Coping with prospective memory failures : an effective reminder system design

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Coping with Prospective Memory Failures: An Effective Reminder System Design

A thesis
Submitted to Interdisciplinary Graduate School

by

Hou Jinghua

in partial fulfilment of the requirement for the
degree of Doctor of Philosophy

December, 2018

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

February 26, 2019

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Date

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[Jinghua Hou]

Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

February 26, 2019

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Date

Liu Yang

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[Liu Yang]

Authorship Attribution Statement

This thesis mainly contains material from 2 papers published in the following peer-reviewed paper accepted at conferences in which I am listed as an author.

Chapter 3 is published as Jinghua Hou, Zhiwei Zeng, Chunyan Miao, Yang Liu. “Prospective Memory Aid: A Reminding Model Based on Fuzzy Cognitive Maps”, In Proceedings of 2016 IEEE International Conference on Fuzzy Systems (IEEE-FUZZ), pages 170–177, 2016.

The contributions of the co-authors are as follows:

- Prof. Miao and Liu provided the initial project direction and revised the manuscript.
- I prepared the manuscript drafts. The manuscript was revised by Zhiwei Zeng.
- Zhiwei co-designed the study with Prof. Miao and performed all the laboratory work at The Joint NTU-UBC Research Centre of Excellence in Active Living for the Elderly (LILY). I also analyzed the data.

Chapter 5 is published as Jinghua Hou, Chunyan Miao, Yang Liu. “Prospective Memory Aid Reminder System Design for Group Tasks”, In Proceedings of The 10th International Conference on Software, Knowledge, Information Management and Application (SKIMA), pages 433–438, 2016.

The contributions of the co-authors are as follows:

- Prof Miao and Prof Liu suggested the study and revised the manuscript draft.
- I conducted the study and wrote the paper.

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Abstract

Forgetting is common in daily life, and 50-80% everyday's forgetting is due to prospective memory (ProM) failures, which have significant impacts on our life. More seriously, some of these memory lapses can bring fatal consequences such as forgetting a sleeping infant in the back seat of a car. People tend to use various techniques to improve their ProM performance. Setting up a reminder is one of the most important techniques. The existing studies provide evidences in support of using reminders to cope with prospective memory failures. However, people are not satisfied with existing reminders because of their limitations in different aspects including reliability, effectiveness and optimization.

Through analysing the functions and features of existing reminder systems, this thesis summarizes their advantages and limitations. This study aims to figure out an optimized reminding way to improve ProM performance. The relevant theories and mechanisms of prospective memory from psychology were complied with, incorporated, and applied in this study. Based on the analysis of prospective memory processes, prospective memory components, and potential factors that influence prospective memory performance, this thesis proposes a new reminding plan generated from a computational model ProMR in order to address three critical challenges which have not been addressed by current systems: (a) determining the appropriate number of reminders, (b) arranging an effective reminder schedule; and (c) selecting an appropriate reminding method based on context. This thesis draws its theoretical foundation from existing ProM research and employs Fuzzy Cognitive Maps to computationally incorporate the theoretical basis. Specifically, poring over extensive ProM literature, many factors and contextual elements are identified in this research, which can help to determine the reminding plan. The proposed reminding model well captures the complex and dynamic relationships among many factors and elements computationally.

In this approach, the reminding model will determine a reasonable number of reminders for a ProM 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.

In order to evaluate the proposed reminding model, it was incorporated into a mobile app, *ReminderPM*. An experiment was carried out to evaluate it. Evaluation results supported that *ReminderPM* can provide a much better overall experience and do the reminding tasks more effectively, which means the proposed reminding model are appropriate in terms of their number, schedule and reminding methods. The results also supported that our approach provides a better overall experience and reminds more effectively than its control version.

At the same time, to identify the effectiveness of the proposed reminding model, a series of experiments were conducted for elderly aged from 60 to 80. The results significantly showed that the proposed reminding model is more effective than its control version of time-based reminders. However, it was also found that some participants got reminders from their peers, which showed that group reminders happen when they are friends and going to do the same task, which means the proposed reminder system produces redundant reminders if there are group reminders. To solve this problem, this study improved the proposed computational model for group tasks. A preliminary experiment was also conducted to identify the appropriateness of the updated model. The results showed that the improvement of the new reminding model is statistically significant.

This study developed a reminding model which provides the approaches to ensure reminding effective, reliable and optimal.

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Chapter 1

Introduction

1.1 Background and Motivation

Forgetting is common in our everyday life. People may forget to do some activities at a particular time, such as forgetting to take medicines after a meal and forgetting a meeting at 3:00 PM, or a particular task, such as forgetting to buy milk when passing by a grocery store. These tasks will all happen in the future. Remembering to perform a future task is referred to as prospective memory (ProM) [1]. According to Kliegel and Martin's study in 2003, everyone undergoes ProM failures everyday. A significant percentage of 50-80% everyday forgetting is due to ProM failures [2, 3]. Some of these memory lapses can bring fatal consequences. Every year we can see the news that an infant died in a hot car after parents left the car, forgetting that the child was sleeping quietly in the back seat. People are eager to learn more techniques for improving ProM performance and coping with ProM failures.

ProM is a very complex cognitive function which consists of several stages and various components [1, 4]. A specific prospective task has its own characteristics, which determine the nature of the ProM task. First of all, the prospective task to be performed at a particular time point or at a specific situation determines the type of ProM (event-based or time-based). Second, the motivation is associated with the performance of prospective tasks. The prospect of attending a stressful and exhausting meeting may not be appealing, while the prospect of meeting a friend could be something to look forward to. However, if the stressful meeting is important since the absence may lead to serious consequences, while the task of meeting a friend may not be so important. On the other hand, a ProM task is often conducted together with many ongoing activities, and requires people to perform it when an appropriate condition is satisfied. The degree of attention resources occupied by ongoing tasks could influence the prospective task performance. Improving the ProM performance requires understanding ProM from its mechanisms to various factors that act on it.

ProM problems are common with older people [5]. Older people tend to use ProM reminders to cope with their ProM decline [6, 7]. Without reminders, the challenge for performing a ProM task is that the intention needs to be initiated while people are simultaneously engaging in the ongoing tasks [8]. Reminders provide a solution to

initiate the prospective task at an intended time, and they range from paper notes to advanced technology-based ones. Originally, most of technology-based reminders (e.g., MEMOS, Memojog) were designed for users with cognitive impairment to promote their independence and assist them in health and wellbeing of individual [9,10]. Currently, technology-based reminders are popularly used by individuals. This study acknowledges their helps in personal time management, such as Google calendar.

1.2 Research Questions

In some cases, people are not satisfied with their reminder system because of its failure in reminding, issuing burdensome reminders (annoyance), or disagreeable signal (e.g., some persons prefer sound reminder to visual reminder). This study is motivated to investigate the improvements to the generic reminder system that will be more reliable, optimal and adaptive. Therefore, the tradeoff between the reliability and the annoyance as how many reminders should be issued to users for a specific ProM task is one of the main objectives. Spontaneously, the question of when to remind arises, since reminders are issued between the time of the first reminder and that of executing the ProM task. Considering the reminder as a created cue to the ProM task, another question of how to make the reminder salient and associated with the ProM task comes up. Therefore,

how many times to remind, when to remind, and how to remind are research questions of this study.

In addition, this thesis learns from some existing intelligent memory assists, such as Autominder with the adaptive feature [9]. It proposed to develop a personalized user model to observe user's behaviors, learn user's preferences for each feature of the reminder plan (e.g., the preference of audio or visual signal), and adapt the reminder plan to meet the personal preferences as much as possible. Therefore, the last research question is how to make the reminder plan adaptive and personalized according to the knowledge learned from users.

Based on literature review and experiment results, we found that existing works on reminder systems only focus on individual tasks such as reminding elderly to take their medicine. However, people with ProM difficulties (e.g., elderly) are often involved in many group tasks. For instance, seniors who enjoy being outside may like to play fun outdoor activities such as treasure hunts, bird watching, picnics, fishing, gardening and going to parks, lakes and many other places of interest. The group of elderly participating in a group task may interact with each other before the date of the event and thus, a group member might be reminded by other group members of the group task. Therefore, it is important to take into account the interaction between group members while designing

an effective reminding system for group tasks, which has not been addressed by any existing system.

Based on the discussion in this section above, the four research questions in this study are:

- How to calculate the optimal number of reminders for a specific ProM task?
- How to determine the optimal reminding schedule for a specific ProM task?
- How to determine the optimal method for a specific ProM task?
- How to make the optimal reminder plan for group tasks?

1.3 Approaches and Methodologies

To address the research questions above, this study proposed a structural model with 4 sub-models: a Fuzzy Rule-Based Model FRBKM for determining the fuzzy rules of factors affect ProM performance in Knowledge Base, a Fuzzy Cognitive Map Model FCMProm for predicting performance of ProM, a Fuzzy Rule-Based Model FRBFM for mapping the performance of ProM task into the number of reminders, and a Fuzzy Rule-Based Model FRBMM for mapping the salience level into the reminding method. This structural model is developed by reasoning various factors affecting ProM performance, by complying with the process model of ProM, and by overcoming the limitations

and learning the advantages from existing reminder systems. To empower the proposed model, mathematical functions are embedded into the model to calculate the optimal number of reminders, the reminding schedule and reminding method.

This model provides a promising ground for improving the prospective memory performance. The reminding plan includes the optimal number of reminders, the optimal reminding schedule and the optimal reminding method, overcomes the limitations of current reminder systems in reliability and optimization. FRBKM supported by psychological research provides a believable diagram of ProM processes. It not only demonstrates important components such as planning and monitoring in processes, but also interprets the important stage for ProM failures. The factors affecting ProM were integrated into the model ensure the reminding happens in ProM processes to resist prospective memory failures.

In addition to designing a reminding model for individual tasks, this study also considers the fact that people with ProM difficulties are often involved in many group tasks. For most senior citizens, group activities can provide useful social contact with the outside world. Assume that a group of people are participating in a group task (say picnics) 10 days later and they have to also prepare for the group task before the event. The group of people also interact before the group task for other occasions such as daily exercises.

Assume that this study wants to design a reminding model for such group activities, the model could simply ignore the group interaction between the group members. In other words, the system can treat each group member separately and directly apply existing approaches for determining the reminding schedule. However, such an approach will lead to many unnecessary reminders as one group member might remind some other group members. Therefore, the comfort level of the group members will decrease dramatically due to the unnecessary annoyance. It is thus important to take into account interactions between group members including the frequency of the interactions. Moreover, we need to differentiate different group members as some group members might interact more with other group members. Thus, different group members might receive different numbers of reminders. Nowadays, with the development of technology such as Apps for tracking human's activities including the reminder system itself, information about interaction frequency is available.

1.4 Contributions

The main contributions of this study are in a comprehensive literature review, in model design, in implementation and in experiments. Here we summarize them as follows:

- This study has done a comprehensive literature review, including three aspects:
 - 1) ProM theories of four stages and six components, 2) a series of potential factors

(type, age, the complexity of ongoing task, the importance of ProM task, and the motivation of ProM task) which influence the ProM performance, and 3) the existing reminder systems to cope with ProM failures, all of which provide theatrical and practical supports for this reminding model development.

- Based on the literature review, this study provided a computational model for determining the optimal reminding plan which includes the number of reminder, the reminding schedule and reminding method.
- Learned from the practical use of the proposed reminding model, this study provided a computational group model for determining the optimal reminding plan for group tasks.
- Based on the proposed model, this study designed a reminder system.
- This study conducted in-depth experiments support elderly ProM performance.

1.5 Thesis Organization

In the following chapters, firstly, this study investigates various factors which potentially influence the ProM performance through reviewing the ProM theories and empirical studies. Secondly, it reviews a series of existing ProM assists, and compares their advantages

and drawbacks. Thirdly, through applying theoretical knowledge, incorporating factors drawn from empirical studies, and learning from the existing ProM assists, this study develops a reminding model for producing a reminding plan. Fourth, a series of experiments are conducted to identify the appropriateness and effectiveness of the proposed reminding plan for elderly. Fifth, this study presents a computational approach for determining the appropriate number of reminders and reminding method for group tasks. Finally, the future work is proposed.

