Arts and Sciences,
School of Architecture and Planning,
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Master of Science

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Abstract

This work introduces the design and exploratory evaluation of a home reminder system for medication and healthcare that situates the timing and location of reminders based on contextual information about the user. The system consists of three major components: 1) a handheld computing interface for providing reminders, 2) a sensor subsystem integrated into the home environment, and 3) a central server that manages medical tasks and reasons over sensor data in real time. A volunteer participant adhering to a complex regimen of simulated medical tasks is closely observed in a residential research facility. The participant is presented with both context-sensitive reminders and reminders that are scheduled at fixed times during the day. The degree of adherence to the regimen, and the participant's own assessment of the usefulness of each reminder (while blinded to the reminder strategy being used), are evaluated over the course of a 10-day study. Quantitative and qualitative results are provided, comparing the efficacy of context-sensitive reminders over fixed-time reminders with respect to adherence and perceived value.

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Chapter 1

Introduction

Poor adherence to medication and lifestyle guidance is arguably one of the greatest challenges facing the healthcare community in the U.S. [33, 6]. According to the American Heart Association, more than half of all Americans with chronic disease do not follow their physician's medication and lifestyle guidance, and nine out of ten make mistakes taking their medication [5]. The direct and indirect costs of nonadherence are estimated to be over $100 billion annually [16]. Despite extensive research into interventions for assisting with adherence (such as providing reminders at fixed times), systematic reviews of such interventions [17, 32, 24] have found that even the most effective ones have been complex, labor-intensive, and not consistently effective. Recent literature indicates that rates of adherence have not changed over the past three decades [6].

Many complex factors contribute to poor adherence including forgetfulness, complexity of the regimen, disruption of daily routines, a lack of understanding about the medication, and, in some cases, intentional experimentation motivated by individual concerns or external suggestions (e.g., advertising). Of the various factors, studies have shown that "forgetting" is the most common [23].

Fixed-time reminders compel users to "script out" their domestic routines, even though home life is often unregimented or unpredictable. This typically results in overly rigid and unworkable reminder schedules. This work explores the idea that the effectiveness of reminders may be improved if their timing and location is sensitive to the day-to-day changes in the user's domestic routines; in other words, if the reminders are *context-sensitive* and adapt to behavior.

In this work, a context-sensitive reminder system for medication and other healthcare tasks is introduced. Two potential benefits of context-sensitive reminders are evaluated: their impact on overall adherence and their perceived usefulness to the end user. For the scope of this work, *context* is defined as: a) location of the person inside the home; b) activities of interest inferred from objects used; c) a person's sedentary or mobile state; d) history of medication taken and health tasks completed; and e) time of day.

Conceptually, the reminder system aims to simulate the ability of an astute caregiver to respond with appropriate reminders and information. Therefore, the system should have the ability to sense and adapt to the spontaneity of home life. In addition, it should attempt to gain the user's attention at a time when he or she is likely to find it convenient to act on a reminder. These design goals are realized through the use of simple, unobtrusive sensors, and a handheld computing interface. The handheld interface is implemented on a PDA - a familiar device that facilitates the presentation of reminders at any location. Sensors enable the system to reason about a user's actions in real time and to provide messages that are well-situated in time and place.

The key contributions of this work are:

1. Specification of an experimental protocol for evaluating a context-sensitive intervention in a naturalistic, complex environment. A volunteer participant was asked to follow a complex regimen of simulated medication and health tasks in an instrumented home (living laboratory) for a 10-day period. The participant received two types of technology-delivered reminders to assist him with these tasks: context-sensitive reminders and fixed-time reminders.

2. Quantitative and qualitative results from the 10-day study comparing the efficacy of context-sensitive reminders over fixed-time reminders with respect to adherence and

perceived value.

3. A description of the guiding principles that helped create an effective system for delivering context-sensitive reminders.

4. A flexible framework used to describe the constraints pertaining to medication and healthcare prescriptions (e.g., timing constraints, activity constraints, drug interactions, missed doses, etc.) in terms of relevant sensor events.

Chapter 2

State of the Art in Medication Adherence Aids

This chapter looks at work that has recently addressed the problem of medication adherence, and concludes with a summary of future trends in enabling technologies.

Table 2.1 categorizes medication adherence systems - both commercial devices and recent research prototypes. Pill boxes with compartments that organize daily pill doses are fairly popular because of their low cost. More complex systems with an emphasis on tracking and reporting have been used primarily in clinical trials [19, 2].

The Medication Advisor [12] is a multi-disciplinary effort at the University of Rochester, designed to converse with users in real time, using speech-recognition combined with a knowledge base extracted from an online listing of prescriptions [30]. This work addresses some knowledge representation problems in providing medication reminders; however, the focus of this project is on intelligent dialogue-based interaction, and the recognition of underlying intentions from users' speech. The interaction for an initial "challenge dialogue" has been demonstrated, but it has not been implemented and evaluated in a naturalistic home.

Among systems that sense medication use, most commercial systems track interactions with

Intervention Strategy	Example Project(s)	Sensing and Actuation
Medication organizing	Divided pill boxes	-
Fixed time cues	Compumed [10]	Beeping alarm, LED display
Medication organizing + Fixed time cues	MedGlider [27]	Beeping alarm, LED display
	Careousel [9]	Beeping alarm, LED display
	InforMedix [19]	Audio Visual alarm, PDA integrated pill containers
Sensing medication use + Context-sensitive cues (where context is medication use and time of day).	MD2 [25]	Button for pill access, beeping alarm, LED display
	AARDEX [2]	Smart cap with EEPROM , microelectronics circuit, and LED display
	Med-ic Digital Package [26]	RFID in packaging
	Wan [38]	RFID in packaging, face-recognition, speech-synthesis
	Floerkemeier; Siegemund [14]	RFID in packaging, Bluetooth equipped mobile phone
	Fishkin; Wong [22]	RFID in packaging, tablet display, sensitive weights
	Agarwala et al. [3]	RFID in packaging, tablet display, speech-synthesis
Context-sensitive conversational agent (where context is language understanding and intention recognition)	Ferguson et al. [12]	speech-recognition, speech-synthesis, computer generated icon
Sensing medication use + Context-sensitive cues, (where context is medication use, time of day, and receptivity of the user (based on location, activities, and ambulatory patterns)).	No prior work implemented.	Sensor fusion in instrumented home.

Table 2.1: Functional categorization of systems that assist with medication adherence

pill dispensers (and optionally provide labor-intensive monitoring services), while research systems frequently use radio frequency identification (RFID) tags.

Although inferring medication use provides a degree of context-awareness, no existing system uses integrated contextual information such as location, activities, and ambulatory patterns of the user to adjust the timing and location of reminders. The innovative aspects in prior systems are centered on sensing methods or user interaction. But limiting context-awareness to the awareness of time and medication provides only an incremental improvement over the delivery of reminders based upon a fixed paper schedule and an alarm clock.

This work takes a qualitatively different approach by assuming that cost-effective and reliable sensing of medication and health information will be readily available to a computational system. Current research in medication dispensing devices and mobile biometric sensing are complementary to this approach, and the focus of this work is on using the information from such systems within an instrumented home. Three key technology trends that support this assumption are summarized below.

RFID in Pharmaceuticals. The U.S. Food and Drug Administration is promoting the widespread use of RFID technology throughout the pharmaceutical industry by 2007. Companies such as Pfizer and GlaxoSmithKline have announced their intention to begin using RFID tags to authenticate and trace some of their current products [15].

Mobile Phones in the (not so distant) Future. Mobile phones continue to grow in popularity as they evolve from accessible communication devices to miniature sensor-enabled computers that are always within reach. On-board pedometers [11, 29] as well as RFID [28] and biometric fingerprint [31] readers are some novel yet commercially available technologies for mobile phones. A 'Diabetes Phone' with a glucose meter embedded into the battery pack [4] is in trial at the Joslin Diabetes Center in Boston and the Indiana University School of Medicine [8].

Context-Aware Living Spaces. There have been notable advances in the creation of context-aware environments using simple sensors [37, 39]. Security systems and medical emergency alert reporting systems represent one generation of sensing that is already present in many homes [35]. As sensors satisfy privacy, reliability, cost, and computational needs, more advanced analysis of sensor data is becoming possible. Existing research systems use machine learning [39], data mining [40], and rule-based [7] techniques to reason over sensor data streams from objects and appliances in homes, in order to infer complex user activities.

Chapter 3

Design Goals

An important challenge when building a reminder device that models the awareness of a caregiver is making it astute and subtle in its interaction with users. Details of the two approaches used to achieve this are presented below.

3.1 Adapting to Everyday Life

While fixed-time reminders can be effective in structured situations (e.g., the office) for many people, everyday domestic life is complex, unregimented, and difficult to predict in advance. Although there are times when life at home can seem structured and predictable, such as when someone gets up in the morning in response to the alarm clock, people are constantly making small adjustments in these typical patterns to accommodate daily events (e.g. a late night watching television, an early meeting, illness, etc.)

In this work, simple low-cost sensors distributed in a home are used to obtain useful information about a user's actions in real time. Heuristics that associate simple patterns of everyday actions with common domestic tasks, and in turn, with potentially optimal times to remind the user about a health task, are employed to trigger reminder delivery. For example, a simple open-closed sensor on the front door and a wearable accelerometer measuring body motion communicate over a home sensor network, and in combination, trigger

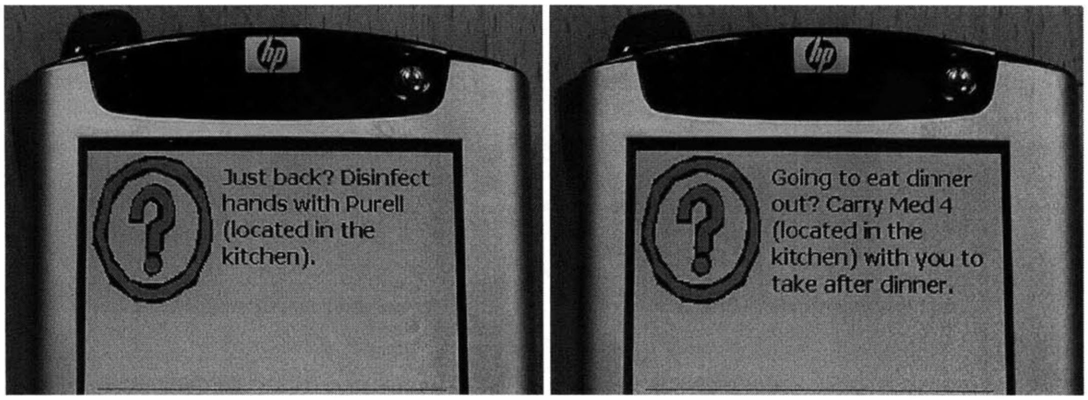


Figure 3-1: Examples of adaptive messages on a handheld interface used in this work

a message relevant for a "leaving the home" or "returned home" context, such as those depicted in Fig. 3-1.

Ideally, an adaptive system should be flexible enough to be trained to recognize new user activities easily and with a minimum of user intervention. Open areas of investigation to achieve this type of adaptive system include elaboration of appropriate contexts for proactive reminder delivery for healthcare (e.g., based on commonsense modeling or repeated observations), identification of the information that is needed about the user's state and actions to detect these contexts, and determination of the technological and interaction requirements for a system that accomplishes the necessary activity detection and modeling. Chapter 7 attempts to address some of these questions.

3.2 Being Convenient

Medication and healthcare tasks often do not need to be precisely timed; and it may be safe to complete them during time windows (e.g., "in the morning" or "after dinner") but fixed-time reminders do not take advantage of this permitted flexibility.

In [18], Ho and Intille succinctly characterize the most common factors that might impact the perceived convenience of an interruption (Table 3.1), which could be the presentation

Factor	Description of the Factor
Activity of the user	The activity the user was engaged in during the interruption
Utility of message	The importance of the message to the user
Emotional state of the user	The mindset of the user, the time of disruption and the relationship the user has with the interrupting interface or device
Modality of interruption	The medium of delivery, or choice of interface
Frequency of interruption	The rate at which interruptions are occurring
Task efficiency rate	The time it takes to comprehend the interruption task and the expected length of the task
Authority level	The perceived control a user has over the interface or device
Previous and future activities	The tasks the user was previously involved in and might engage in during the future
Social engagement of the user	The user's role in the current activity
Social expectation of group behavior	The surrounding people's perception of interruptions and their current activity
History and likelihood of response	The type of pattern the user follows when an interruption occurs

Table 3.1: Factors that impact *interruptability* - reprinted from [18]

of a medication reminder.

This work aims to address the "activity of the user" and the user's "previous and future activities" in order to deliver reminders at convenient but medically acceptable times. Information gathered from simple sensors located throughout the apartment is used to model two features: 1) the *distance* between the user and the location at which the medication is stored or the healthcare task is performed, and 2) the *activity* that the user is engaged in at the time when the reminder is provided.

The two features are combined to compute a *convenience score* for every sensor and task. This score can be summarized in equation 3.1, where $C(n, i)$ represents the convenience of providing a reminder for a medication or healthcare task i upon the activation of sensor n. In the equation, $Distance(n, i)$ represents the distance between sensor n and the location where the task i is executed (e.g., a medicine cabinet), $ActivityBurden(n, i)$ is a heuristic representing the burden of interrupting the primary activity of the user at that moment,

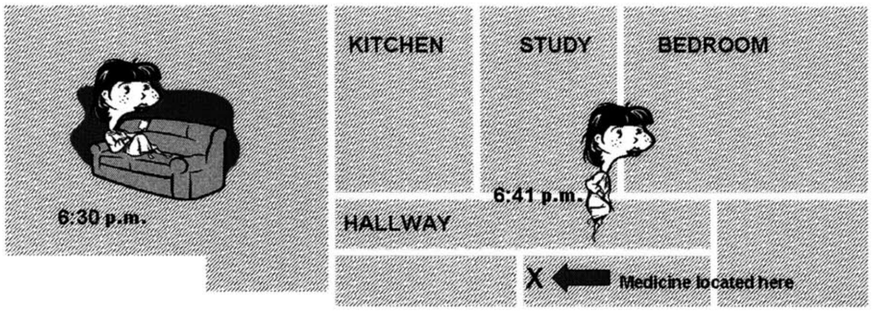


Figure 3-2: Concept of a convenience score

and α, β are normalizing constants for the two features.

$$C(n, i) = Distance(n, i) * \alpha + ActivityBurden(n, i) * \beta \tag{3.1}$$

In this work, medication reminders that can be associated with time windows are adjusted based on the convenience scores of sensors activated by the user and the length of time available in the window. This model for convenience is admittedly a simplified one. Fig. 3-2 illustrates how it might be applied in a case where medication needs to be taken "in the evening". A fixed-time reminder set at 6:30 p.m. may interrupt the user while she is on the couch, reading. But a reminder triggered by the activation of the study door open-closed sensor with a high convenience score, a few minutes later, would be medically acceptable and possibly more convenient because she is close to the medication, and has already self-interrupted her task. As the time window progresses, a wider distribution of sensors (convenience scores) can trigger the reminder. In Fig. 3-2, the system would initially wait for the user to activate sensors that are close to the medication, i.e., it would try to be as convenient as possible. If it turns out that the user is not activating any sensors with high convenience scores, the system would gradually relax its tolerance to lower convenience scores. As the acceptable time window draws to an end, the reminder might be triggered when she activates a sensor with a lower score, perhaps in the kitchen.

Chapter 4

System Design and Implementation

This chapter describes the design and implementation of a prototype system built for exploratory evaluation of the ideas in Chapter 3. It differs from a comprehensive system that might be deployed in real homes in two significant ways.

1. The prototype is customized for use in the PlaceLab research facility [20, 21], a 1000 sq. ft. apartment that consists of a living room, dining area, kitchen, small office, bedroom, full bath and half bath. The PlaceLab is an initiative of the House_n group at the Massachusetts Institute of Technology, and TIAX LLC, and is conceived as a "living laboratory" for the study of technologies in home settings. Fig. 4-1 shows interior photos of the PlaceLab, and a plan can be viewed in Fig. 4-5. The PlaceLab offers rich data recording capabilities in a naturalistic home environment. A user of the system in the PlaceLab could be multitasking, experiencing distractions, and engaging in other complex behaviors that are difficult to simulate in a traditional laboratory.

2. The prototype is customized for the experimental framework described in Chapter 5. The central goal of the experiment is to compare a volunteer participant's reaction to

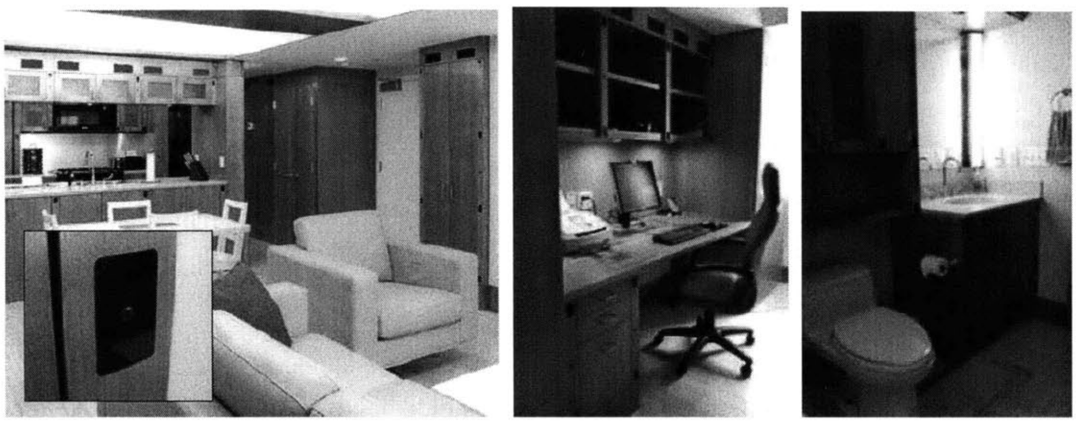


Figure 4-1: The PlaceLab living room and kitchen area, office, and master bath. The inset shows a microphone embedded into a cabinet

context-sensitive reminders against reminders that are scheduled at fixed times during the day. In order to minimize confounds from additional features and to ensure that the participant remains unaware of the two conditions being compared, the prototype system has limited functionality. For instance, help with rescheduling medication doses or summarization of tasks completed during the day are not implemented, because they are extraneous to the core idea being examined, i.e., "how can detection of simple sensor patterns be used to provide context-sensitive reminders, and how do such reminders compare with reminders delivered at fixed times?"

Fig. 4-3 summarizes the interaction between the main components of the system: a subset of PlaceLab sensors, a handheld interface, and a central reasoning application. Each of these is discussed in turn.

4.1 PlaceLab Sensor Subsystem

The following PlaceLab sensors [21, 20] are used:

- 70 switch sensors discreetly integrated into the cabinetry, appliances, furnishings and

Figure 4-2: Researcher trying on a wireless accelerometer

fixtures. These detect on-off and open-closed events, such as the opening of the refrigerator, the shutting of the linen closet, or the lighting of a stovetop burner. In addition, 9 custom push button sensors representing the different medication and other healthcare tasks are enclosed in two "Health Task Panels" located in the kitchen and bedroom.

- 2 flow sensors on the hot and cold water faucets in the shower to detect showering.

- 3 wireless 3-axis, 0-10 G accelerometers (4.5 x 3.5 x 1.5 cm) worn by the participant on the wrists and dominant ankle, as shown in Fig. 4-2, to measure limb motion.

- 1 small (4.5 x 4.0 x 1.75 cm) wireless motion sensor taped onto a 2-pound hand weight, to detect its use.

The PlaceLab infrastructure elements that support the system include the cameras and microphones distributed throughout the apartment, and wireless access points for 802.11 and sensor data. In practice, the network and intermediate microcontrollers introduce a latency of 1 to 2 seconds for limb motion sensors and switch sensors, and up to 15 seconds for the water flow sensors.

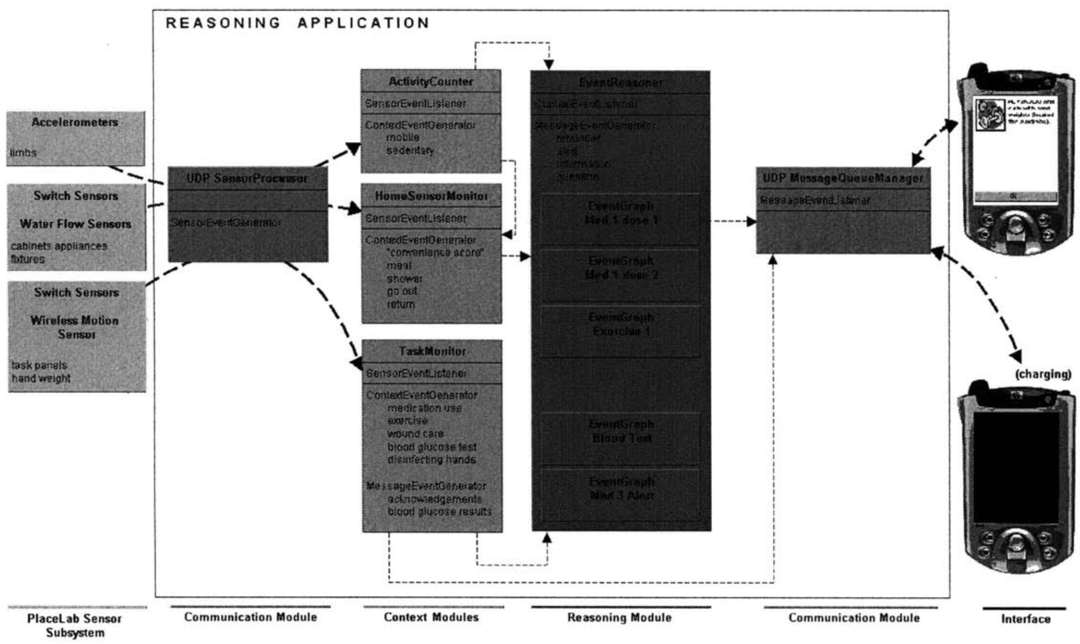


Figure 4-3: Block diagram showing the main components of the reminder system

4.2 Handheld Interface

A wireless handheld computing device allows users to receive reminders and informative messages while carrying on with their lives as usual. When the device receives an incoming message over the home network, it provides an audible alert indicating that a message is waiting (or puts it in a message queue if a previous one is being viewed). A simple procedure allows the user to view and dismiss the message (Fig. 4-4a).

Since power constraints limit the continuous operation of handheld devices, the prototype interface is implemented on two Compaq iPAQ 3870 personal digital assistants (PDA's) that work in tandem; with either one in active use and the other being charged at all times. Both run identical software, but have different LAN addresses on the home network. A message notifies the user when it is time to exchange the active PDA for the one that is charging (Fig. 4-4b).

In this prototype, PDA's are used for message delivery and for the simulation of health activities in combination with the "Health Task Panels" (Fig. 4-4c and Fig. 4-9). However, in commercial deployments of a context-sensitive reminder system, mobile phones with health (biometric) and medication (RFID) sensing capabilities could be used for both delivery and collection of information.

4.3 Communication Modules

UDP communication with the sensing infrastructure and the handheld interface are managed by the `UDPSensorDataProcessor` and `UDPMessageQueueManager` modules, that present a uniform event based representation of data within the central application. A request-response based protocol is used to maintain reliable communication with the two PDA's. See Appendix E for notes on the challenges overcome in creating a reliable UDP-based communication model that adapts to intermittent network breaks, PDA's being taken outside the PlaceLab, and overnight use.

