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Intelligent Reminder System Using Mobile Activity Recognition

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学籍番号 19899033

氏名 Muhammad Fikry

指導教員 井上 創造 教授

九州工業大学大学院 生命体工学研究科
人間知能システム工学専攻 井上創造研究室

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Abstract

In this thesis, we propose new methods to remind people to do their daily activities, calculate the estimated time and predict the best time to remind users, and future activities, and consider whether an activity needs to be performed and whether it needs to be reminded. This is important for addressing the existing challenges related to short-term and long-term memory caused by prospective memory problems, various busyness, distractions, and multi-routine plan problems. We present methods that effectively learn the need for notification or non-notification, when, and how much time to notify by considering the balance between exploration and exploitation. Considering the balance between exploring new time options and exploiting the learned optimal timing policy can be a challenge resolved in this thesis because the reward function needs to align with the desired objectives of the reminder system, such as maximizing user responsiveness or optimizing the balance between effectiveness and user experience. Additionally, in the approaches in this thesis, we propose a notification system for forecasted activities that have not been seen in related work for forecasted activities. In forecasted activity, we need to consider whether the activity needs to be done and needs notification. We are focused on achieving low-probability increases in user activity and user engagement in responding to notifications.

These proposed methods will be very helpful for the development of human activity recognition systems, particularly for people with memory problems or busy schedules, and and healthcare institution such as hospital because we can remind them well that the execution time of notifications is on target, so as to prevent users from stressing out over a lot of notifications, but those who miss notifications can receive them back at a later time step so that the activity information to be completed is still available. Although previous work has used several techniques to remind the users, the difference in our approach is that other researchers have focused on activities that have been scheduled or rescheduled to manage time, then reminded users at one time based on a schedule, whereas daily activities in the future are unpredictable and a variety of factors can make them miss reminders, so we contribute to the addition of forecasting and provide several dynamic alternative reminder times that our model will optimize. Our findings can be used by researchers and practitioners to enhance the quality and quantity of activity data collection, the accuracy of human activity recognition, and user engagement rates.

第 1 章

Introduction

1.1 Introduction

The state of our health has a significant impact on our overall well-being, productivity, and quality of life. It involves multiple facets, including physical, mental, and emotional health. Maintaining good health is essential for engaging in daily activities, pursuing personal and professional goals, and enjoying a fulfilling life. In our daily life, physical health is vital for carrying out routine tasks and activities. It involves taking care of our bodies through proper nutrition, regular exercise, and adequate rest. By adopting healthy habits such as balanced eating, staying hydrated, and engaging in physical activity, we can enhance our energy levels, strengthen our immune system, and reduce the risk of chronic diseases. Physical health also contributes to improved mobility, strength, and endurance, enabling us to participate in activities we enjoy and perform daily tasks with ease. Alongside physical health, mental and emotional well-being is equally important in our daily lives. Mental health encompasses our cognitive and emotional state, affecting our thoughts, feelings, and behaviors. Maintaining good mental health involves managing stress, practicing self-care, seeking support when needed, and nurturing positive relationships. Emotional well-being involves recognizing and expressing our emotions in a healthy manner, cultivating resilience, and developing effective coping strategies. Taking care of our mental and emotional health allows us to handle daily challenges, maintain positive relationships, and experience greater satisfaction and fulfillment in life.

In the context of health and daily life, prospective memory plays a crucial role in maintaining our well-being and managing various health-related tasks and activities. However, several challenges can arise that impede our prospective memory performance. Prospective memory refers to our ability to remember and carry out intended actions in the future. One common problem in prospective memory related to health is cognitive symptoms. Individuals with cognitive impairments or conditions such as dementia may experience difficulties in remembering and executing planned health-related tasks. Forgetting to take medications, attend medical appointments, or engage in necessary self-care activities can have significant consequences on one's health. These cognitive symptoms can impact an individual's ability to effectively manage their health, leading to potential complications and reduced quality of life. Another challenge in prospective memory for health is the busyness and demands of daily life. With busy schedules, multiple responsibilities, and numerous tasks vying for our attention, it is easy to forget important health-related commitments. The constant juggling of work, family, and personal obligations can result in overlooking preventive health measures, neglecting exercise routines, or failing to follow through with necessary dietary adjustments. The fast-paced nature of modern life can hinder our ability to prioritize and remember health-related tasks amidst numerous competing demands. Interruptions and distractions also pose a significant problem for prospective memory in health. Unexpected events, phone calls, social media notifications, or other distractions can disrupt our focus and cause us to forget or delay health-related actions. These interruptions can lead to missed medication doses, skipped exercise sessions, or neglected self-care routines, compromising our overall well-being.

Addressing these prospective memory challenges in health requires implementing strategies such as reminder systems, using technology or alarms, creating routines, and seeking support from caregivers or healthcare professionals. By proactively managing prospective memory difficulties, individuals can improve their ability to effectively remember and perform daily tasks, which improves the overall quality of life.

In this thesis, we propose a new method to address the challenges of task and care management by the utilization of a reminder system for people with memory problems using mobile activity recognition with a reminder system. With a system that explores and learns the best policy to achieve the goal. Through personalized notifications and prompts, the system can provide timely reminders. This thesis presents reminders related to scheduled (for preset plans), and unscheduled (for unpredictable future activities).

1.2 Problem Statement

Health is the aspiration of every individual. Being healthy allows a person to lead a happy life and continue with daily activities, including personal and professional endeavors. However, not everyone enjoys good health, and various factors such as busy schedules, demanding workloads, and difficulty in time management can compromise an individual's well-being. One particular health issue for task and care management is prospective memory, which refers to the ability to remember and execute future activities. While high-level memory impairments are commonly associated with cognitive conditions like dementia or Alzheimer's disease, individuals at a milder level can also experience prospective memory problems due to work/busy schedules or disruptions during activities. As a result, researchers from various fields are focusing on addressing this issue, given the paramount importance of health. One relevant research area in this context is Human Activity Recognition (HAR). To comprehend public health or personal health, researchers need to explore several factors, including behavior, lifestyle, time management, and other related aspects. This exploration also encompasses relevant technologies that can aid in understanding or assisting individuals, both from a personal and medical perspective. To evaluate the relevance of such technologies, comprehensive requirements analysis is crucial. One crucial aspect of this analysis is data, as data collection remains an intriguing field. The accuracy, quality, and quantity of data significantly impact the outcomes of the analysis. In the case of activity recognition, recording target activity data such as start time, end time, activity type, and sensor types used becomes essential. For individuals with memory-related issues, it is crucial to provide reminders for upcoming activities. Due to factors like busyness, activity interruptions, or memory loss conditions such as dementia, they may forget about scheduled activities, their timings, or other relevant details. Hence, it is essential to devise strategies in this domain to ensure individuals do not miss or rush through their activities. This applies to various activities, ranging from personal lifestyle management to healthcare routines or data recording for research purposes. Therefore, the problem statement revolves around implementing activity recognition with reminder system techniques to support prospective memory in health management. The motivation for this research stems from the critical need to develop effective solutions that assist individuals in managing their activities, especially when memory-related challenges exist. In this thesis, we have addressed the extant challenges associated with data collection, reminder time optimization, and future activity recognition in the nursing care domain by introducing various computational approaches.

- **Problem 1. Technology and requirement for the reminder system,** it is needed to feasibility of end-user requirements when they use the system to function effectively, such as the user's ability to know the most urgent or important activity and having a simple reminder design.
- **Problem 2. Schedule-based reminder time optimization,** it is needed to get the best time to send notifications on scheduled activities with dynamic time.
- **Problem 3. Future-based reminder time optimization,** it is needed to get the best time to send notifications on unpredictable activity in the future.
- **Problem 4. Employing technology as an effective research instrument,** it is needed to gather actual data from real-life situations.

1.3 Research Questions

Concerning problem statements, a number of activity recognition and reminder system issues must be resolved in order to design and construct a system that can support people with prospective memory problems. Based on these considerations, we aimed to resolve the following research questions:

- **RQ1:** How can researchers provide requirements of assistive technologies as a research instrument for users with cognitive for mobile computing studies?
- **RQ2:** How can researchers calculate the estimated time and predict the best time to remind the user for mobile computing studies?
- **RQ3:** How can researchers calculate the estimated activity and time to remind the

user for activity recognition studies?

- **RQ4:** How can researchers deploy technology to record data by the utilization of a reminder system in a hospital for activity recognition studies?

1.4 Key Contributions

This thesis intends to optimize time in reminder systems with activity recognition, thereby enhancing the function of devices as research tools. Below is a summary of the research contributions.