Chapter 2

Theoretical and Empirical Background

2.1 ProM Theory

ProM often refers to remembering to perform the intended task after a delay [1]. The intended task is stored in memory and will be executed later [11]. Remembering to take some medicines at 8:00 PM, remembering to get some milk while going out after work, or remembering to deliver some mails when passing by a mailbox are examples of the ProM task. It happens in our health and social life, and directly influences our life quality. According to Kliegel and Martin's study in 2003, a significant percentage of 50-80% memory failures are related to ProM problems [2]. The challenge for ProM tasks is that the intention has to be triggered while people are simultaneously engaging in the ongoing task [8].

Process Model: According to the study of Kliegel et al. [4], a ProM task involves

four stages: 1) *intention formation* (a future task is planned and encoded), 2) *intention retention* (that is, the intention is maintained and waits for the perception of the target while engaging in ongoing tasks), 3) *intention initiation* (that is, the time when the intention execution is just initiated), 4) *intention execution* (that is, the maintained task is performed). From these stages, we can find that in order to completely accomplish a ProM task, people have to remember not only what content is supposed to do, but also when to perform. If people successfully retrieve what they intend to do from memory, less frequently they fail to remember what the task is. Therefore, people with ProM problems often fail to initiate the intention at the right time.

Six-Component Model: A number of studies devoted to investigating the cognitive processes of ProM in order to explain what components are involved in encoding, retention and retrieval [12–14]. Dobbs and Reeves [12] have developed a comprehensive model of six components which are 1) *meta-knowledge*, 2) *planning*, 3) *monitoring*, 4) *recalling the content of the intention*, 5) *compliance*, and 6) *awareness of output*. In this model, it emphasizes that the retrospective memory (the content of intentions) is involved in ProM processes. Meanwhile, it demonstrates that execution functions, including planning things and monitoring, play important roles in ProM. Additionally, it mentions that both the knowledge of understanding how to remember and personal abilities as potential

factors affect the ProM performance.

2.2 Factors in ProM

2.2.1 The Type of ProM

ProM tasks have been primarily identified in two types, *time-based* and *event-based* [15].

The time-based ProM refers to performing an intended task at a specific time point or after some period (for example, remember to take medicines at 7:00 PM or 30 minutes later).

It depends on internal cues of time monitoring and self-initiation. The event-based task refers to performing the delay intention by an event (for example, remember to deliver the mails when passing by a mailbox). This event is an external environment cue, not requiring self-initiation.

A thorough review of existing studies makes clear that there are mechanical differences between the two types of ProM tasks. A majority of researchers stated that overall performance on event-based tasks is significantly better than the performance on time-based ProM tasks because the latter is particularly dependent on monitoring of time and self-initiation [16–18]. For example, in studies of Einstein et al. [17], the experiment 3 involved both time-based and event-based tasks. All the participants were asked to answer some general questions. In each time-based task, the participants were asked to press a keyboard key every 5 minutes, and in the event-based task, they were required to press

the keyboard key when they met the question of president. The results indicated that the participants' (both 18-21 years old and 61-78 years old adults) overall performance was significantly better on the event-based task. However, some researchers presented different results, for example, Ydewalle et al. [19] conducted an interesting face identification task in the ongoing activity, without answering general questions which were used by Einstein et al. [17]. According to their results, the performance on the time-based ProM task was much better than the performance in the event-based ProM task among old adults (55-81 years) (see also [19]).

In the interest of explaining the discrepant results, d'Ydewalle et al. combined experiments both in researches of Einstein et al. and Ydewalle et al. (like [17, 20]). They demonstrated that when participants were involved in the simple problems (low cognition), their performance on the time-based ProM task was higher than the performance on the event-based ProM task, whereas when they were required to resolve complex problems (high cognition), their performance on the time-based ProM task somehow decreased, particularly for older adults (60-86 years) [21]. d'Ydewalle et al. [22] reproduced the experiment by $2 \times 2 \times 2$ design (*old* vs. *young*, *event-* vs. *time-* based task, and *low* vs. *high* complexity of the ongoing task). Their result provides a better explanation to the type-related discrepancy.

2.2.2 Age

2.2.2.1 Development of ProM

According to the review, only two remarkable studies have carefully investigated the development of ProM on very young children (2-5 years old) [23,24]. Some studies compared children of very young age and early school age (4-7 years old)(e.g., [25]). And some studies concentrated on schoolchildren development with a relatively short age range of 3 or 4 years, such as Passolunghi et al. compared the ProM performance between 7 years old and 10 years old children, and Nigro et al. [23] studied children between 7 years old and 11 years old. A few studies concentrated on schoolchildren development with a relatively wider age range of 5 years (e.g., [26–30]).

From 2 to 5 years old. Two studies examined the development of ProM in children aging from 2 to 5 years old [23,24]. These studies found that children have the ProM ability at as early as the age of 2. In the study of Somerville et al. [24], children from 2-4 years old were involved in deliberate ProM activities. The 2 years old, 3 years old, and 4 years old children were arranged to 8 different ProM tasks over a 2-week period. These tasks varied in high motivation level such as “remind me to buy candy at the store” and low motivation level such as “remind me to bring in washing”. The time of delay to carry out the task varied in short (a few minutes) and long (a few hours) level. The results

found that even 2 years old children could recall the ProM tasks and perform very well, with 80% successful in remembering tasks with high interesting and short delay.

Unlike the above study, Guajardo and Best [31] studied the 3 to 5-years old children on the ProM task in a laboratory settings. In their study, the children were introduced a computer-based game in which they received 6 blocks of 10 pictures at frequency of 5 seconds per picture. The ProM task asked the children to press the keyboard when they saw a photo of a house (or a duck). The results showed that the 5-years old children were reliably better at remembering to press the keyboard than 3-years old children. Their study obtained a significant effect of age which means the 5-years old children can performance better on ProM tasks than 3-years old children.

From 5 to 7 years old. Some studies showed ProM has rapidly developed after the age of 5 (e.g., [25, 32]). For instance, Kvavilashvili et al. [25] examined two groups of children's (5 years old and 7 year old) overall performance on event-based ProM tasks in experiment 1. The children participated in an ongoing activity of naming photo cards. They were asked to hide the cards once they saw the animal cards. In the end they found that the 7-years old children performed much better than 5-years old children. However, some other studies obtained discrepant findings. For example, Meacham and Colombo [33] asked the children (from 5 to 8 years old) to play a card game with experimenters.

The ProM task was that when they finished the game, the children reminded the experimenters to open the surprise box which had been placed on the table before they started the game. The data analysis revealed that there was no age effect during this age period.

From 7 to 12 years. There are two studies on children development in the time-based ProM from 7 to 12 years old [26, 27]. The computer game CyberCruiser was applied in Kerns' study [26]. The children from 7 to 12 years old controlled the car by using a joystick. They were required to be very careful about the traffic and hazards around to get points. The points were calculated by whether hitting other vehicles or not and how fast the speed was. The time-based ProM task was to check the fuel gauge by hitting a button in case the gas ran out. The results revealed a significant ProM development from 7 to 12 years old. In the study of Mackinlay et al. [27], the ongoing activity was one-back picture which required the children (7-12 years old) to judge whether the current picture has been seen before by pressing yes or no keys. The time-based ProM task required to remember to press the clock key every 2 minutes. The results indicated that older children had better performance. Passolunghi et al. [34] also acquired the findings that the older children's (10-11 years old) overall performance on the event-based ProM task is far better than that of the younger children (7-8 years old). These findings on development patterns revealed a significant ProM development in schoolchildren.

However, Nigro et al. [23] failed to find interesting development in either time-based or event-based ProM. In their study, the children were engaged in the ongoing task of solving mathematical addition questions and puzzles. They were required to remind the experimenter to do something at a particular time or when seeing another experimenter. The results did not present age effect between 7-years old and 11-years old children. Kvavilashvili et al. [35] said that development of ProM is somehow slow from 7 to 12 years old. This conclusion contradicted the findings in Mackinlay et al. [27] which showed very significant ProM development in the time-based ProM task, and Passolunghi et al. [34] which showed the children's ProM development in event-based tasks.

Conclusions: Why are the findings of these studies discrepant? Firstly, as mentioned before, the complexity of the ongoing task possibly interfered with the results. For example, in the study of Guajardo and Best [31], each block of 10 pictures with 5 seconds per picture to response could have been a difficult ongoing task for 3-years old children. Also, in the research of Kvavilashvili et al. [25], it is obvious that 4-years old children have more challenges to name 20 pictures in each of four stacks of cards than children of 7-years old. Similarly, in the study of Kerns [26], although the game as an ongoing task was equally interesting to both 7-years and 12-years old children, it is still difficult for 7-years old children to play the game.

Secondly, it is also possible that some paradigms cannot eliminate ceiling effects. For example, in the research of Somerville et al. [23], the ProM task of reminding Mom to buy candies in a few minutes was too exciting for either 2-years old children or 3-years old children. The children cannot wait to carry out the exciting task (ProM task). It is not surprising to see 2-years old children's performance on the ProM task is the same as that of older children. Similarly, in the research of Meacham and Colombo [33], the ProM task of reminding the experimenter to open the surprising box is also a temptation target.

2.2.2.2 Aging with ProM

In fact, initially, age was the focus of ProM studies. Craik [16] was the first one to point out that age would be a factor that affect ProM performance. In his study, they found that the older adults have more complaints about their forgetfulness in terms of accomplishing deferred tasks. Later, Dobbs and Rule [36] examined age differences in the ProM performance. They found a deficit for older adults (from 70 to 99 years old) compared with younger adults (from 30 to 65 years old).

Taking ProM types into account, Einstein, et al. [17] pointed out that age effect exists on the time-based ProM by comparing old-adults and young-adults. At the same time, they stated that there was not much age effect on event-based ProM. d'Ydewalle

et al. [21] argued against their results through a set of experiments. d’Ydewalle also [19] conducted three experiments to test the performance on the time-based and the event-based ProM task. They found that there were age effects existed in the event-based task.

To address the discrepancy of the event-based ProM, d’Ydewalle et al. [21] applied two types of ongoing activities into their experiments which included answering general knowledge questions used by Einstein et al. [17] and face-identification used by d’Ydewalle et al. [19]. The answering-questions activity is more complex than face-identification because the former requires more execution functions. The result showed that old adults’ performance in both types of tasks declined regardless of ongoing activities. d’Ydewalle et al. confirmed that age effect exists in both types of tasks.

Additionally, Maylor [5] also conducted experiments to examine the discrepancies. She pointed out the difficulty of ongoing activities might be an interference factor to detect the age-related difference. That is, in case the difficulty level of the ongoing task is manipulated in the experiment, it would equate ProM performance between younger and older participants, such as Einstein and McDaniel’s (1990) study, in which they controlled the older participants’ ongoing task with fewer words in the list of recalled words. Maylor’s experiment asked participants to recognize the face and give response

when they found the person had a beard. This experiment required the attention shifting from face-recognition (one level of processing) to features of face (another level of processing). The attention shifting is a process of execution functions. Compared with younger adults, older adults have diminished execution functions [37]. Therefore, Maylor concluded that older adults also have deficits in the event-based ProM task which requires execution functions. Rose et al. [38] showed that Virtual Week game can improve older adults' prospective memory. Some recent researches [39] show that older adults with low prospective memory ability profit from planning.

Looking through the ProM development across the lifespan, compared with young adults, children generally have less developed ProM. But older adults have gradually declined in ProM, which is attributed to the development of execution functions. These age differences draw an inverted U-shaped developmental trajectory across lifespan as replying on measures of the execution function [1].

It is very clear that age related differences in the time-based ProM performance is related to internal cues of time monitoring and self-initiated. Age related differences in the event-based ProM depend on some variables of execution functions such as the attention shifting from different levels of cognitive processing [5]. Therefore, both types of ProM tasks seem to require the executive control processes [4, 40, 41]. In the laboratory

setting, the ongoing task is manipulated by experimenters. Failure of adjusting the difficulty level of ongoing task across age groups may lead to confusing and contradictory results such as what we mentioned above.