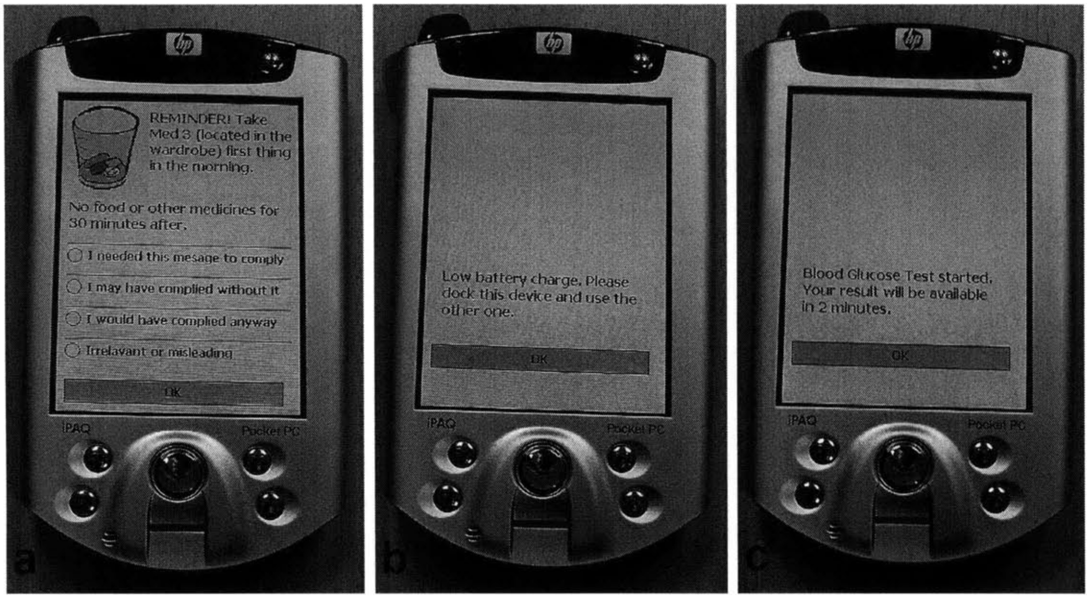


Figure 4-4: a) An example reminder b) A notification to change the active device c) A simulated blood glucose test

4.4 Context Modules

Three context modules process sensor events generated by the `UDPSensorDataProcessor` and translate them to abstract sensor-agnostic context events. In this prototype, the translations are rule-based and heuristic, however, individual components could be replaced if either the sensor inputs or the translation algorithm changes (for example, if a probabilistic classifier is used instead of the current rule-based algorithm).

ActivityCounter

The `ActivityCounter` processes sensor events from limb accelerometers and categorizes them, every two seconds, as `mobile` or `sedentary` context events, based on the running averages of acceleration in the x, y, and z axes. Variations in the running average accelerations that do not cross over heuristic thresholds are filtered as they typically represent short

Heuristic Translation Rule	Context
Refrigerator, Stove burners, Oven (open/closed or on/off)	`meal`
Water flow in shower faucets above threshold	`shower`
Front door open + `ActivityCounter` events present during past 5 minutes	`go out`
Front door open + no `ActivityCounter` events during past 5 minutes	`return`

Table 4.1: Rules used by the HomeSensorMonitor for generating activity context events

bursts of activity, like fidgeting. The `ActivityCounter` also generates `transition` context events when the wearer's inferred state changes from mobile to sedentary or vice versa.

HomeSensorMonitor

The `HomeSensorMonitor` processes context events from the `ActivityCounter` along with sensor events, and categorizes them as context events: `meal`, `shower`, `go out`, and `return`, as shown in Table 4.1.

The `HomeSensorMonitor` also generates context events for the convenience scores (introduced in Chapter 3) of sensors activated. Each switch sensor is mapped to a convenience score normalized between 0.1 and 1 for every relevant task in the experiment. The score is based on the two factors described in Section 3.2; and encapsulates;

1. The distance between the sensor and the location at which the health task must be performed.

2. The inferred activity, if any, from Table 4.1, that the user is engaged in when the sensor is activated.

Coded floor plans with the convenience scores for switch sensors used in the experiment are shown in Fig. 4-5 and Fig. 4-6. Since tasks are expected to occur at two locations (refer Chapter 5), two sets of convenience scores are defined for many sensors.

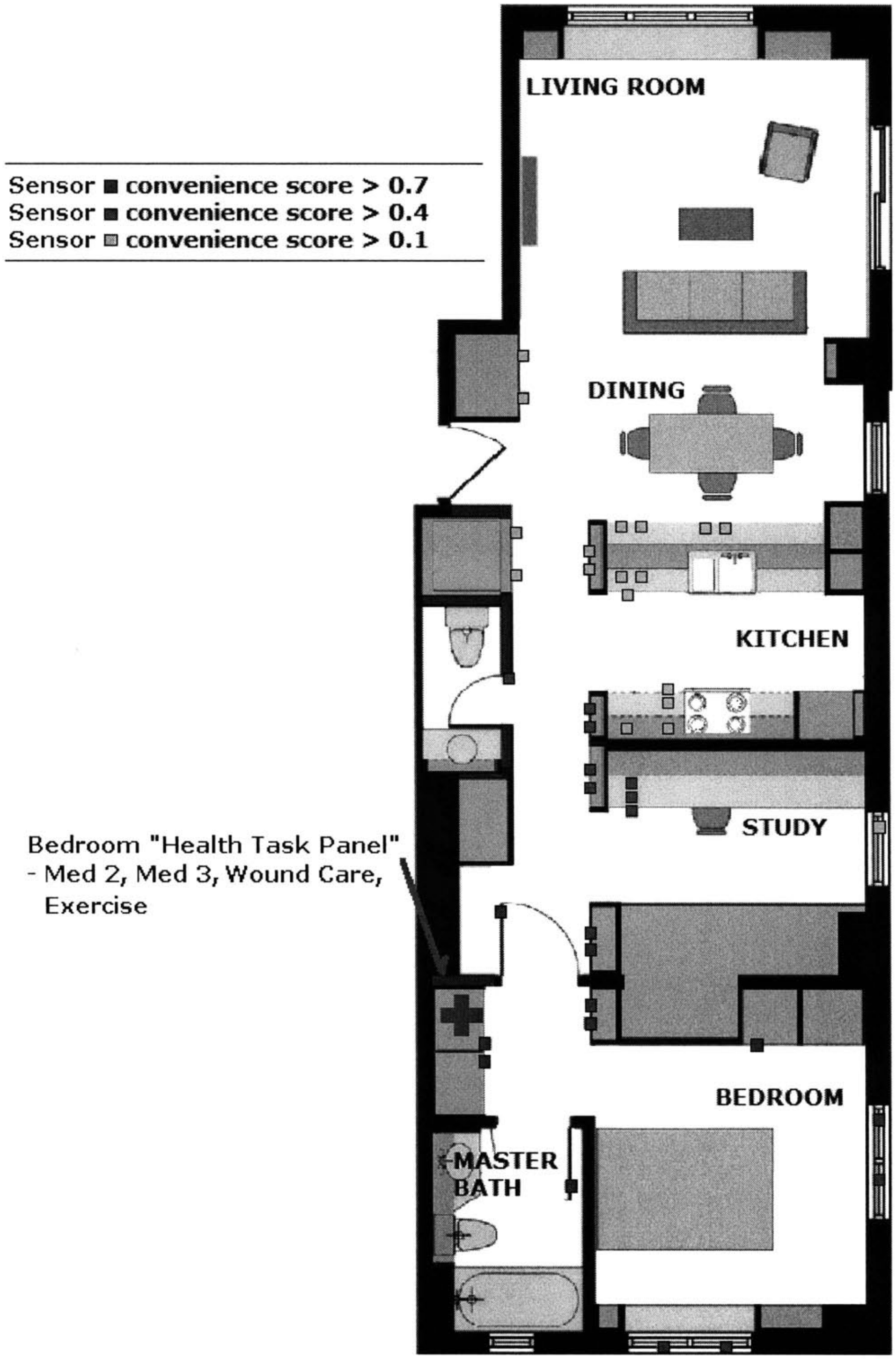


Figure 4-5: Color-coded floor plans showing convenience scores used for the Health Task Panel in the bedroom

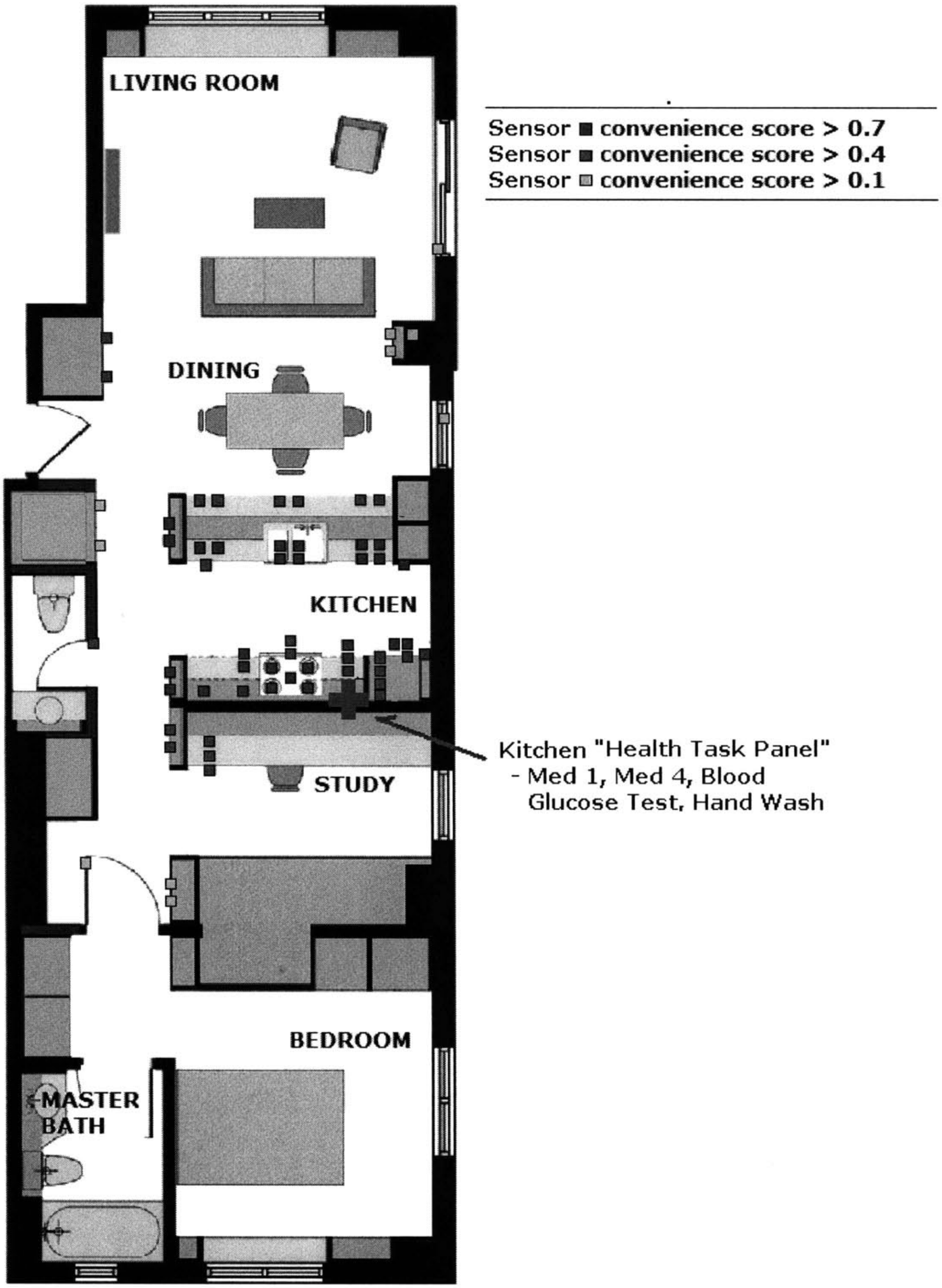


Figure 4-6: Color-coded floor plans showing convenience scores used for the Health Task Panel in the kitchen

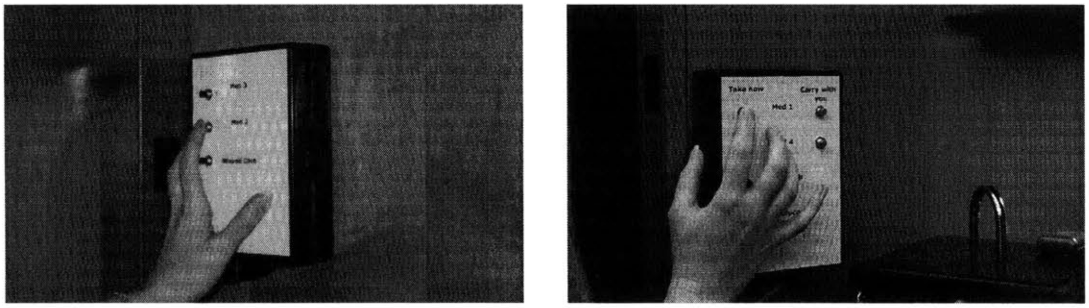


Figure 4-7: Health Task Panels in the bedroom and kitchen

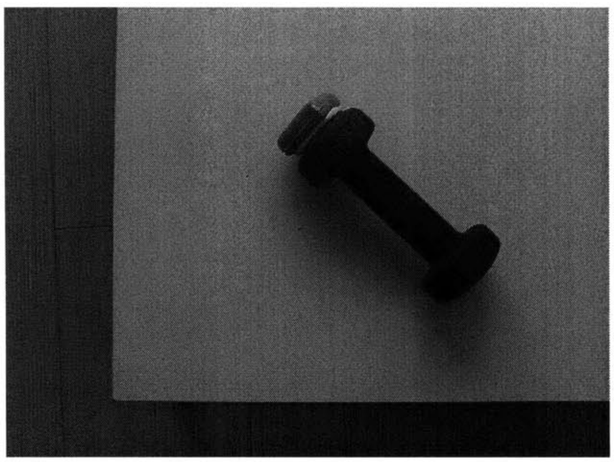


Figure 4-8: Hand weight with wireless motion sensor

TaskMonitor

The `TaskMonitor` processes sensor events from buttons on the "Health Task Panels" (Fig. 4-7) and translates them to unique context events for the start of a task when a button is first pressed, and for task completion if a button is released after being held down for 15 seconds. Sensor events from the wireless motion sensor on the hand weights (Fig. 4-8) are translated to the context event `exercise` after a threshold roughly corresponding to 25 to 30 arm curls. The `TaskMonitor` also generates messages to the user to simulate the sensing of medication and other healthcare tasks (Fig. 4-9).

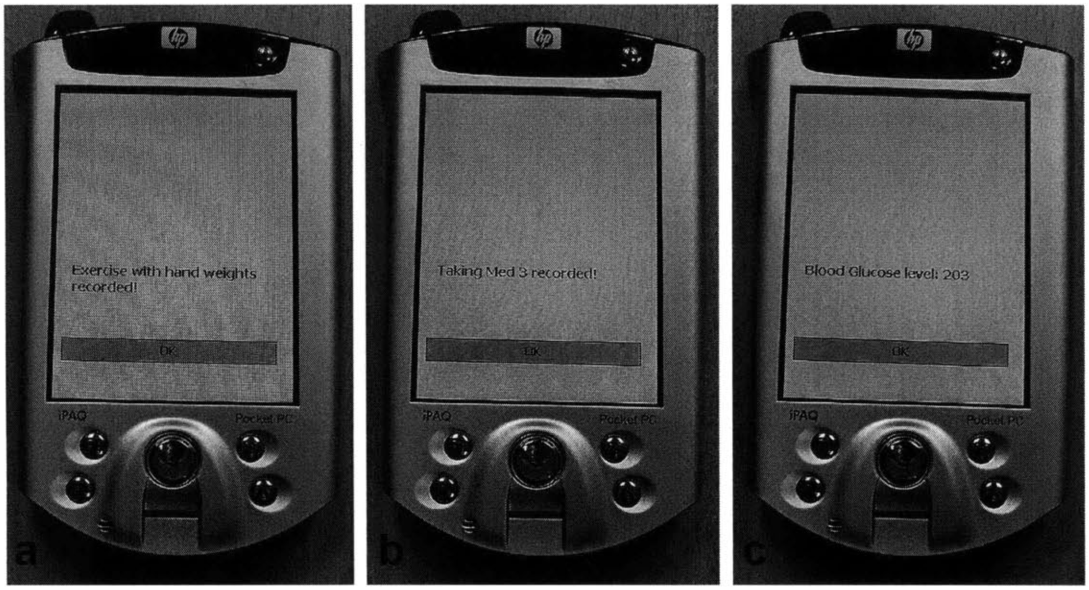


Figure 4-9: Examples of messages simulating the sensing of medication and other healthcare tasks

4.5 Reasoning Module

The context modules set up streams of context events representing actions that originate from within the home environment or are the result of fired actions from the reminder software. These events may be as simple as turning on a faucet or more complex in the form of a convenience event. The Reasoning Module performs the core function of the system; i.e., reasoning over the context events events to provide timely, situation-appropriate reminders.

To achieve this, a collection of `EventGraph` structures model the user's prescribed regimen, the conditions for reminder delivery, and some situations indicating that an error (e.g., overmedication) might be about to occur. The EventGraphs are encoded in XML, and are loaded from a database into the `EventReasoner` module. `EventGraphs` respond to incoming context events, and on occasion, generate messages, that are directed by the `EventReasoner` to the `UDPMessageQueueManager`. The regimen in Chapter 5 is modeled through twenty-five such `EventGraph` structures. The rest of this chapter provides details of the `EventGraph` framework along with some significant underlying considerations.

4.6 EventGraph Framework

The delivery of effective medication reminders requires modeling an extended history of relevant events and possible future events pertaining to prescriptions (name, dosage, etc.) timing constraints (e.g., "take before bed"), activity constraints (e.g., "do not take with food"), or drug interactions. Additional conditions come in the form of events that could vary from day to day such as meal times, or the occasional absence of an event such as the patient missing a dose. In related research [12], the challenges of using a rule-based representation for complex medication conditions have been described at length. Generally, conditions such as the ones listed above cannot be specified without introducing a large number of qualifiers and conjunctions in a rule-based grammar. Furthermore, it is often difficult to tell how rules will impact each other, and this could lead to unintended consequences particularly when there are many complex rules.

In this work, an alternative graphical representation is explored. The `EventGraph` framework aims to model an optimal, safe, and flexible daily schedule through the specification of precedence relationships between primitive context events. Fig. 4-10 is a visualization of an `EventGraph` (with dotted arcs leading to added explanatory annotations). Directed Acyclic Graphs (DAGs) have been used to model scheduling problems in various domains, because they make it possible to explicitly model all of the dependencies between conditions that apply to the scheduling problem (in this case, the scheduling of a reminder).

The `EventGraph` is a DAG with each node representing a context event and each edge representing a temporal precedence constraint: in this example, the directed edge from the parent node `6:00` to the child node `awake` says that event `6:00` must be detected before waiting for event `awake`. Every node has a tag denoting the event it represents, and some optional attributes. An active node is one that represents an event that the graph is currently awaiting. Only root nodes (`6:00` and `11:30`) are initially active.

Fig. 4-10 models the first reminder for the day in the instruction, "Wash hands with disinfectant in the morning and approximately every 2 hours when at home." For a user who might tend to disinfect his hands too frequently, it also models the interaction and

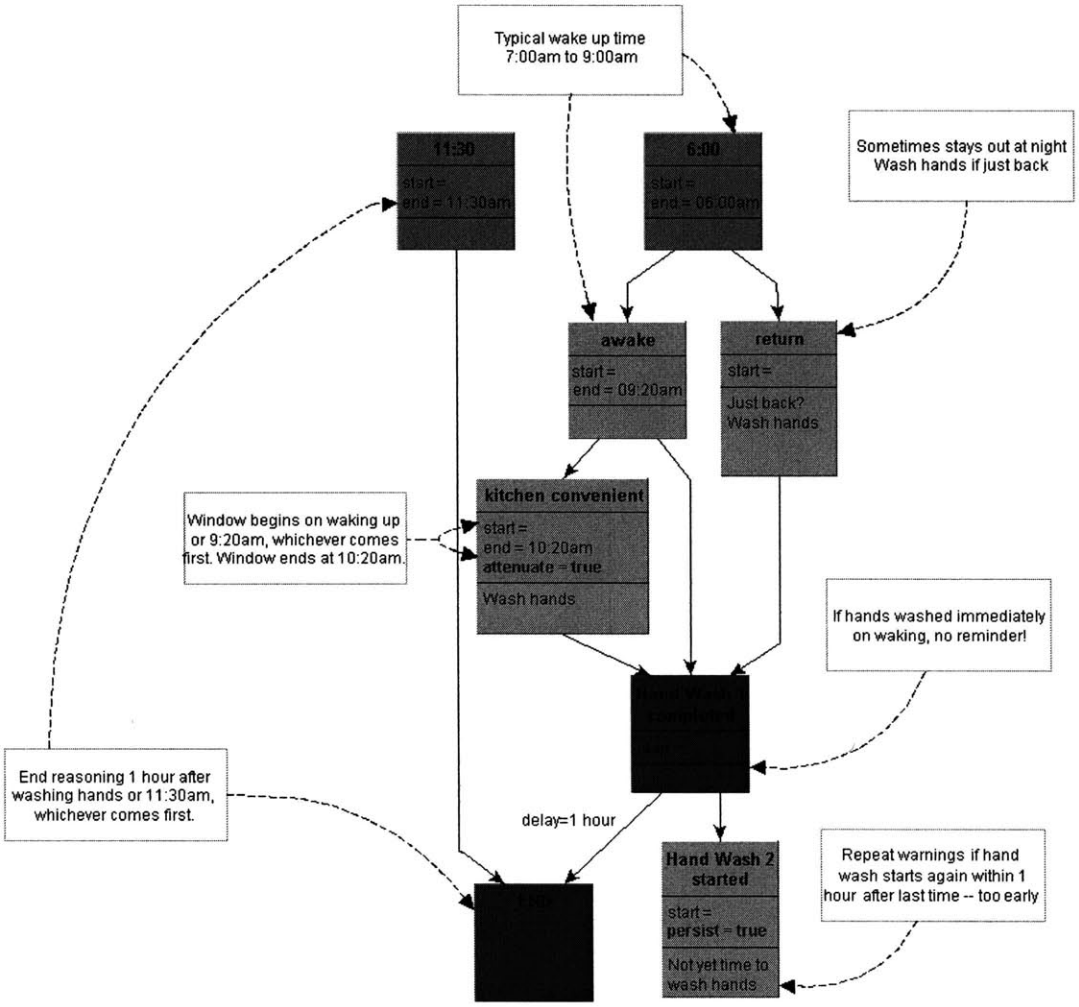


Figure 4-10: Example EventGraph: "Wash hands with disinfectant approximately every 2 hours."

display of information each time the disinfectant is accessed within an hour after the first use.

An active node **ends** if the event denoted in the tag is detected or if an active child node ends. In Fig. 4-10, once the node `awake` ends, `kitchen convenient` and `Hand Wash 1 completed` become active. After this, if the event `Hand Wash 1 completed` occurs, the `kitchen convenient` node automatically becomes inactive (ends), since `Hand Wash 1 completed` is a child node of `kitchen convenient`.

The edges in the graph may optionally be associated with a delay attribute, indicating the delay for the child node to become active after the parent node has ended. In the example below, the node `END` will be reached after a delay of 1 hour past the detection of the `Hand Wash 1 completed` context event.

Node Attributes

The start attribute is an internal default attribute that marks the time when the node becomes active.

The end attribute, unlike start, is optional. When present, it marks the default time when the node must become inactive, thus it forces the node to become inactive when the end time occurs. In the example, the node `awake` has an end attribute, which means that it will become inactive at 9:20am (and `kitchen convenient` will become active) even if the context event `awake` has not been detected. Nodes like `11:30` and `6:00` always default to the corresponding end times, because their tags do not map to any context event generated by the context modules.

The message attribute is also optional, and contains a text message to be sent to the user when the node becomes inactive. In 4-10, messages are shown below the second horizontal line across nodes that trigger responses.

