Prospective Memory Aid: A Reminding Model based on Fuzzy Cognitive Maps

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***Abstract*—Prospective memory (PM) failure, which is the failure to recall future events or intentions, can lead to serious consequences. Although many PM aid systems have been developed, there are three critical challenges which are yet to be addressed by any existing systems: (1) determining appropriate number of reminders, (2) arranging effective reminder schedule and (3) selecting appropriate reminding method based on context. We propose a new reminding model to address these three challenges. The model draws its theoretical basis from existing PM research and employs Fuzzy Cognitive Maps to incorporate the theoretical basis computationally. Specifically, poring over extensive PM literature, a number of factors and contextual elements are identified, which can help determining the number of reminders and selecting appropriate reminding method. The proposed model captures the complex and dynamic relationships among the factors and elements computationally. To evaluate the proposed reminding model, it was incorporated into a mobile app, *ReminderPM*. A field study was carried out to evaluate it. Study results support that *ReminderPM* can provide a better overall experience and remind more effectively.**

I. Introduction

Prospective memory (PM) is a form of memory that involves remembering to perform delayed intentions [1]. PM failure, which is the failure to recall such intentions, is a commonplace. Studies have reported that about 50-80% of all everyday memory problems are caused by PM failures [2]. One may forget to do an intended task at a future point of time, such as to meet someone at 11am, or on a particular occasion, such as to do grocery shopping when passing by the supermarket on the way home. However, PM failures may lead to serious consequences in highly important situations like a patient forgetting to take medications [3].

A prospective memory task (PM task) is encoded and maintained in PM. It will be retrieved from PM and performed later at a planned time or upon the occurrence of an event [4]. There are various forms of PM aid systems that people employ to assist their PM task retrieval, ranging from health applications targeting brain injured or cognitively impaired people [5], [6] to general applications like Google Calendar and AutoMinder [7], [8]. Over the years, PM aid systems are evolving and improving. However, we have identified three challenges which are critical for generating effective reminders, but have not been addressed by any existing systems: 1) *Determining appropriate number of reminders*. How many reminders should be issued for a particular PM task? 2) *Arranging effective reminder schedule*. When should reminders be issued to effectively remind about a PM task? 3) *Selecting appropriate reminding method based on context*. In what formats should reminders be issued so that they can effectively attract attention while also being context-aware?

To cope with the three challenges related to PM, we feel that it is necessary to refer to relevant theories and studies in PM. From a vast number of PM literature, we identified six performance influencing factors and four contextual elements which can help determining the appropriate number of reminders and reminding method. Existing research in PM provides sound theoretical background for building an effective reminding model. However, it is a nontrivial problem to build a computational model that incorporates the identified factors and elements. The relationships among the PM task performance, the general context and their determining factors or elements are intricate, dynamic and hard to model. Fuzzy Cognitive Map (FCM) has gained our attention due to its ability to capture such complex causal relationships and quantify the influence exerted by the factors and elements.

We propose a new reminding model which draws its theoretical basis from existing PM research and employs Fuzzy cognitive Map (FCM) to incorporate the theoretical basis computationally. The reminding model can determine an appropriate number of reminders for a PM task based on the predicted performance of the task. Guided by a reminder schedule function, the proposed model is also capable of generating an effective reminder schedule automatically. Moreover, the reminding model is able to make context-aware decisions regarding the reminding method.

To evaluate the proposed reminding model, it was incorporated into a mobile app, *ReminderPM*. A 4-week user study was conducted for *ReminderPM* and its control version. Generally, the participants felt that the reminders generated according to the reminding model are appropriate in terms of their number, schedule and reminding methods. The results also support that *ReminderPM* provides a better overall experience and reminds more effectively than its control version.

This paper is organized as follow: Section II presents a short review for PM and existing PM aid systems. In section III, we introduce the proposed reminding model. Then in section IV, we describe how the model is incorporated into *ReminderPM*. The pilot study and its results are summarized in section V.

Finally, we conclude in section VI.

II. Related Work

A. Prospective Memory

Prospective memory (PM) involves remembering to perform intended tasks after a delay [1]. According to the process model [4], there are four stages in the life-cycle of a PM task:

1) Intention formation: encoding a future task

2) Intention retention: maintaining the formed intention and waiting for the perception of the target while engaging in ongoing tasks

3) Intention initiation: initiating the execution of the intention at planned timing or upon occurrence of an event

4) Intention execution: performing the initiated task

PM failures are more likely to happen during stage 2, when an individual fails to retrieve and initiate a delayed task.