2.2.3 The Complexity of the Ongoing Task

In laboratory settings, the ongoing task is designed as a background work such as answering a set of questions [17], solving the mathematical or puzzle problems [23], naming a set of pictures [5, 19, 21, 25], or playing a computer-based games [26], etc., from which the participants need to perform ProM tasks by shifting their attention from the ongoing task.

Firstly, take a look at some studies of comparing ProM performances between younger and older adults. The ongoing task requires participants to answer many general knowledge and problems-solving related questions in both types of ProM tasks [17]. d'Ydewalle et al. [19, 21] employed the paradigm which is similar to those in [17], but face-identification as a different ongoing task applied in the paradigm. Similarly, in the study of Maylor [5], the ongoing task was designed as writing down the name of various famous male faces.

In the developmental studies of ProM, Nigro et al. [23] designed their ongoing task as solving a series of mathematical operations and puzzles for children. The difficulty of the ongoing task was previously adjusted according to the age of the participants both types

of ProM tasks. In the research of Kvavilashvili et al. [25], 4-years, 5-years, 7-years old children were asked to look at four stacks of cards with picture and tell the experimenter the details of the picture as accurately as possible. The children were also instructed that they could draw one picture for each stack. Kern [26] employed a computer-based game in the experiment. The ongoing task required the children aged 7 to 12 years to play the Cyber Cruiser game, in which the children used a joystick to control a car on a road with traffic and hazards.

The naturalistic studies carry out experiments in the real-life environment. The study of Somerville et al. [24] is a pioneer of naturalistic study. In this study, children aged from 2 to 4 years were given eight ProM tasks in their real life by their mothers. Their mothers also observed their ProM performance and acted as an experimenter. Ceci and Bronfenbrenner [42] applied a video game to mimic naturalistic study with a real-life scenario. The children were allowed to play the video game, but they were asked to remember to take the cupcakes out of the oven 30 minutes later. The ongoing task of playing the game is very likely to happen in our life. It is the same as watching TV but remembering to turn off the oven after certain minutes. In the research of Kvavilashvili and Fisher [35], the participants did what they did daily as usual. They were asked to remember to make calls to the experimenter either at a pre-arranged time or after

receiving certain text message on the seventh days of their experiment session. The ongoing task was also their real life where the ProM task was embedded as making a phone call at an intended time.

The performance of the ongoing task. Most of ProM studies only pay attention on ProM performance, whereas the performance on the ongoing task is not reported. For instance, Kern [26] emphasized that the computer-based game of Cyber Cruiser made children aged from 7 years to 13 years equally participated in playing, but Kern didn't analyse the performance of ongoing task (game score) to identify the age-related difference. Although Nigro et al. [23] previously adjusted the complexity of the ongoing task (mathematical problems and puzzles) according to the class level for the children aged from 7 to 12 years, they didn't report children's performance on the ongoing task.

Few studies reported the performance of ongoing tasks [21, 43, 44]. d'Ydewalle et al. [21], for example, conducted the experiment by $2 \times 2 \times 2$ design (*old* vs. *young*, *event*– vs. *time*– based task, and *low* vs. *high* complexity of the ongoing task). In their results, they analysed the ongoing task of both answering questions and face identification. Under the condition of answering questions (high complexity), senior adults even performed much better on the ongoing task than younger adults in the time-based task, whereas there was no age difference in the event-based task. On the other hand, under the condition

of face identification (low complexity), younger adults performed significantly better on the ongoing task than older adults both in the time- and event-based tasks, but the age related difference in the event-based task is not significant. The analysis of interactions (ProM and ongoing task; ProM and age; age and ongoing task) suggested that age differences in ProM would disappear under some conditions (relatively low complexity of the task) when taking the performance of the ongoing task into account.

The study of Rendell et al. [43] involved the face recognition as the ongoing task, in which a target cue “with glasses” or “John” is embedded. The ongoing task was measured by the proportion of famous faces that were correctly recognized. In experiment 2, the ongoing task was conducted at a slower pace than in experiment 1. They noticed that younger participants named a larger proportion of faces than the older adults did in both experiment 1 and experiment 2. More importantly, the finding patterns between experiment 1 and 2 indicated that when the ongoing task is not that challenging, the older adults often performed on ProM similarly to the younger adults.

Smith et al. [44] embedded a ProM task in one color matching task. They changed the difficulty level of the task through significantly changing the number of colors: older adults all performed a 4-color version but younger adults did the 4-color version in one trial and a 6-color one in another trial. They observed the following: even if older adults

and younger adults failed to perform the ProM task, they performed similarly or even better than younger adults on the ongoing task. They also concluded that emphasizing importance of an ongoing task can significantly improve the performance of the ongoing task.

Conclusions: The studies indicated that the complexity of a ongoing task is a very essential factor to interfere age related and type related differences.

2.2.4 The Importance of the ProM Task

The existing research supports that the importance level of a ProM task can somehow affect the performance, such that ProM performance would improve when the ProM task makes an individual to allocate increased attentions [44, 45]. Kliegal et al. [45] conducted two experiments, in which the task importance was manipulated. They found that the ProM performance was improved with the higher importance of the ProM task.

Smith et al. [44] also investigated the effects of the task importance. In this study, one group of participants received instructions highlighting the importance of the ProM task (called PMI) compared with another group of participants who received instructions highlighting the importance of the ongoing color matching task (called CMI). The results showed that, on average, participants performed much better on the ProM task under the PMI condition. More interestingly, the age-related differences exist under the

PMI condition: for younger adults, emphasizing the importance of ProM tasks substantially improved their performance and decreased their performance on the ongoing task, whereas older adults under the PMI condition slightly improved their ProM performance and kept the same level of performance on the ongoing task. In other words, younger adults are able to easily adjust their resource allocation between the two types of tasks based on task importance, whereas old adults are not able to change their attention from the ongoing one to the ProM task.

Conclusions: Nonetheless, we clearly understand that highlighting the importance of ProM task improves the ProM performance, although the degree of improvement varies with age.

2.2.5 The Motivation of the ProM Task

Some studies have examined the effect of motivation to the ProM performance, especially in the naturalistic study [24].

The study of Meacham and Singer [46] was the first one to investigate the motivation to ProM. In their study, the participants were asked to send postcards to the experimenter on the rearranged time. The results revealed that the participants who expected to receive a reward performed significantly better than the participants who did not expect to receive a reward.

In the study of Somerville et al. [24], for an example, the children from 2 to 4 years old involved in the deliberate ProM activities. They were given 8 different ProM tasks by their mothers over a period of 2 weeks. These ProM tasks varied in high motivation levels such as “remind me to buy candy at the store” and low motivation level like “remind me to bring in washing”. The results found that even 2-years old children could recall the ProM tasks with 80% successful in remembering high motivation tasks, as well as 4-years old children.

Recently, in order to identify the motivation as an assumed factor for the paradox of age related declines compared with age benefits in naturalistic settings, Aberle et al. [47] conducted a study where participants were asked to remember to contact with the experimenter repeatedly over one whole week. One group has monetary incentives and the other group has no incentives. The results showed that young adults in the high motivation group overcame their age-related deficits and performed better than those in the low motivation group. In other words, increasing the motivation of ProM task can improve the ProM performance.

2.3 Related Work

As mentioned before, ProM is vital for our health and social life. ProM failures produce great challenges to people and directly influence their life quality. According to Kliegel

and Martin [2], a significant number of 50-80% memory failures related to ProM problems.

To avoid the consequences of ProM failures, people are likely to use memory assists to help their memory, especially for old people [48]. Most studies demonstrated that both young and old people benefit from using memory assists (e.g., [15, 49]). Memory assists help users to store information or remind the user an event they might forget [50]. In this research, we investigate the reminder function of memory assists relative to ProM, rather than the storing function relative to retrospective memory.

According to Harris [51], reminders are generally categorized as active or passive reminders. Examples of diaries, lists, and calendars are passive reminders which require the user to actively check them, whereas google calendar and mobile phone are examples of active reminders which attract users' attention and instruct them when and how to perform an intention. ProM reminders vary from the traditional way of pen and paper to technology-based way of electronic devices. The purpose of designing a ProM reminder also varies from specific to generic use. The current study targets on a technology-based reminder of generic use, since our ultimate aim is to produce a reminder system with more flexible and adaptable features.

2.3.1 Current ProM Assists

2.3.1.1 NeuroPage

Originally, the technology-based memory assists have commonly targeted on cognitively impaired people. One of the earliest ProM assists was Neuropage, of which the primary users are brain injured patients [52]. Neuropage is very simple with little learning. Users enter the schedule information through a paging company and, at an appropriate time, all reminder alerts are sent to the user. These functions ensure NeuroPage is a high usable ProM assist. Wilson et al. [53] evaluated the NeuroPage. The result showed that NeuroPage as a ProM assist improved participants' (19-66 years old) performance on ProM tasks such as remembering to take medicines or pack lunch .

However, according to a study of Caprani et al. [9], there are two potential functions relating to the improvement of ProM NeuroPage. The first one is the postpone function. The second one is the task confirmation function. A user may receive a reminder at an inappropriate time. Thus the ProM assist has a better function of task delay so that the users will be asked at an appropriate time point when they are able to successfully perform the intention. Meanwhile, the care-giver should know whether the intended task has been carried out or not. Involving these two functions can improve NeuroPage ability of the assistance.

2.3.1.2 MEMOS

MEMOS is a mobile interactive ProM assist, which was designed for brain injured and older users to remind them of essential facts and dates [54]. MEMOS consists two parts: Personal Memory Assistant (PMA) and a base station. PMA is a mobile electronic device for reminding users of important tasks and providing useful feedback, and the base station will efficiently coordinate all the activities of care-givers and timely notify them about feedback of the task execution.

Walther et al. [55] evaluated the MEMOS. The participants were patients with head injuries. The result showed that users performed best in using PMA from MEMOS compared with other electronic memory assists (palm pilot and mobile phone). MEMOS overcomes the major drawbacks of the NeuroPage. It supports care-givers to encode and input information, and displays important information for patients to successfully perform the task. Furthermore, it allows patients to confirm the task carried out by pressing a button, and PMA can detect this information.

Similar to NeuroPage, the primary users of MEMOS are brain injured patients. The research group has recognized its potential ProM assists for healthy older people, and planned to extend the system for an application in other field [56].

2.3.1.3 Memojog

Memojog was designed as a ProM assist built in a Personal Digital Assistant (PDA) platform for memory impaired persons [57]. Memojog consists of three components of PDA, the central server, and the web-based database. User, care-giver, and care professional can input the schedule of the user and action prompts in the PDA or web-based database. The user can then choose to accept the reminder, postpone the reminder, or even ignore the reminder. The care-giver and care professional can acquire the user's response by data transmitted to the central server. Memojog also has multiple functions of storing personal information for the user.

Memojog system was thoroughly evaluated with old adults and memory-impaired users [58]. They had two real-world evaluations, each with 6 participants (note that different participants are used in different evaluations). The results showed that the participants can well accept the Memojog system and can easily understand how to use it. Users appreciated the system reminded their intended tasks accurately.

However, the participant also gave some negative comments such as coverage problem of the inability to timely connect to relevant websites for changing or updating their schedule, and some problems related to hardware, e.g., the non-sensitive touch screen [58].

2.3.1.4 Google Calendar

Both paper-based and electronic-based calendar are used. Paper-based calendars have a few limitations associated with their use, such as no alerts, forgetting to look at it and no enough space. Electronic-based calendar, such as Google Calendar, is an alternative solution to overcome these limitations. Google Calendar not only provides email reminders and pop-up reminders, but also enables users to link their calendar with their mobile phones. Users can set how far in advance of the task and how many reminders, which enable users to setup the system according to their personal needs [59]. Google calendar is also a simple system to use, such as clicking on the box corresponding to the appropriate date and time to create an event, filling the key words in the blank to set up what the event is.