The persist attribute, when true, overrides the default ending behavior, and keeps the node active even when the event denoted in the tag is detected. Such nodes end only when an active child node becomes inactive. This attribute is useful for modeling persistent actions such as alerts that should be provided more than once if the corresponding event is detected.

The attenuate attribute is a specialized attribute associated with a rule that gradually relaxes the condition that will end the node. Specifically, the rule is related to the convenience scores of sensors. When true, the end attribute must be specified, either as a fixed time or as an interval in minutes after the start time. The start and end attributes define a window, but like in the case of `kitchen convenient`, the duration of the window might vary if the end attribute is fixed and the start attribute depends on a parent node (in this case, `awake`). The attenuate attribute indicates special handling of convenience score events based upon the time when the event is received, and the length of the window.

When a convenience score (normalized to values between 0.1 and 1) is received by an active attenuating node, the node ends only if the score is greater than or equal to the proportion of time available in the window. When a window has just opened, the proportion of time available is (almost) whole, and only sensors with a convenience score of 1 can end the node. As time progresses, and the proportion of the available window decreases, a wider distribution of sensors can end the node. Refer to the plans in Fig. 4-5 and Fig. 4-6 for visualization.

In the previous example, the "Wash hands" message is initially generated only if a high convenience score is received. As time progresses towards 10:20 a.m., lower convenience scores can generate the same message. In the final tenth of the time window, in addition to convenience scores, the node also allows `transition` events from the `ActivityCounter` module to end it. As a result, in the final tenth of a time window, the message is generated when the user transitions from being sedentary to mobile, or vice versa. The end attribute ensures that even if an activity transition has not occurred, the message is finally provided at 10:20 a.m., the end of the window.

The END node has a special meaning, and it does not represent a context event being awaited. If an END node is reached, all active nodes (including those with persist attribute set to true) are immediately deactivated, and a special context event announcing the end of this EventGraph is generated. This node is used in cases where it is necessary to notify one EventGraph about the end of another. Strictly speaking, this attribute is not necessary, as it is possible to combine two interdependent graphs into a single one.

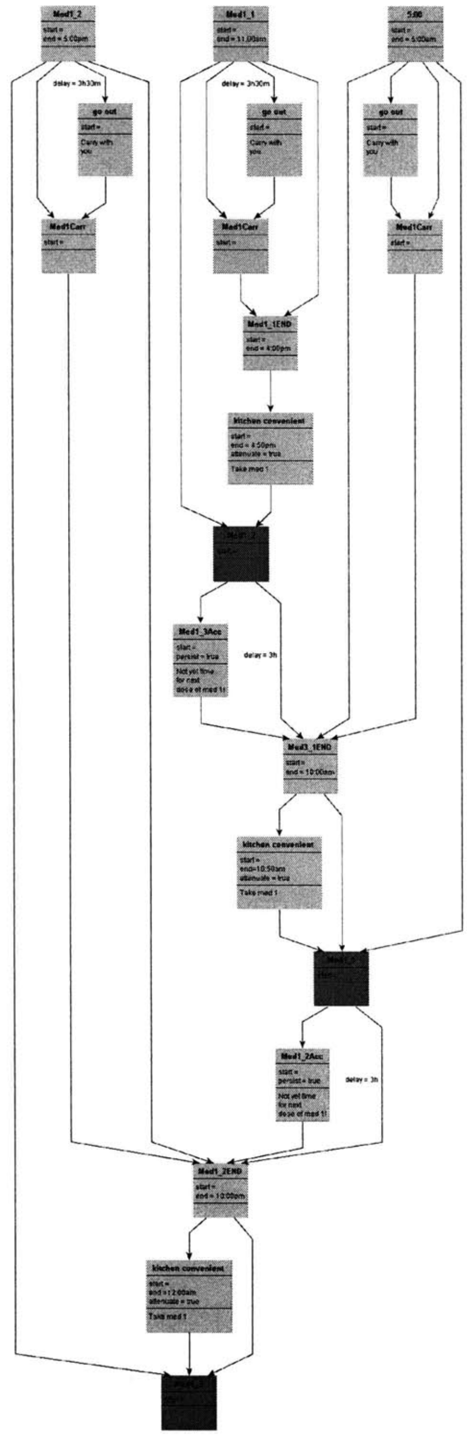


Figure 4-11: Example of a single graph that combines three individual graphs used in the experiment, by eliminating the "END" nodes

EventGraph Construction

For the experimental protocol in Chapter 5, the design of `EventGraphs` for individual doses and alarm conditions, as well as the resolution of dependencies between multiple `EventGraphs` were done manually and iteratively. First, a simulator was developed to rapidly increment time and test the interaction between the `EventGraphs` in various scenarios enacted by the author. Prior to the study described in Chapter 5, two members of the research team and three other friends of the author pilot tested the system independently for periods ranging from 4 to 12 hours. Some iterative improvements to the `EventGraphs` were made during this process as well. Appendix A describes the 5 basic constructs that were finally used to encode the protocol; the level of detail encoded in these graphs is a product of the granularity of information available through the sensing used (listed in Appendix F).

Since the EventGraphs for this prototype were manually constructed, individual graphs were developed for each dose. An expert system for generating graphs from human inputs could efficiently combine such individual graphs and generating a graphical model for an entire day, with all dependencies represented. For example, Fig. 4-11 shows a single graph that combines three individual graphs used in the experiment, by eliminating the END nodes for inter-graph dependency. This is discussed further in Chapter 7.

Chapter 5

Experimental Framework

To test the hypothesis that context-sensitive medication reminders are both effective and perceived as convenient, a 10-day study was conducted at the PlaceLab residential research facility.

5.1 Study Design

A regimen of simulated medication and health tasks was developed with the guidance of healthcare professionals. The regimen consisted of four medicine-taking tasks, and four other healthcare tasks, i.e., exercise, disinfecting hands, caring for a wound, and testing blood glucose. In all, twenty-four tasks were required to be completed at various times during the day. An instruction booklet (shown in Appendix B) containing the full list of tasks, along with other instructions, was given to the participant.

All tasks except the exercise were simulated through buttons on two Health Task Panels (Fig. 5-1) located in the kitchen and in a wardrobe near the bedroom. To complete a medicine-taking task, the button corresponding to the medicine name had to be held down for 15 seconds until the handheld device provided a chime and displayed an acknowledgement message (Fig 5-2). Two of the medicines that involved doses prescribed during the day had an additional button to allow the participant to "carry" a dose outside the PlaceLab.

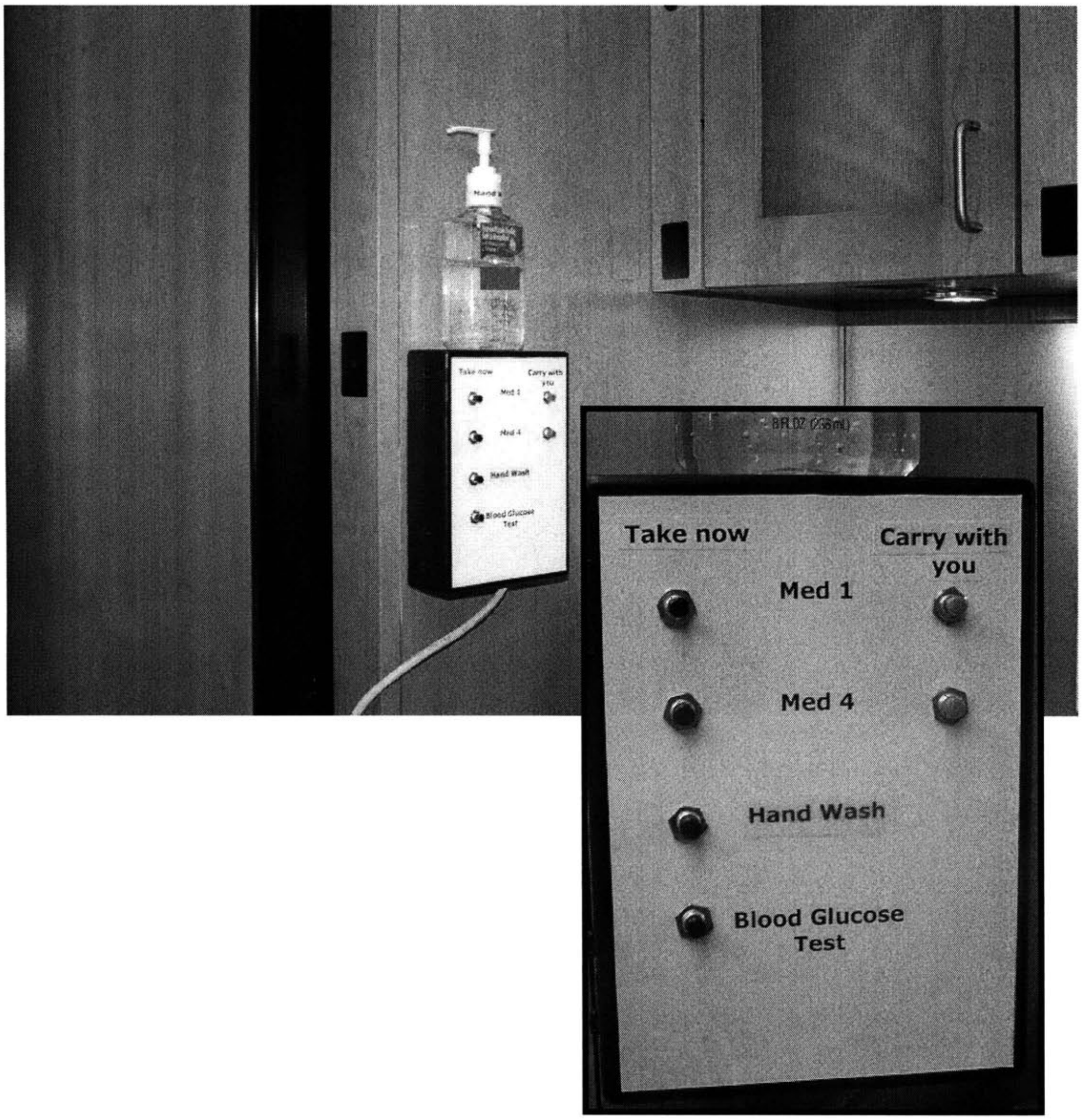


Figure 5-1: Health Task Panel in the kitchen

Figure 5-2: Medicine-taking: (top) Press correct button on panel, (bottom) wait for acknowledgement on PDA.

For non medicine-taking tasks, the participant was required to complete other steps that depended on the type of task. The sequence of steps involved in completing each type of task can be seen through the series of anonymized camera views of the participant in Fig. 5-3 through Fig. 5-6.

The goals of this experimental design were,

1. To mimic the real burden involved in taking medication or completing a non-medication healthcare activity for someone with normal cognitive and perceptual capabilities; for instance, a normal older person not suffering from amnesia,

2. To be able to unambiguously measure adherence through the use of simple sensors, and video.

Admittedly, there is a fair degree of subjectivity in the design of this regimen and the criteria listed in Appendix C for defining adherence. This was necessary given the lack of generalizable adherence data or standard adherence metrics. For example, adherence data is available for individual drugs, but there is little data regarding overall adherence to a complex medication regimen, even though patients over 70 take an average of 7 prescription medicines and 3 over-the-counter drugs [13].

The iterative pre-study pilot testing mentioned in Chapter 4 was helpful in evaluating the clarity and perceived complexity of the protocol; for instance, the decision to introduce a task acknowledgement screen (instead of just an audible chime) so that the participant would clearly know which task had been recorded was an outcome of one of these tests.

A participant willing to move into the PlaceLab and adhere to the regimen for a period of 10 days was recruited. A complete audio-visual record of his stay in the PlaceLab and the activation times of all sensors were recorded. In particular, repeated measures of the following aspects of his activities were made: 1) times when the various medical tasks were started and completed.; 2) times when reminders were received; and 3) rated perceived value of all messages received (reminders, alerts, questions) as described in section 5.4.3.

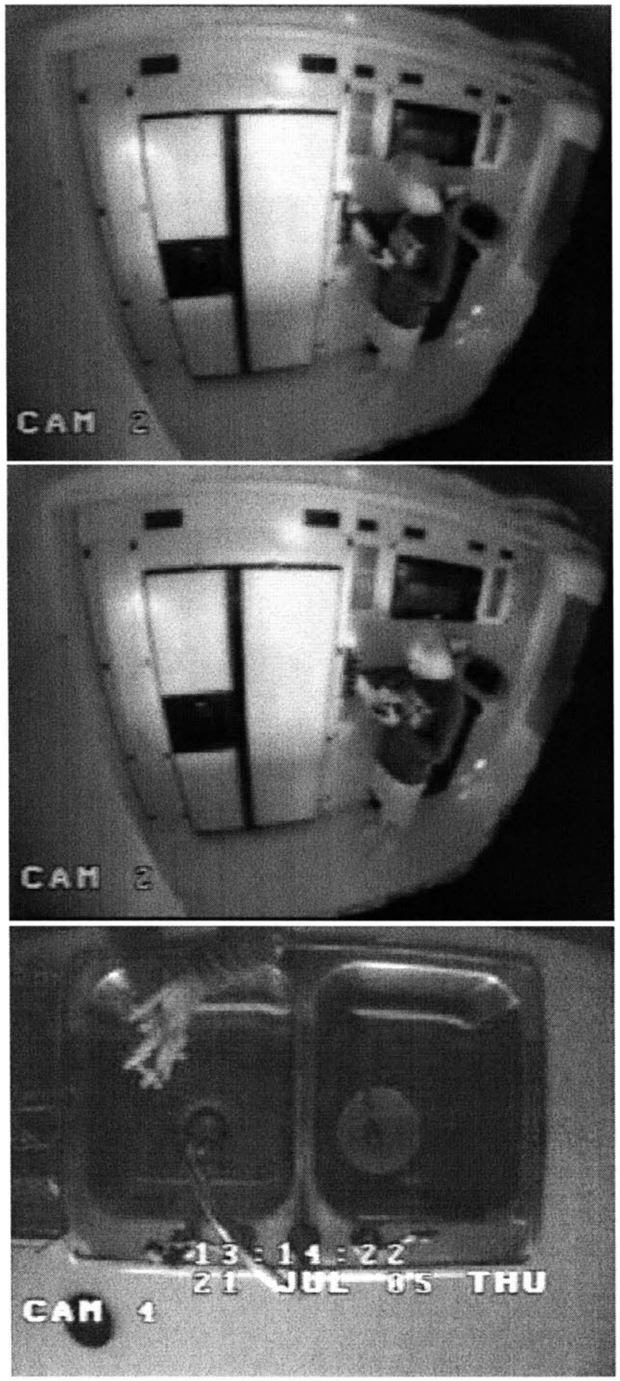


Figure 5-3: Disinfecting hands: (top) Press correct button on kitchen panel, (middle) wait for acknowledgement on PDA, (bottom) wash hands with Purell.

Tuesday, July 19, 2005		
First	**Second**	**Third**
262	280	
Wednesday, July 20, 2005		
First	**Second**	**Third**
220	280	
Thursday, July 21, 2005		
First	**Second**	**Third**
279	262	
Friday, July 22, 2005		
First	**Second**	**Third**
232	233	

Figure 5-4: Testing blood glucose: (top) Press correct button on kitchen panel and wait for acknowledgement on PDA, (middle) get result after 2 minutes and record it, (bottom) scan of blood glucose recording sheet

Figure 5-5: Exercise: 15-20 curls with each arm, using a hand weight.

The two conditions of the independent variable were:

C1. Reminders scheduled at fixed times during the day, and

C2. Context-sensitive reminders as described in Chapter 4.

Each condition was applied on alternating 24 hour periods of the study, beginning at 5:00 a.m. on the morning after moving in. This strategy was chosen to minimize the order effect; however it had significant effects on results. The implication of this design choice was that the context-sensitive system would start up at 5:00 a.m. on alternate days, and run for 24 hours. Consequently, on each instantiation, it would operate with a 24-hour break in its short-term memory of adherence and sensor data.

The study protocol was approved by the Massachusetts Institute of Technology Committee on the Use of Humans as Experiment Subjects. To avoid bias, the participant was blinded to the reminder strategy being used, and had minimal contact with the investigator prior to the completion of the study. As far as possible, interaction between the author and the participant was kept to a minimum and all communication with the participant was managed through a different member of the research team.

Figure 5-6: Wound care: (top) Press correct button on bedroom panel, (middle) wait for acknowledgement on PDA, (bottom) sit still for 5 minutes until PDA lets you know wound care has been completed.

5.2 Participant

A 50 year-old freelance professional (college graduate with an advanced degree) who was married and who generally worked at home was selected to be the participant. He fit the desired age range, was active, spent less than 6 hours a day outside the house, and was in good physical and cognitive health. He had been in the PlaceLab volunteer pool since June 2004, after he responded to a poster advertisement that contained lines such as, "Teach Researchers about Your Everyday Life ... help us design better technologies and homes..." He had stayed in the PlaceLab in an unrelated experiment in July 2004, and as a result, was familiar with the PlaceLab sensing capabilities. The researcher who interacted with the participant described his temperament as follows;

"Based on interactions before, during, and after the experiment, I would describe the participant as conscientious, detail oriented, and deliberate. Given instructions or information about the experiment, he would pause to think and then carefully repeat back his understanding of the task. He frequently made insightful inferences that suggested high general comprehension of the regimen. He seemed willing to get assistance, adjust his pace, and adjust his method of his actions in order to fully execute a task. For example, he gave me verbal feedback when he needed more time to read provided materials and spent several minutes practicing changing the batteries on the on-body sensors."

5.3 Method

A telephone screening and interview were conducted one week prior to the study. The participant was told that the general purpose of the study was to evaluate strategies to assist in medication adherence, and that he would be required to complete simulated medical tasks. He was not told about the alternating fixed-time and context-sensitive reminders. He was shown pictures of the buttons representing medical tasks, and was requested to answer questions about his daily routine (questions and responses in Appendix C), which were then used to schedule the timing of the fixed reminders and to adjust some time-dependant nodes for the `EventGraph` structures representing context-sensitive reminders.

The participant moved into the PlaceLab on July 18, 2005. He was directed to treat the facility like a temporary home for the duration of the study and to conduct his life as normally as possible. The move-in day was used for a protocol instruction session, and a demonstration of the system. He was given the instruction booklet that can be found in Appendix B. The screening, pre-study interview and protocol information session were conducted by a member of the research team who had been given details about the protocol and trained in operating the handheld interface. Care was taken to ensure the participant recognized his right to withdraw from the study at any time. He was informed of all the sensor locations in the apartment.

The study officially began at 5:00 a.m. on July 19, 2005 and ended at 5:00 a.m. on July 29, 2005. The participant was not interrupted during that period, except for an occasional scheduled phone call by the researcher he was in contact with to check if he was comfortable, and one short visit by a researcher to deliver supplies. Samples of 348 completed tasks, 233 reminders, and 228 participant rated messages (reminders, alerts, questions) were obtained. A post-study debriefing occurred on August 3, 2005.

5.4 Evaluation Plan

The activation times of all sensors (in text logs) and a complete audio-visual record of the stay (in 1-hour chunks of video) were recorded. The evaluation of this data covered three metrics listed in the following sections. In particular, the following aspects were logged,

1. Times when the medical tasks were started and completed.

2. Times when reminders were received.

3. Rated perceived value of all messages (reminders, alerts, and questions.)

Adherence

Between one to three conditions for nonadherence were defined for each medication or other healthcare task. In addition to missing a task entirely, tasks were assigned other conditions such as, overmedication, incorrect timing, not completing additional instructions, and interaction, (with drugs or food), as applicable. The details of this scheme in the form of annotator instructions are listed in Appendix C. Missing a dose or task, drug interaction, and overmedication were marked as errors and the rest as warning conditions. Completing non medication- taking tasks (exercise, disinfecting hands, testing blood glucose, and caring for a wound) more frequently than prescribed did not count as overmedication errors.

Interval between Reminder Reception and Task Execution

The time interval between the reception of each reminder and the execution of the associated task was measured. Reminders that did not receive a response were not included in the analysis. Since it was not always possible to determine how to measure the time interval between a reminder and a task (for example, in the case of a missed dose, a reminder time may be available, but there is no corresponding task execution time), some simplifying assumptions were made.

- Missed doses, were treated as gaps in the data, and the reminders for any missed doses were not included in the analysis of this metric.
- Exercise was prescribed four times a day, and the hand disinfecting task was prescribed eight times a day, when "at home". On both fixed-time and context-sensitive days, four reminders for exercise and eight reminders for hand disinfecting were provided. However, in the protocol information session, the participant had asked if he was allowed to wash hands and exercise more often than prescribed, and had been told that he could.

  This made it difficult to match reminders with tasks for these two types of tasks, since the number of times the tasks were executed per day was always greater than the number of reminders provided. To decide which instances to include, each reminder was matched with the task instance immediately following it. The remaining tasks were excluded from the analysis. For example, on almost all days, the participant completed exercise tasks without a reminder several times before the first reminder for the day was delivered. In such cases, the tasks that occurred before the reminder were excluded from the analysis.

- Because of the permitted flexibility in the exercise and hand disinfecting tasks, it was necessary to control for the variations in the times when the participant was outside the PlaceLab on different days. Therefore, reminders for such tasks were removed from the dataset for this metric, so as to not contribute an unduly high time interval when there was no urgency to complete the task.
- Negative time intervals were recorded if a reminder occurred after the execution of the corresponding task, and negative intervals were analyzed separately.

After filtering the data on all days, as described above, the p value of the time intervals across the two reminder conditions for both positive and negative intervals, were calculated using the t-test for two samples assuming unequal variances.

Rated Perceived Value of Messages

A strategy was developed to measure the perceived value of every message at the instant it was viewed with minimal effort for the participant. The perceived value of a message is a subjective quantity that might be affected by several dependent or independent factors each time. Initially, a Likert scale was considered, but it was dropped because it required narrowing down the scope of the response to describing a single aspect like convenience, usefulness, urgency, etc., rather than reaction to the message as a whole.

Instead, the following options were presented on the PDA as shown in Fig. 5-7: "I needed this message to comply", "I may have complied without it", "I would have complied anyway", and "Irrelevant or misleading". Although these choices were displayed in the same

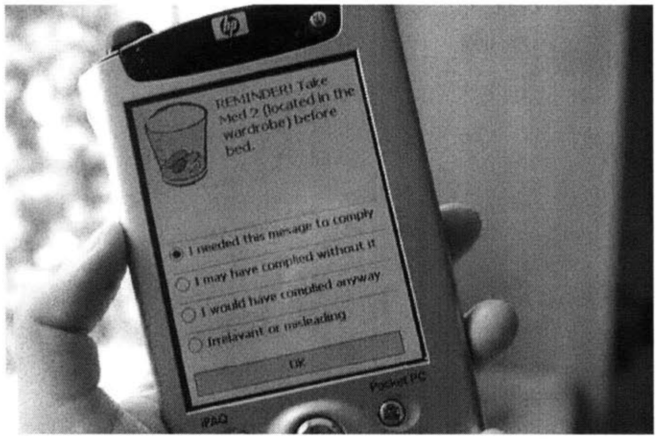


Figure 5-7: Reminder interface showing perceived rating choices.

order each time, it was not expected that the participant would interpret the scale as being linear. For this reason, the two-tailed t-test comparing the rated perceived value of context-sensitive reminders with that of fixed time reminders was not performed, however the distribution in frequency of the different choices was examined. The choices were also compared to the time interval metrics described above.

Video Data

In the first pass by an undergraduate intern, all periods of sleep and time spent outside of the house were marked; and these were then confirmed by the author. Subsequently, sensor activations were used to locate the times when tasks were completed. The five to ten-minute period before task execution was observed with two goals: first, to determine the participant's primary activity before executing the task, and second, to estimate what strategy had been used to remember the task. Finally, video segments corresponding to reminders that were rated poorly were viewed with the goal of determining what caused them.