1. This thesis provided assistive technology and requirements analysis as a research instrument for users with cognitive for mobile computing studies.
2. This thesis proposed using reinforcement learning with multiple-time alternatives for the reminder system instead of using schedule-based reminders to address prospective memory problems for mobile computing studies.
3. This thesis proposed forecasted activity using probabilistic and reinforcement learning instead of rescheduling to address the problem of unpredictable activity in the future for activity recognition studies.
4. This thesis deployed the proposed systems to realistic settings demonstrating their capability and feasibility for activity recognition studies.

1.5 Thesis outline

This thesis contains eight chapters, including the current one. The subsequent chapters of this thesis are as follows:

- In Chapter 2, we present a research survey related to mobile activity recognition and reminder systems. This could include an overview of the current state of activity recognition and reminder system methods. We examine previous research on the use of sensors and mobile devices for activity recognition and monitoring, as well as the development of reminder systems and their effectiveness in supporting daily activities.

- In Chapter 3, we provide the requirements analysis for the reminder system in the form of technological assistance, which refers to all tools or systems that enable people to carry out daily activities in a more comfortable and secure manner, particularly for the elderly and people with dementia. The information obtained is necessary to get the estimated time for each activity as feedback to the reminder system.
- In Chapter 4, we propose that the modeling is able to optimize the notification delivery time with eight alternative times. This knowledge can adjust to individual personality characteristics and solve multi-routine planning problems.
- In Chapter 5, we propose the modeling of optimizing notifications for forecasted activities, and evaluate the effect of activities with low probabilities for forecasted activities.
- In Chapter 6, we investigate complex nurse care activity recognition using barometric pressure sensors and show several characteristics of pressure features, such as identifying activity classes that can improve when we use the barometric pressure sensors and investigating the relationship of pressure features with the modification of label durations which are often required in complex and realistic applications. For modification of label durations, we propose timestamp extension methods using sequential and dynamic with two approaches (T1 and T2) for inaccurately labeled behaviors. In addition, to deploy technology in healthcare institution, we propose a system that collects activity record data in a university hospital and provides feedback based on this information. Feedback to users via notifications on the smartphone. We provide this knowledge to be able to optimize notification content, notification time, and the number of notifications.
- In Chapter 7, we discuss this thesis, especially how it was researched, built, evaluated, and solved. Furthermore, we discuss the remaining limitations and challenges that stimulate future research.
- In Chapter 8, we present a summary of the thesis and offer concluding remarks.

第 2 章

Related Works

2.1 Prospective Memory

Prospective memory involves the ability to remember to perform a specific action at a given time or when encountering a particular cue. It can be categorized into two types [198, 127, 114]: event-based and time-based prospective memory. Event-based prospective memory relies on external cues or events to trigger the intended action [126], whereas time-based prospective memory requires individuals to initiate the intended action at a specific time or after a specific duration [247].

Prospective memory plays a crucial role in our daily lives. It allows us to remember to perform future actions that are not part of our ongoing activities. For example, remembering to pick up groceries on the way home from work [57] or to take medication [182] at a specific time requires prospective memory.

Research suggests that prospective memory involves multiple cognitive processes, including attention [149], encoding [56], retrieval [164], and monitoring [263]. Attention is crucial for noticing the cues that trigger prospective memory tasks, while encoding ensures that the intention is stored in memory. Retrieval involves recalling the intention at the appropriate time, and monitoring helps individuals keep track of their progress and ensure successful execution.

Failures in prospective memory can lead to various consequences. Forgetting to perform intended actions can result in missed opportunities, decreased productivity, or even jeopardized safety. Understanding the factors that influence prospective memory performance can help develop strategies to enhance memory retrieval and decrease the likelihood of memory failures.

Research has identified several factors that influence prospective memory performance. These include the importance of the intended action [126], the saliency of the cue, the complexity of the task [234], and individual differences such as age [237] and cognitive abilities [237]. For instance, older adults may experience declines in prospective memory due to age-related cognitive changes.

There are various techniques and strategies to improve prospective memory. These include using external reminders such as alarms or calendars [107], forming habits or routines [117], breaking tasks into smaller subtasks [235], and utilizing mnemonic devices or mental imagery techniques [201]. These strategies can help individuals enhance their prospective memory performance and reduce the likelihood of forgetting intended actions.

Prospective memory deficits can occur in certain clinical conditions, such as dementia disease [228, 239], traumatic brain injury [41], or attention deficit hyperactivity disorder (ADHD) [275, 13]. Understanding the specific impairments in prospective memory associated with these conditions can assist in developing targeted interventions and support strategies for individuals affected by these disorders.

Prospective memory research has practical implications in various domains, including healthcare, and daily planning. By understanding the underlying mechanisms of prospective memory, educators can design interventions to improve students' memory for future tasks. In healthcare settings, strategies can be developed to enhance medication adherence or promote healthy lifestyle behaviors.

Prospective memory is a vital cognitive function that allows individuals to remember and perform intended actions in the future. It involves multiple cognitive processes and can be influenced by various factors. Understanding prospective memory has important implications for daily life, clinical interventions, and the development of strategies to enhance memory performance.

2.2 Activity Recognition

Activity recognition refers to the process of automatically identifying and classifying human activities based on data captured from sensors or input devices. It is a subfield of computer science and artificial intelligence that aims to understand and interpret human behavior and activities in various contexts. Activity recognition vary from single tasks done per time duration to multiple activities delivered synchronously. Among the challenges of activity recognition is activity labeling which sometimes do not match the expected duration. There is skew in the timestamps of activity labels and there are instances where the duration is shorter than the actual activities. Modification of labels like extending durations can improve activity recognition [108]. However, it is also necessary to investigate how differences in the sensor data can affect the extended duration and performance of the system.

Sensors, wearables, and smartphones are commonly used to collect data for activity recognition. Wearable devices can capture activity recognition attributes such as motion, location, temperature, and ECG, among others. Smartphones are preferable over other wearables considering the integrated sensors and software capability allowing the device to collect various types of data, possibly, all day long [73]. In activity recognition study areas such as nursing care, smartphones are often used for labeling and recording other patient data in an effort to overcome manual writing and pave the way to readily accessible collated information.

Other studies reveal that data from pressure sensors depending on their placement can extract more relevant information regarding the activities performed. Smart-surface pressure sensors placed on-body could detail pressure generated by muscle movement, body posture, or direct user input [50]. Additional information from pressure sensors is used for activity recognition of sitting, standing, lying, running, walking, climbing stairs [161] [162] [81] [262] and gait [89]. Elevation is one factor considered in pressure sensors as this generally affects sensor data. It has been observed that both temperature and air or atmospheric pressure get lower as you climb. Considering latency problems and air conditioning, built-in pressure sensors in mobile phones can still be used to determine heights indoors for positioning and navigation if specific requirements are met [142].

The performance of activity recognition studies is dependent on the quality of the data processed. Data cleaning, normalization, and transformation are examples of data preparation [128]. Among the critical steps of data handling is pre-processing and segmentation which enable feature extraction needed by machine learning algorithms. To obtain higher activity recognition performance, adequate data pre-processing is essential [269]; and as input to the model, the segmented data has to be transformed into the appropriate forms. More precisely, since the raw inertial data from wearables changes significantly over time, segmentation processes are needed when executing activity recognition tasks to utilize the data [272]. Characteristics of data segments or windows are influenced by window size, type, and overlapping [73]. Among the techniques implemented in activity recognition for segmentation are grid search strategy to optimize window size [70], and sliding window [81] [110] [262] with window size commonly not exceeding 3 s [73].

Feature selection is a technique for decreasing the input variable to a model through the use of just pertinent data and the elimination of irrelevant data. With feature selection, pertinent characteristics for a machine learning model are selected according to the kind of issue that is being attempted to be solved. The properties of the data that are used to train machine learning models have a significant impact on the results that may be obtained. The quality and type of features extracted from various sensor data can affect the performance of activity recognition models. Features extracted from sensor data used for HAR are usually statistical features with mean as the most common [161] [260] [44] [81] [110] [273] [252] [232]. Other studies utilizing pressure sensors extract additional features such as maximum and minimum of the approximate 1st derivative [232], time gap [161], difference between maximum and minimum values [163], mean crossing rate [252], time domain, frequency domain [89], H-FIS (Hierarchical FIS) [162], and CARIN features [25].

The effectiveness of trained machine learning models is determined using performance evaluation metrics. This helps in determining how a more effective model may perform on the dataset. Various ways to evaluate a machine learning model’s performance, such as confusion matrix, accuracy, precision, recall, specificity, F1 score, and precision-recall curve. We must be able to choose a way to evaluate the performance of the model, especially the data imbalance. The issue of the imbalanced dataset has become a concern in recent years[29] [125] [270] [83]. Certain class imbalances in the dataset may make certain prediction approaches less effective for learning[125]. Some studies utilize F1 Score[108] [29] [125] [270] [158], Accuracy[108] [29] [158], or even both [108] [29] [158] for this issue, although there are obviously many more. While retaining strong overall performance in terms of macro F score, Katrin Tomanek and Udo Hahn [241] can increase classifier performance and lessen class imbalance.