McDonald et al. [59] evaluated the effectiveness of Goolge Calendar by comparing the standard diary use. The results showed that the participants (19-65 years old) completed more intentions when they used the Google Calendar than when they used some standard diaries. In other words, Google calendar is more effective than the diary to support people to achieve their ProM tasks. They also noticed that Google Calendar was rated much higher as compared with the standard diary in assist preference. Compared to the diary, Google Calendar reduces the need for monitoring by alerting the participants to complete

the events; the active reminder (linking to mobile phone) reduces the need for actively or frequently checking the calendar. Therefore, Google Calendar appeared to support the retrieval of ProM tasks, and maximize the probability that ProM tasks can be carried out within the necessary response window.

However, the participants in McDonald et al. [59] complained that they finally failed in the task execution even if they noticed a timed reminder to perform a task. The main reason is that the reminder issued at users' unavailable time, but reminders cannot interact with users to update the reminders in real-time.

2.3.1.5 AutoMinder

Autominder is one of the most advanced technological reminder systems, which assists a broad population such as older adults in general [60]. The purpose of Autominder is to help the older adults live perfectly in their home environment. Compared to the previous ProM assists, Autominder has the ability to model user's daily plans, track user's task execution through the behaviors detected by the sensors at home, and make significantly different decisions related to whether/when to issue reminders.

There are mainly three components in Autominder [60]. The first component is called Plan Manager which is in charge of storing user's initialized daily plan and updating the user's plan as the day progresses to avoid the inconsistent/conflicting activities. The

second component is called Client Modeler, which is in charge of monitoring the execution of the user's plan through the information of observable behaviors, as well as knowledge of whether and when any reminders were issued. The third component is called Personalized Cognitive Orthotic, which is in charge of deciding what and when to issue the reminder. These three components illustrate Autominder's main functions. Its impressive abilities provide older adults an intelligent and smart living home.

However, according to Caprani et al. [9], the sensors and observable information are not always reliable, which may result in assumption failures. Assumption failures decrease the reliability of reminders. Furthermore, the old users may be afraid of intelligent technology, for example, they may feel wary of a mobile robot and sensors working at home.

2.3.1.6 Amazon Alexa, Google Home, Mi

Alexa is an intelligent personal assistant developed by Amazon, first used in the Amazon Echo and the Amazon Echo Dot devices developed by Amazon Lab126. It is capable of voice interaction, music playback, making to-do lists, setting alarms, streaming podcasts, playing audiobooks, and providing weather, traffic, and other real-time information, such as news. Reminders via Alexa speakers work much like those we have come to know through other voice assistants, such as Siri or Google Now. Users can tell Alexa when to

Assist	NeuroPage	MEMOS	Memojog	Google Calendar	Autominder	Alexa/Google Home
Function	Alert users to perform tasks	Alert users to perform future tasks	Alert users to perform future tasks. Hold personal information	Alert users to perform future tasks. Hold past events	Adaptive reminder that alters schedule based on users actions	Users tell them when to remind through voices
Event-based					✓	
Time-based	✓	✓	✓	✓	✓	✓

Table 2.1: Comparisons of ProM Assists

remind and the alarm. Alexa has no capability of intelligently deciding when to remind and how to remind, which is the focus of our research.

Google Home and Mi are also powerful speaker and voice assistants. Similar to Alexa, users need to decide when to remind while using their reminder function. Therefore, these well known personal assistants do not provide the reminding function studied in our research.

2.3.2 Comparisons of ProM Assists

Based on a review paper [9], this thesis lists functions and memory supports of several electronic ProM assists in Table 2.1.

Each memory assist has its evaluation studies to support its effective use of helping users to execute prospective tasks. From the review above, memory assists have their own advantages and limitations. We compare their relevance on each stage of ProM

theory: 1) intention formation: All of them support encoding, as they require users to form intentions. Some of them provide voice inputs (e.g., MEMOS, Autominder). 2) intention retention: All of them support short or long term delays, unlike the retention time in human memory which is limited. However, most of them are restricted to the time-based ProM, and only Autominder supports both time-based and event-based ProM. 3) intention initiation: All of them can trigger users' intentions to reduce the need for monitoring. 4) intention execution: Their text-based prompts help users to execute ProM tasks.

2.4 Summary

In this chapter, we have reviewed the factors affecting prospective memory performance, including the type, the edge, the complexity of ongoing tasks, and the importance/motivation of the task. This chapter also analyzes the limitation of existing assistance systems based on prospective memory theory which brings forward our motivation.

Chapter 3

The Proposed Reminding Model Design

3.1 Introduction

ProM corresponds to a form of memory which is related to remember to perform some delayed intentions [61]. ProM failure, which is the failure to recall such intentions, is a commonplace. Studies have reported that about 50-80% of daily memory problems are caused by ProM failures [62]. 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, to do grocery shopping when passing by the supermarket on the way home. However, ProM failures might lead to many serious consequences in highly important situations like a patient forgetting to take medications [63].

A prospective memory task (ProM task) is encoded and maintained in ProM. It will be retrieved from ProM and performed later at a planned time or upon the occurrence

of an event [64]. There are various forms of ProM aid systems that people employ to assist their ProM task retrieval, ranging from health applications targeting brain injured or cognitively impaired people [65, 66] to general applications like Google Calendar and AutoMinder [67, 68]. Over the years, ProM 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 ProM task? 2) *Arranging an effective reminder schedule*. When should reminders be issued to effectively remind about a ProM task? 3) *Selecting appropriate reminding method based on contexts*. 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 ProM, we feel that it is necessary to refer to relevant theories and studies in ProM. From a vast amount of ProM literature, we identify six performance influencing factors and four contextual elements which can help determining the appropriate number of reminders and the reminding method. Existing research in ProM provides sound theoretical background for building an effective reminding model. However, it is a nontrivial to build a successful computational model that incorporates the identified factors and elements. The relationships among the ProM 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.

This study proposes a new reminding model which draws its theoretical basis from existing ProM research and employs FCM to incorporate the theoretical basis computationally. The reminding model can determine an appropriate number of reminders for a ProM task based on the estimated overall task performance. Guided by a reminding schedule function, the proposed model is also capable of generating an effective reminding schedule automatically. Moreover, the reminding model is able to make context-aware decisions regarding the reminding method.

This study proposes a structural model ProMR with 4 sub-models (Figure 3.1): a fuzzy rule-based model FRBKM for determining the fuzzy rules of factors in Knowledge Base, a Fuzzy Cognitive Map Model FCMProm for predicting the performance of ProM, a fuzzy rule-based model FRBFM for mapping the performance into the number of reminders, and a fuzzy rule-based model FRBMM for mapping the salience level into the reminding method. Knowledge Base includes factors which affect performance ProM task. Knowledge Base gets information from user, task and environment. To empower

the proposed model, mathematical functions are embedded into the model. According to the ProM performance and salience level predicted from FCMPProM, FRBFM and FRBMM determine the reminding plan which includes optimal number of reminders, the reminding schedule and reminding method.

Figure 3.1: The Proposed Reminding Model

To evaluate the proposed reminding model, it was incorporated into an evaluation system, *ReminderProM*. Demonstrations were shown in this chapter to understand how *ReminderProM* works.

3.2 Challenges in Designing an Effective Reminding Model

According to the process model [64], there are four stages in the life-cycle of a ProM task:

Intention formation encoding a future task; *Intention retention* maintaining the formed

intention and waiting for the perception of the target while engaging in ongoing tasks; *Intention initiation* initiating the execution of the intention at planned timing or upon occurrence of an event; *Intention execution* performing the initiated task. ProM failures are more likely to happen during stage 2, when an individual fails to retrieve and initiate a planned task. Some recent researches (e.g., [69]) also propose that both top-down and bottom-up processes are interconnected and dynamically interact to support prospective memory.

There are two main types of ProM tasks: time-based tasks and event-based tasks [61]. The former type involves performing an intention at a specific time point or after some time duration. A time-based task 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-based ProM task generally requires less self-initiation than a time-based one.

Various forms of ProM aids have been developed to assist the retrieval of ProM 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 ProM aids were mainly targeting brain injured or cognitively impaired people, e.g. MEMOS [65] and Memojog [66]. There are also general purpose ProM aid systems,

such as Google Calendar and AutoMinder. McDonald et al. evaluated the performance 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 ProM tasks even if they noticed reminders from Google Calendar [67]. AutoMinder is a ProM aid system that targets to help older adults in their home environment [68]. By monitoring users' execution of ProM tasks through feeds from sensors at home, AutoMinder decides whether/when to issue reminders. According to Caprani et al., observable information from sensors was not always reliable, which may result in assumption failures [70].

Similar to Google Calendar, most existing ProM aid systems only support manual creation of reminders. Users of these systems manually decide the number, schedule and reminding methods of the reminders. AutoMinder attempts 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 [70].

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

- **Determining an 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 ProM task?

- **Arranging an effective reminding schedule.** While a reminder for a task one month away may be too early, a reminder issued just before the ProM task may leave the user in a hurry to perform the task. When should reminders be issued to effectively remind about a ProM task?
- **Selecting an appropriate reminding method based on contexts.** 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?

3.3 The Proposed Reminding Model

3.3.1 Factors and Elements Identified from ProM Research

To cope with the three challenges related to ProM, this study forms the theoretical basis of our reminding model from relevant ProM theories and studies. In this section, it first introduces six factors that influence the performance of a ProM task and summarizes their

influence on ProM task performance. Then, it defines four contextual elements which help determining how salient a reminding method needs to be in a particular context.

3.3.1.1 Factor affecting ProM task performance

Time-based and event-based ProM tasks differ in various aspects. Hence, for each factor, this study discusses its influence on the performance of two types of tasks separately where applicable.

Delay of ProM task. The delay of a ProM task refers to the length of ProM retention interval. In other words, it is the time period from the encoding to the initiation of a ProM task. Generally, longer delay would reduce the performance of a ProM task [71].

Complexity of ongoing tasks. Ongoing tasks refer to the activities that individuals are involved in at the time they need to perform their ProM tasks. The complexity of an ongoing task is defined as the relative number of executive resources required by it. To perform their ProM tasks, individuals need to shift executive resources occupied by ongoing tasks to the ProM tasks. Thus, as the complexity of ongoing tasks increases, it becomes increasingly hard for individuals to shift their executive resources and retrieve ProM tasks successfully [72]. That is, the complexity of ongoing tasks negatively affects the performance of a ProM task [73].

Relatedness of tasks. Relatedness of tasks describes the degree of relatedness between a ProM 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 ProM task. Contrarily, it is considered relatively low when the ongoing task does not attract attention towards evaluating the ProM task features [74]. High relatedness between a ProM task and its ongoing task will yield easier retrieval of the ProM task, thus lead to significantly better ProM task performance [74, 75].

Importance of ProM tasks. The importance of one ProM task refers to its perceived importance by an individual. The importance of a ProM task improves its performance to the degree it requires accurate allocation of attention [76]. The performance of a time-based ProM task would improve greatly when its importance increases, since it requires more attention. While for an event-based ProM task, it experiences less performance improvement when its importance increases, since its retrieval is more spontaneous [77].

Motivation. Motivation refers to incentives or drive to perform a ProM task, which tends to be better when it is associated with a higher level of motivation. Experiments in [78] and [79] reported that when social motives were presented, the performance of both the time-based and event-based ProM tasks was significantly improved.

Age. Age can affect the performance of a ProM task, since the ProM of an individual develops and then deteriorates gradually as age grows. During childhood, ProM task performance of an individual improves as he/ she grows in age [80, 81]. The ProM task performance peaks during adulthood and gradually decreases as the individual grows older [82].

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 ProM task performance.

Motivation and importance. The presence of social motivation in a ProM task could reinforce its importance. Experiments in [83] 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 ProM. As a result, age affects the degree to which the ProM task performance is influenced by other factors. When ongoing task was made more complex or the relatedness between the ongoing and ProM task was lower, a greater performance decline was observed among the elderly compared to their younger counterpart [72, 84]. On the other hand, when social motivation was presented, a more significant performance improvement was reported

among the older adults than the young adults [79].

3.3.1.2 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 ProM 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 [73], a more salient reminding method should be used to intuitively attract attention and reduce monitoring under such condition.

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

Tolerance for disturbance. Tolerance for disturbance indicates 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 ProM research, this study has identified six performance influencing factors and four contextual elements. The relationships among the ProM 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 able to capture casual relationships among many different concepts. Next, it will present a brief introduction to FCM.