Chapter 6

Results

This chapter presents exploratory results based on experiment logs and video data, for the three metrics discussed above: 1) adherence, 2) interval between reminder reception and task execution, and 3) rated perceived value. Observed participant behaviors that may be relevant to the interpretation of the results are also listed.

6.1 Summary

1. The participant completed 348 medication and other healthcare tasks in all, and he missed 4 tasks. A total 240 (24 per day) tasks has been prescribed. Therefore, a total of 112 tasks not prescribed were completed. Of these, only 1 was a medicine-taking task. The rest comprised of non medicine-taking tasks: 70 exercise tasks, 39 hand washes and 2 blood tests.

2. A total of 264 messages (233 reminders, 28 alerts, 3 questions) were generated.

3. Of the 233 reminders, 120 were delivered at fixed times (24 per day on 5 alternate days), and the rest (113) were context-sensitive.

4. The times when the participant executed tasks are summarized in Fig. 6-1 along with the time intervals he spent sleeping and outside the PlaceLab.

Some of the participant's actions and observed behavior patterns made the data analysis more difficult. Patterns that significantly affected the quantitative results are given below. Two of the effects described are labeled Case A and Case B for easy reference over the rest of this chapter.

High level of commitment to following the regimen. The participant did not make a single nonadherence error between days 1 to 6 of the study. The number of warning conditions was generally consistent across all days. Refer to Appendix C for detailed annotator instructions, for an elaboration of what constitutes an error or warning condition.

Significant variation in sleep times from those estimated in the interview in response to questions about daily schedule, and an unforeseen pattern of executing morning tasks. The participant had indicated he would typically go to sleep between 12:00am to 2:00am and wake up between 9:00am and 11:00am. Based on this, the condition switch from context-sensitive reminders to fixed-time reminders was set at 5:00 a.m., assuming that the participant would begin his day sometime after 5:00 a.m. But his observed sleep pattern varied from this estimate.

Case A: On 8 out of the 10 days, he was awake until after 1:30am (on 3 days, until after 4:30am), and he often completed morning tasks of the following day prior to 5:00 a.m. On context-sensitive reminder days, if this behavior occurs the previous night, this prevented the system from accurately tracking medication taken, and caused certain irrelevant messages to be delivered. For example, when the participant took Med 4 (to be completed after breakfast) at 4:56am on day 5, this was not recorded by the context reasoning system which began at 5:00 a.m. As a result, the participant was provided a reminder to take Med 4 after waking up later in the morning. This was observed on 2 out of 5 context-sensitive days: day 5 and day 9.

This problem could have been avoided by setting the condition switch (start of a new "day") time a few hours earlier, or preferably, by designing a study where the context-sensitive reminders and fixed-time reminders were allowed to run over a continuous window of a few days or weeks; allowing for a longer history of medication events to inform decisions about reminders.

Case B: Based on his estimated sleeping time, it had been decided to end all convenience windows for nighttime tasks at 12:30am, and schedule all fixed-time reminders by midnight, in order to maintain a "quiet period" between 12:30am and waking. Only reminders associated with specific activities (e.g., showering) were provided during the quiet period. As a result, many nighttime reminders (for both context-sensitive and fixed-time) were delivered several hours before the participant was, in fact ready to sleep.

Fig. 6-2 and Fig. 6-3 show reminder reception times along with time intervals spent sleeping and outside the PlaceLab, for fixed-time reminders and context-sensitive reminders separately. The context-sensitive reminders generally occur on waking, on all days. They also occur just before he leaves the PlaceLab or just after he returns. Reminders did occur when the participant was outside on all days; however, a summary view of Fig 6-2 and Fig. 6-3 suggests that fewer reminders were delivered when the participant was outside on context-sensitive days.

6.2 Adherence

The participant adhered to the regimen almost exactly, making only 5 errors during the course of the study. Although warning conditions (e.g., not drinking a glass of water with a dose of Med 1) occurred on all days, they were also balanced in frequency across the days when context-sensitive and fixed-time reminders were provided. Fig. 6-4 summarizes the instances of errors and warning conditions over 10 days. The upward trend in the number of both errors and warning conditions suggests that adherence may decline further over time and that a longer study may be effective at distinguishing the two conditions. Fig. 6-5 is a condensed version of the adherence scorecard; adherence was annotated according to the instructions in Appendix C.

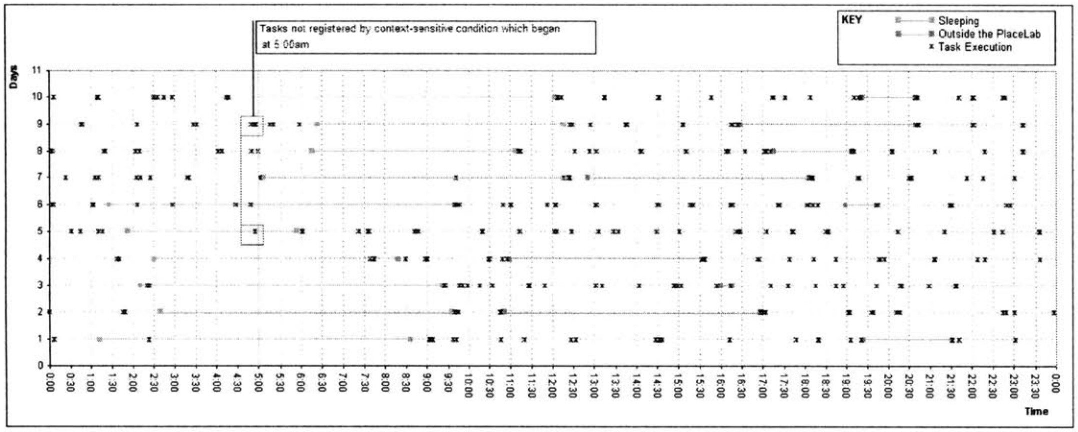


Figure 6-1: Summary Plot: Task execution times, time spent sleeping, and time spent outside the PlaceLab

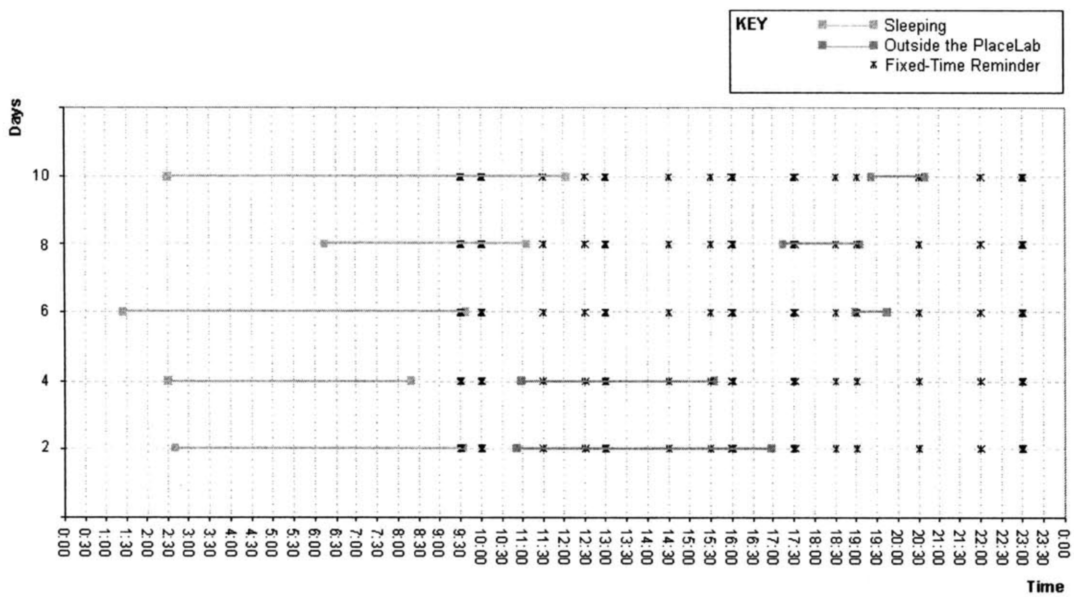


Figure 6-2: Summary Plot: Fixed-time reminders, time spent sleeping, and time spent outside the PlaceLab

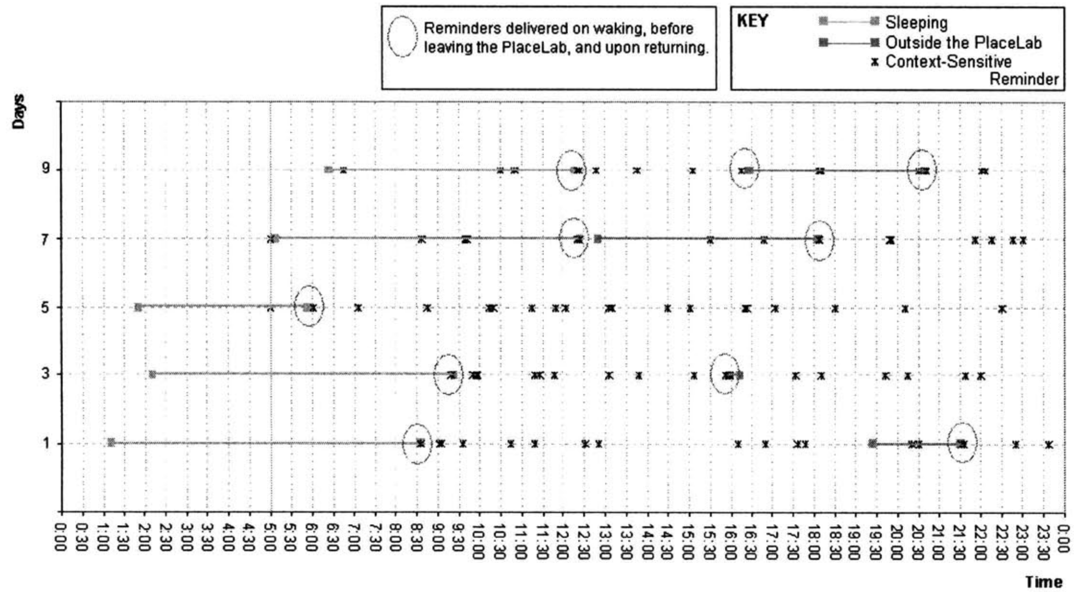


Figure 6-3: Summary Plot: Context-sensitive reminders, time spent sleeping, and time spent outside the PlaceLab

6.3 Interval between Reminder Reception and Task Execution

The time intervals between the reception of reminders by the participant, and the time at which the execution of the corresponding tasks started were measured. 113 observations in both groups (fixed-time reminders and context-sensitive reminders) were analyzed. The reasons for eliminating some reminders and tasks from the analysis have been described previously in the evaluation plan (Section 5.4).

There was high variance in time intervals between reminder reception and task execution for both context-sensitive and fixed-time reminders ($\mu = 53.86min$, $\sigma = 96.30min$ for context-sensitive reminders, and $\mu = 103.66min, \sigma = 114.96min$ for fixed-time reminders). A significant factor in the variance for both conditions of reminders was the early delivery of nighttime reminders to allow for a quiet period after 12:30am (Case B).

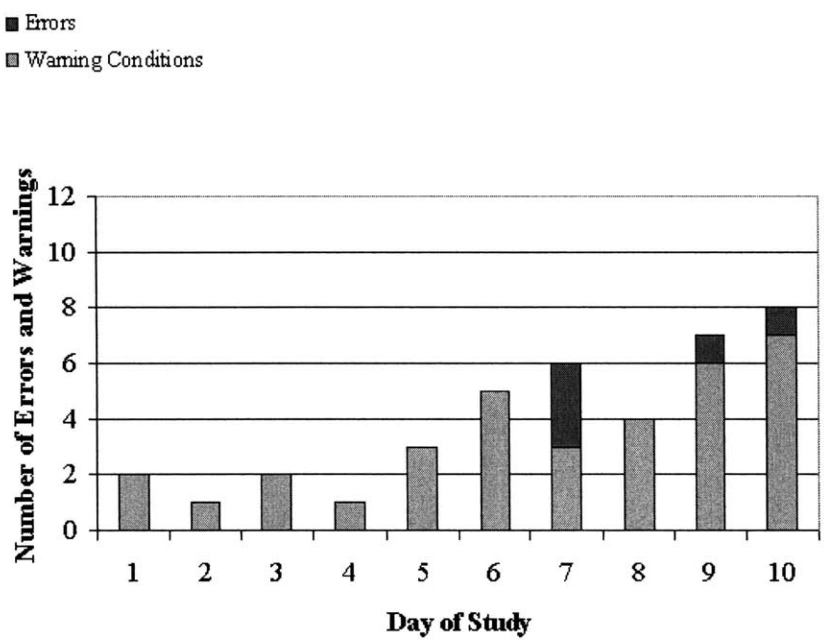


Figure 6-4: Nonadherence summary indicating medication adherence errors and warnings

		Context-Sensitive					Fixed-Time					
		1	3	5	7	9	2	4	6	8	10	
Med 3	dose 1	9:04	9:24	4:54	5:02	4:50	9:39	7:39	9:40		4:17	**Case A** **morning task occurring before condition switch**
	interaction	y	y	y	y		y	y	y	y		
	timing	y	y	y	y	y	y	y	y	y	y	
	no overmed	y	y	y	y	y	y	y	y	y	y	
Med 1	dose 1	9:37	9:58	7:35	12:25	4:54	10:44	8:29	10:50	4:50	4:13	**Case A** **morning task occurring before condition switch**
	drank water within	y	y	y	y	y	y	y	y	y		
	dose 2	14:27	15:03	13:06	18:10	12:55	17:03	10:54	16:16	11:13	12:13	
	additional instr.	y	y	y	y	y	y	y	y	y	y	
	timing	y	y	y	y	y	y	y	y	y	y	
	dose 3	19:20	20:17	18:34		16:24	23:01	19:54	21:31	16:35	17:32	
	additional instr.	y	y	y	unclear		y	y	y	y	y	
	timing	y	y	y	y	y	y	y	y	y	y	
	no overmed	y	y	y	y	y	y	y	y	y	22:45	
Med 4	dose 1	9:41	10:15	7:36		5:57	10:46	8:59	11:53	4:59	4:14	
	timing		y	y			y	y		y		
	dose 2	18:18	18:15	17:04	20:30	16:25	19:35	18:12	18:05	17:10	19:17	
	timing	y	y	y	y		y	y	y	y		
	no overmed	y	y	y	y	y	y	y	y	y	y	
Blood	1	9:03	9:25	4:55	9:41	4:56	9:39	7:39	9:44	4:50	4:14	**Case A** **morning task occurring before condition switch**
Test	timing				y					y		
	additional instr.	y	y	y	y	y	y	y	y	y	y	
	2	11:19	11:27	8:47	12:16	12:29	17:00	10:48	12:05	11:14	12:09	
	additional instr.	y	y	y	y	y	y	y	y	y	y	
	3	14:36	14:54	12:27	18:11	15:07	19:04	17:38	15:20	14:07	14:31	
	additional instr.	y	y	y	y	y	y	y	y	y	y	
	4	17:47	17:35	16:27		20:43	20:11	15:36	18:18	17:04	17:15	
	additional instr.	y	y	y		y	y	y	y	y	y	
Hand	1	9:07	9:50	5:03	12:24	4:55	9:45	7:44	9:41	11:13	12:08	
Wash	interval	y	y	y	y		y	y	y	y	y	
extras	2	10:46	11:26	8:44	out	5:15	out	9:01	11:01	12:53	13:16	
omitted	interval	y	y	y	y	y	y	y	y		y	
	3	12:26	13:02	10:20	out	12:25	out	10:30	12:04	13:03	14:32	
	interval	y	y	y	y	y	y	y	y	y	y	
	4	14:32	14:04	12:06	18:07	13:46	16:56	out	13:03	14:07	15:46	
	interval	y		y	y	y	y	y	y	y	y	
	5	17:47	14:58	13:34	19:18	15:06	19:03	out	14:32	15:11	17:13	
	interval	y	y	y	y	y	y	y		y		
	6	19:05	16:14	15:01	20:33	16:17	20:16	15:33	15:18	16:11	18:08	
	interval	y	y	y	y	y	y	y		y	y	
	7	21:31	17:35	16:23	21:53	20:42	22:48	16:54	16:15	17:03	19:21	
	interval	y	y	y	y	y	y	y	y	y	y	
	8	0:06	18:54	17:43	23:01	22:03	0:00	18:45	17:23	19:07	20:39	
Exercise	1	12:33	9:47	6:01	9:41	4:53	9:43	7:43	9:47	11:12	12:07	
extras	2	14:31	10:34	7:22	12:23	5:20	16:59	8:57	10:59	12:32	13:14	
omitted	3	16:12	11:25	8:42	18:06	12:25	19:02	10:28	11:53	14:06	15:46	
	4	18:20	11:49	10:18	19:16	13:45	19:38	15:35	13:02	15:10	17:13	
Med 2	dose 1	2:22	2:20	1:10	3:18	3:26	1:45	1:36	4:27	4:03	2:31	**Case B** **nighttime task several hours after 0030**
	timing	y	y	y	y	y	y	y	y		y	
	no overmed	y	y	y	y	y	y	y	y	y	y	
Wound	1	2:22	2:24	1:16	3:20	3:31	1:49	1:40	4:27	4:08	2:36	**Case B** **nighttime task several hours after 0030**
Care	additional instr.	y	y	y	y	y	y	y	y	y	y	

KEY

- Errors
- Warning Conditions

Figure 6-5: Adherence scorecard indicating errors and warnings

Since it was predicted that there would be a difference in the perceived convenience of context-sensitive reminders and fixed-time reminders, and the data is related because of the repeated measures design; the two conditions were compared using the two-sample t-test assuming unequal variances. The resulting $p < .003$ indicated that the reminder strategy had a significant effect on the response time to reminders. If the response time is assumed to be an indicator of the perceived convenience of a reminder, the above results suggest that context-sensitive reminders were perceived to be more convenient than fixed-time reminders.

A total of 31 fixed time reminders and 22 context-sensitive reminders were delivered after the associated task was completed. It was revealed on closer examination of the data, that nearly all the context-sensitive reminders in this category were a direct result of morning tasks not getting recorded by the context-reasoning system because they occurred before 5:00 a.m. (Case A).

Fig. 6-6 to Fig. 6-8 show reminder reception times on the central axes and the times when associated tasks were executed on the left and right side, indicating whether task execution occurred before or after the corresponding reminder. The context-sensitive reminders that lie to the left of the axis are almost in all cases, a direct result of Case A. The points immediately to the right of the axis represent tasks that were completed soon after receiving the reminder, suggesting that the reminder prompted task execution. These plots reveal that a majority of context-sensitive reminders were acted upon within 5 minutes of the reminder, further supporting the assessment that context-sensitive reminders were more convenient than fixed-time reminders.

6.4 Rated Perceived Value of Messages

The participant rated 228 messages of the total 264 delivered. 62.3% of the messages that received a rating were context-sensitive and the rest were fixed-time messages. The distribution of the perceived value of messages is shown in Table 6.1.

A significant number of messages received the rating "Irrelevant or misleading" (57% of

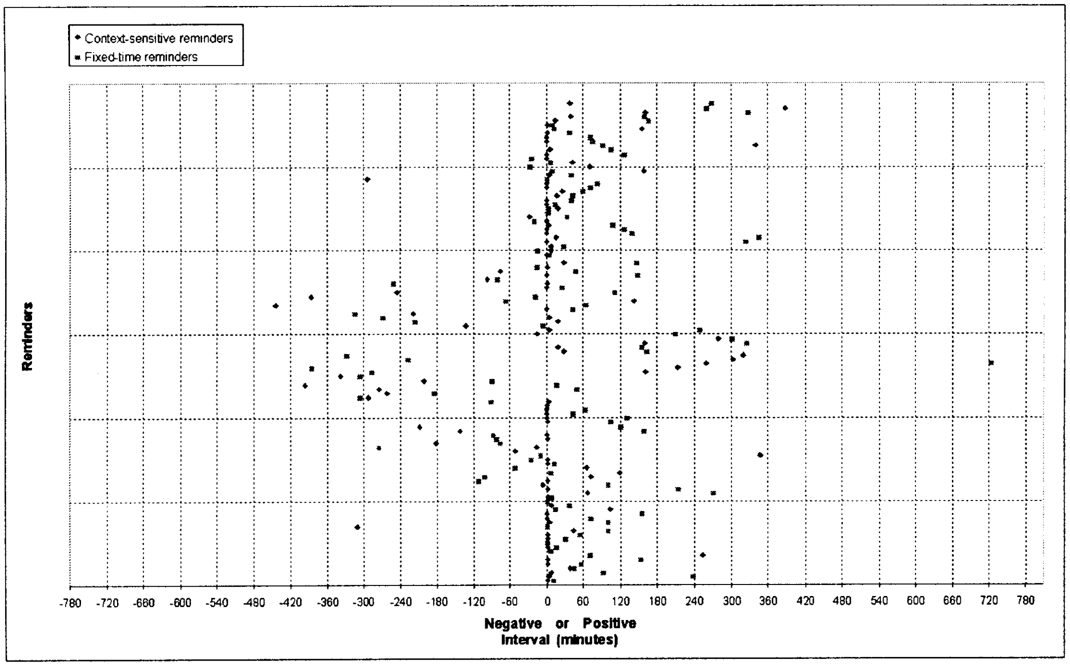


Figure 6-6: Time intervals between reminder reception and task execution (all)

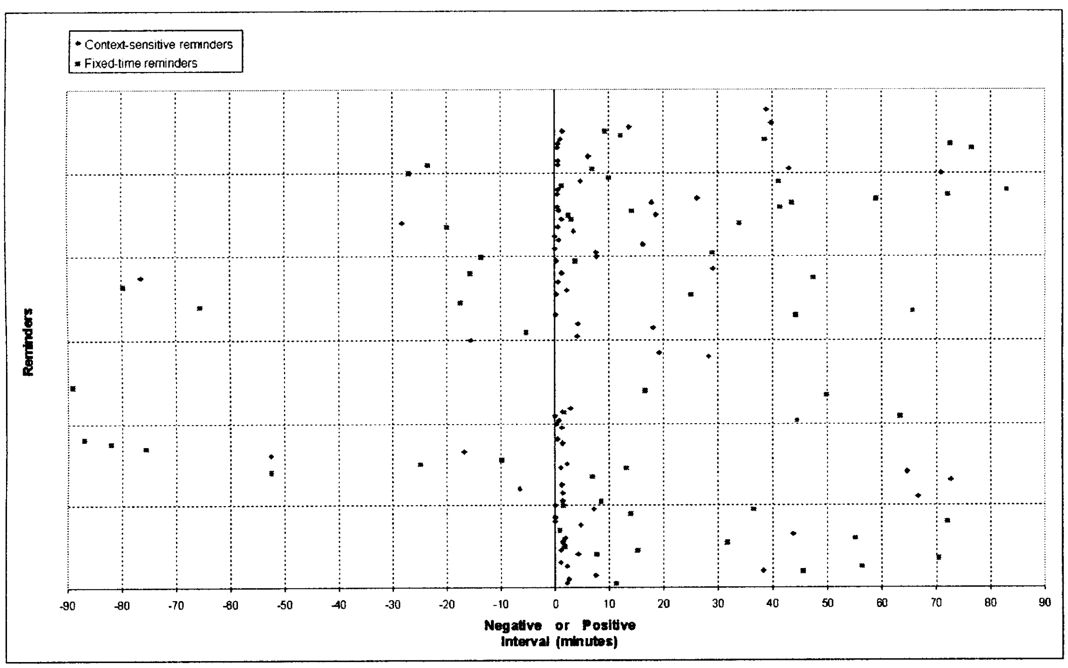


Figure 6-7: Time intervals between reminder reception and task execution (zoomed to +/- 90 minutes on time axis)

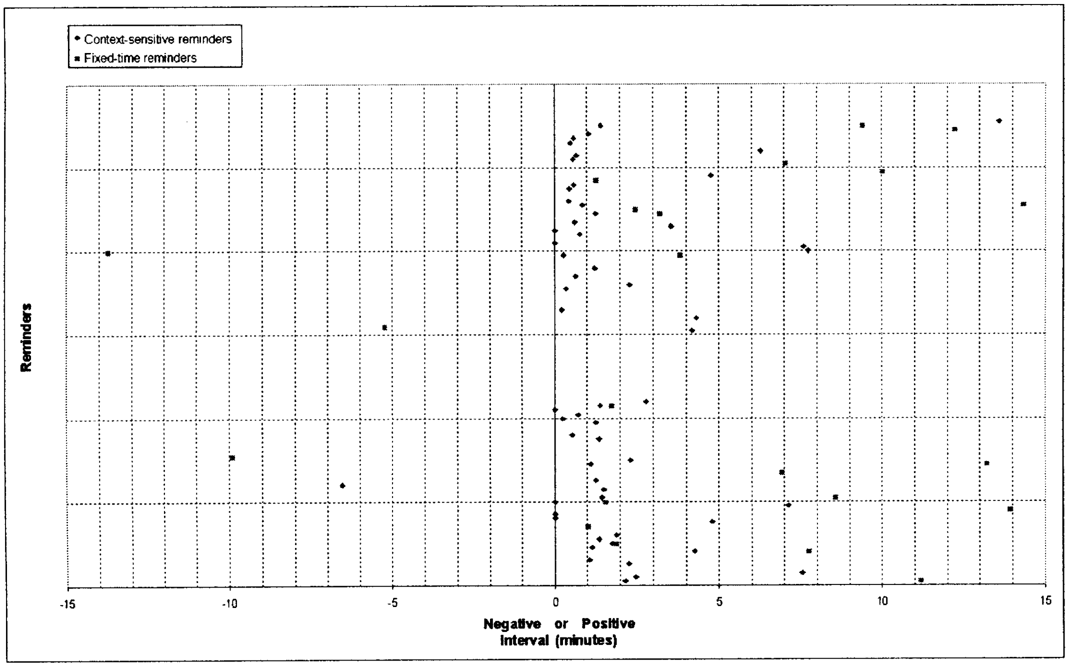


Figure 6-8: Time intervals between reminder reception and task execution (zoomed to +/- 15 minutes on time axis)

Meaning of Rating	Context Sensitive	Fixed Time
Irrelevant or misleading	35.2% (50)	57% (49)
I would have complied anyway	35.2% (50)	33.7% (29)
I may have complied without it	4.2% (6)	0% (0)
I needed this message to comply	25.4% (36)	9.3% (8)
Total	142	86

Table 6.1: Distribution of rating of fixed time messages and context-sensitive messages

Frequency of Messages	Time when morning tasks were begun	
Day 1	14% (7)	9:04am
Day 3	14% (7)	9:24am
Day 5	**34%** (17)	**4:54am**
Day 7	18% (9)	5:02am
Day 9	**20%** (10)	**4:50am**

Table 6.2: Distribution of messages rated "Irrelevant or misleading"

fixed-time reminders and 35.2% context-sensitive reminders), however many were the result of the two special cases described in the beginning of this chapter. Nearly all 20 "before bed" reminders were delivered too early and rated poorly. They were instances of Case B, which affected the rating of both fixed-time and context-sensitive reminders. Several irrelevant or unhelpful reminders and alerts were received throughout the day on 2 out of 5 context-sensitive reminder days; a result of Case A (medication or healthcare tasks completed before 5:00 a.m. did not get registered by the reasoning graphs). This affected only context-sensitive reminders, since fixed-time reminders were not dependent on the user's medication pattern.