2.3 Reminder System

A reminder system is used to aid memories. Various reminder strategies are used by people to support in daily life, such as calendars, diaries, sticky notes, or smartphones [7]. Reminders have good in many aspects of life, for example, taking medication, exercising, or meeting. Many studies related to reminder systems have been carried out with various technologies to help humans. Using RFID technology to detect objects when the user leaves the house, this system compares the object in his pocket with the thing with a list of items so that the user can retrieve the forgotten object [103]. Automatic reminder system for medical orders from the doctor's office to the smart box in the nurse's room, accompanied by text messages from doctors to nurses [253]. Using the accelerometer and camera sensors, the system provides reminders for Coupling Activities, such as having to close an opened bottle [46]. A reminder system using a smartphone was developed to support patient self-medication management [96] because it can improve medication adherence through short messages from mobile phones [141]. Technologies for reminder systems can be used separately or in combination to achieve the goals of context-aware reminder systems.

Reminder systems help people to improve cognitive disabilities, such as instructional prompts and scheduling assistance [205]. In smartphones, information to be delivered to users is one of them through notifications [171, 173, 204, 180]. Notifications become visual cues, auditory signals, or haptic alerts generated by the application to convey information to the user [102]. However, with the increasing number of notifications that demand the attention of smartphone users, often notifications appear at inopportune times or carry irrelevant content. Notifications at inappropriate times can cause annoyance; Previous research has shown that notifications at inappropriate times can increase anxiety [204], and interfere with task completion time [101, 60], people find it difficult to refocus on their previous task after being distracted by calls or instant messages [101] let alone if the task demands cognitive work, it will certainly have a more pronounced effect [139].

In self-medication management of patients, forty-six percent (41.1%) forget or are late to take their medicine more than two hours from schedule [96], to monitor dementia patients taking medicine or monitoring glucose, 38.4% of caregivers require a reminder feature on their smartphones [38] because dementia patient often forgets to take their medication and even forget their personal belongings [129]. This issue makes researchers develop various assistive technologies to remind individuals with dementia [75, 10, 19] that have impaired cognitive function. Dementia is mostly experienced by older people, they require special requirements for reminders [75, 4] even previous research carried out a combination of human and artificial intelligence to design reminder systems [48, 215].

To optimize the time when sending notifications, one method that can be used is reinforcement learning. Bo-Jhang Ho et al [97] explored the use of reinforcement learning by modeling the problem as a Markov decision process and the advantage actor-critic algorithm to identify interruptible moments, to schedule microtasks while minimizing user distraction, by setting sensor data as state, notify and stay silent as an action. James Obert and Angie Shia [187] analyzed dynamic time optimization with reinforcement learning to reduce time and resources in manufacturing ASICI/VLSI chips. Reinforcement learning is an algorithm that can make agents work automatically to determine the ideal behavior in order to improve the performance of the algorithm. From experimental tests and feedback, reinforcement learning learns effective strategies for an agent; an agent is able to actively adapt to the environment to optimize time by maximizing future rewards.

2.4 Notification System

A notification system is a collection of protocols and procedures that involve both human and computer components, specifically designed to generate and send messages to individuals or groups of people. Notification systems play a vital role in our daily lives by keeping us informed and reminding us of important events and activities. The objective of these systems is to deliver timely and relevant notifications, thereby enhancing users' productivity and overall experience. Extensive research has been conducted to explore various aspects of notification systems, including notification timing [180, 189], content personalization [140, 6], and user preferences [112].

In daily activities, notifications can be utilized as reminders for specific events [32, 115], location-based alerts [28, 113, 143, 220], and activity prompts [77, 188, 143, 220]. The importance of notifications has led to an increasing demand for user attention on smartphones, as notifications serve as the primary means of conveying information to the intended recipients. However, untimely notifications can have adverse effects on individuals receiving them. Consequently, researchers have analyzed the impact of notification disruptions [101, 60, 204], such as their potential to disrupt work routines [102, 60, 26]. Therefore, determining the most appropriate time to deliver notifications remains crucial to ensure that they capture users' attention without causing interruption or annoyance.

As reminders, notifications can help provide important information about appointments [166], deadlines [223], or tasks that need to be completed [208]. With notifications, individuals can avoid delays or forgetting to carry out important activities. Additionally, notifications as reminders can also assist users in building positive habits. Systems can be used to remind users about physical exercise [148], health routines [178, 248], or self-care activities [271] that need to be regularly performed. With the presence of notifications, individuals can stay consistent and organized in carrying out activities that support their well-being. For example, notifications can be used to remind individuals to exercise daily or take time for meditation and relaxation. Furthermore, notifications as reminders also aid in prioritizing and enhancing productivity. Systems can assist users in planning their schedules effectively and remind them of tasks that need to be prioritized. With timely notifications, users can avoid procrastination and manage their time efficiently. People can set their own reminders according to their preferences, but they cannot foresee upcoming events. Many things can occur beyond their scheduled activities due to busyness[82] or activity disruptions. Therefore, schedule changes [53] may happen, rendering pre-set reminders ineffective. Several studies have explored personalized notification strategies by employing techniques such as collaborative filtering [249], user profiling [27, 176], and preference modeling [112]. By understanding users' preferences and behavior, notification systems can deliver customized notifications that align with their interests and improve their engagement.

2.5 Forecasted Activity Notification

Forecasting is the process of predicting future outcomes based on present and historical data. Forecasting has been the subject of research in various fields, such as health informatics [243, 179, 9], human-computer interaction [153, 90], and artificial intelligence [276, 79]. This study aims to develop methods for predicting future activities, events, monitoring, or accidents. Several techniques have been proposed for forecasting, such as machine learning, probabilistic modeling, and rule-based systems [79]. The selection of a forecasting method is contingent on a number of variables, such as the context of the forecast, the availability and relevance of historical data, the desired degree of accuracy, the time period to be forecasted, and the business value of the forecast.

Forecasting enables researchers to assess potential risks and uncertainties. By analyzing historical patterns and trends, researchers can identify potential risks, such as a company's response if market awareness is lower than expected [119], or challenges that may arise during their research projects. This allows for the development of contingency plans, risk mitigation, and necessary adjustments. The results of forecasting provide insights into potential changes, enabling information recipients to make better decisions. For example, flood forecasting for early preparedness [207, 147], or flood recovery [200], is crucial for authorities and communities to implement short-term and long-term prevention measures. This is closely related to the delivery of information to users because if the information is not conveyed timely, such as the preparation of evacuation and rescue missions will be delayed. One way to deliver forecasted results is through notifications.

Previous studies have utilized the delivery of forecasted results through notifications in various domains. For example, messages sent via notifications to feed animals and manage dairy cows [61], notifying farmers about preventive actions and disinfectant spraying in agriculture [240], weather forecasting notifications [130, 147, 240, 137], malaria notifications [45, 88, 155], and air quality notifications [217, 195, 118]. However, most researchers primarily focused on consent to forecasting, considering notifications merely as information regarding the forecasted results. They did not much attention to whether the delivered information through notifications was received by users or not. Some researchers sent notifications after obtaining forecasted results or based on predefined thresholds [61, 147, 138, 137], while others scheduled separate delivery times for forecasted results [45, 155]. Consequently, the delivery of notifications for forecasted results remains a challenge, particularly in the context of human daily activities.

In daily activities, the timing of notification delivery needs to be considered to avoid information overload or irrelevant information, ensuring that the activities are not missed, such as drinking enough water [259] and turning off the lights [225]. By delivering relevant and timely information through notifications to those involved, they can prepare and adapt to potential changes in the situation. However, forecasted activities often involve uncertain or disruptive aspects. Therefore, the timing of notification delivery for forecasted activities needs to be optimized.

In this work, we adopt a different approach to the delivery timing of forecast results via notifications, especially in the case of daily activities, by considering multiple alternative timings for notifications. In order to ensure that forecasting results information is received by the user at the appropriate time. We take into account the probability of whether the activity needs to be performed and whether notification is necessary for the forecasted activity. Ultimately, the available timing options are optimized using reinforcement learning to determine the best time for notification delivery.

第 3 章

Requirements Analysis

3.1 Introduction

Advances in technology have brought about the development of various new devices, integrating the power of computers into everyday life. This transformation has also influenced how the general public interacts with computer science. With the introduction of more sophisticated systems, individuals no longer need to be computer experts to benefit from computing resources. Ambient intelligence (AMI) systems have emerged as a solution, aiming to make computational applications easily accessible to society by minimizing direct interactions and seamlessly integrating them into daily routines [23].