There are two main types of PM tasks: time-based and event-based [1]. A time-based PM task involves performing an intention at a specific time or after a period. As a time-based task provides few if any external cues to help remembering, it depends more on internal processes of time monitoring and self-initiation. An event-based task involves performing the delayed intention upon the occurrence of an event. Since the event itself acts as an external cue, an event-base PM task generally requires less self-initiation than a time-based one.

B. Existing PM Aid Systems

Various forms of PM aids have been developed to assist the retrieval of PM tasks, ranging from the traditional way of paper and pen (e.g. diaries, calendars) to technology-based aids which involve the use of electronic devices.

Earliest technology-based PM aids were mainly targeting brain injured or cognitively impaired people, e.g. MEMOS [5] and Memojog [6]. There are also general purpose PM aid systems, such as Google Calendar and AutoMinder. McDonald et al. evaluated the effectiveness of Google Calendar. When compared with standard diary use, the participants found Google Calendar was much more effective. However, they also mentioned that sometimes they failed to perform PM tasks even if they noticed reminders from Google Calendar [7]. AutoMinder is a PM aid system that targets to help older adults in their home environment [8]. By monitoring users′ execution of PM tasks through feeds from sensors at home, AutoMinder decides whether and when to issue reminders. According to Caprani et al., observable information from sensors were not always reliable, which may result in assumption failures [9].

Similar to Google Calendar, most existing PM aid systems only support manual creation of reminders. Users of these systems manually decide the number, schedule and reminding methods of the reminders. AutoMinder attempted to determine the number and schedule of reminders automatically based on sensory information. However, assumptions based on sensory data decrease the reliability of its reminders [9].

Over the years, PM aid systems are evolving and improving. However, we have identified three challenges which are critical for generating effective reminders, but have not been addressed by any existing systems:

1) Determining appropriate number of reminders: While too few reminders may fail their purpose, too many of them can be annoying. How many reminders should be issued for a particular PM task?

2) Arranging effective reminder schedule: While a reminder for a task one month away may be too early, a reminder issued just before the PM task may leave the user in a hurry to perform the task. When should reminders be issued to effectively remind about a PM task?

3) Selecting appropriate reminding method based on context: Text reminders are appropriate at places which require silence. On the other hand, more attention attracting reminding methods, e.g. vibration and sound, are desired in noisy environments as they require less monitoring. In what formats should reminders be issued so that they can effectively attract attention while being context-aware at the same time?

III. Proposed Reminding Model

A. Factors and Elements Identified from PM Research

To cope with the three challenges related to PM, we form the theoretical basis of our reminding model from relevant PM theories and studies. In this section, we first introduce six factors that influence the performance of a PM task and summarize their influence on PM task performance. Then, we define four contextual elements which help determining how salient a reminding method needs to be in a particular context.

1) Factor affecting PM task performance: Time- and event-based PM tasks differ in various aspects. Hence, for each factor, we discuss its influence on the performance of time- and event-based tasks separately where applicable.

Delay of PM task. The delay of a PM task refers to the length of PM retention interval. In another word, it is the time period from the encoding to the initiation of a PM task. Generally, longer delay would reduce the performance of a PM task [10].

Complexity of ongoing task. Ongoing tasks refer to the activities individuals are involved in at the time they need to perform their PM tasks. The complexity of an ongoing task is defined as the relative amount of executive resources required by it. In order to perform their PM tasks, individuals need to shift executive resources occupied by ongoing tasks to the PM tasks. Thus, as the complexity of ongoing tasks increases, it becomes increasingly hard for individuals to shift their executive resources and retrieve PM tasks successfully [11]. In other words, the complexity of ongoing task negatively affects the performance of a PM task [12].

Relatedness of tasks. Relatedness of tasks describes the degree of relatedness between a PM task and its ongoing task. The relatedness of the two tasks is high when the ongoing task involves processing features that are associated with the PM task. Contrarily, it is considered low when the ongoing task does not direct attention towards evaluating the PM task features [13]. High relatedness between a PM task and its ongoing task will yield easier retrieval of the PM task, thus lead to better PM task performance [13], [14].

Importance of PM task. The importance of a PM task refers to its perceived importance by an individual. The importance of a PM task improves its performance to the degree it requires strategic allocation of attention [15]. The performance of a time-based PM task would improve greatly when its importance increases, since it requires more attention. While for an event-based PM task, it experiences less performance improvement when its importance increases, since its retrieval is more spontaneous [16].