This is supported by the distribution of the number of messages rated "Irrelevant or misleading" on the different context-sensitive days, as in Table 6.2. The majority of messages rated poorly were on days when morning tasks were begin before 5:00 a.m.

6.5 Interview Results

Relevant results from the protocol instruction session and the post-study debriefing are presented below. The participant's responses to questions about his daily schedule elicited during the pre-study interview and are presented in Appendix B.

Protocol Instruction Session

During the protocol instruction session, when asked to confirm that he comprehended the regimen, the participant had reflected on his daily routine and verbalized (and made notes about) when he would complete the different tasks in his regimen, by interspersing tasks with his own daily activities. He had then requested that his notes be typed and printed. Video data revealed that this sheet was left on the dining table and referred to several times a day. The participant followed this list of activities fairly closely, and eventually added annotations such as "Lights & (turning down) shades", in effect, incorporating more activity-based reminders. This was collected at the end of the study and is shown in Fig 6-9.

Post Study Debriefing

An account of the debriefing interview in the words of the researcher who interacted with the participant is given below. The author was involved with the interview, and took independent notes. The experimental protocol of alternating days with each condition, ruled out the possibility of obtaining qualitative results (through interviews) about the perceived difference between the two conditions. A future study will be more revealing if each condition is sustained for a few days or weeks, and the order of the conditions is alternated for different participants.

The participant began by describing the alerts and reminders for which he had negative feedback as falling under two categories: "technically accurate, but irritating" and "erroneous." He noted that many alerts warning him about taking medications too soon were delivered within 10 minutes of when the system expected him to have been executing the task. He felt that adherence, in this instance, was too rigidly enforced; his understanding of when a task should be executed was more approximate, including a range of time. He suggested that alerts should be "scaled," with some more softly worded (or with less strident alarm sounds) for situations where the user is early or late, but only by a few minutes. He also described reminders that were delivered "annoyingly soon" for repeated tasks (such as hand washing and blood glucose testing). These were delivered within the first 5-10 minutes of the task window, which was the shortest time possible since the last execution of the task. He suggested instead that these reminders should be delivered toward the end of the task window. He estimated that he received reminders/alerts that were "accurate, but irritating" *about a couple dozen times during the study period.*

He classified reminders/alerts as "erroneous" if they reminded him to take a medication too soon (by his estimation) or if they referenced tasks he had already completed. He gave as examples for the former category a hand washing reminder that came 40 minutes after his last hand washing event and a reminder for medication 1 that came 3 hours after taking it previously. For the latter category, he noted that he was uncertain how to interpret the "first thing in the morning" instruction on days when his sleep-wake schedule was erratic. If he couldn't get to sleep or woke up in the middle of the night, he often decided that the new day had begun and took the morning medications. He would then receive repeated reminders and alerts later in the morning, as though he had not completed the task. He then tried to "fool the system" by telling it he was carrying the medications with him and going out for short walks.

The participant was asked to describe his personal strategies for adhering to the medication regimen. He stated that he relied on a reminder chart that he called his "cheat sheet", adding "little notes" to himself about good times to take the medications (e.g., before shaving, in association with pulling up the blinds). In order to remember the repeated tasks, such as hand washing and blood glucose testing, he put himself on a schedule of stopping work every hour and a quarter to attend to the tasks. Because some tasks (e.g., blood glucose testing) were less frequent, he would do those every other break.

He found that he "scheduled his life around" the experimental task, showering and eating meals at more consistent times. He also did focused work for shorter periods, stopping to attend to medication tasks, but noted that this may have been a "healthy development" for him. He thought that he took fewer trips out of the home than he normally would; except for the short walks he took to "fool the system" when it gave him erroneous alerts related to the morning tasks.

He was asked what he would do if he had to maintain a regimen this complex over the long term. He stated the he would need to internalize or memorize the schedule, but that his need for reminders would approximate what he reported during the study. When asked if

Wake up

Put on sensors
Lights & shades
Test Blood Glucose at about 9

Take Med 3

Wait 30 minutes

Exercise during wait

Hand wash (now and every 2 hours)

Take Med 1 just before breakfast

Breakfast

Take Med 4 after breakfast

Exercise

Test blood at about 12

Lunch

Take Med 1 one hour after lunch (about 1:30)

Exercise

Test blood at about 3 & 6!

Dinner (take Jen's call)

Med 4 and Med 1 after dinner (about 6:30 for ~~b~~otter)
Lights & shades
Exercise

Test blood if not done

Shower

Wound care

Med 2

Bedtime

Figure 6-9: Participant's reminder chart *he would use a system like the one he tried during the study, he said he would be "much happier to have a PDA-based system than pill boxes."*

The participant noted that he often received reminders just as he was about to press the button to complete the task. As he experienced more reminders, he tried to understand how they were being triggered and assumed they were "context sensitive" (phrase introduced by participant, not interviewer). He was therefore confused about getting bedtime task reminders when he was still sitting in the living room watching TV, and described these as "absurd." He said he often questioned whether time-alone was triggering the reminder, but thought the system would be more advanced. He was asked what activities he had thought the system would have detected and associated with reminders and he suggested that for showering, when he went into the bathroom at night; for bedtime, when he went to the bedroom, took out his night clothes, turned down the bed, and pulled down the blinds; for meals, when he went to the kitchen, opened the fridge, and turned on an appliance; and for waking up, when he shaved and opened the blinds.

When asked if he had become more aware of his routines in association with the medication regimen, he noted that his routines were more "front and center" in his consciousness. In particular, he had noted how opening and closing the blinds and turning on and off the radio or TV were good activities around which to organize the regimen. When further asked about what would have been "convenient times" for reminders, he suggested first that reminders should occur as late as possible, or should gradually become more frequent and strongly worded as the last possible time for the task approached. He identified being in the bathroom, washing hands, and at the door to leave as times/activities when he would not want to receive these types of health task reminders.

The participant was asked about his actions in response to reminder, in particular, why he would sometimes delay following through with a task even though he had rated the reminder highly. He responded that he rated reminders with the highest rating if he had "genuinely forgotten" about the task. After receiving such reminders, he would finish with his current activity and then attend to the task, usually within 5 minutes. He was not concerned that he would forget again. He thought that the middle two rating values were of questionable *value. He would sometimes use these ratings if had thought about the task in the last 30 minutes, but had temporarily forgotten.*

Chapter 7

Discussion and Future Work

This chapter summarizes the key issues raised by this project, and presents ideas for future related research.

7.1 EventGraph Framework

Context-aware systems in the past have modeled sensor inputs into aspects of activity [40], location [36], identity [34], or domain-specific conditions like "high_blood_pressure", or "cooker_in_use" [7], etc. Such systems are typically concerned with modeling information at an instant (or over a short window). The delivery of effective medication reminders, however, required the modeling of an extended history of relevant events, possible future events, and the dependencies between them. The extensibility of the `EventGraph` framework developed made it easy (editing XML files) to adjust the task frequency or adherence requirements as the protocol was being developed. This flexibility could be leveraged to modify details of a regimen over time in longer studies, and may have applicability to other context-aware systems that require context to be not just about information gathered "in the moment".

Directions for Future Research

Strategies must be developed to efficiently generate EventGraphs (or similar structures) that respond to a patient's prescriptions (name, dosage, etc.) timing constraints (e.g., "take before bed"), activity constraints (e.g., "do not take with food"), or drug interactions. Additional conditions will come in the form of events that could vary from day to day such as meal times, or the occasional absence of events when doses are missed.

Expert systems to achieve this must differ qualitatively based on target users, who could be physicians, pharmacies, patients, or applicable software agents. A key requirement for such systems will be the ability to to optimally resolve all the dependencies between the various conditions and rules. For example, a patient interface might allow tuning the graph to recognize a personal behavioral routine, but doing so might contradict a "drug-drug interaction" rule encoded by a pharmacist.

7.2 Evaluation Protocol

The participant was extremely focused on remembering the regimen and adhering to every aspect of it. This is evidenced by the video data, in which he was seen referring to the reminder chart several times a day, and just before executing many tasks. The repetitive patterns of some of his mistakes in following supplementary instructions point to a lack of understanding of these instructions rather than forgetting. In the debriefing interview, he mentioned having difficulty interpreting some instructions like "First thing in the morning" when he was awake all night. Also, he revealed that he had put himself on a schedule of stopping his primary activity every hour and a quarter, to exercise and disinfect his hands, and "scheduled his life around" the experimental tasks. He mentioned that he was able to strategize ways to suppress irrelevant alerts for instance, by using the "carry with" option and going out for short walks on certain days. On one occasion, the data indicated that he might have been deliberately promoting an alert by starting out on a task that he had just been warned not to do (he did this three times within an hour).

A combination of factors may have contributed to the high level of adherence: a desire to "please" the researchers, fewer day-to-day distractions from social sources (he normally lives with his wife), the relatively short length of the study (adherence declined over time, as possibly the novelty of the experience wore off), and the limited costs (e.g., real world costs to compliance like side effects, social stigma, etc.) to executing the tasks. The participant had been asked to judge each medication or health task as being equally important, with the intention that his inclination to follow through on a reminder should simply be guided by the burden of completing the task (e.g., pressing a button vs. having to sit still for 5 minutes). But this meant that the other than an interruption to his current activity, he had limited additional costs to complying. The participant's curiosity about the working of the system might have led to some attempts at second-guessing it.

Directions for Future Research

While evaluating intervention for everyday life, it is not easy (and perhaps impossible) to control for contingencies and variations in subjects' comprehension, curiosity, or degrees of commitment. Projects that take advantage of living laboratories will help researchers better understand how to design experiments that capture these effects and how to build interactive systems that adapt and respond to them.

7.3 Tailoring the System to Individual Patterns and Activities

The results highlighted the fact that self-reflection and interviewing might not always lead to accurate recall and description of daily routines. On the other hand, the participant mentioned in the interview that as a consequence of the experimental protocol, his routines at the PlaceLab had become "front and center" in his mind within a few days. He identified several patterns of activities (going into the bathroom at night, taking out his night clothes, turning down the bed, opening and pulled down the blinds, opening the fridge, turning on an appliance, shaving, and switching the television on and off) that he expected the reminder system to have detected and associated with reminders. The ability to "attach" customized reminders to activities performed in the home seems to be useful from a user's perspective. By situating reminders in existing behavioral routines, users can greatly increase the likelihood that they will act upon them.

Directions for Future Research

Interventions in which users are able to draw on insights about their own patterns of living to set up lifestyle-related reminders could provide a new and viable approach to augmenting human memory. This is a rich area of research.

7.4 Commonsense Reasoning

On over 5 occasions in a 40-minute interview, the participant mentioned that he expected the system to be "context-sensitive" or to have "common sense". It is possible that his educational background, combined with reading about the researcher's interests on the internet, may have contributed to the usage of the term. When asked to elaborate, he identified "absurd" bedtime reminders when he was watching television, and provided a diverse list of activities that he had begun to notice in his routine, and that he expected a context-sensitive reminder system to recognize.

The participant's comment about the reminders not having "common sense" indicated his frustration at the system not being able to recognize concepts such as "a person is in the living room and watching television, is not about to go to bed." But there are thousands of such pieces of commonsense knowledge, even in a restricted domain (the home), and a system capable of truly learning by itself is not an easy vision to realize.

Directions for Future Research

The ability to recognize domestic activities is useful in many application domains. Appendix G details relevant prior work that leverages a long standing effort of putting pieces of ordinary knowledge or common sense into computers. The work explores a novel approach to building a classifier of domestic activities (like making breakfast, taking a pill, or exercising) by mining data from freely available commonsense knowledge bases. It points the way to exciting research that could enhance the type of system described in this paper.

7.5 Communication and Interface

In general, the participant's mindset was to put personal convenience aside in favor of adhering. The participant said he was not particularly sensitive to whether he received reminders at convenient locations (although quantitative results indicate that context-sensitive reminders were acted upon significantly faster).

On the other hand, his annoyance at early reminders ("annoyingly soon" / "accurate, but irritating" / suggestion that reminders should occur at the end of a window) is supported by 31.25% of fixed-time reminders and 37.1% of context-sensitive reminders being rated "I would have complied anyway". When asked about what would have been "convenient times" for reminders, he misunderstood the question, and responded that he would have appreciated receiving multiple suggestions asking him if it was a convenient time to take a medication rather than an authoritarian, one-time reminder interrupting his primary task. Contradictory to the previously articulated preference for late reminders, this indicates that there were also times when more frequent reminders beginning early in an acceptable time-window were preferable, particularly if such reminders were offered with the understanding that they could be ignored. Moreover, a less authoritative interface that explained some of the behind-the-scenes reasoning would appear to make more intelligent errors than one that simply provided reminders.

Directions for future research

Detecting users' affective states and responding with reminders of varying tones accordingly (e.g., congratulatory, mild, "softly-worded", etc.) is an interesting approach to reminder delivery. It also further exemplifies the notion of modeling the awareness of a caregiver.

Appendix A

Additional EventGraph Details

The EventGraph used in the experiment and illustrated in this document were created using the yEd Java graph editing application to efficiently generate drawings and apply automatic layouts. The application software is available as a free download. Fig. A-1 shows a screenshot of the application in use. After the drawings are created through the graphical interface, they can be saved in one of several standard graph-encoding formats. Fig. A-2 shows the format used in this prototype; (a simplified version of) GraphML [1].

EventGraph Constructs Used in the Prototype

Fig. A-3 shows the basic graph constructs that were used to encode the experiment protocol in Chapter 5. These are;

a) A graph representing a reminder with a fixed time window. The nodes encode start time, the target task and a reminder triggered by a single convenience node.

b) A graph representing a reminder without a time window, but dependent on an event (`awake`) that could occur at different times. The node (`awake`) has an end attribute representing the latest time up to which the event will be awaited.

Different types of alert nodes;

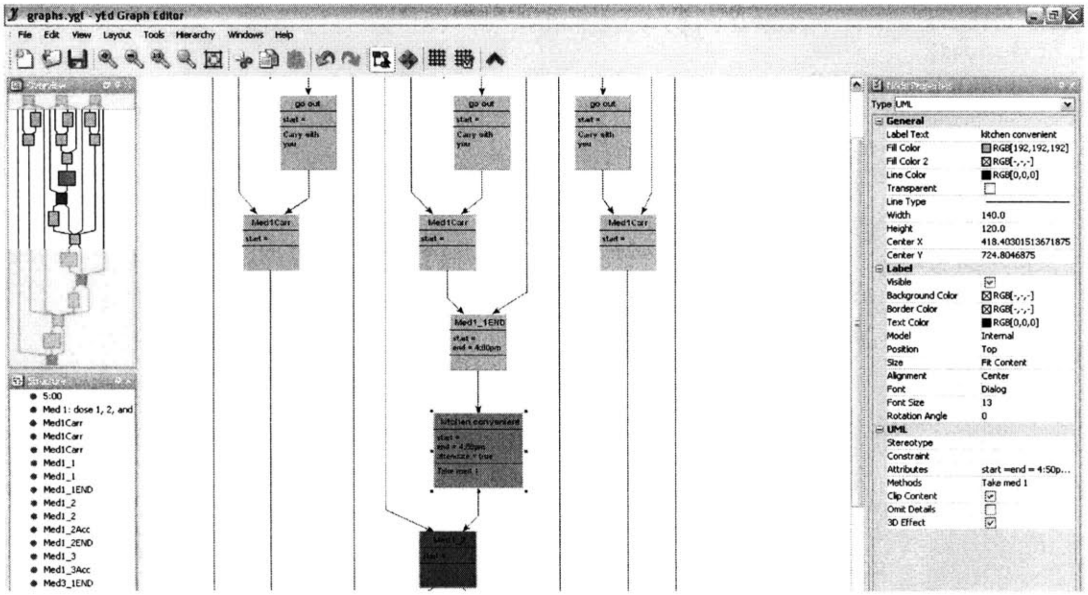


Figure A-1: An EventGraph for a medication dose being constructed using a graph editing application

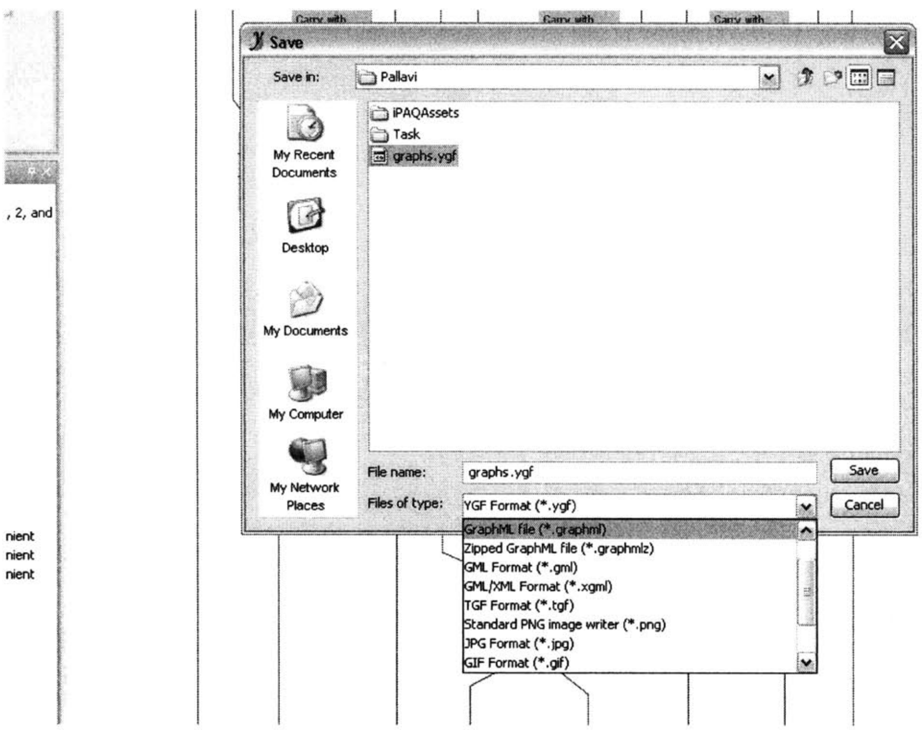


Figure A-2: Saving the visual into a standard XML based format

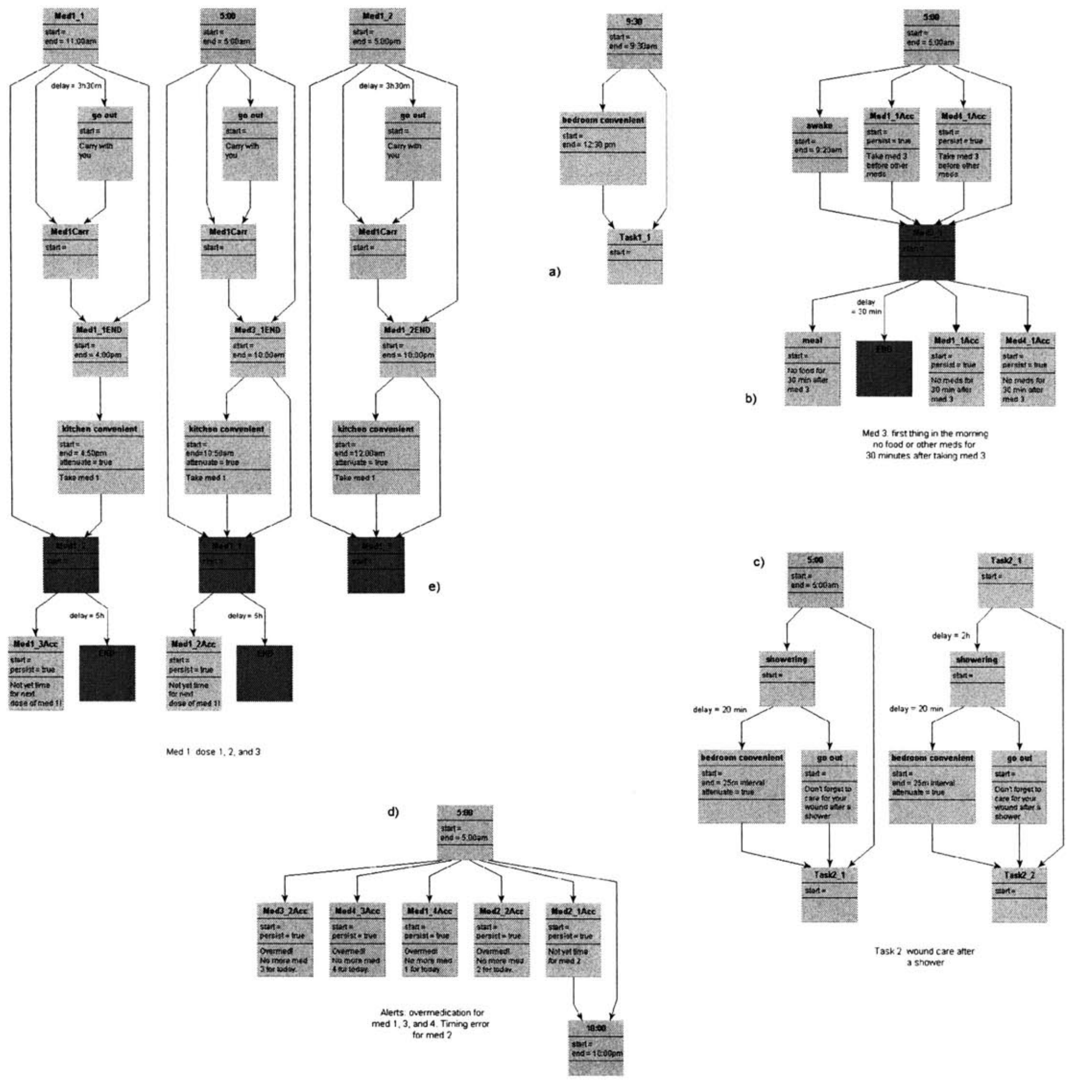


Figure A-3: The 5 graph types used to encode the protocol

- a one-time alert that will not repeat if the event `meal` is detected more than once,
- a set of persisting alerts (upon access of Med 1 and Med 4) that will repeat until `Med3_1` is detected,
- a set of persisting alerts (upon access of Med 1 and Med 4) that will begin after `Med3_1` is detected and repeat until the END node is reached (and all nodes are deactivated), after a delay of 30 minutes.

c) A set of graphs that represent reminders dependent on an event (showering) that could occur more than once. The number of reminders provided depends on the number of times showering occurs. The first graph begins at 5:00 a.m. and ends after the target task (wound care) is completed. The second graph waits 2 hours after the first time the target task is completed, and is ready to provide another reminder if showering is detected again. In the prototype, three such graphs were used per day.

d) A graph that remains active throughout the day, representing alerts for overmedication or timing related nonadherence situations.

e) A set of three reminders, for doses that must be separated by 5 hour intervals. The END node is used in each case, to notify one graph of the end of a previous one. Two of the graphs remain active until the 5 hour interval has been passed, and provide an alert if the next dose is accessed during that time. The nodes `Med3_1END`, `Med1_1END`, and `Med1_2END` which wait for end events from other graphs, have explicit end attributes themselves, because an event leading to the END of a previous graph might not completed; (e.g., a pill is missed).