On the other hand, people with memory problems such as Alzheimer's disease and related dementia (ADRD) have become a significant global concern, affecting approximately 50 million people worldwide. This number is expected to rise to 152 million by 2050 due to the growing aging population [191]. Despite the availability of dementia diagnostic tools, a considerable portion of ADRD cases, around 62%, remain undiagnosed globally. Additionally, 91% of cases are diagnosed at a very late stage [206]. The lack of timely diagnosis can further strain healthcare systems, resulting in unnecessary expenses on investigations, symptom-driven treatments, and inadequate support for families and caregivers [135].

Ubiquitous computing and intelligent data analysis present innovative methods and tools for early detection and continuous monitoring of cognitive impairment symptoms [211]. As dementia advances, the decline in prospective memory becomes more pronounced. The ability to form and retain new intentions, monitor ongoing activities, and retrieve the intended actions becomes increasingly challenging. This can lead to increased reliance on external aids, such as reminders, alarms, or assistance from caregivers. This chapter focuses on reviewing solutions based on activity recognition that aims to address the challenges posed by dementia.

Dementia symptoms, such as agitation, aberrant motor activity, anxiety, depression, and cognitive impairments, significantly impact daily activities, goal-directed behavior, and emotional well-being [43]. Consequently, technology assistance is recommended to assist individuals with cognitive symptoms such as dementia, in regulating their daily activities and providing reminders. However, conventional reminder systems solely rely on preset time-based events, lacking the ability to confirm whether the event has occurred. This limitation calls for improved solutions. Therefore, this research focuses on estimating the time required for daily activities and conducting a feasibility analysis to address the relevant routine activities effectively.

3.2 Assistive Technology for Dementia

In the case of dementia, the technology of activity recognition has an important role because patients with dementia experience damage or lose the connection of nerve cells in parts of their brains. Recognizing activities can help monitor activities to detect abnormal scenarios, detect missing activities to provide reminders such as medication reminders based on context, or provide other types of care.

In the area of computer science, researchers are contributing to helping people with dementia. We looked at the objectives of the research that has been done to find the parts that are not clear. We categorized the objectives of the application into eight parts. (1) Algorithmic comparison: We include papers that focus on comparing the performance of algorithms into this category, such as those comparing a series of machine learning classification techniques for activity recognition [105], and classifying aphasic and non-aphasic speakers [116]. (2) Analysis: We classify papers related to the discussion of investigations, assessments, explorations, or evaluations of an object with the aim of determining the actual scenario or determining the level of accuracy of the research. For example, behavioral analysis based on visual understanding [254], behavioral anomalies [211], and activity transitions [74]. (3) Diagnosis: Research related to determining development, and providing solutions to the problems of people with dementia; for example, decision support for diagnosing AD and Mild cognitive impairment (MCI) [190], diagnosis to determine the severity of the disease [150], detection of the earliest stages of AD [8]. (4) Guidance: Part of the paper describes assistive technology support for people with dementia [5] or caregivers [66], and there are studies that discuss the tools for the quality of life measures [58]. (5) Identification: We provide information about papers for discussing ongoing activities [34], and we determine the characteristics of people with dementia. (6) Monitoring: We grouped papers that observe the daily activities of people with dementia, both in the home environment [170] [257] [159], hospital [168], and nursing home [245] to reduce stress because of constant patient monitoring [86]. (7) Prediction: This category contains papers that provide information about the probable behavior [192] of people with dementia. For example, actions that users will take next [12] after performing an activity. (8) Prevention: We group research that discusses actions to prevent dementia from worsening [242] and prevent synchronization errors in applications [80]. We perform grouping for that category every year, we show the list in Table 3.1.

System developments and experiments for the analysis, diagnosis, monitoring, identifying, and prevention of dementia are conducted to alleviate the burden on the patient with dementia. We show the various technologies that develop applications related to dementia. We categorize these applications based on (1) Audio, wherein existing sounds are detected; (2) Design, new applications are created for people living with dementia; (3) EEG (Electroencephalography) includes recording the electrical activity of the brain; (4) Framework involves the development of a workflow method for the initial stage of making an application such that it forms a new system; (5) Magnetic resonance imaging (MRI), which includes the examination using radio wave technology; (6) Sensors, wherein research is conducted on motion detection using devices placed on certain body parts; (7) Smart environment, wherein an environment or patients with dementia employs technology (motion sensor or camera); (8) Speech, where research involves the concept of dialogue or recorded conversations with people with dementia; (9) Video, where research is conducted using data derived from a video; (10) Wearable, where research is conducted using wearable de-

表 3.1: Applications for Dementia

Algoritm comparison	[116] [105]
Analysis	[2] [99] [229] [246] [42] [47] [136] [104] [177] [123] [14] [222] [227] [74] [183] [30] [211] [16] [122] [254] [266] [35] [154]
Diagnosis	[267] [68] [144] [199] [150] [24] [37] [218] [85] [91] [133] [185] [134] [169] [69] [264] [55] [132] [190] [216]
Guidance	[5] [66] [72] [174] [258] [193] [213] [51] [210] [36] [58] [231] [39] [62] [209] [8]
Identification	[151] [34] [18]
Monitoring	[156] [194] [257] [145] [244] [196] [184] [251] [159] [152] [265] [236] [203] [202] [63] [146] [181] [175] [230] [86] [168] [192] [111] [131]
Prediction	[186] [65] [54] [14] [100] [226] [20] [245] [170] [160]
Prevention	[242] [80] [12]

vices or wearable software such as touchscreen interactions, computerized cognitive drug research (CDR), and smartwatch to collect data. Table 3.2 lists various systems/sensors related to activity recognition for handling dementia cases.

Most monitoring approaches employ a smart environment system to detect activities using various sensors such as smart carpet, a posture sensor, bed sensor, door sensor [86] to assess possible risks faced, RFID sensors [264] to track the functional degradation of Alzheimer's disease [244] [184]. Further, the monitoring design employs devices such as ambient sensors, wireless communication protocols, and smart home testbeds [203] to ensure remote maintenance in smart homes. The diagnosis employs a variety of devices to detect people with dementia such as MRI [68] [216], mobile conversational agents [91], RFID [199], and some are making prototypes of iKnow [169] that employ energy con-

表 3.2: Systems/Sensors support to Dementia

AUDIO	[116]
DESIGN	[5] [196] [193] [51] [203] [146] [177] [36] [55] [69] [132] [154] [216]
ELECTRO ENCEPHALOGRAPHY (EEG)	[229] [190]
FRAMEWORK	[152] [168] [91] [230] [169] [170]
MRI	[68] [37] [222] [104] [131]
SENSOR	[175] [122] [16]
SMART ENVIRONMENT	[194] [257] [244] [184] [2] [251] [159] [213] [246] [151] [210] [265] [199] [236] [202] [136] [34] [63] [14] [15] [74] [181] [80] [183] [85] [30] [86] [211] [219] [264] [124] [12] [254] [8] [35] [105]
SPEECH	[150] [133]
VIDEO	[145] [258] [99] [24] [123] [185]
WEARABLE	[268] [66] [39] [111]

sumption sensors, motion sensors, wrist-worn sensors, sleep sensors, and magnetic sensors in different parts of the house. Another interesting approach is the analysis of daily life activities using videos captured by wearable cameras [123] and the activity of comparing manual annotations with hand tracking [99]. However, the routine monitoring of daily activities at home that employs many devices with high costs and configurations is difficult to use for the elderly, and it is therefore a challenge for researchers. Thus, we need to develop a system/sensor to support people with dementia.

3.3 Challenge and Motivation

Sensor systems in the case of dementia have become popular because people with dementia have cognitive disorders and irregular activities, thereby making it easy to trigger emotions. However, other problems remain because sensor applications such as smart environments or video cameras still have limitations, and often, dementia patients do not live at home alone. Therefore, it would be problematic if the sensor detects someone who is not the patient and performs data calculations based on the data for that person. This problem results in a decrease in the level of accuracy when analyzing the development of dementia; further, these activities must be performed to obtain the datasets that are more accurate; in particular, if the sensor system is implemented in nursing homes or hospitals. In addition, collecting data on multiple people at the same time is a challenge that must be overcome.

We are motivated to propose a new device that can precisely identify objects as the most likely solution to this problem. A smartphone is optimal for transmitting unique information to the sensor to ensure that the sensor captures the activity of the correct individual. In addition, prevention receives the least amount of research, despite its importance in preventing stress and melancholy in persons with dementia. To prevent dementia patients from missing out on daily activities, we, therefore, propose a reminder system for this area. However, we must be cautious when determining the strategy for developing a system of reminders for individuals with dementia.

3.4 Reminder System Requirements

In this section, we will look at approaches based on requirements analysis, a condition or capability must be possessed by a system to solve a problem. We show in table 3.3 the requirements that are needed for people with dementia. We consider the patient's properness when they use the system to work properly, and all the requirements in table 3.3 are sufficiently feasible.