3.4 Fuzzy Rule-Based Model FRBKM for Defining Factors Affecting ProM Task

3.4.1 Definition

Knowledge Base gets information from the user, the ProM task and environment. People input their age, hobbies, routine and tolerance of being disturbed. They also input basic ProM task information such as the time of the ProM task, the location of the ProM task, the task categories and the perception of importance of the ProM task. Task categories are defined as working, socializing, sleeping, transport, housework and others. How long the ProM task is delayed is calculated by the time of the ProM task. Other technologies such as GPS and sensors could provide the ongoing time, the location and noise level of

environment. Here we define:

- User = $\langle \text{age}, \text{hobby}, \text{routine}, \text{tolerance_disturbance} \rangle$

$$\text{User.routine} = \langle \text{take.time}, \text{task.category} \rangle$$

- Task = $\langle \text{time}, \text{category}, \text{location}, \text{importance}, \text{delay} \rangle$

$$\text{Task.category} = \langle \text{working}, \text{socializing}, \text{sleeping}, \text{transport}, \text{housework}, \text{others} \rangle$$

- Environment = $\langle \text{time}, \text{location}, \text{noise} \rangle$

- Knowledge_Base = $\langle \text{age}, \text{relatedness}, \text{motivation}, \text{delay}, \text{importance}, \text{complexity}, \text{noise}, \text{tolerance_disturbance} \rangle$

3.4.2 Fuzzy Rules and Membership Functions

Knowledge Base includes factors affecting the ProM task performance and factors deciding the salience level of the ongoing environment. Knowledge Base is defined as KB .

According to Ministry of Social and Family Development, Republic of Singapore, Singapore's population of the elderly is defined as persons aged 65 and very old people defined as aged 85. In this study, it defines person aged 65-85 as old, aged less than 65 as per_old, and aged more than 85 as super_old. When the ProM task category and the ongoing task are the same category, the relatedness of them is defined as high, otherwise as low. For

example, if you will have a meeting at 5:00PM and you are working from 1:00 to 5:00 in the office, it assumes that the relatedness is high. Otherwise, if you will have the ProM task as cleaning the desk, the relatedness between the ProM task and the ongoing work is low. The motivation of the ProM task is decided by user's interests. For example, if your ProM task is shopping and you love shopping so much, the motivation is defined as high. The delay of the ProM task is defined as low, middle and high depending on hours, days, or weeks. The importance of the ProM task is input by users who decide the importance level as low, middle and high from their perspectives. The complexity of the ongoing task is defined as low, middle and high according to the category of ongoing task. Working and socializing are defined as high. Transport is defined as middle. Sleeping, housework and others are defined as low. The noise level depends on the environment. Office and meeting room have low noise level. Home has middle noise level, and shopping center has high noise level. Location information is from sensors. The tolerance of disturbance is decided as high, middle and low by users. The fuzzy rules stated above are summarized as following:

- $User.age \rightarrow KB.age = \{per_old, old, super_old\};$
- $Task.category \cap User.routine.task.category \rightarrow KB.relatedness = \{low, high\};$

- $Task.category \cap User.hobby \rightarrow KB.motivation = \{low, high\};$
- $Task.time \rightarrow KB.delay = \{low, middle, high\};$
- $User.importance \rightarrow KB.importance = \{low, middle, high\};$
- $User.routine.task.category \rightarrow KB.complexity = \{low, middle, high\};$
- $Environment.noise \rightarrow KB.noise = \{low, middle, high\};$
- $Environment.tolerance_disturbance \rightarrow KB.tolerance_disturbance = \{low, middle, high\};$

After collecting the crisp values and defining the linguistic values for each factor.

The crisp values are then transformed into fuzzy values in the interval of $[0,1]$ using corresponding membership functions. 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. For example, delay of ProM task is measured in terms of hours and has a trapezoid membership function in Figure 3.2. For example, the function of $f_M(x)$ represents middle delay of ProM task. It is defined by its lower limit a and its upper limit d , and the lower and upper limits of its nucleus, b and c respectively.

- a is 6 hours.
- b is 48 hours (2 days).

- c is 72 hours (3 days).
- d is 120 hours (5 days).

Figure 3.2: An Example of Membership Function

3.5 The Computational Model FCMPProM

In Knowledge Base, all factors are ruled into fuzzy values between $[0,1]$ through FR-BKM. They are inputs of the computational model called FCMPProM for predicting the performance of ProM task.

3.5.1 Fuzzy Cognitive Maps

Fuzzy Cognitive Map (FCM), first developed by Kosko [85], is well suited for modeling dynamic systems [86]. FCM is widely used to represent the cause-effect relationships among concepts in real-world systems [87–89]. More specifically, FCMs have been used for brain tumor grading [90] and differential diagnosis of language impairment [91].

Graphical representation of an FCM consists of a set of nodes and directed arcs. As shown in Figure. 3.3, 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 often characterized by a 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 relationship strength between c_i and c_j . A positive weight (i.e., $w_{ij} > 0$) represents a causal increase, while a negative weight (i.e., $w_{ij} < 0$) represents a causal decrease.

Figure 3.3: A Fuzzy Cognitive Map with Two Factors

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

- (i) $C = \{c_i | c_i \in [0, 1]; i = 1, 2, \dots, n; c_i \in \mathbb{R}\}$ denotes a set of concepts, and each with a numerical state value associated with it. $\mathbb{R}$ is the set of real numbers;
- (ii) $W = \{w_{ji} | w_{ji} \in [-1, 1]; i = 1, 2, \dots, n; j = 1, 2, \dots, n; i \neq j; w_{ji} \in \mathbb{R}\}$ denotes a set of weights, each with a numerical value.

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

3.5.2 The Model of FCMProm

The proposed reminding model addresses the three challenges highlighted in Section 3.2. It determines an appropriate number of reminders (τ) for a ProM task based on the predicted task performance. 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.

3.5.2.1 Predicting the Performance of ProM Task

This Model is used for predicting the performance of ProM task. V_{perf} is defined to predict the performance of a ProM task. It determines the joint-effect of the factors that influence ProM task performance. Figure.3.4 shows a visual representation of V_{perf} .

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

$$C = \{c_1, c_2, c_3, c_4, c_5, c_6, c_7\};$$

$$W = \{w_{12}(-), w_{15}(+), w_{16}(+), w_{17}(-)w_{27}(+), w_{37}(+), w_{47}(-), w_{53}(+), w_{57}(+), \\ w_{67}(-)\};$$

where

- c_1 denotes *age*: measuring the degree to which age adversely affects the performance of a ProM task.
- c_2 denotes *relatedness of tasks*: measuring the degree of relatedness between a ProM task and its ongoing task.
- c_3 denotes *motivation*: measuring the incentive strength of a ProM task.
- c_4 denotes *delay of ProM task*: measuring the length of the period from encoding to initiation of a ProM task.

- c_5 denotes *importance of a ProM task*: measuring the perceived importance level of a ProM task.
- c_6 denotes *complexity of ongoing task*: measuring the relative amount of executive resources required by the ongoing task.
- c_7 denotes *ProM performance*: measuring the likelihood an individual will remember and perform a ProM 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 $[-1, 1]$.

Figure 3.4: FCM for Predicting ProM Task Performance

Except for c_7 which denotes the ProM task performance, each concept in V_{perf} corresponds to a performance influencing factors defined in Section 3.3. It is worth noting

that the interrelationships among the factors are modeled in different ways. The relationship between motivation (c_3) and importance of ProM 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_7 . For example, the complexity of ongoing task (c_6) has a negative causal relationship with the ProM task performance (c_7). Age affects the strength of this relationship as older adults experience a greater performance decline as complexity increases. Thus, the values of w_{15} and w_{16} vary with the value of c_1 .

A 7×7 adjacency matrix W could be set up to hold all the weight values. When there is no edge from c_i to c_j , we have $w_{ij} = 0$. A 1×7 state vector $C(t)$ is used to store all the state values of the concepts at simulation iteration 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 following two components:

the state vector $C(t)$ with the weight matrix W ,

$$\tilde{C} = [\tilde{c}_1, \tilde{c}_2, \dots, \tilde{c}_7] = C(t) \times W$$

$$\tilde{c}_i = \sum_j w_{ji} c_j(t)$$

where $\tilde{c}_i$ denotes the sum of products of the state values of all concepts connecting to c_i

and the weights of the edges (or arcs) connecting them. The state values of the concepts

in the next simulation step can be calculated as follows:

$$c_i(t+1) = f_i(\tilde{c}_i) = f_i\left(\sum_j w_{ji} c_j(t)\right)$$

where f_i denotes concept c_i 's squeezing function. It converts the interim state value $\tilde{c}_i$

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 ProM task.

3.5.2.2 Fuzzy Rule-Based Model FRBFM for Mapping the Number of Reminders

This model FRBFM determines an appropriate number of reminders on the predicted

task ProM performance. 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 ProM task well, fewer reminders will be generated to minimize disturbance.

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. Refer to the Table 3.1.

Table 3.1: Rules for Mapping the Performance to the Number of Reminders

ProM Performance	The Number of Reminders
Very High [0.8, 1]	1 (Very Low)
High [0.6, 0.8)	2 (Low)
Medium [0.4, 0.6)	3 (Medium)
Low [0.2, 0.4)	4 (High)
Very Low [0, 0.2)	5 (Very High)

3.5.2.3 Arranging an 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 ProM

task (Figure.3.5). 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 ProM task approaches. Assume that the length of the reminding window is T_w and the total number of reminders is τ .

Figure 3.5: Example: 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 starting time of the task.

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

3.5.2.4 Determining an 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 3.3 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 Figure. 3.6.

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

$$C = \{c_5, c_6, c_8, c_9, c_{10}\};$$

$$W = \{w_{58}(+), w_{68}(+), w_{98}(+), w_{108}(+)\};$$

where

Figure 3.6: FCM for Deriving Saliency Level

- c_8 denotes *saliency level*: measuring the extent to which a reminding method attracts attention.
- c_6 denotes *complexity of ongoing task*: measuring the relative amount of executive resources required by the ongoing task.
- c_5 denotes *importance of a ProM task*: measuring the perceived importance level of a ProM 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 3.3. 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.

Next, it gives details about how the reminding model was incorporated into a mobile app for evaluation.

3.6 Incorporating the Reminding Model into a Reminder Application

To evaluate the proposed reminding model through human subject experiments, this study developed a simple mobile application using JAVA, the *ReminderProM*, which

incorporates the model. The architecture of *ReminderProM* is illustrated in Figure. 3.7. It has three components: the Reminder Planner, the ProM Agent and the Personalized User Model. The Reminder Planner realizes the reminding model proposed. For every ProM created task, it produces a reminding plan which consists of an appropriate number of carefully arranged reminders, and each is with a selected reminding method. The ProM Agent, which is designed in the light of the process model [64], manages the ProM processes, including the encoding of a ProM 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.

Figure 3.7: The Architecture of *ReminderProM*

3.6.1 Some Screenshots from Reminder Application

Creating a task in the application is rather straight forward, going from input of task details to editing and saving the reminder schedule (Figure 3.8).

(a) New Task input details.

(b) propose schedule according to inputs, profile, and weekly routine

(c) Dialog to add a new reminder

Figure 3.8: Screenshots for Creating a New Task in *ReminderProM*

When the user chooses to open the task once receiving a notification, the application will open the page as shown in Figure 3.9. In this page, the user can choose to move the task as Completed or simply change the details of the task. If there are changes made to the tasks date/time or the next reminders date/time, the reminder schedule will be changed, and the user can edit it again to his/her preference.

Figure 3.9: Opening an Existing Task from To-do List or from Notification

The user has to (or encouraged to) input his/her schedule weekly routine. Figure 3.10 shows the key screenshots of adding the weekly schedule.

Figure 3.10: Adding Activities into Ones Weekly Routine

3.6.2 How *ReminderProM* works

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

Step 1: collection of crisp values. From user inputs and profile information, *ReminderProM* obtains crisp values of the performance influencing factors and the contextual elements. Table 3.2 summarizes how the crisp values are collected. Upon the creation of a new ProM task, besides general task details like description, date and time, *ReminderProM* also requires the user to specify the task category and rate the importance level of the task. The task date is used to calculate the delay of ProM task.