Appendix B

Participant Instruction Booklet

Introduction to the experiment

More than half of all Americans with chronic diseases do not follow their physician's medication and lifestyle guidance, and **nine out of ten make mistakes** taking their medicines. The risk of poor medication adherence is particularly high among the elderly, who may have onerous pill taking schedules that become harder to stick to with advancing age and memory loss. Patients over 70 take an average of 7 prescription medicines and 3 over-the-counter drugs.

We have developed a medication reminder device that could eventually be integrated into cell phones, although the prototype version runs on a handheld computer called a PDA. (Research shows that many ageing Baby Boomers will continue to use cell phones and PDA's in retirement.)

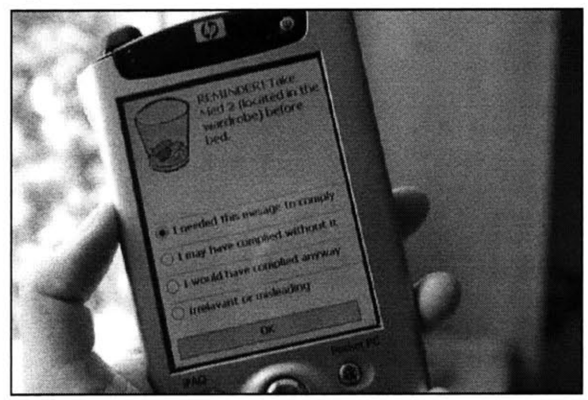
The purpose of this experiment is to evaluate the use of this device for assisting patients with complex medical regimens. As a first step, we are conducting this study with a healthy person. The participant will not consume actual medication, but will perform simulated medication and health tasks.

We would like you to imagine you have a chronic health condition and that you need to take medicines and complete other types of health tasks in a timely manner everyday. These include,

- taking prescription medicines
- testing your blood glucose level
- caring for a wound
- frequently disinfecting your hands
- mild rehabilitation exercise

Your regimen (on the next page) has been developed in consultation with medical professionals, and closely matches that of a real person. Since this is an experiment, we would like you to treat **all tasks** as being **equally important**.

When you are inside the apartment, you will receive reminder messages on the PDA, and you will be asked to rate how useful each message was to you.



PDA - slightly larger than a cell phone

Doctor's instructions

Do your best to complete these medication and health tasks along with the accompanying instructions.

Med 1
Take three times daily, with a glass of water each time. Leave at least 5 hours between doses.

Med 2
Take once daily, before bed.

Med 3
Take once daily, first thing in the morning. No other medicines or food for 30 minutes after taking Med 3.

Med 4
Take two times daily, immediately after breakfast and dinner.

Hand Wash
Wash hands with Purell at least 8 times a day, approximately every 2 hours. Do not use more frequently than once an hour. If you are out for longer than an hour, wash hands when you return to the apartment.

Blood Glucose Test
Test four times a day, about every three hours. The first time should be on an empty stomach in the morning, and you should also test once before dinner. You will be prompted when you begin testing and prompted again when the result is available. Write down the result in the form provided to you.

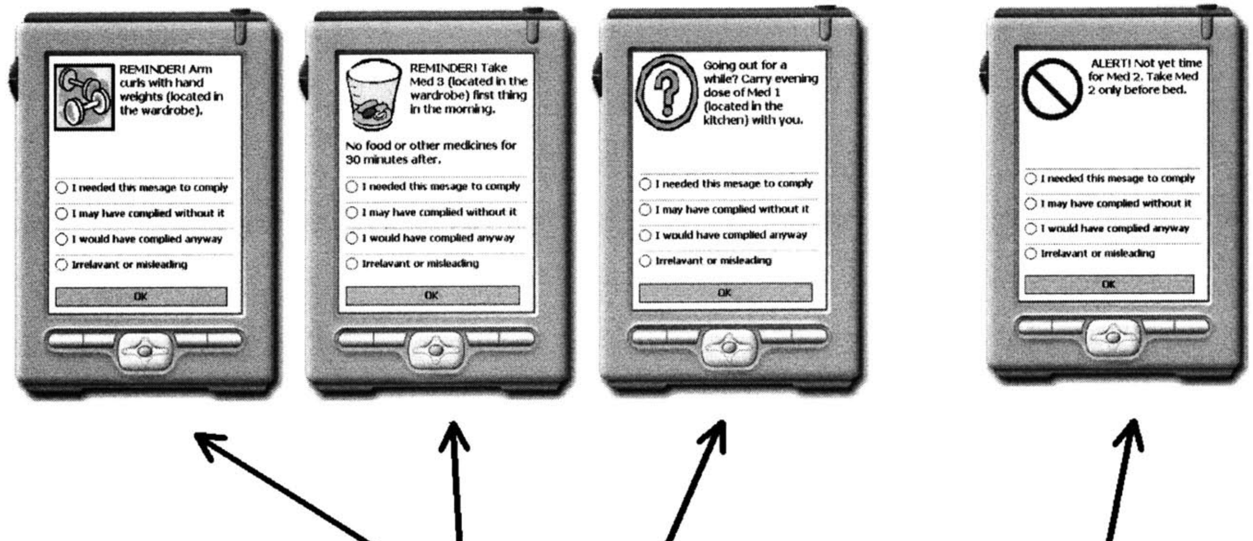
Wound Care
Care for a wound after every time you take a shower and once before bed. You will be prompted to sit still for 3 minutes, and prompted again when 3 minutes are up.

Exercise with Hand Weights
Do about 20 arm curls with the hand weights, four times a day.

NOTE: As part of your health regimen, you may have to make some effort to keep a regular sleeping and meal schedule.

Examples of messages

The number and timing of the messages may vary from day to day.



The PDA will **ring** when it displays a <u>reminder</u> or asks a <u>question</u>.

It may sometimes play a loud **buzz** and deliver an <u>alert</u> about a situation that could lead to breaking one or more of the doctor's instructions.

Rating the messages

Your goal is to evaluate the utility of the different messages you receive in helping you follow the medical regimen on page 2.

You will need to rate every message according to the scale shown below. If none of the choices seem to fit perfectly, pick the option that most closely matches how you feel about the message at the time you receive it. Do not consider previous messages when rating a message.

If you believe that a reminder was essential in keeping you on the proper schedule, because you might have forgotten otherwise, you would respond, "I needed this message to comply"

- ● **I needed this mesage to comply**
- ○ **I may have complied without it**
- ○ **I would have complied anyway**
- ○ **Irrelavant or misleading**

Although the system is trying to be helpful, you could sometimes receive reminders that are inappropriately timed or even misleading. Sometimes, the computer may not be right.

If that happens, you must rate the reminder accordingly, and **complete the task on your own**.

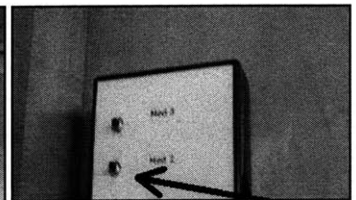
An example of this situation is - You receive a message reminding you to take Med 4 after dinner, but you are not planning to eat dinner for another two hours. In this instance, you would rate the reminder as "Irrelevant or misleading" and then, **remember** on your own **to take Med 4 after dinner**.

- ○ **I needed this mesage to comply**
- ○ **I may have complied without it**
- ○ **I would have complied anyway**
- ● **Irrelavant or misleading**

If you remember a task on your own, and it is convenient, you can complete it before you receive a reminder.

If you receive a reminder for a task that you have already completed, you would rate that instance of the reminder as "Irrelevant or misleading".

Simulated medical and health tasks



All medicines and health tasks (except the exercise) correspond to buttons on two panels located in the kitchen and near the bedroom of the apartment. Each panel has a row of labeled buttons, with each button representing a health task..

To take a medicine or complete a health task, press the black button labeled with the medicine or task name, and hold it down for 10 to 12 seconds until you hear a chime and receive a text acknowledgement on the PDA, telling you that your action has been recorded.

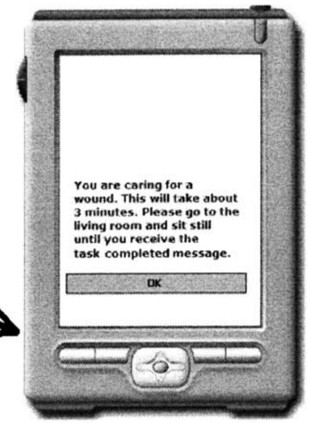
Click 'OK' on the acknowledgement screen.

If you realize you have pressed the wrong button, release it immediately. Releasing a button before the acknowledgement is like "spitting out" a pill.

There is a 3 lb hand weight in the wardrobe, which you must use for the exercise task.

Special cases

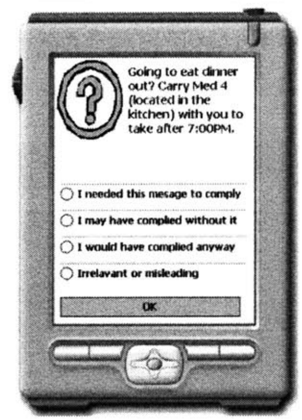
In some cases, the acknowledgement screen will prompt you to complete another step, like washing your hands or sitting still for some time. Follow these instructions.



Med 1 and Med 4 have a **red button** next to the black one. The red button stands for carrying the next dose of the medicine with you when you leave the apartment. If you expect to be outside the apartment for your next dose of Med 1or Med 4, press the corresponding red button **just before** you leave the apartment.

You may receive a reminder to carry a dose with you. Follow this reminder only if you are going to be out for the dose.

For example, you receive this reminder when you are taking trash out at 6:00PM. Since you are going to be back in the apartment soon, you **do not press the red button**.



Instructions for handling the PDA's

Unfortunately, PDA batteries are not yet powerful enough to last for a whole day. To work around this, you will receive reminders on a set of two PDA's working in tandem.

Please **ensure that you are carrying one PDA on you,** and that the other PDA is docked at all times, when it will be charging. There are cradles for docking the PDA's in the bedroom and next to the entry door of the apartment.

What to do when you leave the apartment?
When you leave the apartment, take one PDA with you and leave the other one docked near the entry door.

When you are outside, you may receive a message asking if you have left the apartment. Answer this question appropriately.

What to do at night?
Dock both PDA's before bed.

If the battery charge on the PDA you are carrying becomes low, you will receive a message asking you to swap the PDA. When this happens, dock the PDA you are carrying, and pick up the other one.

Do not keep both PDA's docked at the same time, except when sleeping at night.

Appendix C

Participant's Responses to Daily Routine Questionnaire

Question	Response
When do you wake up? (please provide an approximate time window, considering weekends)	9-10, weekends maybe around noon
Do you usually eat breakfast	Yes
Will you be working outside home during the week? If yes, what hours will you be out?	No plans
For any other reason will you be out at a consistent time every-day?	Go out for lunch
On an average day of the study, how many hours do you expect to spend outside?	1 or 2
When do you eat dinner? (please provide an approximate time window)	6 or 7 (sometimes later)
When do you go to bed? (please provide an approximate time window)	Around midnight. 3-4 on weekends
Does your eating schedule change? How?	Pretty constant
Does your sleeping schedule change? How?	Pretty constant
Will you be able to make the following change to your morning schedule easily: eating breakfast	Yes
Will you be able to make the following change to your morning schedule easily: staying at home for at least one hour after waking up	Yes

Table C.1: Responses to questions asked in the pre-study interview

Appendix D

Annotator Instructions for Adherence

Med 1 (located in the kitchen)

Doctor's Instructions

Take three times daily, with plenty of water, minimum 5 hours between doses.

Checklist for Annotator (please note down time if yes)

1. **Missed Dose:** a) Completed first dose of Med 1 or b) Carried Med 1 along. (yes / no)

2. **Additional Instruction:** If 1a is true, drank a glass of water within 2 minutes of the first dose of Med 1. If 1b is true mark yes. (yes / no)

3. **Missed Dose:** a) Completed second dose of Med 1 or b) Carried Med 1 along. (yes / no)

4. **Additional Instruction:** If 3a is true, drank a glass of water within 2 minutes of the second dose of Med 1. If 3b is true mark yes. (yes / no)

5. **Timing:** If 3a is true, second dose was completed 5 hours after the first dose. If 3b is true mark yes. (yes / no)
6. **Missed Dose:** a) Completed third dose of Med 1 or b) Carried Med 1 along. (yes / no)
7. **Additional Instruction:** If 6a is true, drank a glass of water within 2 minutes of the third dose of Med 1. If 6b is true mark yes. (yes / no)
8. **Timing:** If 6a is true, third dose was completed 5 hours after the second dose. If 6b is true mark yes. (yes / no)
9. **Overmedication:** Did not complete a fourth dose of Med 1. (yes / no)

Med 2 (located in the bedroom)

Doctor's Instructions

Take once daily, before bed.

Checklist for Annotator (please note down time if yes)

1. **Missed Dose:** Completed Med 2 within 30 minutes before going to bed. (yes / no)
2. **Timing:** Before bed. If ambiguous, mark yes. (yes / no)
3. **Overmedication:** Did not complete another dose of Med 2 during the day. (yes / no)

Med 3 (located in the bedroom)

Doctor's Instructions

Take once daily, first thing in the morning. No other medicines or food for 30 minutes after taking Med 3.

Checklist for Annotator (please note down time if yes)

1. **Missed Dose:** Completed Med 3 within 30 minutes of waking. (yes / no)
2. **Interaction:** If 1 is true, did not eat or complete Med 1, 2, or 4 before completing Med 3 or for 30 min after completing Med 3. (yes / no)
3. **Timing:** First thing in the morning. If ambiguous, mark yes. (yes / no)
4. **Overmedication:** Did not complete another Med 3 task after this. (yes / no)

Med 4 (located in the kitchen)

Doctor's Instructions

Take two times daily, immediately after breakfast and dinner.

Checklist for Annotator (please note down time if yes)

1. **Missed Dose:** a) Completed first dose of Med 4 or b) Carried Med 4 along (yes / no)
2. **Timing:** If 1a is true, the dose was completed within 10 minutes of eating breakfast. If 1b is true mark yes. (yes / no)
3. **Missed Dose:** a) Completed second dose of Med 4 or b) Carried Med 4 along (yes / no)
4. **Timing:** If 3a is true, the dose was completed within 10 minutes of eating dinner. If 3b is true mark yes. (yes / no)
5. **Overmedication:** Did not complete another dose of Med 4 during the day. (yes / no)

Disinfectant Hand Wash (located in the kitchen)

Doctor's Instructions

Wash hands with a disinfectant every 1 to 2 hours when at home. Do this 8 times a day.

Checklist for Annotator (please note down time if yes)

1. **Missed Task:** Completed button interaction + washed hands with Purell within 2 hours of waking up. (yes / no)
2. **Missed Task:** Completed button interaction + washed hands with Purell, unless out. (yes / no)
3. **Timing:** If 2 is true, interval was 1 to 2 hours before 1. (yes / no)
4. **Missed Task:** Completed button interaction + washed hands with Purell, unless out. (yes / no)
5. **Timing:** If 4 is true, interval was 1 to 2 hours before 2. (yes / no)
6. **Missed Task:** Completed button interaction + washed hands with Purell, unless out. (yes / no)
7. **Timing:** If 6 is true, interval was 1 to 2 hours before 4. (yes / no)
8. **Missed Task:** Completed button interaction + washed hands with Purell, unless out. (yes / no)
9. **Timing:** If 8 is true, interval was 1 to 2 hours before 6. (yes / no)
10. **Missed Task:** Completed button interaction + washed hands with Purell, unless out. (yes / no)
11. **Timing:** If 10 is true, interval was 1 to 2 hours before 8. (yes / no)
12. **Missed Task:** Completed button interaction + washed hands with Purell, unless out. (yes / no)
13. **Timing:** If 12 is true, interval was 1 to 2 hours before 10. (yes / no)
14. **Missed Task:** Completed button interaction + washed hands with Purell, unless out. (yes / no)

15. **Timing:** If 14 is true, interval was 1 to 2 hours before 12. (yes / no)
16. **Missed Task:** Add as necessary (yes / no)
17. **Timing:** Add as necessary (yes / no)

Blood Glucose Test (located in the kitchen)

Doctor's Instructions

Check four times a day, once on an empty stomach in the morning, once before dinner, and two other times, about 2 to 4 hours apart.

Checklist for Annotator (please note down time if yes)

1. **Missed Task:** Completed Blood Glucose Test button interaction within 20 minutes before breakfast. (yes / no)
2. **Additional Instruction:** Acknowledged Blood Glucose Value after 2 minutes, and recorded it. (yes / no)
3. **Timing:** Before breakfast? (yes / no)
4. **Missed Task:** Completed Blood Glucose Test button interaction within 2 to 4 hours of previous test. (yes / no)
5. **Additional Instruction:** Acknowledged Blood Glucose Value after 2 minutes, and recorded it. (yes / no)
6. **Missed Task:** Completed Blood Glucose Test button interaction within 2 to 4 hours of previous test. (yes / no)
7. **Additional Instruction:** Acknowledged Blood Glucose Value after 2 minutes, and recorded it. (yes / no)
8. **Missed Task:** Completed Blood Glucose Test button interaction within 20 minutes before dinner. (yes / no)

9. **Additional Instruction:** Acknowledged Blood Glucose Value after 2 minutes, and recorded it. (yes / no)
10. **Timing:** One of last two was before dinner? (yes / no)

Wound Care (located in the bedroom)

Doctor's Instructions

Care for your wound after taking a shower and before bed.

Checklist for Annotator (please note down time if yes)

1. **Missed Task:** Completed Wound Care button interaction within 30 minutes of taking a shower. (yes / no)
2. **Additional Instruction:** Sat still for 3 minutes. (yes / no)
3. **Missed Task:** Completed Wound Care button interaction within 30 minutes before going to bed. (yes / no)
4. **Additional Instruction:** Sat still for 3 minutes after this. (yes / no)

Exercise Hand Weights (located in the bedroom)

Doctor's Instructions

Do 12 to 15 arm curls with hand weights, four times a day.