Motivation. Motivation refers to incentives or drive to perform a PM task. The performance of a PM task tends to be better when it is associated with a higher level of motivation. Experiments in [17] and [18] reported that when social motives were presented, the performance of both time-based and event-based PM tasks was improved.

Age. Age can affect the performance of a PM task, since the PM of an individual develops and then deteriorates gradually as age grows. During childhood, PM task performance of an individual improves as he/ she grows in age [19], [20]. The PM task performance peaks during adulthood and gradually decreases as the individual grows older [21].

The six performance influencing factors identified above are not completely independent from each other. Some factors directly influence other factors or indirectly affect the relationship between another factor and the PM task performance.

Motivation and importance. The presence of social motivation in a PM task could reinforce its importance. Experiments in [22] showed that the perceived task importance was higher when there was a social motivation.

Age and other factors. The process of aging is generally associated with declined cognitive capabilities and slowing mental functioning, which gradually deteriorates PM. As a result, age affects the degree to which the PM task performance is influenced by other factors. When ongoing task was made more complex or the relatedness between the ongoing and PM task was lower, a greater performance decline was observed among the elderly compared to their younger counterpart [11], [23]. On the other hand, when social motivation was presented, a more significant performance improvement was reported among the older adults than the young adults [18].

2) Contextual elements affecting salience level: Four contextual elements are identified to characterize the task-related and environmental context to help determining how salient a reminding method needs to be in that particular context. The two performance influencing factors, complexity of ongoing task and importance of PM task, are also the contextual elements used to characterize the task-related context. In addition to them, two elements describing the surrounding environment, tolerance for disturbance and noise level, are used to characterize the environmental context.

Complexity of ongoing task. As a complex ongoing task requires more executive resources [12], a more salient reminding method should be used to intuitively attract attention and reduce monitoring under such condition.

Importance of PM task. When the perceived importance of a PM task is high, a more salient reminding method should be selected to ensure its performance.

Tolerance for disturbance. Tolerance for disturbance refers to the degree to which an individual can tolerate disturbance. If an individual does not want to be disturbed (low tolerance), a less salient reminding method should be selected.

Noise level. Noise level refers to the noise level of the surrounding environment when the reminder is issued. In a noisy environment, a more salient reminding method should be selected to increase the chance the reminder gets noticed.

Drawing from relevant studies and experiments in PM research, we have identified six performance influencing factors and four contextual elements. The relationships among the PM task performance, the salience level and their determining factors or elements are intricate, dynamic and hard to model. FCM is well-suited for modeling such relationships as it is capable of capturing casual relationships among multiple concepts. Next, we will present a brief introduction to FCM.

B. Fuzzy Cognitive Maps

Fuzzy Cognitive Map (FCM), first developed by Kosko [24], is well suited for modeling dynamic systems [25]. FCM is widely used to represent the cause-effect relationships among concepts in real-world systems [26]–[28]. More specifically, FCMs have been used for brain tumor grading [29] and differential diagnosis of language impairment [30].

Graphical representation of a FCM consists of nodes and directed arcs. As shown in Fig. 1, node c_i is a concept which can represent a variable, an input or an output in a computational model. The state value of a concept c_i represents the degree to which the concept is active. The state value is a real number in the interval of [0,1], which can also be interpreted as the degree of membership in a fuzzy set. A fuzzy set is characterized by its membership function. The fuzzy value of a concept c_i is derived by mapping its crisp value to a degree of membership using the membership function. The directed arc connecting c_i and c_j represents the cause-effect relationship between the two nodes. The arc is also associated with a weight, w_{ij}, which denotes the strength of the relationship between c_i and c_j. A positive weight ($w_{ij} > 0$) represents a causal increase, while a negative weight ($w_{ij} < 0$) represents a causal decrease.

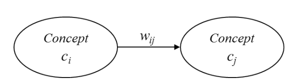

Fig. 1. A Fuzzy Cognitive Map with Two Factors

Definition 1: A FCM V with n concepts, is defined as: $V = \{C, W\}$:

1) $C = \{c_i | c_i \in [0, 1]; i = 1, 2, \cdots, n; c_i \in \mathbb{R}\}$ represents a set of concepts, each has a numerical state value associated with it. $\mathbb{R}$ is the set of real numbers;

2) $W = \{w_{ji} | w_{ji} \in [-1, 1]; i = 1, 2, \cdots, n; j = 1, 2, \cdots, n; i \neq j; w_{ji} \in \mathbb{R}\}$ represents a set of weights, each has a numerical value.