The *ReminderProM* provides default ProM task categories, such as working, socializing, transport, sleeping, housework and others. The user can also define customized ProM 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 *ReminderProM* 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 then transformed into fuzzy values in the interval of $[0, 1]$ using corresponding membership functions shown in Figure.3.11. 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 ProM 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 ProM task performance. Its fuzzy value increases as one grows into 60s and beyond, representing increasing age deficit

of ProM 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 increase as the user rating for complexity increases. Contrarily, the fuzzy value of tolerance for disturbance decreases as the corresponding user rating increases.

Table 3.2: Collecting the Crisp Values of FCM Inputs

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

Step 3: FCM computation and result mapping. The fuzzy values of performance

Figure 3.11: Membership Functions for FCM Inputs

influencing factors and contextual elements are feed into the two FCMs to predict ProM task performance and derive salience level. After completing the computational processes in FCMs, the predicted performance (value of c_7) 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 *ReminderProM* are shown in Table 3.3. Finally, the reminders are organized according to the reminder schedule function.

Table 3.3: Mappings for Number of Reminders and Reminding Method

Value of c_7	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, this study describes two real-life ProM tasks (shown in Table 3.4) to show how a reminding plan is

generated for each of them following the aforementioned 3 steps.

Table 3.4: Two Scenarios: Meeting Vs Medication adherence

	ProM task 1 values		ProM task 2 values	
Factor/Element	Crisp	Fuzzy	Crisp	Fuzzy
Delay of ProM 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 ProM 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 ProM task		0.7342		0.1989
Salience level		0.4143		0.7471

ProM 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 having high relatedness to the ongoing tasks he is engaged recently. Considering the effect of all performance influencing factors, his predicted performance for this ProM task is 0.7342. According to the mappings in Table 3.3, *ReminderProM* generates 3 reminders for this task. At the planned issuing time of 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 3.3, 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 3.5.2.3.

ProM task 2 (Taking Medication) is created by an elderly user for reminding her to take dementia medication tomorrow. This ProM 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), *ReminderProM* 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.

3.7 Summary

This chapter models the theories and research findings in ProM computationally to address the three critical challenges we identified from existing ProM aid systems. (1) *Determining appropriate number of reminders.* The reminding model determines the appropriate number of reminders for a ProM task based on the predicted performance of the

task. Six performance influencing factors were defined from extensive ProM literature.

The reminding model provides a reasoning mechanism for inferring ProM 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 *ReminderProM*. This chapter demonstrated how *ReminderProM* works to predict the performance of ProM task.

Chapter 4

Experiments to Evaluate the Proposed Reminding Model

In Chapter 3, it was proposed a reminding model based on FCM to predict the ProM task performance. According to our research, 6 factors containing delay of ProM task, complexity of ongoing task, relatedness of tasks, importance of ProM task, motivation, and age are related to the performance of a ProM task. In this chapter, firstly we will verify the validity of the model. At the same time, we will evaluate the proposed reminding model to identify its effectiveness.

4.1 Verification Experiment of the Proposed Model

This experiment aims to showcase the usage of the model in real world scenario and verify the validity of the model as well.

Subject

A total of 12 senior participants aged from 48-88 ($mean=59$, $SD=11$) were recruited

through online social network in the study. The participants were all Chinese and equal in gender. They were all healthy in both mobility and cognition ability.

Method

To evaluate the effectiveness of our proposed reminding model, the researchers transformed the concepts of the 6 factors and the participants' performances into quantitative data as follows.

- Performance of a ProM task. The participants will follow the researchers' guidelines to finish some ProM tasks. Their performance will be recorded as R for "remembering" which represents the participant completing the task successfully and F for "forgetting" which means the participant failing to complete the task.
- Delay of ProM task. Each participant will go through 2 tasks with different time requirements with all other factors controlled.
- Complexity of ongoing task. After the participant finishes 1 task, he/she will be asked the question of "What were you doing before the ProM tasks?". Then the researchers will rate the tasks based on its workload in both memory pool and cognition process from 1 to 5.
- Relatedness of tasks. After the task completion, the participant will be asked the

question of “What motivated you to do the task?”. Then, the researchers will rate the relatedness of the ProM task based on their expertise and rules.

- Importance of ProM task. After each task, the participant will rate their perceptions of the importance of the task from 1 to 5 (1: not important at all, 5: very important).
- Motivation. 2 groups of the participants will receive a Hongbao with 5 RMB after each successful completed task as an incentive. They will be acknowledged about this award before the experiment.
- Age. The age of each participant will be collected before the experiment.

Pre-experiment

Each participant was interviewed by our researchers for about 5 minutes about the demographic information as age. They were asked to rate their own ProM from 1 to 5 (1 represents very poor while 5 represents very strong). The results were recorded by our researchers.

- 4 participants as Group 1 went through Task 1 “*Please talk to me through WeChat after 5 hours*” and Task 2 “*Please talk to me through WeChat after 1 week*”. The

task as “*talk to me*” is defined as the ProM task. The time difference between Task 1 and 2 represents the factor of “*delay of the ProM task*”.

- 4 participants marked as Group 2 went through Task 3 “*Please remind me that I need to submit a paper after 5 hours*” and Task 4 “*Please remind me that I need to submit a paper after 1 week*”. In this group, the task is designed as “*remind me to submit a paper*” instead of “*talk to me*”. It aims to verify the factor of importance.
- 2 participants as Group 3 went through Task 5 “*Please talk to me through WeChat after 5 hours. If you do this successfully, you will receive a Hongbao with 5 RMB*” and Task 6 “*Please talk to me through WeChat after 1 week. If you do this successfully, you will receive a Hongbao with 5 RMB*”. The reward of Hongbao is a motivation factor.
- 2 participants as Group 4 went through Task 7 “*Please remind me to submit a paper after 5 hours. If you do this successfully, you will receive a Hongbao of 5 RMB*” and Task 8 “*Please remind me to submit a paper after 1 week. If you do this successfully, you will receive a Hongbao of 5 RMB*”. Comparing with Group 2, the tasks for this group were added the motivation factor. While comparing with Group 3, this group has higher importance tasks.

The performances of the participants were recorded by our researchers.

After the experiment

The participants were interviewed for about 10 minutes after each task. The interview questions were pre-designed as following:

- What were you doing during the time slot?
- What evokes you to do the task?
- How do you rate the importance of the task? (1 not important at all to 5 very important)
- Did anybody remind you about the task during the experiment?
- How do you remind yourself to do something in your daily life?

Results

In Table 4.1, the seven factors were coded with discrete scales between 1 to 5 (except for the Delay of ProM task and Age). The scales were decided by the interview to the participants after each task. For example, the levels of complexity of ongoing task were determined by asking what the participants were doing just before they completed the task. If the participants answered they were having a rest or watching TV, they would

Table 4.1: The Predicted FCMProM Results and Experiment Results

Participant	1		2		3		4	
Age	51		48		63		63	
Delay of ProM task	0.2	7	0.2	7	0.2	7	0.2	7
Complexity of ongoing task	5	5	1	5	2	3	5	5
Relatedness of task	1	1	1	1	1	1	1	1
Importance of ProM task	3	1	5	5	4	4	3	3
Motivation	4	4	4	4	3	3	3	3
FCM Result	0.6309	0.2142	1.0000	0.6844	0.7199	0.3468	0.2099	0.0852
Experiment Result	R	F	R	R	R	R	R	F
Participant	5		6		7		8	
Age	51		52		53		55	
Delay of ProM task	0.2	7	0.2	7	0.2	7	0.2	7
Complexity of ongoing task	4	1	3	5	2	1	1	2
Relatedness of task	3	1	1	1	1	1	3	1
Importance of ProM task	1	1	1	1	4	4	4	4
Motivation	3	3	3	3	4	4	4	4
FCM Result	0.5266	0.4860	0.3056	0.0321	1.0000	1.0000	1.0000	0.8835
Experiment Result	F	R	F	F	R	R	R	F
Participant	9		10		11		12	
Age	65		64		55		88	
Delay of ProM task	0.2	7	0.2	7	0.2	7	0.2	7
Complexity of ongoing task	2	1	4	3	2	2	4	3
Relatedness of task	3	2	1	4	2	5	2	1
Importance of ProM task	5	5	5	5	5	5	5	5
Motivation	3	3	3	3	3	3	3	3
FCM Result	0.9648	0.9134	0.3728	0.6144	1.0000	1.0000	0.5009	0.2077
Experiment Result	R	R	R	R	R	R	R	F

receive a lower score; if they answered they were working or doing housework, a higher score would be assigned.

The coded seven factors were transformed into fuzzy values in the interval of $[0, 1]$ using corresponding membership functions. The final FCM results are shown in the above tables. The FCM results mean the probability that the participants would remember the tasks. If we assume the participants would remember the tasks when the computed FCM results are greater than 0.5, we can find from the results that 18 (bold parts) out of 24 tasks were accurately predicted. The *Accuracy* of prediction is 75% and the *Precision* of prediction is 87%.

Summary

From these results we believe that our proposed seven factors and FCM method can predict participants ProM in most of the cases.

4.2 Experiment to Evaluate the Overall Experience of the Proposed Reminding Model

This experiment aims to evaluate the appropriateness of the proposed reminding model.

Subjects and Method

To evaluate our reminding model, we conducted a 4-week user study for the proposed reminding model (ProMR) in naturalistic settings, involving 5 participants aged from 20

to 30. A control version of time-based reminders (TbR) 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 ProM aid systems functionally as it only supports manual creation of ProM tasks and reminders. The participants have installed both ProMR and TbR on their own mobile phones. They first used the control version TbR for 2 weeks and then ProMR for 2 weeks. After that, they completed survey questionnaires and sat through individual interviews.

Results

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 4.2. 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.

The participants also compared ProMR with its control version TbR ($\alpha = 0.5$) in

Table 4.2: 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

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 ProMB and the control version TbR (Table 4.3). The means of the ratings for overall experience were tested with the null hypothesis: the mean of the ratings for overall experience with ProMR (μ) is smaller than or equal to that for TbR ($\mu_{control}$). Since $p = 0.0231 < \alpha = 0.05$ ($t_0 = 2.357 > t_{0.05,8} = 1.86$), the study rejected 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 ProMR (μ') is smaller than or equal to that for the control version ($\mu'_{control}$). Since $p = 0.0328 < \alpha = 0.05$ ($t_0 = 2.132 > t_{0.05,8} = 1.86$), the study also rejected the null hypothesis. The test statistics were in favor of the alternative hypotheses, which supported that ProMR provides a better overall experience and reminds more effectively than the control version.

Table 4.3: Hypothesis Tests for Comparing ProMR and TbR ($\alpha = 0.05$)

H_0	p value	t score	t_0	Result
Overall Ex- perience $\mu - \mu_{control} \leq 0$	0.0231	1.860	2.357	Reject H_0
Effective Re- minding $\mu' - \mu'_{control} \leq 0$	0.0328	1.860	2.132	Reject H_0

4.3 Experiment to Evaluate the Effectiveness of the Proposed Reminding Model

This experiment aims to test the elderly performance of ProM task by using the proposed model.

4.3.1 Quantitative Study and Results

Subjects

A user study was conducted in game platform for elderly aged from 60-80 ($M = 71.7$, $SD = 7.88$).

Method

We used an adaptation computerized game called *Pumpkin Garden*. Participants played this game before. Each participant had an iPad installed with *Pumpkin Garden*. There are 2 games in *Pumpkin Garden*. The game of *Weeding* which requires participants to move their two fingers to remove the grasses automatically appeared on the screen.

Weeding has been used as the ongoing task. The game of *Watering* has been used as the prospective task. The interfaces of the game and the tasks are shown in Figure 4.1.

Figure 4.1: Interfaces of the Game and Tasks

The 24 participants were required to play the game of *Weeding* 3 rounds (a numerical timer displayed on the screen), but they needed to remember watering the pumpkins when they play *Weeding* until 100 seconds (time-based ProM task). 12 participants in control group used a simple time-based reminder TbR. Another 12 participants in experimental group used ProMR as reminders. As the proposed reminding model, when the time approaches to the ProM task, reminders were given to participants more frequently.