Requirements are created to perform an analysis that focuses on the time duration of the work completion. To support this, it is necessary to collect data on the types of routine activities that are possible, consider feature extraction techniques for speech recognition, and design a system that is easy to use by people with dementia. This is intended to reduce the possibility of irrelevant responses or long delay times. This model can be implemented in the form of a dementia-specific reminder application on smartphones.

表 3.3: Requirements Analysis

Requirements	**Justification**
The reminder has categories of events or activities	User can know the information priority [4]
The synchronization should be made between computer and smartphone	Users have a choice of devices [4]
The reminder can be viewed from two perspectives (personal and family)	Family can monitor users from a distance [4]
The reminder has priority the events	User can know the most urgent or important event [4]
A smiley icon will appear to show an accomplishment	Appreciate for the user have successfully set a reminder or confirmation the information [4]
The reminder design is simple	The reminder should be easy to use [4][11]
The reminder should be able to differentiate between alert and alarm	User can find out the information priority [4]
User can see activities has in that period (day, week, month)	User can see activity history [4]
The reminder can be brought anywhere	User can be confirmed the activity anywhere [4]

Continued on next page

表 3.3 – continued from previous page

Requirements	**Justification**
The reminder was related to wake up calls	The reminder can be an alarm for the user [4]
The reminder has a note to save the important numbers and facts	User can see the detail information [4]
The reminder has several colors in the application	Users can see the reminder category clearly [4][11]
The reminder supported to location tracking	User can find out the location if they get lost [11]
The reminder supported speech recognition	User can confirm by voice
Alert in the reminder system can use text-to-speech	User can know the information in a notification
The system supported the motion sensor	The system will record user activity

3.5 Reminder System Architecture

The proposed reminder technology system architecture shown in Figure **??** consists of three interconnected parts, namely Model, View, and Controller (MVC). MVC is a software design pattern by separating the data (Model) from the view (View) and how to process it (Controller). Model to use represent an object and have logic to update controllers in case of data changes; View to represent the visualization of the data contained in the model so that it can be presented to the user; Controller to manage the flow of data to the model object and updates the display whenever the data changes.

The reminder system is supported by a notification that has two notification methods, namely ringtone, and text-to-speech. To confirm the status of a dementia patient, speech recognition is used which is the program's ability to receive and identify spoken words, GPS to help patients to be easily found, and emergency calls connected to caregivers if

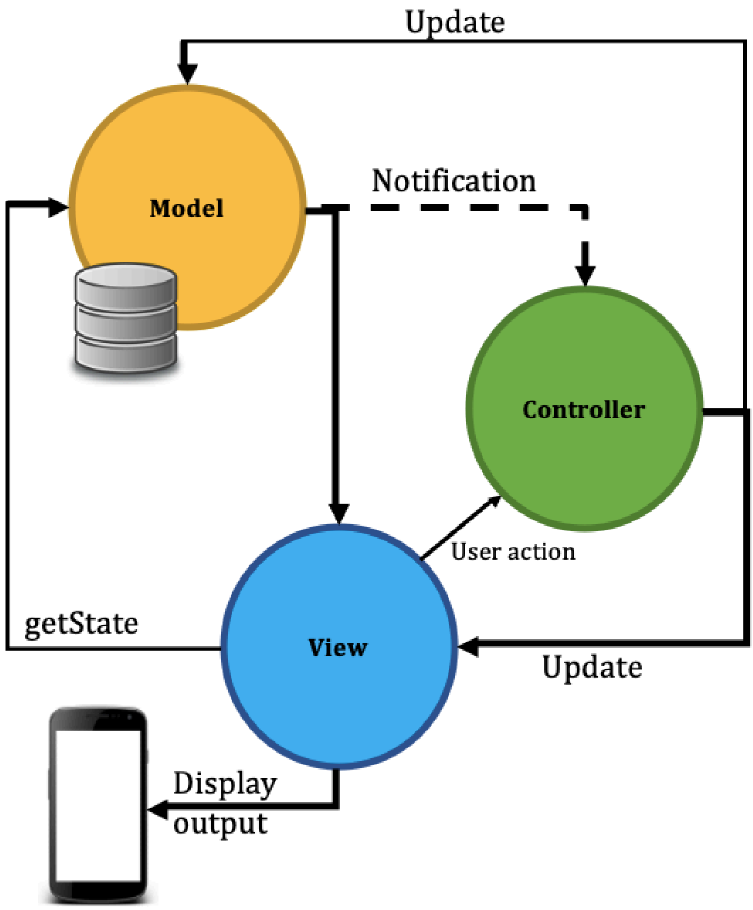


図 3.1: The Architectural Design

the patient has an accident. The system will record all events performed by the patient, the start and end times for each activity, then send them to the database with a cloud system. Data collection can be done by many people at the same time, filtering data based on the identity of each patient will be done in the database. The available dataset will be analyzed continuously for the feasibility of daily activity recognition and the time needed to complete daily activities.

3.6 Discussion

By observing and studying further, monitoring is dominant in the classification based on applications applied for patients with dementia from 1999 to 2019. Therefore, dementia patients will be greatly helped if the results of the monitoring can be used to prevent patients with dementia from forgetting their routine activities automatically; further, it is necessary to ensure that this technology does not disrupt their daily activities. This is important because there is no cure for people with dementia [268]. In brief, a solution to this problem is employing a smart environment. This support sensor system is the most popular system for monitoring, analyzing, and diagnosing people with dementia. For example, the smart carpet, posture sensors, bed sensors, and door sensors [86] and RFID [184] placed in various places in every corner of the house record activities with the video cameras placed in the room [145] provides an alternative solution to the problem. This sensor system has become very popular because people with dementia have cognitive disorders and irregular activities, thereby making it easy to trigger emotions. However, other problems remain because sensor applications such as smart environments or video cameras still have limitations, and often, dementia patients do not live at home alone. Therefore, it would be problematic if the sensor detects someone who is not the patient and performs data calculations based on the data for that person. This problem results in a decrease in the level of accuracy when analyzing the development of dementia; further, these activities must be performed to obtain the datasets that are more accurate; in particular, if the sensor system is implemented in nursing homes or hospitals. Therefore, we need a tool that can provide a unique identity to the sensor so that the sensor can perform its job appropriately.

We recommend that the most likely solution to the problem is adding a new device that can identify the object precisely. Currently, a smartphone or smartwatch is the right choice to transmit unique information to the sensor to ensure that the sensor captures the activity of the right person. This is a considerable advantage because data collection can be performed on a large scale, and chances of misidentification are lowered. The sensor records the activities conducted and identifies the nearest device to be stored the data in the database via a cloud system. If the patient' s identity has been uniquely identified by the sensor, the data can be filtered easily based on the identity of each patient will be easily carried out. This is a solution that can also be applied to sensors that are used in nursing homes or hospitals. Sensors can distinguish activities performed by patients, nurses, and nonpatients. To analyze data from people with dementia, we can eliminate other users than patients in the database. Further, we can collect more data in one day if the monitoring is conducted at a nursing home or hospital because the activities of many patients are performed together; the data obtained is stored in a database with a cloud system and is used to train data for the next training.

Data are a major problem in research related to technology for people with dementia. Although real data or cases are the most widely used, they require more data [211] [8] [218] [14]. The disadvantage of collecting data individually is that we have to repeat the recording in the same way to get more datasets. We recommend adding identity recognition through a smartphone or smartwatch for improving sensor performance. To this end, data recording is not performed individually; instead, it is conducted simultaneously with large numbers of people to store data directly in the database. Meanwhile, smartphones and smartwatches have alarms and GPS, which greatly help the system.

Data are a major problem in research related to technology for people with dementia. Although real data or cases are the most widely used, they require more data [211] [8] [218] [14]. The disadvantage of collecting data individually is that we have to repeat the recording in the same way to get more datasets. We recommend adding identity recognition through a smartphone or smartwatch for improving sensor performance. To this end, data recording is not performed individually; instead, it is conducted simultaneously with large numbers of people to store data directly in the database. Meanwhile, smartphones and smartwatches have alarms and GPS, which greatly help the system. The goal is to create a tool that can be used as a reminder that is based on the requirements for people with dementia to avoid activities that are not in accordance with daily activities performed generally. People with dementia are often stricken with cognitive impairments that can make them confused [17]; can help people with dementia to be easily found and saved. This assists researchers in apprehending the technology implemented and identifying open research problems in this area. This information can help design methods, sensors, applications, and algorithms for dementia case solutions.