FCM not only offers a way to capture the complex relationships among identified factors and elements, but also provides a reasoning mechanism for inferring the PM task performance and the salience level of reminding method. Next, we will show how an effective reminding model can be constructed by computerizing the theoretical basis using FCMs.

C. The Reminding Model based on PM Research

The proposed reminding model addresses the three challenges highlighted in section II. It determines an appropriate number of reminders (τ) for a PM task based on the predicted performance of the task. To arrange an effective reminder schedule ($r\_schedule$), the model follows a reminder schedule function to determine the issuing time of each reminder. The reminding model selects an appropriate reminding method (r_method) for each reminder based on the salience level required.

1) Determining appropriate number of reminders: The reminding model determines an appropriate number of reminders for a PM task based on the predicted PM performance of the task. If the predicted performance is poor, i.e. the likelihood the user will perform the task without reminding is low, more reminders will be generated for the task. If the predicted performance is good, i.e. the user is likely to remember the PM task well, fewer reminders will be generated to minimize disturbance. V_{perf} is defined to predict the performance of a PM task. It determines the joint effects of the factors that influence PM task performance. Fig.2 shows a visual representation of V_{perf}.

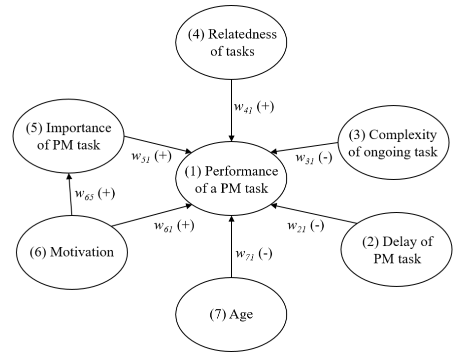

Fig. 2. FCM for Predicting PM Task Performance

Definition 2: V_{perf} can be formally defined as $V_{perf} = \{C, W\}$:

$$C = \{c_1, c_2, c_3, c_4, c_5, c_6, c_7\};$$
$$W = \{w_{21}(-), w_{31}(-), w_{41}(+), w_{51}(+), w_{61}(+), w_{71}(-), w_{65}(+)\};$$

where

- c_1 denotes *PM task performance*: measuring the likelihood an individual will remember and perform a PM task.
- c_2 denotes *delay of PM task*: measuring the length of the period from encoding to initiation of a PM task.
- c_3 denotes *complexity of ongoing task*: measuring the relative amount of executive resources required by the ongoing task.
- c_4 denotes *relatedness of tasks*: measuring the degree of relatedness between a PM task and its ongoing task.
- c_5 denotes *importance of PM task*: measuring the perceived importance of a PM task.
- c_6 denotes *motivation*: measuring the incentive strength of a PM task.
- c_7 denotes *age*: measuring the degree to which age adversely affects the performance of a PM task.

The plus (+) or minus (−) sign following a weight w_{ij} indicates whether the weight is positive or negative. The weight values are within the range [-1, 1].

Except for c_1 which denotes the PM task performance, each concept in V_{perf} corresponds to a performance influencing factors defined in section III.A. It is worth noting that the interrelationships among the factors are modeled in different ways. The relationship between motivation (c_6) and importance of PM task (c_5) is modeled by an arc joining the two concepts as they are casually related —high motivation can indicate high importance. The relationships between age and other factors are modeled by assigning variable weights, whose values are dependent on age, to the arcs directed from the factor concepts to the performance concept c_1. For example, complexity of ongoing task (c_3) has a negative causal relationship with the PM task performance (c_1). Age affects the strength of this relationship as older adults experience a greater performance decline as complexity increases. Thus, the value of w_{31} is a function of the value of the age concept (c_7). Similarly, value of w_{41} and w_{61} also varies with the value of c_7.