The participants had individual interviews after they finished playing game.

Results

Table 4.4 shows the performance of ProM task. In TbR group, 7 participants forgot to do their ProM task of watering. In experimental group, only 2 participants forgot to perform the ProM task of watering.

Table 4.4: Performance of ProM Task ProMR vs. TbR

	Remember the ProM Task	Forget the ProM Task	Total
ProMR	10	2	12
TbR	5	7	12

Table 4.5: Summary of Performance of ProM Task ProMR vs. TbR

	ProMR	TbR
Performance (%)	83%	41%

Summarized from Table 4.4, 83% participants performed the ProM task successfully with the proposed reminding model, and 41% participants failed in performing the ProM task with simple reminders (Table 4.5). We conducted a Chi-squares test. $\chi^2(1) = 4.44$ and $p = 0.035$ which significantly showed that their performance in the ProM task with the proposed reminding model was much better. The result showed that the proposed reminding model improved elderly's performance in ProM task.

4.3.2 Qualitative Study and Results

After participants finished the ProM task, a couple questions were asked through interviews: 1)Would you want reminders in your life? 2)Do you think the reminders are redundant? Only one participant said reminders are not necessary for him since he could remember to do the planned tasks very well. All other participants wanted reminders. Some of them said a lot of forgetting in their daily life, especially taking medicine at a regular time. They said if there are reminders in their life, it would be very helpful to

cope with forgetting. This study also identifies that reminders are important for elderly in their daily life.

There were 18 participants said “*I don’t think reminders were redundant.*” They appreciated multiple reminders. 6 participants said “*Yes, there were redundant reminders which were not necessary for me.*” The interesting findings were within these 6 participants. 1 of them was the participant who said he does not need reminders, and 5 of them got reminders from other participants. Results were summarized as following:

- 96% participants need reminders.
- 100% participants who got reminders from peers felt reminders redundant.
- 83% participants who felt reminders redundant were those who got reminders from peers.

4.4 Experiment to Explore Group Reminders Making Redundant Reminders

This experiment aims to explore group reminders making redundant reminders.

Subjects

A user study was conducted in game platform settings for elderly aged from 60-80 ($M = 68$, $SD = 7.48$). 6 participants were divided into 2 groups (Group A and Group B) and

6 participants were individuals.

Method

We used an adaptation computerized game called *Pumpkin Garden*. Participants played this game before. Each participant had an iPad installed with *Pumpkin Garden*. There are 2 games in *Pumpkin Garden*. The game of *Weeding* requires participants to move their two fingers to remove the grasses automatically appeared on the screen. *Weeding* has been used as ongoing task. The game of *Watering* has been used as the prospective task. The interfaces of the game and the tasks are shown in Figure 4.1. The 12 participants were required to play the game of *Weeding* 3 rounds (a numerical timer displayed on the screen), but they needed to remember watering the pumpkins when they play *Weeding* until 100 seconds (time-based ProM task). 3 participants in group A used ProMR with 3 reminders. Group B used ProMR with 1 reminder. 6 individual participants used ProMR with 3 reminders.

Results

In group A and B, all participants remembered to perform the ProM task. In group C, 4 out of 6 participants remembered to perform the ProM task (Table 4.6). Summarized from Table 4.6, 100% participants remembered the ProM task with 3 reminders. 100% participants remembered the ProM task with 1 reminders. 67% participants remembered

Table 4.6: Participants Remembering the ProM Task in Groups and by Individual

	Remember the ProM Task	Forget the ProM Task	Total
Group A	6	0	6
Group B	6	0	6
Individual	4	2	6

Table 4.7: Summary of Performance in Groups vs. by Individuals

	Group A	Group B	Individual
Reminder	3	1	3
Performance (%)	100%	100%	67%

the ProM task without group reminders and with 3 reminders (Table 4.7).

4.5 Summary

The experiment was conducted in real world scenario and verified the validity of the model as well. The results supported that FCM works very well to predict the performance of ProM task. A 4-week user study was conducted for *ReminderProM* 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 supported that *ReminderProM* provides a better overall experience and reminds more effectively than its control version. The qualitative and quantitative studies were carried out to evaluate the effectiveness of the proposed reminding model. The results showed that the proposed reminding model could significantly improve the performance of ProM task. At the same time, it was found that group reminders hap-

pen when people are friends and going to do the same task, and group reminders make redundant reminders, which means that the proposed reminding model needs to take group reminders into consideration to avoid redundancy. Next chapter will work on a reminding model with group tasks.

Chapter 5

Prospective Memory Aid Reminder System Design for Group Tasks

5.1 Introduction of Group Tasks

Nowadays ProM failure becomes quite prevalent. Studies have shown that ProM failures result in almost 50-80% of total daily memory problems [62]. The consequences caused by ProM failures could be quite serious, e.g., a patient forgets to take medications [63]. Prospective memory tasks have highly penetrated into people's daily life. The procedures of prospective memory task (ProM task) consist of encode and maintenance in ProM, and then retrieval from ProM and performance later at a planned time or upon the occurrence of an event [64]. ProM aid systems have been applied by people in assisting their ProM task retrieval in many fields, from health applications targeting at brain injured or cognitively impaired people [65, 66] to general applications, like Google Calendar and AutoMinder [67, 68]. Over these decades, ProM aid systems are in progress of improving

and evolving.

There are different types of ProM tasks and existing works on reminder systems only focus on individual tasks such as reminding elderly people to take their medicine. However, people with ProM difficulties (e.g., elderly) are often involved in many group tasks. For instance, seniors who enjoy being outside may like to play fun outdoor activities such as treasure hunts, bird watching, picnics, fishing, gardening and going to parks, lakes and many other places of interest. The group of elderly participating in a group task may interact with each other before the date of the event and thus, a group member might be reminded by other group members of the group task. Therefore, it is important to take into account the interaction between group members while designing an efficient reminding system for group tasks, which has not been addressed by any existing system and is focus of this chapter.

To design an efficient reminding system for group tasks, this study addresses three key issues including 1) determining the appropriate number of reminders; 2) arranging an effective reminder schedule; and 3) selecting an appropriate reminding method based on contexts. This chapter refers to relevant theories and studies in ProM to cope with these three challenges. Specifically, based on the theoretical background of ProM, this study thoroughly analyzes the factors (including the potential interaction between group

members) that will affect the ProM task performance. Based on the analysis, it proposes a computational approach for determining the appropriate number of reminders and reminding method. The problem of determining the optimal reminding schedule is very complex due to many interdependent factors and uncertainty, it is thus difficult to build an integrated framework in which all the interdependent factors are concurrently optimized. Rather than modeling all the interdependent factors explicitly and then determine the optimal reminding schedule by an complicated combinatorial optimization, this study tries to connect all the inter-dependent factors indirectly and design novel heuristics to well approximate the optimal reminding schedule.

In this approach, the reminding model can determine an appropriate number of reminders for a ProM 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, a series of experiments were conducted and the participants felt that the reminders generated according to the reminding model are appropriate in terms of their number, schedule and reminding methods. The evaluation results also support that this approach provides a better overall experience and reminds more effectively than its

control version.

5.2 The Problem of Reminding Group Tasks

Under certain circumstances, we can observe the disadvantages of reminder systems, e.g., the failure in reminding, sending out redundant reminders, or disagreeable signal (e.g., some people's preference is sound reminder instead of visual reminder). Therefore, it is better to make enhancements to the generic reminder system to make it more reliable, optimal and adaptive. Hence, one of the main aims of this study is to make balance between the reliability and the annoyance as how many reminders should be issued to users for a specific ProM task.

Figure 5.1: Group Elderly Activities

There are different types of ProM tasks and existing works on reminder systems only focus on individual tasks such as reminding elderly people to take their medicine. However, people with ProM difficulties (e.g., elderly) are often involved in many group tasks

as shown in Figure.5.1. For most senior citizens, group elderly activities can provide beneficial social contact with others. Assume that a group of people are participating in a group task (say picnics) 10 days later and they have to also prepare for the group task before the event. The group of people also interact before the group task for other occasions such as daily exercise. Assume that we want to design a reminder system for such group activities, we can simply ignore the group interaction between the group members. In other words, we can treat each group member separately and direct apply existing approaches for determining the reminding schedule. However, such an approach will lead to many *unnecessary* reminders as one group member might remind some other group members. Therefore, the comfort level of the group members will decrease dramatically due to the unnecessary annoyance.

Figure 5.2: Different Group Interaction Patterns. (Each node represents a group member and the edges represent interactions. Different edge size represents different interaction frequency.)

It is thus important to take into account interactions between group members including the frequency of the interactions. Moreover, we need to differentiate different group members as some group members might interact more often with other group members (as shown in Figure.5.2). Thus, different group members might receive different number of reminders. Nowadays, with the development of technology such as Apps for tracking human's activities including the reminder system itself, information about interaction frequency is available.

Besides determining the number of reminders for each group member, the question of when to remind comes out because reminders are send out between the period of the first reminder and the time of executing the ProM task. Concerning that the reminder is a created cue to the ProM task, we have to think of another question how to keep the reminder salient and connected with the ProM tasks. Moreover, from the existing intelligent memory assists, such as Autominder with the adaptive feature [70], we can gain experiences. It is essential: 1) to develop a personalized user model to observe the users' behaviors; 2) to learn the users' preferences for each feature of the reminder plan; 3) to adapt the reminder plan to satisfy personal preferences as much as possible.

Therefore, our research questions is boiled down to how many times to remind, when to remind, and how to remind. As a consequence, our plan considers the number of

reminders, the reminding schedule and the reminding way. To answer the first question, while too few reminders may fail, too many of them can be annoying, it is crucial to take into account the interactions between group members to determine the number of reminders. Also it is important to issue the reminder at an appropriate time. A reminder for a task one month away may be too early. Meanwhile, a reminder issued just before the ProM task may leave the user in a hurry to perform the task. To select appropriate reminding methods in terms of contexts, text reminders are appropriate at places which require silence. For noisy environments, more attention attracting reminding methods, e.g., vibration and sound are needed. Considering that a lot of work has already realized the function to attract attention and be context-aware at the same time, this chapter focuses on the first two research issues especially the first one.

5.3 The Reminding Model for Group Tasks

This section presents the approach for computing the reminder plan for group tasks. It starts with discussing the factors that can affect ProM performance and how the factors will affect the optimal number of reminders. Then it builds a computational model for determining the number of reminder for each group member.

5.3.1 Determining the Number of Reminders for Each Group Member

As known as in Chapter 3, many factors influence ProM performance. Some factors directly influence other factors or indirectly affect the relationship between another factor and the ProM task performance. Moreover, the importance of a ProM task can be reinforced with the presence of social motivation [83]. People's cognitive capabilities and mental functioning are gradually weakened with aging [92]. Accordingly, ProM will be deteriorated gradually. Hence, the degree to which age affects the ProM task performance is affected by other factors. With more complex ongoing task and lower relatedness between the ongoing task and the ProM task, there is a significant performance decline among the elderly compared with the younger [72, 84]. Contrarily, a higher performance improvement was observed among the older adults than the young adults [79]. In order to determine the number of reminders for each group, this study should apply existing approaches [93] to calculate the number τ'_i of reminders for each group member i . The calculating procedures are as follows: 1) assuming that the task is an individual task; 2) aggregating the results to determine the number of τ_i , of reminders for each group member i considering the interaction between group members. In the following, it will firstly discuss how to compute the number τ'_i of reminders for each group member i with

the assumption that the task is an individual task.

The appropriate number of reminders for a ProM task should be determined according to the predicted ProM performance of the task. If the predicted performance is poor, more reminders will be generated for the task. On the contrary, fewer reminders will be generated if the predicted ProM performance is good. V_{perf} is the term used to predict the performance of a ProM task. It determines the joint-effect of the factors which will influence the ProM task performance. Fig.5.3 shows a visual representation of V_{perf} based on Fuzzy Cognitive Map (FCM) [86]. FCM is widely used to represent the cause-effect relationships among concepts in real-world systems.