3.7 Conclusions

Patients with dementia experience memory impairment and have unstable emotions, and therefore, technology with the concept of a smart environment that places sensors, RFID, smartphone, and cameras in several places and products is the right choice to monitor the activities of patients and recognize any changes in the observed behavior. The person with dementia can experience different symptoms, and their life changes may vary, thereby resulting in the difficulty of setting fixed rules for each individual. Therefore, it is necessary to diagnose, analyze, and monitor regularly for each person. The machine learning classification technique for activity recognition can summarize recorded data to recognize the activities of daily life and assess the performance of various algorithms to determine the decision with the best accuracy. This work demonstrated the development of technology to help patients with dementia and provide insight into the feasibility of systems that might be used in the analysis, diagnosis, monitoring, or other needs. Improved results illustrated in this work are achieved by gathering considerable information and providing an idea of solutions that might be better for handling dementia cases. This work aimed to further understand the benefits to provide solutions to change the level of monitoring and analysis for people with dementia so as to improve the quality of life using technological assistance by adding several devices to maximize system performance and warning features to prevent people with dementia to perform activities beyond the rules of habit. In future research, determining the right method for a smartphone reminder system in the case of people with memory problems such as dementia needs to be developed.

第 4 章

Reminder System Using Reinforcement Learning

4.1 Introduction

Using a mobile phone as an assistant while carrying out regular activities is commonplace for some people. This is due to many activities for humans, which might cause them to miss planned activities, particularly for persons with memory issues. Stress or depression can make it difficult for people to receive information and concentrate, causing frequent forgetting. The people may have to reschedule their plans because they forgot to have previous commitments. Even people who live an organized life can forget promises over time. The ability to recall to do something in the future is referred to as prospective memory [165], time-based prospective memory refers to remembering to do something at a specific time. Prospective memory can impact anyone, but it is most common in people with dementia because prospective memory affects various cognitive functions. Therefore, assistive technology to remind activities based on an existing schedule needs to be developed.

A reminder is a system that can help everyone remember something and record essential things so that people are not forgotten. Through reminders, it can make it easier for users to remember various important information. Some reminder systems only notify predefined time-based events and then send notifications based on that plan. Normal people can set the reminder system themselves according to their wishes because they can know the best time for them. They can set the time of reminder on schedule, some hours or minutes before the schedule, and make one, two, or more notifications. However, it will be very difficult for people with memory function disorders; they can forget their mobile phones, so they don't see reminders or be through forgetting the activity again even though the system has previously reminded them. Even for people with dementia who also have the effects like abnormal motor activity, anxiety, irritability, depression, apathy, disinhibition, delusions, and hallucinations, the reminder system will be complicated to do set by manually because the best time to remind for today is not necessarily to be an excellent time to remind for the next day, one or two notifications may not be enough for them, on the other hand too many notifications might be a harmful impact for them because people with dementia can have unstable emotions.

To solve this problem, we aim to leverage the reinforcement learning method [233] to estimate the time it will take to remind the user to perform an activity. The goal is to remind the user before the schedule at the right time with or without repetition that does not distract the user from the notification and does not hallucinate the schedule of activities, for example, the user has an activity at 09:00 am, then the system will remind the user before 09:00 am. The agent in reinforcement learning is learning based on the experience, the reminder technology with this method is considered suitable for people with memory problems like dementia to overcome difficulties in setting fixed rules for each individual because of the variety of symptoms and life changes they face [76]. We introduce a new model in the initial definition using the q-learning algorithm [255] to evaluate the time, taking into account the user's response. So that users will get effective time feedback to remind the activity that will occur, the time for sending notifications and repeating reminders may vary for each user according to the response given. We have eight-time options (see details in Table 4.2) to remind the users, we will start from the longest time to the nearest time before the scheduled time. The reminder system with our proposed model is capable of being dynamic, meaning that if the user can respond to notifications appropriately, the time will be optimized, and the number of notifications sent can be minimized. This solves a number of issues that dementia patients have, including forgetting things, ignoring notifications, multi-routine plans, and difficulties in establishing permanent rules for each individual.

4.2 Method

In this section, we present our approach to modeling the exact timing of sending notifications to users ahead of schedule. In the reminder system that we propose, the user can set the scheduled time according to their needs, but the system will remind the user before the scheduled time, not the time that has been set by the user. We set a reminder time starting from the furthest distance to the time that is closest to the schedule. The system will choose an action to be applied to the user; if the action is silent then the user response will automatically be ignored, but if the action is notified then the user is asked to respond by selecting the option that appears on the notification, such as accept or dismiss. Accept response means that the user likes the time and considers the information sufficient to send a notification of time schedule. Dismiss response means that the user does not like the time or needs the information the next time. If the user does not select that option within fifteen minutes due to forgetting or something else, then our system decides that the user's choice was ignored at that point. After we get the user's response, we optimize the time for the next notification based on the response for each user. In Fig. 4.1, we provide an overview of the relationship between an agent and the environment.

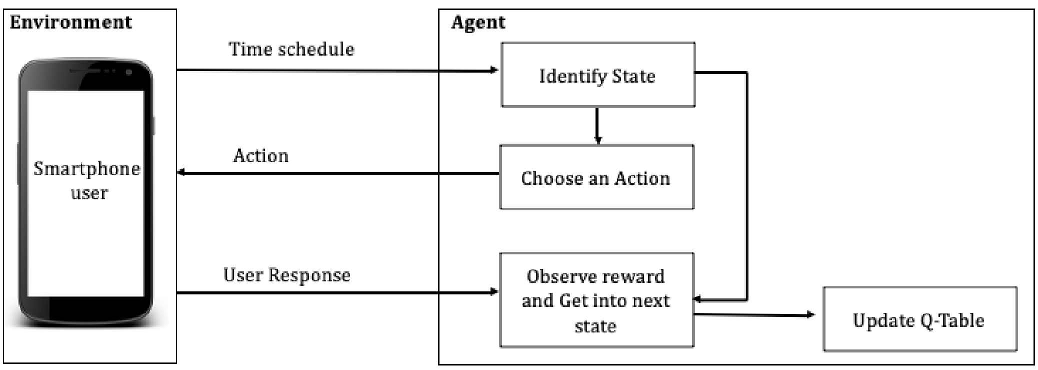


図 4.1: Reinforcement learning setup

In our framework, the agent is our system, and the environment is the smartphone. The agent observes the user context to take the action of sending a notification or remaining silent. From the notification that appears, it allows the user to make a response that will be input for the agent to assign the reward. The possible response for the user is to accept, dismiss, or ignore the notification.

The relationship between the agent and the environment is that the agent makes observations to get a representation of the environment called the state, then takes action based on its policies. Based on the action taken, the environment moves from one state to the next state and returns the reward. The agent will maximize the amount of the accumulated future reward discount. We use q-learning as a reinforcement learning algorithm. We show the processing flow of the method proposed in Algorithm 1, and Table 4.1 summarizes the definitions of the mathematical expressions used in the algorithm.

In the reinforcement learning algorithm we use, time step t is the time to send a notification if the action chosen by an agent is notify; the state is the product of time and input. The selection of actions will be applied using the epsilon greedy method. After applying the action, an agent will observe the reward and go to the next state based on the user's response, the reward function shows how the agent benefits from action A at time t in state S at time t, while the next state is determined from the transition state S at time t after taking action A at time t; after that, the agent will calculate the q-value to be updated into the q-table.

The furthest time is two hours before the schedule, and the shortest time is fifteen minutes before the schedule. Two hours will move to schedule time every fifteen minutes, so we have eight times to remind the user. Table 4.2 shows the time features of our approach.

Our method focuses on the time before the schedule, so we propose that the state is the product of time and input. For each time it has the same possible response from the user shown in Table 4.3 so that each time has three states because we have eight times to remind the user, then the number of states we have is twenty-four, Table 4.4 shows the relationship between time and inputs that make up the state of our method.

Algorithm 1: Proposed reminder system using reinforcement learning

Initial definition:

T = {120, 105, 90, 75, 60, 45, 30, 15}

A = {notify, silent}

R = {+1, -1, 0}

X = {accept, dismiss, ignore}

S = T × X

S = {S1, S2, S2, ..., S24}

r: $S \times A \rightarrow R$

δ: $S \times A \rightarrow S$

π(s) = a

1. Initialize, for all $S_t \in$ S; $A_t \in$ A;

t = 0.

2. Start with S_0

3. At time step t, choose action $A_t = argmax_{(a \in A)}$ Q(S_t,a), ϵ-greedy is applied

4. Apply action A_t

5. Observe reward $R_{(\mathrm{t+1})}$ and get into the next state $S_{(\mathrm{t+1})}$

6. Update the Q-value function:

$Q(S_t,A_t\ ) \leftarrow Q(S_t,A_t)+\alpha(R_{(t+1)}+\gamma max_{(a \in A)}\ Q(S_{(t+1)},a)\text{-}Q(S_t,A_t))$

7. Set t=t+1 and repeat from step 3

4.3 Experimental Evaluation

To evaluate our proposed model, we conducted several experiments to see if the system worked as intended. To calculate the estimated time of each activity, the agent needs to get initial feedback from the user when the notification appears to remind the user based on the existing schedule and optimize it with reinforcement learning, then conduct tests the next time based on the response carried out before for each activity.