Checklist for Annotator (please note down time if yes)

1. **Missed Task:** Completed exercise (yes / no)
2. **Missed Task:** Completed exercise, distinct from previous time (yes / no)
3. **Missed Task:** Completed exercise, distinct from previous time (yes / no)
4. **Missed Task:** Completed exercise, distinct from previous time (yes / no)

Appendix E

Detailed Results

Task	Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10
sleep	1:11	2:39	2:10	2:30	1:52	1:25	5:07	6:16	6:23	2:30
wake	8:35	9:35	9:23	8:18	5:53	9:39	12:23	11:06	12:15	12:03
out	19:24	10:51	15:59	10:58		18:58	12:51	17:14	16:27	19:22
back	21:31	16:56	16:14	15:34		19:43	18:06	19:07	20:40	20:39
med 3	9:04	9:39	9:24	7:39	4:54	9:40	5:02		4:50	4:17
med 1	9:37	10:44	9:58	8:29	7:35	10:50	*12:25*	4:50	4:54	4:13
med 1	14:27	17:03	15:03	10:54	13:06	16:16	18:10	11:13	12:55	12:13
med 1	19:20	23:01	20:17	19:54	18:34	21:31		16:35	16:24	17:32
med 1									22:03	22:45
med 4	9:41	10:46	10:15	8:59	7:36	11:53		4:59	5:57	4:14
med 4	18:18	19:35	18:15	18:12	17:04	18:05	20:30	17:10	16:25	19:17
blood test	9:03	9:39	9:25	7:39	4:55	9:44	9:41	4:50	4:56	4:14
blood test	11:19	17:00	11:27	10:48	8:47	12:05	12:16	11:14	12:29	12:09
blood test	14:36	19:04	14:54	17:38	12:27	15:20	18:11	14:07	15:07	14:31
blood test	17:47	20:11	17:35	15:36	16:27	18:18		17:04	20:43	17:15
blood test										20:42
blood test										2:45

Continued on next page

Task	Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10
hand wash	9:07	9:45	9:50	7:44	6:03	9:41	12:24	11:13	4:55	12:08
hand wash	10:46		11:26	9:01	8:44	11:01		12:53	5:15	13:16
hand wash	12:26		13:02	10:30	10:20	12:04		13:03	12:25	14:32
hand wash	14:32	16:56	14:04		12:06	13:03	18:07	14:07	13:46	15:46
hand wash	17:47	19:03	14:58		13:34	14:32	19:18	15:11	15:06	17:13
hand wash	19:05	20:16	16:14	15:33	15:01	15:18	20:33	16:11	16:17	18:08
hand wash	21:31	22:48	17:35	16:54	16:23	16:15	21:53	17:03	20:42	19:21
hand wash	0:06	0:00	18:54	18:45	17:43	17:23	23:01	19:07	22:03	20:39
hand wash			20:18	19:49	18:32	18:11	0:23	20:06	23:13	22:02
hand wash			21:38	21:07	20:14	19:43	1:11	21:07	0:47	22:45
hand wash				22:19	21:21	21:29	2:11	22:18	2:06	0:06
hand wash				23:37	22:43	22:55		23:13		1:10
hand wash					23:37	0:05		0:04		2:57
hand wash					0:44	1:03		1:20		
hand wash						2:06		2:10		
hand wash						2:57				
hand wash						4:48				
exercise	12:33	9:43	9:47	7:43	6:01	9:47	9:41	11:12	4:53	12:07
exercise	14:31	16:59	10:34	8:57	7:22	10:59	12:23	12:32	5:20	13:14
exercise	16:12	19:02	11:25	10:28	8:42	11:53	18:06	14:06	12:25	15:46
exercise	18:20	19:38	11:49	15:35	10:18	13:02	19:16	15:10	13:45	17:13
exercise	21:42	20:14	13:10	16:52	11:13	14:30	20:32	16:08	15:05	18:07
exercise	23:02	22:45	14:53	19:47	12:03	15:17	2:25	17:02	16:15	19:11
exercise		23:56	15:54	21:05	13:27	16:14	22:16	19:10	20:40	21:41
exercise			17:11	22:07	14:28	17:22	23:00	20:05	22:01	22:01
exercise			18:44		16:21	18:02	1:06	21:07	23:12	22:47
exercise			19:43		17:42	18:18	2:05	23:12	0:46	1:09
exercise			20:58		18:30	19:45		0:02	2:06	2:57

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Task	Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10
exercise			21:36		20:13	21:28		1:18		
exercise					21:20	22:50		2:04		
exercise					22:31	0:04				
exercise					23:35	1:02				
exercise					0:31	2:06				
med 2	2:22	1:45	2:20	1:36	1:10	4:27	3:18	4:03	3:26	2:31
wound care	2:22	1:49	2:24	1:40	1:16	4:27	3:20	4:08	3:31	2:36

Table E.1: Raw Data: Task completion times

Date		Time		Time	Task	Interval(minutes)
20-Jul-05	REM	9:32:01	TASK	9:43:13	armcurls	11.2
20-Jul-05	REM	13:01:01	TASK	16:59:45	armcurls	238.7333333
20-Jul-05	REM	17:31:01	TASK	19:02:25	armcurls	91.4
20-Jul-05	REM	22:00:01	TASK	22:45:38	armcurls	45.61666667
22-Jul-05	REM	9:32:01	TASK	10:28:21	armcurls	56.33333333
22-Jul-05	REM	13:01:01	TASK	15:35:31	armcurls	154.5
22-Jul-05	REM	17:31:01	TASK	18:41:34	armcurls	70.55
22-Jul-05	REM	22:00:00	TASK	22:07:45	armcurls	7.75
24-Jul-05	REM	9:32:01	TASK	9:47:13	armcurls	15.2
24-Jul-05	REM	13:01:01	TASK	13:02:55	armcurls	1.9
24-Jul-05	REM	17:31:00	TASK	18:02:40	armcurls	31.66666667
24-Jul-05	REM	22:00:00	TASK	22:55:01	armcurls	55.01666667
26-Jul-05	REM	9:32:00	TASK	11:12:21	armcurls	100.35
26-Jul-05	REM	13:01:00	TASK	13:02:01	armcurls	1.016666667
26-Jul-05	REM	17:31:00	TASK	19:10:44	armcurls	99.73333333
26-Jul-05	REM	22:00:00	TASK	23:12:06	armcurls	72.1

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Date		Time		Time	Task	Interval(minutes)
28-Jul-05	REM	9:31:59	TASK	12:07:03	armcurls	155.0666667
28-Jul-05	REM	13:01:00	TASK	13:14:56	armcurls	13.93333333
28-Jul-05	REM	17:31:07	TASK	18:07:40	armcurls	36.55
28-Jul-05	REM	22:00:06	TASK	22:01:41	armcurls	1.583333333
20-Jul-05	REM	9:31:01	TASK	9:39:36	bloodtest	8.583333333
20-Jul-05	REM	12:30:01	TASK	17:00:51	bloodtest	270.8333333
20-Jul-05	REM	15:30:01	TASK	19:04:51	bloodtest	214.8333333
20-Jul-05	REM	18:31:01	TASK	20:11:03	bloodtest	100.0333333
22-Jul-05	REM	9:31:01	TASK	7:39:31	bloodtest	-111.5
22-Jul-05	REM	12:30:01	TASK	10:48:01	bloodtest	-102
22-Jul-05	REM	15:30:01	TASK	15:36:57	bloodtest	6.933333333
22-Jul-05	REM	18:31:01	TASK	17:38:40	bloodtest	-52.35
24-Jul-05	REM	9:31:01	TASK	9:44:14	bloodtest	13.21666667
24-Jul-05	REM	12:30:01	TASK	12:05:05	bloodtest	-24.9333333
24-Jul-05	REM	15:30:01	TASK	15:20:07	bloodtest	-9.9
24-Jul-05	REM	18:31:00	TASK	4:50:49	bloodtest	-820.1833333
26-Jul-05	REM	9:31:01	TASK	4:56:21	bloodtest	-274.6666667
26-Jul-05	REM	12:30:01	TASK	11:14:32	bloodtest	-75.48333333
26-Jul-05	REM	15:30:01	TASK	14:07:57	bloodtest	-82.06666667
26-Jul-05	REM	18:31:00	TASK	17:04:00	bloodtest	-87
28-Jul-05	REM	9:31:00	TASK	12:09:24	bloodtest	158.4
28-Jul-05	REM	12:30:01	TASK	14:31:41	bloodtest	121.6666667
28-Jul-05	REM	15:30:07	TASK	17:15:20	bloodtest	105.2166667
28-Jul-05	REM	18:31:07	TASK	20:42:13	bloodtest	131.1
20-Jul-05	REM	10:00:00	TASK	10:44:25	Med 1	44.41666667
20-Jul-05	REM	16:00:01	TASK	17:03:18	Med 1	63.28333333
21-Jul-05	REM	23:00:00	TASK	23:01:45	Med 1	1.75
22-Jul-05	REM	10:00:01	TASK	8:29:16	Med 1	-90.75

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Date		Time		Time	Task	Interval(minutes)
22-Jul-05	REM	16:00:11	TASK	10:54:47	Med 1	-305.4
23-Jul-05	REM	23:00:01	TASK	19:54:52	Med 1	-185.15
24-Jul-05	REM	10:00:06	TASK	10:50:00	Med 1	49.9
24-Jul-05	REM	16:00:06	TASK	16:16:43	Med 1	16.61666667
25-Jul-05	REM	23:00:06	TASK	21:31:03	Med 1	-89.05
26-Jul-05	REM	10:00:01	TASK	4:54:44	Med 1	-305.2833333
26-Jul-05	REM	16:00:01	TASK	11:13:46	Med 1	-286.25
27-Jul-05	REM	23:00:01	TASK	16:35:45	Med 1	-384.2666667
28-Jul-05	REM	10:00:01	TASK	22:03:24	Med 1	723.3833333
28-Jul-05	REM	16:00:08	TASK	12:13:47	Med 1	-226.35
29-Jul-05	REM	23:00:08	TASK	17:32:57	Med 1	-327.1833333
21-Jul-05	REM	23:01:00	TASK	1:45:03	Med 2	164.0333333
23-Jul-05	REM	23:01:01	TASK	1:36:21	Med 2	155.3166667
25-Jul-05	REM	23:01:06	TASK	4:27:05	Med 2	325.9666667
27-Jul-05	REM	23:01:01	TASK	4:03:46	Med 2	302.7333333
29-Jul-05	REM	23:01:08	TASK	2:31:39	Med 2	210.5
20-Jul-05	REM	9:30:01	TASK	13:40:05	Med 3	250.0666667
22-Jul-05	REM	9:30:01	TASK	9:24:47	Med 3	-5.233333333
24-Jul-05	REM	9:30:01	TASK	5:54:54	Med 3	-215.1166667
26-Jul-05	REM	9:30:06	TASK	5:02:14	Med 3	-267.8666667
28-Jul-05	REM	9:30:06	TASK	4:17:45	Med 3	-312.35
20-Jul-05	REM	10:02:00	TASK	10:46:19	Med 4	44.31666667
20-Jul-05	REM	18:30:01	TASK	19:35:47	Med 4	65.76666667
22-Jul-05	REM	10:02:01	TASK	8:56:33	Med 4	-65.46666667
22-Jul-05	REM	18:30:01	TASK	18:12:29	Med 4	-17.53333333
24-Jul-05	REM	10:02:00	TASK	11:53:02	Med 4	111.0333333
24-Jul-05	REM	18:30:00	TASK	18:55:08	Med 4	25.13333333
26-Jul-05	REM	10:02:06	TASK	5:50:55	Med 4	-251.1833333

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Date		Time		Time	Task	Interval(minutes)
26-Jul-05	REM	18:30:00	TASK	17:10:16	Med 4	-79.73333333
28-Jul-05	REM	10:02:01	TASK	12:30:40	Med 4	148.65
28-Jul-05	REM	18:30:08	TASK	19:17:35	Med 4	47.45
20-Jul-05	REM	10:01:01	TASK	9:45:29	wash	-15.53333333
20-Jul-05	REM	14:30:01	TASK	16:56:15	wash	146.2333333
20-Jul-05	REM	19:00:01	TASK	19:03:51	wash	3.833333333
20-Jul-05	REM	20:30:01	TASK	20:16:18	wash	-13.71666667
22-Jul-05	REM	10:01:01	TASK	10:30:01	wash	29
22-Jul-05	REM	11:30:01	TASK	16:54:05	wash	324.0666667
22-Jul-05	REM	13:00:01	TASK	18:45:36	wash	345.5833333
22-Jul-05	REM	17:30:01	TASK	19:49:52	wash	139.85
22-Jul-05	REM	19:00:01	TASK	21:07:46	wash	127.75
22-Jul-05	REM	20:30:01	TASK	22:19:31	wash	109.5
24-Jul-05	REM	10:01:00	TASK	9:41:00	wash	-20
24-Jul-05	REM	11:30:00	TASK	12:04:02	wash	34.03333333
24-Jul-05	REM	13:00:01	TASK	13:03:15	wash	3.233333333
24-Jul-05	REM	14:30:01	TASK	14:32:29	wash	2.466666667
24-Jul-05	REM	16:01:00	TASK	16:15:21	wash	14.35
24-Jul-05	REM	17:30:00	TASK	18:11:22	wash	41.36666667
24-Jul-05	REM	19:00:00	TASK	19:43:29	wash	43.48333333
24-Jul-05	REM	20:30:00	TASK	21:29:04	wash	59.06666667
26-Jul-05	REM	10:01:01	TASK	11:13:19	wash	72.3
26-Jul-05	REM	11:30:00	TASK	12:53:00	wash	83
26-Jul-05	REM	12:59:59	TASK	13:01:16	wash	1.283333333
26-Jul-05	REM	14:30:01	TASK	15:11:11	wash	41.16666667
26-Jul-05	REM	16:00:59	TASK	16:11:01	wash	10.03333333
26-Jul-05	REM	17:30:00	TASK	17:03:05	wash	-26.91666667
26-Jul-05	REM	19:00:00	TASK	19:07:03	wash	7.05

Continued on next page

Date		Time		Time	Task	Interval(minutes)
26-Jul-05	REM	20:30:01	TASK	20:06:30	wash	-23.51666667
28-Jul-05	REM	10:01:06	TASK	12:08:31	wash	127.4166667
28-Jul-05	REM	11:30:06	TASK	13:16:01	wash	105.9166667
28-Jul-05	REM	13:00:06	TASK	14:32:04	wash	91.96666667
28-Jul-05	REM	14:30:07	TASK	15:46:44	wash	76.61666667
28-Jul-05	REM	16:01:06	TASK	17:13:52	wash	72.76666667
28-Jul-05	REM	17:30:07	TASK	18:08:42	wash	38.58333333
28-Jul-05	REM	19:00:06	TASK	19:12:21	wash	12.25
28-Jul-05	REM	20:30:07	TASK	20:39:32	wash	9.416666667
20-Jul-05	REM	22:59:01	TASK	1:45:24	woundcare	166.3666667
22-Jul-05	REM	22:59:01	TASK	1:39:07	woundcare	160.0833333
24-Jul-05	REM	22:59:01	TASK	4:27:49	woundcare	328.7833333
26-Jul-05	REM	22:58:59	TASK	3:20:22	woundcare	261.3666667
28-Jul-05	REM	22:59:06	TASK	3:27:24	woundcare	268.2833333

Table E.3: Raw Data: reminder to task intervals for fixed-time reminders

Date		Time		Time	Task	Interval(minutes)
19-Jul-05	REM	12:31:34	TASK	12:33:43	armcurls	2.15
19-Jul-05	REM	16:09:31	TASK	16:12:00	armcurls	2.483333333
19-Jul-05	REM	21:34:36	TASK	21:42:08	armcurls	7.533333333
21-Jul-05	REM	9:56:02	TASK	10:34:14	armcurls	38.2
21-Jul-05	REM	11:47:22	TASK	11:49:37	armcurls	2.25
21-Jul-05	REM	15:53:00	TASK	15:54:05	armcurls	1.083333333
21-Jul-05	REM	19:42:17	TASK	23:56:29	armcurls	254.2
23-Jul-05	REM	10:13:58	TASK	10:18:14	armcurls	4.266666667
23-Jul-05	REM	12:02:31	TASK	12:03:40	armcurls	1.15

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Date		Time		Time	Task	Interval(minutes)
23-Jul-05	REM	16:20:57	TASK	16:22:42	armcurls	1.75
23-Jul-05	REM	20:11:56	TASK	20:13:17	armcurls	1.35
25-Jul-05	REM	9:39:27	TASK	9:41:21	armcurls	1.9
25-Jul-05	REM	19:48:58	TASK	20:32:33	armcurls	43.58333333
27-Jul-05	REM	10:30:00	TASK	5:20:02	armcurls	-309.9666667
27-Jul-05	REM	12:20:38	TASK	12:25:26	armcurls	4.8
19-Jul-05	REM	9:01:21	TASK	9:01:21	bloodtest	0
19-Jul-05	REM	11:18:20	TASK	11:18:20	bloodtest	0
19-Jul-05	REM	12:50:46	TASK	14:34:28	bloodtest	103.7
19-Jul-05	REM	17:36:22	TASK	17:43:29	bloodtest	7.116666667
21-Jul-05	REM	9:25:21	TASK	9:25:21	bloodtest	0
21-Jul-05	REM	11:26:20	TASK	11:27:47	bloodtest	1.45
21-Jul-05	REM	13:47:27	TASK	14:54:08	bloodtest	66.68333333
21-Jul-05	REM	17:34:23	TASK	17:35:53	bloodtest	1.5
23-Jul-05	REM	6:02:04	TASK	5:55:31	bloodtest	-6.55
23-Jul-05	REM	8:44:11	TASK	8:45:27	bloodtest	1.266666667
23-Jul-05	REM	11:14:46	TASK	12:27:32	bloodtest	72.76666667
23-Jul-05	REM	14:29:12	TASK	16:27:31	bloodtest	118.3166667
25-Jul-05	REM	8:37:07	TASK	9:41:47	bloodtest	64.66666667
25-Jul-05	REM	9:42:02	TASK	9:43:08	bloodtest	1.1
25-Jul-05	REM	12:23:47	TASK	12:26:05	bloodtest	2.3
25-Jul-05	REM	12:23:52	TASK	18:11:00	bloodtest	347.1333333
27-Jul-05	REM	5:07:18	TASK	4:14:43	bloodtest	-52.58333333
27-Jul-05	REM	12:45:59	TASK	12:29:07	bloodtest	-16.86666667
27-Jul-05	REM	18:09:18	TASK	15:07:36	bloodtest	-181.7
27-Jul-05	REM	20:42:20	TASK	20:43:42	bloodtest	1.366666667
19-Jul-05	REM	9:36:55	TASK	9:37:27	Med 1	0.533333333
19-Jul-05	REM	16:50:01	TASK	14:27:35	Med 1	-142.4333333

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Date		Time		Time	Task	Interval(minutes)
19-Jul-05	REM	22:49:02	TASK	19:20:44	Med 1	-208.3
21-Jul-05	REM	9:57:27	TASK	9:58:42	Med 1	1.25
21-Jul-05	REM	15:06:38	TASK	15:06:53	Med 1	0.25
21-Jul-05	REM	20:16:17	TASK	20:17:00	Med 1	0.716666667
23-Jul-05	REM	7:35:29	TASK	7:35:29	Med 1	0
23-Jul-05	REM	13:04:46	TASK	13:06:10	Med 1	1.4
23-Jul-05	REM	18:31:41	TASK	18:34:28	Med 1	2.783333333
25-Jul-05	REM	9:41:52	TASK	4:50:12	Med 1	-291.6666667
25-Jul-05	REM	16:47:18	TASK	12:25:39	Med 1	-261.65
25-Jul-05	REM	22:45:38	TASK	18:10:19	Med 1	-275.3166667
27-Jul-05	REM	10:50:00	TASK	4:13:57	Med 1	-396.05
27-Jul-05	REM	16:16:21	TASK	12:55:03	Med 1	-201.3
27-Jul-05	REM	22:02:22	TASK	16:24:21	Med 1	-338.0166667
19-Jul-05	REM	22:48:47	TASK	2:22:39	Med 2	213.85
21-Jul-05	REM	22:00:39	TASK	2:20:00	Med 2	259.3333333
23-Jul-05	REM	22:29:57	TASK	1:10:20	Med 2	160.3666667
25-Jul-05	REM	22:14:38	TASK	3:18:23	Med 2	303.7333333
27-Jul-05	REM	22:06:38	TASK	3:26:35	Med 2	319.9333333
19-Jul-05	REM	8:35:58	TASK	9:04:11	Med 3	28.21666667
21-Jul-05	REM	9:20:01	TASK	9:39:10	Med 3	19.15
23-Jul-05	REM	6:00:01	TASK	7:39:01	Med 3	99
25-Jul-05	REM	5:00:49	TASK	9:40:56	Med 3	280.1166667
27-Jul-05	REM	5:06:07	TASK	4:50:30	Med 3	-15.61666667
19-Jul-05	REM	9:37:00	TASK	9:41:11	Med 4	4.183333333
19-Jul-05	REM	20:30:01	TASK	18:18:17	Med 4	-131.7333333
21-Jul-05	REM	9:57:32	TASK	10:15:41	Med 4	18.15
21-Jul-05	REM	18:10:41	TASK	18:15:01	Med 4	4.333333333
23-Jul-05	REM	11:14:41	TASK	7:36:53	Med 4	-217.8

Continued on next page

Date		Time		Time	Task	Interval(minutes)
23-Jul-05	REM	17:03:47	TASK	17:04:00	Med 4	0.216666667
25-Jul-05	REM	12:23:42	TASK	4:59:05	Med 4	-444.6166667
25-Jul-05	REM	18:07:22	TASK	20:30:13	Med 4	142.85
27-Jul-05	REM	12:23:50	TASK	5:57:53	Med 4	-385.95
27-Jul-05	REM	20:30:01	TASK	16:25:22	Med 4	-244.65
19-Jul-05	REM	9:06:38	TASK	9:07:00	wash	0.366666667
19-Jul-05	REM	10:44:35	TASK	10:46:52	wash	2.283333333
19-Jul-05	REM	16:10:03	TASK	14:32:46	wash	-97.28333333
19-Jul-05	REM	17:46:27	TASK	17:47:06	wash	0.65
19-Jul-05	REM	20:21:23	TASK	19:05:06	wash	-76.28333333
19-Jul-05	REM	21:31:24	TASK	21:32:37	wash	1.216666667
20-Jul-05	REM	23:37:22	TASK	0:06:10	wash	29
21-Jul-05	REM	9:49:50	TASK	9:50:07	wash	0.283333333
21-Jul-05	REM	11:19:07	TASK	11:26:51	wash	7.733333333
21-Jul-05	REM	13:04:59	TASK	13:12:35	wash	7.6
21-Jul-05	REM	14:04:53	TASK	14:04:53	wash	0
21-Jul-05	REM	15:57:48	TASK	16:14:03	wash	16.25
21-Jul-05	REM	17:34:18	TASK	17:35:05	wash	0.783333333
21-Jul-05	REM	18:54:35	TASK	18:54:35	wash	0
21-Jul-05	REM	20:15:01	TASK	20:18:34	wash	3.55
21-Jul-05	REM	21:38:09	TASK	21:38:47	wash	0.633333333
22-Jul-05	REM	23:31:09	TASK	23:02:50	wash	-28.31666667
23-Jul-05	REM	6:01:59	TASK	6:03:15	wash	1.266666667
23-Jul-05	REM	7:05:31	TASK	7:24:05	wash	18.56666667
23-Jul-05	REM	8:44:06	TASK	8:44:58	wash	0.866666667
23-Jul-05	REM	10:19:48	TASK	10:20:14	wash	0.433333333
23-Jul-05	REM	11:48:36	TASK	12:06:22	wash	17.76666667
23-Jul-05	REM	13:08:36	TASK	13:34:45	wash	26.15

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Date		Time		Time	Task	Interval(minutes)
23-Jul-05	REM	15:01:27	TASK	15:01:54	wash	0.45
23-Jul-05	REM	16:22:49	TASK	16:23:24	wash	0.583333333
25-Jul-05	REM	9:41:57	TASK	4:48:46	wash	-293.1833333
25-Jul-05	REM	12:20:00	TASK	12:24:46	wash	4.766666667
25-Jul-05	REM	15:30:01	TASK	18:07:51	wash	157.8333333
25-Jul-05	REM	18:07:27	TASK	19:18:21	wash	70.9
25-Jul-05	REM	19:50:21	TASK	20:33:18	wash	42.95
25-Jul-05	REM	21:53:01	TASK	21:53:35	wash	0.566666667
26-Jul-05	REM	23:00:49	TASK	23:01:30	wash	0.683333333
27-Jul-05	REM	5:08:47	TASK	5:15:03	wash	6.266666667
27-Jul-05	REM	6:45:01	TASK	12:25:50	wash	340.8166667
27-Jul-05	REM	13:45:50	TASK	13:46:19	wash	0.483333333
27-Jul-05	REM	15:05:58	TASK	15:06:34	wash	0.6
27-Jul-05	REM	16:16:26	TASK	16:17:28	wash	1.033333333
27-Jul-05	REM	18:07:18	TASK	20:42:57	wash	155.65
27-Jul-05	REM	22:02:27	TASK	22:03:52	wash	1.416666667
20-Jul-05	REM	2:09:22	TASK	2:22:58	woundcare	13.6
22-Jul-05	REM	1:40:38	TASK	2:20:20	woundcare	39.7
23-Jul-05	REM	22:30:02	TASK	1:11:10	woundcare	161.1166667
25-Jul-05	REM	22:14:43	TASK	4:43:00	woundcare	388.2666667
28-Jul-05	REM	3:25:53	TASK	4:04:47	woundcare	38.9