Definition 2: V_{perf} can be 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 represents *ProM task performance*: measuring the likelihood an individual will remember and perform a ProM task.

- c_2 represents *delay of ProM task*: measuring the length of the period from encoding to initiation of a ProM task.
- c_3 represents *complexity of ongoing task*: measuring the relative amount of executive resources required by the ongoing task.
- c_4 represents *relatedness of tasks*: measuring the degree of relatedness between a ProM task and its ongoing task.
- c_5 represents *importance of a ProM task*: measuring the perceived importance level of a ProM task.
- c_6 represents *motivation*: measuring the incentive strength of a ProM task.
- c_7 represents *age*: measuring the degree to which age adversely affects the performance of a ProM task.

The plus (+) or minus (−) following a weight w_{ij} implies whether the weight is positive or negative. The weight values lie in the range $[-1, 1]$.

Each concept in V_{perf} accords to one performance influencing factor, except c_1 which represents the ProM task performance. FCM both provides a way to capture the complicated relationships among identified factors and elements and a reasoning mechanism for

Figure 5.3: FCM for Predicting ProM Task Performance

inferring the ProM task performance and the salience level of reminding method. The weight values can be held by a 1×7 adjacency matrix W . If there is no direct arc from c_i to c_j , we have $w_{ij} = 0$. A 1×7 state vector $C(t)$ is used to store the state values of the concepts at simulation iteration t .

Adaptation methodologies are used to adapt the FCM model (used in the last chapter) and adjust the weights. The state values of concepts in the next step are determined by both their current values and causal effects imposed by other concepts. To calculate the interim state vector, it can multiply the state vector $C(t)$ with the weight matrix W .

$$\tilde{C} = [\tilde{c}_1, \tilde{c}_2, \dots, \tilde{c}_7] = C(t) \times W$$

$$\tilde{c}_i = \sum_j w_{ji} c_j(t)$$

where $\tilde{c}_i$ denotes the total 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 computed as the following equation:

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

where f_i denotes concept c_i 's squeezing function. It converts the interim state value $\tilde{c}_i$ 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 ProM 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.

After we compute the number τ'_i of reminders for each group member i assuming that the task is an individual task, we compute the number of τ_i of reminders for each group member i taking into account the interaction between group members. Intuitively, the number of reminders can be decreased, as during the group members' interaction, a group member might be reminded of the task by some other group members. Furthermore, if a group member has more interaction with other members, the number of needed

reminders can be smaller as the chance of being reminded by other group members is higher. Motivated by the intuitions, in the following it will discuss how to compute τ_i based on τ'_i based on the interaction between group members.

First define the interaction between group members using a graph $G = (N, E, W)$, where N is the set of group members, E is the set of edges representing the interaction between group members, and W represents the interaction strength between group members, shown as in Figure.5.2. For an edge (i, j) between two group members i and j , $w_{i,j} > 0$ represents the frequency of interaction between two group members i and j . The higher $w_{i,j}$, the more interaction between two group members i and j . A group member i 's interaction strength IS_i can be defined as

$$IS_i = \sum_{j \in N} w_{ij}$$

which represents how frequently group member i interacts with others.

Then define the number of τ_i of reminders for group member i as

$$\tau_i = \lfloor \alpha \cdot \sum_{j \in N} \tau'_j \cdot \max\{\epsilon, \frac{e^{-IS_i}}{\sum_{j \in N} e^{-IS_j}}\} \rfloor$$

where $\alpha \in (0, 1]$ is used to reflect the intuition that the total number of reminders can be decreased in consideration of group interaction, and $\epsilon \in (0, 1)$ is used to constrain the

minimum number of reminders for each group member. The values of α and ϵ can be set by experimental tuning. It shows that with the increase of group member i 's interaction strength IS_i , the number of τ_i of reminders for group member i will decrease.

5.3.2 Reminder Schedule and Method

The way to determine the appropriate number τ (τ is used instead of τ_i for ease of explanation) was explained above. Then the reminding model arranges the reminders into a reminder schedule, $r_schedule$, according to a reminder schedule function. From Figure.5.4, it can be seen that the reminders are distributed over the reminding window, and the whole window represents the time interval from the time of the first reminder to the starting time of the ProM task (Figure.5.4). The first reminder is defined by the user. While other reminders are automatically generated by the reminding model. The reminders are arranged in a way under which the reminding frequency gradually increases with the approaching of the starting time of the ProM task.

Figure 5.4: An Example of a Reminder Schedule

Under the assumption that the length of the reminding window is T_w and the total number of reminders is τ , the following reminder schedule function can be used.

$$T_k = (1 - e^{-\lambda k} + e^{-\lambda(\tau+1)})T_w$$

where $0 \leq k \leq \tau$ and T_k denotes the scheduled issuing time of reminder r_k ($r_k \in r_schedule$). It can be easily inferred that the time interval between two consecutive reminders is decreasing.

The reminding model also determines an appropriate reminding method, r_method , for each reminder r_k 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. For each method, the model can measure its effectiveness using the FCM model introduced before. Then, the model chooses the best reminding method.

5.4 Experimental Evaluation

To evaluate this reminding model, a user study was conducted in naturalistic settings, involving 6 participants aged from 20 to 30. It assumes that there are 4 members in a group and the interaction strength is randomly generated. The values of α and ϵ are set to be 0.6 and 0.2 respectively. The proposed reminder design (RMGT) was compared

against 1) the reminder design without considering group interaction (RMIT); and 2) the reminder design manually generated by human beings (RMH). In the end, users 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 5.1. Generally, the participants felt that the reminders generated by our approach RMGT were appropriate in terms of their number, schedule and reminding methods. Each of these three aspects (number, schedule and reminding methods) received an average appropriateness rating greater than or equal to 8. Among them, ratings for reminding method RMGT have the largest mean and the smallest standard deviation, suggesting that the participants thought the reminding methods selected by the model were the most appropriate. The improvement of our approach RMGT over the other two benchmarks is statistically significant.

Table 5.1: Summary Statistics for User Rated Appropriateness

Aspect	Mean	Standard Deviation
RMGT	8.5	0.8544
RMIT	6.9	1.1354
RMH	6.7	0.8756

5.4.1 Summary

To our best knowledge, the reminding model proposed in this chapter is the first-of-its-kind. Based on the theoretic background of ProM, this chapter thoroughly analyzes the factors that will affect the ProM task performance and proposes a computational approach for determining the appropriate number of reminders and reminding method considering interaction between group members. To evaluate the proposed reminding model, a preliminary user study was conducted and the participants felt that the reminders are appropriate and this approach provides a better overall experience and reminds more effectively than its control version. Currently, the proposed reminding model only supports time-based ProM tasks. It is building up support for event-based ProM tasks and incorporating the consideration for travel time. The reminding model will be able to track locations and remind based on locations. Moreover, this study will also consider improving customization of the proposed reminding model. The model will be able to cater to individual differences, since individual ProM task performance may respond to the six performance influencing factors differently.

Chapter 6

Conclusions and Future Directions

6.1 Summary of Main Contributions

This study proposed to develop a reminding model to improve the ProM performance.

It draws lessons from the existing reminder systems by learning their strengths and overcoming their limitations. At the same time, it analyzes the mechanisms of ProM and follow the ProM theory. In this context, the reminding model has been developed with four sub-models: FRBKM, FCMProm, FRBFM and FRBMM. FRBKM gets information from user, ProM task and environment and defines fuzzy rules to determine the values of each factors in Knowledge Base. FCMProm is responsible for computing the performance of ProM task by considering factors in Knowledge Base. FRBFM is responsible for mapping the performance to the number of reminders and FRBMM is responsible for mapping the salience level to the reminding method.

To realize the functions of different components of this new reminding model, a series

of principles and algorithms are presented in this thesis. Six potential factors (the relatedness of the ProM task and the ongoing task, the complexity of the ongoing task, the importance of the ProM task, the motivation of the ProM task, the delay of the ProM task and user's age) that influence the ProM performance determine the optimal number of reminders. The environmental factors such as the locations of the ProM task and the current task, the objective factor of the user's initial expectation of the reminder's starting time, and the number of reminders determine the reminding schedule. Besides the six factors in determining the number of reminders, another factor (the type of the ProM task, such as working and socializing) also determines the way to remind. The reminders strongly associated with the ProM task type make users retrieve the intention successfully as much as possible. Based on the problem of group reminders when people are friends and going to do the same ProM task, this study provides a computational model for improving the proposed reminding model to reduce the redundant reminders. A series of experiments were conducted to identify the validity, appropriateness and effectiveness of the proposed reminding model.

6.2 Future Work

This study builds a reminding model to generate the optimal number of reminders, the optimal reminding schedule, and the optimal reminding method. These results depend

on formulating and optimizing a series of factors, such as the user's age, ongoing tasks, the environmental context, and individual differences. Although these factors have been identified to influence the ProM performance and we have known how they influence the ProM performance, this study still needs to figure out the weight of each factor. Similarly, this study also needs to figure out the distribution of reminders between the time of starting the reminder and the time of performing the ProM task. These results would help to achieve the optimal reminder plan, which maximizes the probability of remembering to perform the prospective task and minimizes the potential annoyance. In the future, the study will conduct research in the following directions.

First, the study needs better models for learning user's behaviors and preferences. It might not only look at users' behaviors related to reminders but also consider users' actions in other aspects of daily life. Supervised learning techniques can be applied to learn user's preferences and behaviors.

Second, this study designs the reminding plan by solving an optimization problem. However, this model might not be accurate and it might ignore some aspects. Furthermore, the environment might evolve with time. It is thus more reasonable to use some adaptive strategy so that the reminding plan can change over time based on the feedbacks. Reinforcement learning is a plausible solution in which the optimal policy will

evolve based on the feedbacks from users.

Third, preference elicitation could be applied to elicit user's preferences and behaviors as needed in order to design reminder plans that can meet user's preferences as much as possible. The system might have bad performance if we do not know the preferences. However, there may be infinitely many ways of asking questions for learning the preferences. Therefore, it is a promising direction to adopt a mixed-initiative approach where human users and software assistants can efficiently collaborate to make good reminding decisions.

Fourth, the study needs to further understand how to make users to accept future smartphone reminder applications. Some preliminary studies revealed six key themes that impact uptake of reminder apps: Perceived Need, Social Acceptability, Experience/Expectation, Desired Content and Functions, Cognitive Accessibility and Sensory or Motor Accessibility [94,95]. How to consider these revealed issues by designers and researchers when developing and testing reminding software for people should be further investigated.

Fifth, given that there is no existing model for measuring the ProM task performance, this study provides the first model considering different important factors as well as their inter-dependency. Hopefully this model is general in the sense that it can be applied to

different domains and scenarios. The complexity of ongoing task measures the relative amount of executive resources required by the ongoing task. While we apply the model for some real scenarios, we need to decide the exact meaning of “resources” as well as other aspects that could affect the complexity of the task. One future research direction could be giving more realistic and refined definitions of the factors that can affect ProM task performance and how to compute the factors. However, generating a general model is a very important step towards reaching this ultimate goal.

List of Author's Publications

Jinghua Hou, Xuehong Tao. “Neurocomputational Modeling of Prospective Memory”,

In *International Journal of Information Technology*, vol.23, No.2, pages 1-19, 2017.

Jinghua Hou, Chunyan Miao, Yang Liu. “Prospective Memory Aid Reminder System

Design for Group Tasks”, In *Proceedings of The 10th International Conference on*

Software, Knowledge, Information Management and Application (SKIMA), pages

433–438, 2016.

Jinghua Hou, Zhiwei Zeng, Chunyan Miao, Yang Liu. “Prospective Memory Aid: A

Reminding Model Based on Fuzzy Cognitive Maps”, In *Proceedings of 2016 IEEE*

International Conference on Fuzzy Systems (IEEE-FUZZ), pages 170–177, 2016.

Han Lin, Jinghua Hou, Han Yu, Zhiqi Shen, Chunyan Miao. “An Agent-Based Game

Platform for Exercising People’s Prospective Memory”, In *Proceedings of IEEE/WIC/ACM*

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