表 4.1: Nomenclature reference

Symbol	Summary
α	the learning rate
γ	the discount factor
s	state
a	action
r	reward
t	time step
n	final time step
S	set of all states (the product of time and input)
A	set of action possible in state s
R	set of possible rewards
T	time
St	state at t
At	action at t
Rt	reward at t
π	policy, decision making rule
X	input
δ(s, a)	the state-transition

4.3.1 Data description

The dataset that we use in the experiment is the EngagementService dataset [97] and synthetically generated data as a proof-of-concept study. The EngagementService dataset contains some information such as CreationTime, AssignmentStatus, AcceptTime, SubmitTime, Input.content, and Answer.sentiment. However, in this case, we only use Answer.sentiment information as a user response that we will test on our system; there are 100 user responses that will be used in our experiment. As for synthetically generated data, we have 124 actions of notify and 126 actions of silent, we create a synthetic dataset

表 4.2: Feature of Time

Time (T)	Description
120	2 hours before time schedule
105	1 hour 45 minutes before time schedule
90	1 hour 30 minutes before time schedule
75	1 hour 15 minutes before time schedule
60	1 hour before time schedule
45	45 minutes before time schedule
30	30 minutes before time schedule
15	15 minutes before time schedule)

表 4.3: Feature of Input

Input (X)	Description
accept	user response: accept
dismiss	user response: dismiss
ignore	user response: not answer

by giving random user responses. When sending notifications, we have 30.65% of responses that are accept, 31.45% of responses are dismiss, and 37.9% do not answer. In this process, the system will call the available user responses directly, agents learn by trial and error while interacting with the environment and get rewards for their actions. An example of synthetically generated data is shown in Table 4.5.

We also generate data that is resulted by the system to simulate an agent learn from the environment, from the experiments we conducted we got 1324 actions is notify, and 1426 actions is silent. To choose an action, the agent does random exploration occasionally with probability ϵ and takes the optimal action most of the time with probability 1-ϵ.

表 4.4: Feature of State

State (S)	Description	State (S)	Description
S1	(120, accept)	S13	(60, accept)
S2	(120, ignore)	S14	(60, ignore)
S3	(120, dismiss)	S15	(60, dismiss)
S4	(105, accept)	S16	(45, accept)
S5	(105, ignore)	S17	(45, ignore)
S6	(105, dismiss)	S18	(45, dismiss)
S7	(90, accept)	S19	(30, accept)
S8	(90, ignore)	S20	(30, ignore)
S9	(90, dismiss)	S21	(30, dismiss)
S10	(75, accept)	S22	(15, accept)
S11	(75, ignore)	S23	(15, ignore)
S12	(75, dismiss)	S24	(15, dismiss)

表 4.5: An example of synthetically generated data

Activity ID	User ID	Time Schedule	Action	Time Action	Time Response	User Response
1	1	9:00	notify	7:00		
1	1	9:00	notify	7:15		
1	1	9:00	notify	7:30	07:34	dismiss
1	1	9:00	notify	7:45	07:48	accept

4.3.2 Evaluation method

To evaluate our proposed method, we performed a synthetic simulation in which the human responses are collected in the wild and approximated from two datasets: 1)Engagement service dataset and 2) Synthetically generated data to show the advantage of repeatedly and systematically iterating over our proposed algorithms. Three performance measures are defined in this paper: number of notifications, user response rate, and time optimization. The number of notifications is number of the alert that are sent to remind users of the activities they will be doing. Next, we count the number of users who responded to the notification divided by the number of notifications sent. This is a critical metric for determining the algorithm's performance. Time optimization relates to the status of the q-table, and it is an essential measure for the next action, whether to send a notification or remain silent. It is defined as the ratio of updated entries in the q-table of our proposed algorithm.

4.4 Result

As explained in section 4.2, we have eight alternative times to notify the user. For people with dementia, eight times are certainly better than one or two timestamps, as the algorithm is able to achieve higher response rates over time. Because each time has three possible responses that result in three states for each time, we conducted an experiment to see the state transition by assuming the user's response is always accept, dismiss, ignore and the action is always silent. The results show the transition can occur from the time to the next time, not the transition from the state to the next state at the same time as shown in Fig. 4.2.

In the next experiment, we use the dataset from EngagementService, we take the existing user responses, in this dataset, all the answers are filled in, so we assume that the action that occurs is notified, then we experiment on our system assuming that the activity occurs at one time and the notification sent before the scheduled activity. The result is shown in Fig. 4.3 that all silent values in our q-table are zero, and the transition of state to the next state occurs based on the response from the user. Then we perform simulations to see the agent work automatically to determine the ideal behavior to maximize the performance of the algorithm because the goal of reinforcement learning is to choose the most appropriate action in each particular state. To prevent overfitting, we balance exploration and exploitation by applying an epsilon greedy action selection, we choose a random action with probability ϵ and otherwise the max q-value. If the action is notify

図 4.2: State Transition

then the user response will be retrieved from the EngagementService dataset. The number of rounds performed is until the agent gets the last response from the user in the dataset. The result shows that 53.5% reminder system sends a notification to notify the user and 46.5% reminder system stays silent as shown in Fig. 4.4. From this result, we can see that an agent can work well by learning from the environment based on user feedback. In other words, the system can decide the right time to send notifications to users, which means we do not send notifications every time so as not to disturb the user.

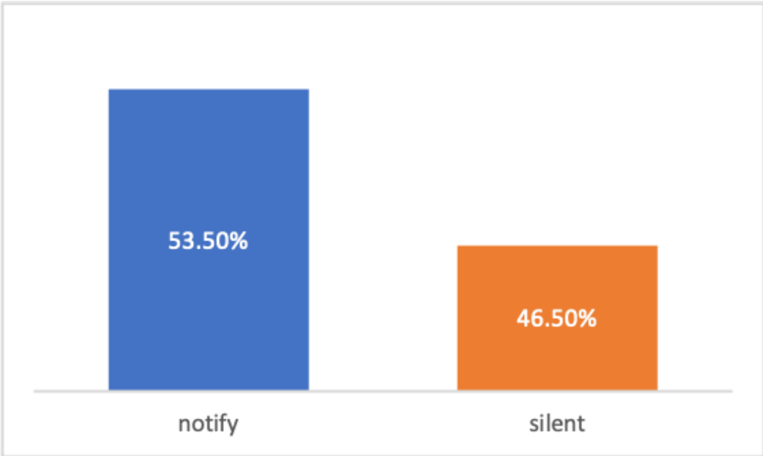
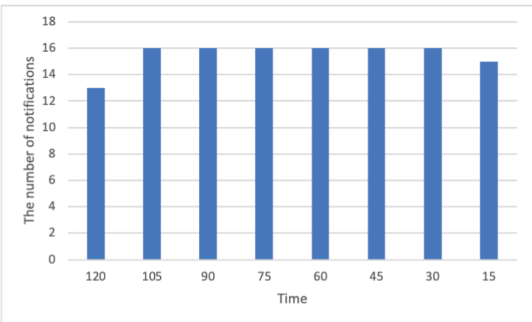
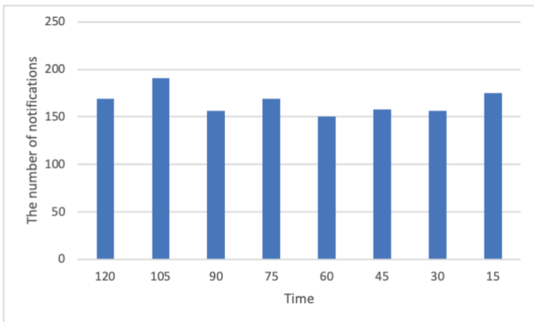


図 4.4: The percentage of actions with user responses from the EngagementService dataset

Fig. 4.8 for synthetically generated data in the wild and synthetically generated data with iterating by our proposed algorithms, for the user response rate we show in Fig. 4.6 (see details for each user in Fig. 4.7). From this process, it can be seen that when the first process is done, the agent can calculate properly and set the state correctly, but the agent does not learn directly from the environment, while during the second process, the agent learns more from the environment so that the reminder system gets the best time to send notifications to users.