A 7×7 adjacency matrix W can be set up to hold the weight values. If there is no arc from c_i to c_j, $w_{ij} = 0$. A 1×7 state vector $C(t)$ is used to store the state values of the concepts at simulation step t.

$$W = \begin{vmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,7} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,7} \\ \vdots & \vdots & \cdots & \vdots \\ w_{7,1} & w_{7,2} & \cdots & w_{7,7} \end{vmatrix}$$

$$C(t) = [c_1(t), c_2(t), \cdots, c_7(t)]$$

During each simulation step, the state values of the concepts in the next step are jointly determined by their current values and causal effects imposed by other concepts. An interim state vector can be calculated by multiplying the state vector $C(t)$ with the weight matrix W.

$$\widetilde{C} = [\widetilde{c_1}, \widetilde{c_2}, \cdots, \widetilde{c_7}] = C(t) \times W$$

$$\widetilde{c_i} = \sum_j w_{ji} c_j(t)$$

where $\widetilde{c_i}$ is the sum of products of the state values of all concepts connecting to c_i and the weights of the arcs connecting them. The state values of the concepts in the next simulation step can be calculated as follow:

$$c_i(t+1) = f_i(\widetilde{c_i}) = f_i(\sum_j w_{ji} c_j(t))$$

where f_i is the squeezing function of concept c_i. It converts the interim state value $\widetilde{c_i}$ of concept c_i into the new state value $c_i(t+1)$, which is within required range [0, 1].

After the value of c_1 is stabilized, its value is used as a prediction for the performance of the PM task. The number of reminders, τ, is derived by mapping the predicted performance to a corresponding number of reminders. If the value of c_1 is close to 0, i.e. the predicted performance is poor, it will be mapped to a larger number of reminders. On the contrary, if the value of c_1 is close to 1, it will be mapped to a smaller number of reminders.

2) Arranging effective reminder schedule: After determining the appropriate number of reminders, the reminding model arranges the reminders into a reminder schedule, $r\_schedule$, according to a reminder schedule function. The reminders are distributed over the reminding window, which is a time interval ranging from the time of the first reminder to the starting time of the PM task (Fig.3). The first reminder is user-defined whereas others are automatically generated by the reminding model. The reminders are organized in a way such that the reminding frequency gradually increases as starting time of the PM task approaches. Assume that the length of the reminding window is T_w and the total number of reminders is τ.

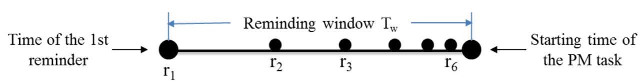

Fig. 3. An Example of a Reminder Schedule

Definition 3: The reminder schedule function is defined as:

$$T_i = (1 - e^{-\lambda i} + e^{-\lambda(\tau+1)})T_w$$

where $0 \leq i \leq \tau$ and T_i denotes the scheduled issuing time of reminder r_i ($r_i \in r\_schedule$).

The reminder schedule function satisfies the following constraints: 1) the time interval between two consecutive reminders is shortening; and 2) the interval between the last two reminders is longer than the interval between the last reminder and the time of the task.

In the case of a location-based PM task, if the estimated travel time is longer than the time interval between the first reminder and the time of the PM task, the model should adjust the reminder schedule accordingly to factor in the travel time.

3) Determining appropriate reminding method: The reminding model also determines an appropriate reminding method, r_method, for each reminder r_i in $r\_schedule$. It selects a reminding method according to the salience level required in a particular context. An appropriate reminding method should effectively attract attention without being intrusive. Its appropriateness is contingent on the context.

Previously, we have identified four contextual elements in section III.A to help deriving the salience level required. $V_{salience}$ is defined to infer the salience level from the joint-effect of the four contextual elements. The graphical representation of $V_{salience}$ is shown in Fig. 4.

Definition 4: $V_{salience}$ can be formally defined as $V_{salience} = \{C, W\}$:

$$C = \{c_3, c_5, c_8, c_9, c_{10}\};$$
$$W = \{w_{38}(+), w_{58}(+), w_{98}(+), w_{108}(+)\};$$

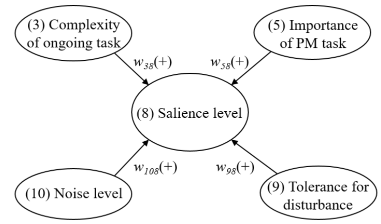

Fig. 4. FCM for Deriving Salience Level

where

- c_8 denotes *salience level*: measuring the extent to which a reminding method attracts attention.
- c_3 denotes *complexity of ongoing task*: measuring the relative amount of executive resources required by the ongoing task.
- c_5 denotes *importance of PM task*: measuring the perceived importance of a PM task.
- c_9 denotes *tolerance for disturbance*: measuring the degree to which an individual can tolerate disturbance.
- c_{10} denotes *noise level*: measuring the noise level of the surrounding environment.