Table E.4: Raw Data: reminder to task intervals for context-sensitive reminders

Reminder	Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10
sleep	1:11	2:39	2:10	2:30	1:52	1:25	5:07	6:16	6:23	2:30
wake	8:35	9:35	9:23	8:18	5:53	9:39	12:23	11:06	12:15	12:03
out	19:24	10:51	15:59	10:58		18:58	12:51	17:14	16:27	19:22
back	21:31	16:56	16:14	15:34		19:43	18:06	19:07	20:40	20:39
med 3	8:35	9:30	9:20	9:30	5:00	9:30	5:00	9:30	5:06	9:30
med 1	9:36	10:00	9:57	10:00		10:00	9:41	10:00	10:50	10:00
med 1	16:50	16:00	15:06	16:00	13:04	16:00	16:47	16:00	16:16	16:00
med 1	22:49	23:00	20:16	23:00	18:31	23:00	22:45	23:00	22:02	23:00
med 4	9:37	10:02	9:57	10:02	11:14	10:02	12:23	10:02	12:23	10:02
med 4	20:30	18:30	18:10	18:30	17:03	18:30	18:07	18:30	20:30	18:30
blood test	9:01	9:31	11:26	9:31	6:02	9:31	8:37	9:31	5:07	9:31
blood test	11:18	12:30	13:47	12:30	8:44	12:30	9:42	12:30	12:45	12:30
blood test	12:50	15:30	17:34	15:30	11:14	15:30	12:23	15:30	18:09	15:30
blood test	17:36	18:31		18:31	14:29	18:31	12:23	18:31	20:42	18:31
hand wash	9:06	10:01	9:49	10:01	6:01	10:01	9:41	10:01	5:08	10:01
hand wash	10:44	11:30	11:19	11:30	7:05	11:30	12:20	11:30	6:45	11:30
hand wash	16:10	12:59	13:04	12:59	8:44	12:59	15:30	12:59	13:45	12:59
hand wash	17:46	14:30	15:57	14:30	10:19	14:30	18:07	14:30	15:05	14:30
hand wash	20:21	16:00	17:34	16:00	11:48	16:00	19:50	16:00	16:16	16:00
hand wash	21:31	17:30	20:15	17:30	13:08	17:30	21:53	17:30	18:07	17:30
hand wash	23:37	19:00	21:38	19:00	15:01	19:00	23:00	19:00	22:02	19:00
hand wash		20:30		20:30	16:22	20:30		20:30		20:30
exercise	12:31	9:32	9:56	9:32	10:13	9:32	9:39	9:32	10:30	9:32
exercise	16:09	13:01	11:47	13:01	12:02	13:01	19:48	13:01	12:20	13:01
exercise	21:34	17:31	15:53	17:31	16:20	17:31		17:31		17:31
exercise		22:00	19:42	22:00	20:11	22:00		22:00		22:00
med 2	22:48	23:01	22:00	23:01	22:29	23:01	22:14	23:01	22:06	23:01
wound care	2:09	22:59	1:40	22:59	22:30	22:59	22:14	22:59	3:25	22:59

Table E.2: Raw Data: reminder reception times

	Fixed-Time Reminders	Context-Sensitive Reminders
Mean	103.66	53.86
Variance	13215.86	9274.61
Observations	82	85
SD	114.96	96.30
P two-tail	0.0028	
t Critical two-tail	1.97	

Table E.5: t-Test: two sample assuming unequal variance (positive time intervals between reminder reception and task execution)

Appendix F

List of Sensors Used

Sensor ID	Type	Description
1200000022B43312Y	1WireSwitch	Kitchen upper island rightmost cabinet right door
1200000022B43312Z	1WireSwitch	Kitchen upper island rightmost cabinet left door
1500000022CFF412Y	1WireSwitch	Kitchen refrigerator freezer door (left)
1500000022CFF412Z	1WireSwitch	Kitchen refrigerator fridge door (right)
1600000022B41512Y	1WireSwitch	Dining room upper island leftmost cabinet right door
1600000022B41512Z	1WireSwitch	Dining room upper island leftmost cabinet left door
180000002239F512Z	1WireSwitch	Dining room light box cabinet left door upper
2000000022C17812Y	1WireSwitch	Bedroom window sideyard left
2000000022C17812Z	1WireSwitch	Bedroom window sideyard right
2400000022B3F812Z	1WireSwitch	Kitchen stove counter rightmost cabinet door
29000000222E0712Y	1WireSwitch	Kitchen stove oven drawer
29000000222E0712Z	1WireSwitch	Kitchen stove oven door
2D00000022BBF912Y	1WireSwitch	Kitchen tall cabinet door
2E00000022CDAD12Z	1WireSwitch	Office desk drawers top drawer
2F00000022B46D12Y	1WireSwitch	Hallway master suite door

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Sensor ID	Type	Description
350000002233C912Z	1WireSwitch	Kitchen spice cabinet door
3700000022B4B912Z	1WireSwitch	Hallway entrance front door
4700000022408612Y	1WireSwitch	Kitchen stove counter drawers bottom drawer
4700000022408612Z	1WireSwitch	Kitchen refrigerator inside fridge top interior drawer
49000000224B1C12Z	1WireSwitch	Living room corner closet door
4B000000222E6F12Y	1WireSwitch	Kitchen lower island dishwasher door
4E00000022B3DC12Z	1WireSwitch	Hallway island pantry right door
4E00000022B3DC12Y	1WireSwitch	Hallway island pantry left door
5300000022C47012Z	1WireSwitch	Dining room window
5C00000022B41812Y	1WireSwitch	Kitchen refrigerator water dispenser
5C00000022B41812Z	1WireSwitch	Kitchen refrigerator ice dispenser
6800000022C35412Y	1WireSwitch	Office window
6E00000022C15312Y	1WireSwitch	Bedroom wardrobe right door
6E00000022C15312Z	1WireSwitch	Bedroom wardrobe left door
7D0000002228BD12Z	1WireSwitch	Living room sliding door to yard
7E00000022B42212Y	1WireSwitch	Living room coat closet left door
7E00000022B42212Z	1WireSwitch	Living room coat closet right door
8700000022B3E312Y	1WireSwitch	Office desk drawers bottom drawer
8700000022B3E312Z	1WireSwitch	Office desk drawers middle drawer
9000000022242112Z	1WireSwitch	Kitchen microwave cabinets right cabinet door
9000000022242112Y	1WireSwitch	Kitchen microwave cabinets left cabinet door
9E00000022B94812Y	1WireSwitch	Hallway laundry closet left door
9E00000022B94812Z	1WireSwitch	Hallway laundry closet right door
A00000002258A812Y	1WireSwitch	Dining room upper island center cabinet right door
A00000002258A812Z	1WireSwitch	Dining room upper island center cabinet left door
A300000022583E12Z	1WireSwitch	Kitchen lower island rightmost cabinet left door
A300000022583E12Y	1WireSwitch	Kitchen lower island rightmost cabinet right door

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Sensor ID	Type	Description
A300000022B3EC12Y	1WireSwitch	Bedroom window rearyard right
A300000022B3EC12Z	1WireSwitch	Bedroom window rearyard left
A4000000223AA112Y	1WireSwitch	Bedroom side closet door
A800000022B47912Z	1WireSwitch	Kitchen stove burner knobs left rear
A800000022B47912Y	1WireSwitch	Kitchen stove burner knobs left front
AA00000022B46A12Y	1WireSwitch	Bedroom door to master bath
B000000022B4AD12Y	1WireSwitch	Kitchen upper island center cabinet right door
B000000022B4AD12Z	1WireSwitch	Kitchen upper island center cabinet left door
B2000000224CCE12Z	1WireSwitch	Living room window left
B400000022CFFC12Y	1WireSwitch	Dining room light box cabinet right door lower
B400000022CFFC12Z	1WireSwitch	Dining room light box cabinet left door lower
B7000000222D6912Y	1WireSwitch	Kitchen refrigerator inside fridge middle interior drawer
B7000000222D6912Z	1WireSwitch	Kitchen refrigerator inside fridge bottom interior drawer
C800000022B40212Z	1WireSwitch	Kitchen microwave microwave door
D600000022B3AC12Y	1WireSwitch	Hallway office storage cabinet right door
D600000022B3AC12Z	1WireSwitch	Hallway office storage cabinet left door
DA00000022C35212Y	1WireSwitch	Dining room upper island rightmost cabinet right door
DA00000022C35212Z	1WireSwitch	Dining room upper island rightmost cabinet left door
DD000000222F7F12Y	1WireSwitch	Kitchen stove counter drawers middle drawer
DD000000222F7F12Z	1WireSwitch	Kitchen stove counter drawers top drawer
E300000022B3BE12Y	1WireSwitch	Hallway utility closet door
E300000022B3BE12Z	1WireSwitch	Hallway powder room door
E6000000224B6D12Y	1WireSwitch	Kitchen lower island cabinet under sink right door
E6000000224B6D12Z	1WireSwitch	Kitchen lower island cabinet under sink left door

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Sensor ID	Type	Description
F400000022A45012Y	1WireSwitch	Hallway stove pantry left door
F400000022A45012Z	1WireSwitch	Hallway stove pantry right door
FB000000222B0712Y	1WireSwitch	Kitchen stove burner knobs right rear
FB000000222B0712Z	1WireSwitch	Kitchen stove burner knobs right front
FB00000022B42512Y	1WireSwitch	Kitchen upper island leftmost cabinet right door
FB00000022B42512Z	1WireSwitch	Kitchen.upper island leftmost cabinet left door
8400000022B43A12Y	1WireSwitch	Med 3
B500000022B40E12Y	1WireSwitch	Med 2
0F00000022B44412Y	1WireSwitch	Wound Care
8500000022B3F012Y	1WireSwitch	Blood Glucose Test
C900000022B48712Y	1WireSwitch	Hand Wash (disinfectant)
1300000022B4B612Y	1WireSwitch	Med 4
1300000022B4B612Z	1WireSwitch	Carry Med 4 with you
AE00000022C0BC12Y	1WireSwitch	Med 1
AE00000022C0BC12Z	1WireSwitch	Carry Med 1 with you
4800000053C01026	1WireFlow	Full Bath Shower Cold
7200000053D35C26	1WireFlow	Full Bath Shower Hot
1PL16	MITesOnBody	On-Body Channel 1
7PL16	MITesOnBody	On-Body Channel 7
8PL16	MITesOnBody	On-Body Channel 8
172	MITesStatic	Hand Weight

Table F.1: List of PlaceLab sensors used

Appendix G

Prior Relevant Work: Activity Recognition Using Commonsense Reasoning

Activity Recognition Using Commonsense Reasoning

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ABSTRACT

In this paper we present a novel approach to building a classifier of domestic activities (such as making breakfast, taking a pill, or exercising) by mining data from freely available commonsense knowledge, thus greatly reducing the need for supervised training data. The ability to classify domestic activities is useful in many application domains, and it is anticipated that this work will enable a new set of interactive applications for homes, that will be both useful and welcome.

Keywords

Unsupervised learning, activity recognition, commonsense reasoning, home, sensor.

INTRODUCTION

In Commonsense-Based Interfaces [1], author Marvin Minsky predicts that a machine capable of truly learning by itself will require a commonsense knowledge representing the kinds of things even a small child already knows. This work is an attempt to bring that vision one step closer to reality.

Over the last few years, considerable progress has been made in the long standing effort of putting pieces of ordinary knowledge that constitute commonsense into computers. The Open Mind Common Sense project at the MIT Media Lab has accumulated a corpus of 700,000 pieces of knowledge (as of January 2004) over the past three years. A related initiative, the Open Mind Indoor Common Sense (OMICS) project [2] has captured thousands of pieces of knowledge about home environments from non-experts through public online collaboration over the Internet.

There have also been notable advances in the creation of living spaces that are human-aware (able to perceive human activity and estimate human internal state). As sensors satisfy privacy, reliability, cost, and computational needs, [3] it is our hypothesis that they will become ubiquitous in homes.

In this paper, we will demonstrate an unsupervised and commonsense-based learning approach that will enable new behavioral interventions to deliver context sensitive information based on a passive awareness of users' domestic activities.

USER SCENARIO

It is envisioned that this foray into human-awareness will enable behavioral interventions in which users are able to make use of insights about their own patterns of living to situate interventions in existing behavioral routines. One potential user scenario follows:

Bob has an elderly mother living alone one hour away. Last week she knocked the phone off the hook and was unavailable for an entire day.

That weekend, Bob walks into a hardware store and emerges with a large brown box. The box contains several dozen quarter-sized sensors that stick to any surface. Following directions, he attaches the sensors to appliances, furniture, and household objects, installs software on a personal computer and plugs a device into a USB port. The software instructs him to perform a quick walk-through of the house, touching every sensor. Later that week Bob logs onto the Internet, types a password, and checks to see that his mother has eaten lunch. One week later he checks that she has been cooking and eating meals.

One month later he receives an alert on his mobile phone indicating that his mother's activity levels are abnormally low. He calls and finds that she seems to be coming down with the flu.

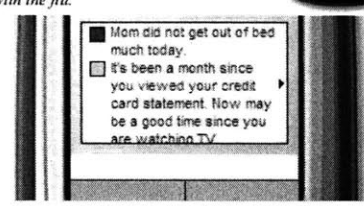

Figure 1

RELATED WORK

Prior research by the House_n research group at the MIT Media Lab includes a portable sensor toolkit, electronic experience sampling, and promising preliminary work with wearable sensors and sensors in the environment. We have developed algorithms using Naïve Bayes' classifiers [4] and Decision Trees [5] to interpret human activities in real-time. The approach thus far has been in line with classical machine learning; with feature selection and training performed in a supervised fashion from labeled training sets. Recently, researchers at Intel Research, Seattle have used radio frequency identification tags to recognize several activities of daily living [6].

THE COMMONSENSE APPROACH

In most classification problems, training data is fairly easy to obtain. Music classification, for example, is a frequently attempted task for which it is not difficult to find hundreds of training examples for the different composers, styles, or instruments that must be classified. Similarly, when training a classifier to differentiate between a malignant and benign tumor, one may have access to thousands of anonymous medical records.

However, training classifiers for domestic activities using the conventional machine learning approach demands great effort and expense. Due to the lack of training data, examples of different activities of interest need to be collected and labeled manually, or user have to explicitly provide training examples for each activity. Table 1 shows the number of training examples required to achieve approximately 70% classification accuracy using different machine learning algorithms. It is unreasonable to assume that an end user of the system would 'teach' the system by providing 8 to 85 examples of each activity.

Number of Examples per Class		
Activity	**Subject 1**	**Subject 2**
Preparing dinner	8	14
Preparing lunch	17	20
Listening to music	-	18
Taking medication	-	14
Toileting	85	40
Preparing breakfast	14	18
Washing dishes	7	21
Preparing a snack	14	16
Watching TV	-	15
Bathing	18	-
Going out to work	12	-
Dressing	24	-
Grooming	37	-
Preparing a beverage	15	-
Doing laundry	19	-
cleaning	8	-

Algorithm	Accuracy (%)	Training Time (S)
SVM	70.57	41.2
KNN	71.27	NA
ID3 Decision Tree	68.47	0.11
Naïve Bayes	67.77	0.01
MLPerceptron	70.27	135
HMMs	71.7	67

Table 1 Number of training examples required to achieve ~70% recognition accuracy using conventional machine learning algorithms.

The greatest advantage of mining commonsense knowledge bases in this context is that they provide vast amounts of ordinary information, making up for the difficulty in obtaining training examples for individual activities.

Secondly, conventional machine learning requires the user or an expert to choose features of interest, and wait an extended amount of time for the classifiers to train. With conventional machine learning, it is infeasible to create an interactive tool to generate classifiers.

Commonsense reasoning provides ways to describe a variety of everyday concepts, and then to reason about those descriptions. This makes it possible to build a system that generates classifiers for activities of interest to users, and then allows users to incrementally enhance these classifiers, without any knowledge of the features and models that underlie these classifiers.

SYSTEM DESIGN

We have utilized extensive datasets from [4] to implement commonsense-based activity classifiers, and identified what about this methodology is working and what is not. We have made modifications and improvements when possible, however, we have not yet deployed and evaluated the system in real time, and we plan to accomplish this shortly. Figure 2 shows a block diagram of the proposed system, which is detailed in the rest of this paper.

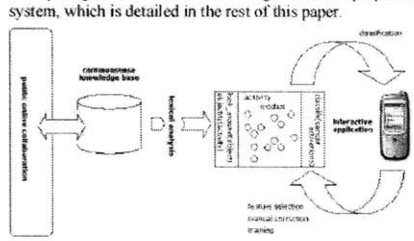

Figure 2

For every activity of interest (e.g. "doing laundry"), we generate a candidate model using bi-directional inference over the OMICS knowledge base. The main parts of this process are:

Objectify

A commonsense model builder written in Java, and using MySQL Connector/J for accessing the OMICS database. From top down, Objectify infers a list of household objects related to the activity (e.g. {clothes, washing machine, hanger, laundry, clothing, washer, etc.}. There are three steps involved in this - First, the *paraphrase* relation in OMICS is used to infer alternate ways of describing the activity. So in the above example, it infers that "wash clothes", "fold clothes", "hang clothes", "do laundry" are all related to "doing laundry". Next, the *steps* and *tasks* relations are queried to obtain different lists of steps involved in completing each of these tasks. This typically produces 12 to 14 sets of short instructions such as shown in Figure 3.

stepnum	step
0	gather dirty clothes
1	fill washing machine with dirty clothes
2	turn on washing machine
3	when washing machine is done, take out clothes
4	put clothes in dryer
5	turn on dryer
6	when dryer is done, take out clothes
0	gather dirty laundry
1	take dirty laundry to washing machine
2	put laundry inside
3	add detergent
4	select washing program
5	turn on machine
6	wait for clothes to wash; remove
0	collect dirty clothes
1	put in laundry machine
2	pour out detergent
3	activate
4	put clothes in dryer
5	wait 1 hour
6	collect clothes
0	find dirty laundry
1	pick up dirty laundry
2	find clothes washing machine
3	place clothes into washing machine
4	add laundry soap to washing machine
5	turn on washing machine
0	gather laundry in basket
1	separate laundry into piles
2	put proper amount of detergent into washer
3	do not wash white clothes with colored clothes
4	wash towels on hot and other clothes on cold
0	need dirty clothes
1	need washing machine
2	put clothes in machine
3	dry clothes

Figure 3 Instructions from the OMICS database

Finally, Objectify filters out all nouns that are ***hypernyms*** of any of the objects in the set {"utensil", "silverware", "room", "furniture", "appliance", "container", "food", "clothing"}. This lexical analysis is accomplished using WordNet [7]. Figure 4 shows some examples of models generated by Objectify for three everyday activities.

Bathing	Laundry	Preparing dinner
shower	clothes	pot
spray	washing	microwave
cleaner	machine	soup
sponge	hanger	stove
water	clothing	gas
brush	laundry	pan
drain	washer	heat
agent	fold	table
tub	piece	Container
wash	closet	refrigerator
bathtub	gather	timer

Figure 4 Examples of activity models generated by Objectify

LookAround

A commonsense inference function written in Java, and using MySQL Connector/J for accessing the OMICS database. LookAround makes use of the ***proximity*** relation in OMICS to infer a list of possible objects that might be found in the neighborhood of a given object. LookAround bridges the gap between a sensor affiliated object like a drawer, and objects such as pencils, pens, and clips, that may not have sensors on them, and allows the propagation of probabilities from sensor-affiliated objects to objects that appear in the models, but are not affiliated to sensors. Figure 5 shows an example of the LookAround function outputs for "television", "spoon", and "bed". In this way, commonsense reasoning helps prune down the object list generated by Objectify, far enough to be able to attach the primitives to known objects in the environment, each of which is affiliated with individual sensors.

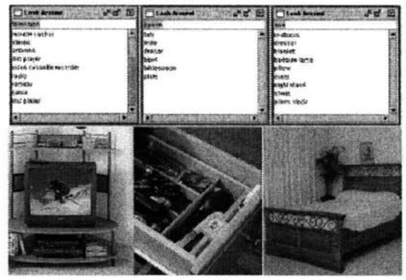

Figure 5 Output examples for the Look Around inference function.

Weighted Voting Scheme

The final component of the activity classification system is a naïve Bayesian weighted voting scheme. We used naïve Bayesian voting because this approach has been proven to perform particularly well in several real-world domains, despite its computational simplicity. Its ability to handle noisy data and incorporate prior knowledge makes it easy to bootstrap it with a generic commonsense model of human activities, which can then be personalized over time, as users provide explicit examples of activities in their homes.

We selected the following three attributes as model parameters to our voting scheme: (1) the observation probabilities of each **Object** for each class of activity, (2) the observation probabilities of each **Room** for each class of activity, and (3) the observation probabilities of each **Time of Day** for each class of activity.

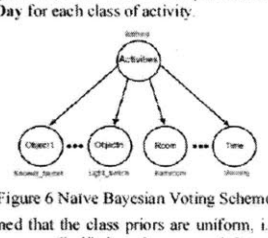

Figure 6 Naïve Bayesian Voting Scheme.

We assumed that the class priors are uniform, i.e., that all activities are equally likely to happen, and that observation probability for each **Object** associated with an activity model is to P(on)=95%. We calculated the observation probabilities for **Room** and **Time of Day** by executing Google searches as follows:

$$P(\text{Bathing}|\text{Bathroom}) = \frac{\text{GoogleSearch(Bathing and Bathroom)}}{\text{GoogleSearch(Bathroom)}}$$

$$P(\text{Bathing}|\text{Morning}) = \frac{\text{GoogleSearch(Bathing and Morning)}}{\text{GoogleSearch(Morning)}}$$

We call the attributes Object, Room, and Time of Day commonsense attributes because they can not only be extracted from training data (sensor activations), but also from commonsense reasoning databases.

EVALUATION

For demonstration purposes, we decided to classify the following 6 activities:

1. Entering the house
2. Preparing lunch
3. Preparing dinner
4. Doing laundry
5. Bathing
6. Cleaning

We used the datasets from [4] to evaluate the performance of our activity recognition application, using a sliding window to segment the sensor data into windows and then classify each window independently according to our commonsense attributes.

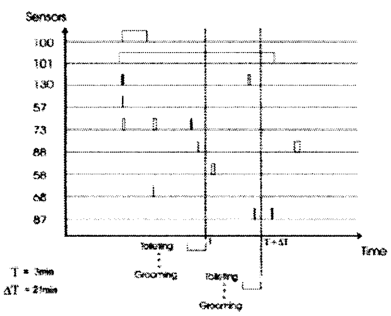

Figure 7 Sliding window approach to classification.

We then generated a plot of the probability output for each activity at any given time in the day. Figure 8 shows an example of the system's output.

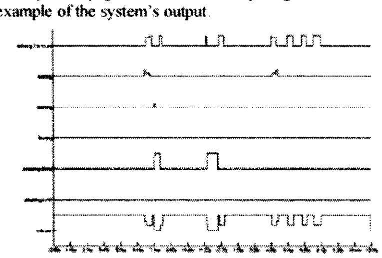

Figure 8 Activities probabilities generated by the commonsense activity recognizer.

We were unable to run extensive comparative tests on the dataset due to the following constraints of the dataset:

Difficulty in mapping activity models to labeled activities in the dataset:

The activity labels in the dataset were not designed with commonsense models in mind. One example where such labeling caused problems was with the activities preparing lunch and preparing dinner. The commonsense models for both these activities are alike, and our classifier often misclassified these two activities. If the class had actually been Meal Preparation, the resulting classifications would not have counted as errors. Here are some examples of this activityModel->activityExample mapping include the following

one-to-one
- laundry->doing laundry

one-to-many
- preparing meal->preparing breakfast
- preparing meal->preparing lunch
- preparing meal->preparing dinner

many-to-one
- cleaning bathroom->cleaning
- cleaning kitchen->cleaning
- cleaning study->cleaning

We addressed this problem by hand-crafting a mapping file to specify the activities in the activity models that the activities carried out by the subject map to.

Difficulty in mapping model objects to sensor objects:

Objects in the models don't map directly to the labels assigned to the different sensors in the house. Some examples of this mapping problem include:

sensorLabel -> modelObjectLabel
Shower->Faucet
Stood->Chair
Dishwashing liquid->detergent

We addressed this problem by writing a similarity function that used the WordNet lexical analyzer.

FUTURE WORK

1. Converting the classifier into a real-time classification agent that continuously updates its models of different user activities and their corresponding sensor activations. An agent architecture will allow the integration of the training and online classification phases into a single process. The present separation of these phases means that once the models are generated a priori there is no opportunity to improve them as new data are collected.
2. Creating an online-learning agent will overcome the present restriction to activities selected a priori, and will allow user specification of new, personalized activities that the user may wish to recognize.
3. Encoding of temporal information such as sequential order, periodic variations, and time scale could be a possible future extension, in order to add additional discrimination power.

4.Implementing user-identification technology to permit reliable detection of individual users and activities performed for each.

5.Making the classification infrastructure a stand-alone module will allow provision of a set of standardized interfaces for use by different clients. By doing so, activity classification can be leveraged by any number of applications in a specialized home environment such as the MIT PlaceLab.

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