Except for c_8 which denotes the salience level, each concept in $V_{salience}$ corresponds to a contextual element defined in section III.A. The relationship between a contextual element and the salience level is depicted by an arc as they are causally related. For example, when the noise level (c_{10}) is higher, the salience level required (c_8) for the reminding method is higher. Thus, c_{10} has a positive causal relationship with c_8 and $w_{108} > 0$.

The computation of $V_{salience}$ can be done with the help of a 5×5 matrix W' and a 1×5 state vector $C'(t)$, using steps similar to those described for V_{perf}.

After the value of c_8 is stabilized, an appropriate reminding method, r_method, is derived by mapping its value to a corresponding reminding method. When the value of c_8 is high, it will be mapped to more salient reminding methods, e.g. sound. Contrarily, it will be assigned to non-intrusive reminding methods, e.g. text and pictures.

In the next section, we describe how the reminding model was incorporated into a mobile app for evaluation.

IV. Incorporating the Reminding Model into a Reminder Application

To evaluate the proposed reminding model, we developed a mobile application, the *ReminderPM*, which incorporates the model. The architecture of *ReminderPM* is illustrated in Fig. 5. It has three components: the Reminder Planner, the PM Agent and the Personalized User Model. The Reminder Planner realizes the reminding model proposed. For every PM task created, it produces a reminding plan which consists of an appropriate number of carefully arranged reminders, each with a selected reminding method. The PM Agent, which is designed in the light of the process model [4], manages the PM processes, including the encoding of a PM task, maintaining the task, issuing reminders based on the schedule produced by the Reminder Planner. The Personalized User

Model customizes the reminding plan according to user profile and user′s interactions with the application.

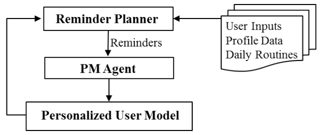

Fig. 5. The Architecture of *ReminderPM*

ReminderPM supports the management of time-based PM tasks. The cardinal processes a user can perform with it include encoding PM tasks, managing reminding plans, customizing task tags and entering personal routine. *ReminderPM* follows 3 main steps to generate a reminding plan for a PM task.

Step 1: collection of crisp values. From user inputs and profile information, *ReminderPM* obtains crisp values of the performance influencing factors and the contextual elements. Table I summarizes how the crisp values are collected. Upon the creation of a new PM task, besides general task details like description, date and time, *ReminderPM* also requires the user to specify the task category and rate the importance of the task. The task date is used to calculate the delay of PM task. The *ReminderPM* provides default PM task categories, such as health, work, family, social, and others. The user can also define customized PM task categories. Each category is associated with a motivation level. It can also be associated with a specific alert tone to serve as an external cue. The *ReminderPM* supports the user to input personal weekly routines by creating routine activities for each day in a week. The user can specify the start/end time, category, complexity, surrounding environment (noise level) of a routine task and the tolerance for disturbance while performing the routine task.

Step 2: converting crisp values to fuzzy values. The crisp values are transformed into fuzzy values in the interval of [0, 1] using corresponding membership functions shown in Fig. 6. These membership functions are defined based on the most commonly used types of membership functions and tuned according to the characteristic of each individual concept. Delay of PM task is measured in terms of days and has a rational membership function. As the number of days increases, its fuzzy value approaches 1. Age is represented in years and has a membership function which is the difference between two sigmoidal functions. As one approaches adulthood, the fuzzy value of age decreases from 1 to 0, representing diminishing adverse influence on PM task performance. Its fuzzy value increases as one grows into 60s and beyond, representing increasing age deficit of PM task performance. The other six performance influencing factors and contextual elements have sigmoidal membership functions. For instance, complexity of ongoing task is measured by user rating and has a sigmoidal membership function. Its fuzzy values increases as the user rating for complexity increases. Contrarily, the fuzzy value of tolerance for disturbance decreases as the corresponding user rating increases.

Step 3: FCM computation and result mapping. The fuzzy values of performance influencing factors and contextual elements are feed into the two FCMs to predict PM task performance and derive salience level. After completing the computational processes in FCMs, the predicted performance (value of c_1) is mapped to a corresponding number of reminders, while the resulting salience level (value of c_8) is mapped to a corresponding reminding method. The mappings used by *ReminderPM* are shown in Table II. Finally, the reminders are organized according to the reminder schedule function.

TABLE I
COLLECTING THE CRISP VALUES OF FCM INPUTS

Factor/Element	Source used to determine its value
Delay of PM task	The difference between the time to perform the PM task and the time the task is encoded
Complexity of ongoing task	User rating for task complexity (if the ongoing task is recorded in personal routine)
Relatedness of tasks	The number of tags shared by the PM task and the ongoing task (if the ongoing task is recorded in personal routine)
Importance of PM task	Users rating for task importance in the PM task inputs
Motivation	User rating for motivation of the PM task
Age	The difference between current date and date of birth in profile
Tolerance for disturbance	User rating specifying the degree to which they do not wish to be disturbed during the period of an ongoing task
Noise level	User input for noise level of surrounding environment in personal routine

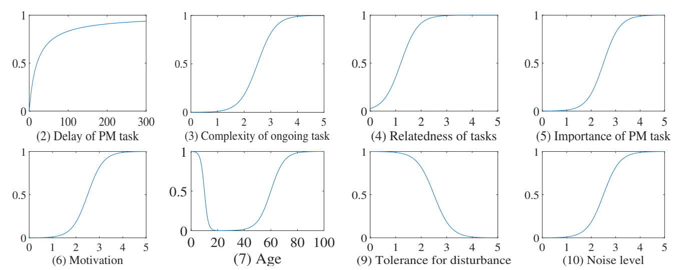

Fig. 6. Membership Functions for FCM Inputs

TABLE II
MAPPINGS FOR NUMBER OF REMINDERS AND REMINDING METHOD

Value of c_1	No. of Reminders	Value of c_8	Reminding method
[0, 0.1]	6	[0, 0.2]	Text
(0.1, 0.5]	5	(0.2, 0.5]	Text + Vibration
(0.5, 0.9]	3	(0.5, 0.8]	Text + Sound
(0.9, 1]	2	(0.8, 1]	Text + Vibration + Sound

To better illustrate the behaviors of the proposed reminding model, we describe two real-life PM tasks (shown in Table III) to show how a reminding plan is generated for each of them following the aforementioned 3 steps.

PM task 1 (Company Meeting) is created by a middle-aged user for a company meeting a week later. The meeting is for a project he is currently working on, thus have high relatedness to the ongoing tasks he is engaged in recently. Considering the effect of all performance influencing factors, his predicted performance for this PM task is 0.7342. According to the mappings in Table II, *ReminderPM* generates 3 reminders for this task. At the planned issuing time of

TABLE III
TWO SCENARIOS: MEETING VS MEDICATION ADHERENCE

	PM task 1 values		PM task 2 values	
Factor/Element	**Crisp**	**Fuzzy**	**Crisp**	**Fuzzy**
Delay of PM task	7	0.2593	1	0.0476
Complexity of ongoing task	3	0.8176	3	0.1824
Relatedness of tasks	2	0.9168	1	0.3543
Importance of PM task	3	0.8176	5	0.9994
Motivation	3	0.8176	2	0.1824
Age	35	0.0067	60	0.7311
Tolerance for disturbance	4	0.011	1	0.989
Noise level	1	0.011	3	0.8176
Performance of PM task		**0.7342**		**0.1989**
Salience level		**0.4143**		**0.7471**

the first reminder, he usually works in his office, where the surrounding is quiet and he does not want to be disturbed. Based on the values of contextual elements, the salience level calculated for the first reminder is 0.4143. According to the mappings in Table II, the first reminder will be issued in "Text + Vibration" format. Reminding methods for the other 2 reminders are determined in a similar way. Then, the 3 reminders are scheduled according to the reminder schedule function described in section III.C.

PM task 2 (Taking Medication) is created by an elderly user for reminding her to take dementia medication tomorrow. This PM task is given a high importance rating as her doctor has stressed that it is important for her to adhere to prescribed medication. However, she does not like to take medicines and always forgets to do so on time. According to her predicted performance for the task (0.1989), *ReminderPM* generated 5 reminders to remind her. She lives alone in an apartment which is a bit noisy during the day. The first reminder is scheduled to be issued in the afternoon. With a calculated a salience level of 0.7471, it will be issued in "Text + Sound" format. Reminding methods for the other 4 reminders are determined in a similar way. Then, the 5 reminders are arranged according to the reminder schedule function.

V. FIELD STUDY AND RESULTS

To evaluate our reminding model, we conducted a 4-week user study for *ReminderPM* in naturalistic settings, involving 5 participants aged from 20 to 30. A control version of *ReminderPM* was developed to facilitate the evaluation and filter out the influence of aspects which are not the focus of the study, e.g. interface design, task work flows and style of interactions. The control version resembles the existing PM aid systems functionally as it only supports manual creation of PM tasks and reminders. The participants have installed both *ReminderPM* and the control version on their own mobile phones. They first used the control version for 2 weeks and then *ReminderPM* for 2 weeks. After that, they completed survey questionnaires and sat through individual interviews.

The participants were requested to rate the appropriateness of the reminders generated according to the proposed reminding model. They rated on a scale from 1 to 10 and the ratings are summarized in Table IV. Generally, the participants felt that the reminders generated were appropriate in terms of their number, schedule and reminding methods. Each of these three aspects received an average appropriateness rating greater than or equal to 8. Among them, ratings for reminding method have the largest mean and the smallest standard deviation, suggesting that the participants thought the reminding methods selected by the model were most appropriate.

TABLE IV
SUMMARY STATISTICS FOR USER RATED APPROPRIATENESS

Aspect	Mean	Standard Deviation
Number of Reminders	8	1.4142
Reminder Schedule	8.2	1.4832
Reminding Method	8.4	0.8944

The participants also compared *ReminderPM* with its control version in terms of their overall experience and reminding effectiveness (with vs without the proposed reminding model). Pooled t-tests were performed to compare the means of the ratings for *ReminderPM* and the control version (Table V). The means of the ratings for overall experience were tested with the null hypothesis: the mean of the ratings for overall experience with *ReminderPM* (μ) is smaller than or equal to that for the control version ($\mu_{control}$). Since $p = 0.0231 < \alpha = 0.05$ ($t_0 = 2.357 > t_{0.05,8} = 1.86$), we reject the null hypothesis. Similarly, the means of the ratings for reminding effectiveness were tested with the null hypothesis: the mean of the ratings for reminding effectiveness of *ReminderPM* (μ') is smaller than or equal to that for the control version ($\mu'_{control}$). Since $p = 0.0328 < \alpha = 0.05$ ($t_0 = 2.132 > t_{0.05,8} = 1.86$), we also reject the null hypothesis. The test statistics are in favor of the alternative hypotheses, which support that *ReminderPM* provides a better overall experience and reminds more effectively than the control version.

TABLE V
HYPOTHESIS TESTS FOR COMPARING *ReminderPM* AND ITS CONTROL VERSION ($\alpha = 0.05$)

H_0	p **value**	t **score**	t_0	**Result**
Overall Experience $\mu - \mu_{control} \leq 0$	0.0231	1.860	2.357	Reject H_0
Effective Reminding $\mu' - \mu'_{control} \leq 0$	0.0328	1.860	2.132	Reject H_0

VI. CONCLUSION AND FUTURE WORK

To our best knowledge, the reminding model proposed in this paper is the first-of-its-kind. It models the theories and research findings in PM computationally to address the three critical challenges we identified from existing PM aid systems. (1) *Determining appropriate number of reminders*. The reminding model determines the appropriate number of reminders for a PM task based on the predicted performance of the task. Six performance influencing factors were defined from extensive PM literature. The reminding model provides a reasoning mechanism for inferring PM task performance from the joint effects of the factors. (2) *Arranging effective reminder* *schedule*. The model proposes a reminder schedule function to determine the issuing time of each reminder automatically. (3) *Selecting appropriate reminding method based on context*. The reminding model selects an appropriate reminding method for each reminder based on how salient it needs to be. Four contextual elements were defined to help deciding the salience level. The reminding model also offers a reasoning mechanism for inferring the salience level from the contextual elements. The proposed reminding model was incorporated into a mobile app, *ReminderPM*, and evaluated in a field study. Study results support that *ReminderPM* provides a better overall experience and reminds more effectively than its control version.

Currently, the proposed reminding model only supports time-based PM tasks. We are building up support for event-based PM tasks and incorporating the consideration for travel time. The reminding model will be able to track locations and remind based on locations. Moreover, we will also consider improving customization of the proposed reminding model. The model will be able to cater to individual differences, since individual PM task performance may respond to the six performance influencing factors differently. To achieve so, Dynamic Fuzzy Cognitive Map (DFCM) can be used, as it can learn the weights of its arcs from user behaviors and history data to generate more customized results.

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