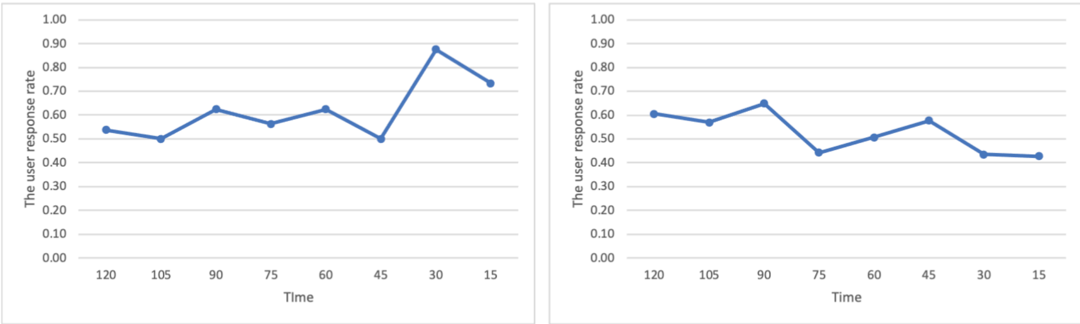
(a) Synthetically generated data (in the wild)



(b) Synthetically generated data (iterating by our proposed algorithms)

図 4.5: The number of notifications

The result of this process is the accept rate of user responses processed using our proposed algorithm is better (see details in Table 4.8), as our proposed algorithm is able to send notifications at the right time, this depends on the preferred time of each user, near



(a) Synthetically generated data (in the wild)　(b) Synthetically generated data (iterating by our proposed algorithms)

図 4.6: The user response rate

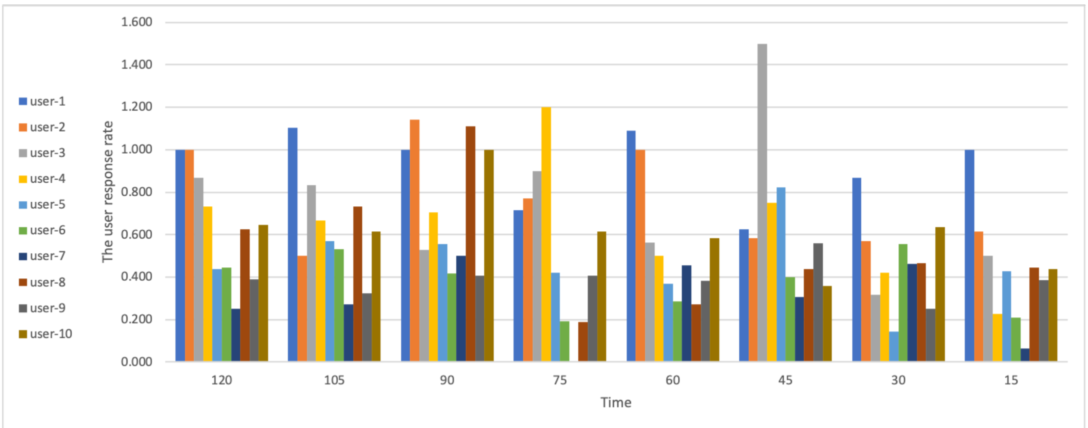


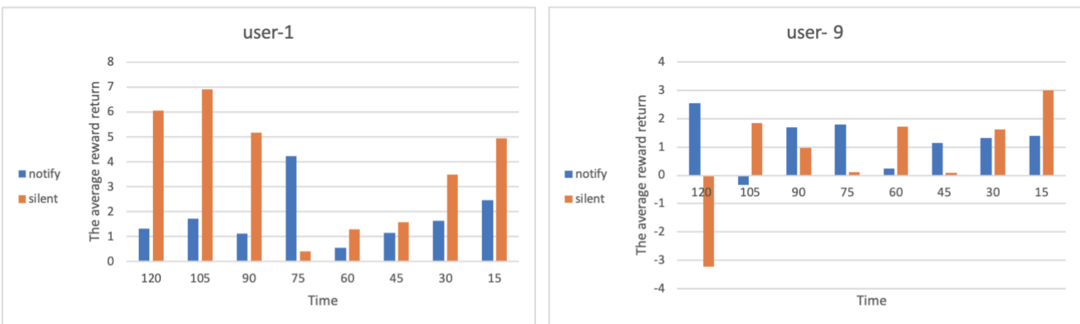
図 4.7: The response rate comparison for each user

or far from the schedule; some users with dementia might be like reminders that are far from the schedule because they have time to prepare some items, other people may like near time schedule, so they can immediately do activities. The more often users choose to dismiss or ignore, the more notifications they receive; we show the average number of notifications for each user in Table 4.6, the average reward return per user for each action in Table 4.7, and we show in Fig. 4.8 the comparison of response rates for each user. Timing optimization is based on the response of each user, the user with the highest response rate may only need one notification for the time, the user with the lowest response rate in this experiment will still have to be reminded four times for the next time; indeed, optimize time-consuming to remind users in this experiment is not an absolute requirement at that time, as changes in notification delivery timings may vary again based on subsequent responses. This implies that our algorithm can adjust to individual personality

表 4.6: The average number of notification for each user

User	The average number of notification
1	0.084
2	0.085
3	0.090
4	0.088
5	0.099
6	0.089
7	0.091
8	0.088
9	0.194
10	0.093

characteristics, which might be a stumbling block in the care of dementia patients. Our propose can work for people with dementia because we can remind very well, the high accept rate proves the execution time of notifications is right on target, so it can prevent users with dementia from stressing out over a lot of notifications, but for those who missed notifications can receive them back at a later time step, with the result that information on activities to be carried out is still available.



(a) The highest user response rate　(b) The lowest user response rate

図 4.8: The average reward return

表 4.7: The average reward return per user for each action based on times

Times	A1	A2	A1	A2	A1	A2	A1	A2	A1	A2	A1	A2	A1	A2	A1	A2	A1	A2	A1	A2
120	1.3	6.1	1.7	5.5	0.0	3.3	-7.0	6.9	0.5	0.6	0.6	2.1	0.1	2.1	1.2	0.4	2.6	-3.2	1.4	0.1
105	1.7	6.9	2.3	-1.6	3.0	0.8	0.3	2.9	1.7	0.0	5.0	-0.8	3.6	-0.5	-1.4	2.3	-0.3	1.8	2.0	5.0
90	1.1	5.2	0.0	3.8	4.6	0.3	0.4	4.3	2.2	-0.6	0.7	1.5	6.4	1.7	-0.9	2.1	1.7	1.0	0.7	4.2
75	4.2	0.4	1.4	3.1	3.3	4.1	4.5	19.3	0.9	3.8	0.1	0.6	6.5	5.5	-0.8	1.4	1.8	0.1	-2.3	10.7
60	0.5	1.3	-1.5	10.0	1.9	11.3	1.0	23.6	2.0	0.5	0.9	0.4	0.2	1.8	0.2	1.8	0.2	1.7	-6.1	8.4
45	1.2	1.6	-8.1	9.3	-9.2	10.5	2.9	33.5	0.9	0.0	0.3	1.2	-1.5	5.3	1.7	1.6	1.1	0.1	1.5	6.7
30	1.6	3.5	-1.8	14.9	2.7	1.8	9.9	1.5	0.8	1.0	0.0	0.8	1.1	3.9	-1.0	-0.2	1.3	1.6	-1.2	6.5
15	2.5	4.9	5.3	9.3	1.4	1.0	-15	87.0	-1.7	0.8	0.9	0.7	-2.4	3.2	0.6	0.3	1.4	3.0	0.8	3.9

A1: The action is notify; A2: The action is silent

4.5 Discussion and Future Work

By evaluating with dataset and conducting various experiments, the results reflect that our proposed model using the reinforcement learning method can optimize the time to send notifications. The eight alternative times to send notifications can be optimized to get the best time to alert the user. We set eight alternatives of times because in this case we have users with dementia, which means if healthy people do not need a system with time optimization. After all, they can set the times of reminder manually as they wish unless they are also having problems with memory such as dementia symptoms, then

表 4.8: Comparison of synthetically generated data

	In the wild		Iterating by our proposed algorithms	
Time	Accept rate	Dismiss rate	Accept rate	Dismiss Rate
120	0.31	0.23	0.32	0.28
105	0.13	0.38	0.36	0.21
90	0.38	0.25	0.42	0.23
75	0.38	0.19	0.26	0.18
60	0.38	0.25	0.26	0.25
45	0.19	0.31	0.31	0.27
30	0.44	0.44	0.27	0.21
15	0.27	0.47	0.28	0.15

this system might be able to help them. Although this model allows us to optimize time effectively, there are some limitations that we would like to address.

In this work, we do not claim that the data can represent the actual user data, so the dynamic time only occurs in eight parts. If the data has been obtained from humans, we can make the eight parts of the time more flexible based on the response time of the user, which can make the notification delivery time even more precise.

We also do not know how many notifications the user receives on their phone because interruptions from notifications can cause people to turn off notifications or make them ignore notifications more often. Examining the number of notifications that appear at any given time may give better results for increasing user engagement.

We cannot tell if the user is doing the activity as scheduled or not after being reminded. In the future, we are interested in identifying user activities because it could be that the user accepts the notification on the reminder system but does not carry out activities according to schedule, or otherwise, the user directly carries out their activities after responding to the notification.

We believe that real-world application and testing are critical to developing practical solutions for people with dementia. We hope that our proposed method and the results of our trial will ease the burden on caregivers and families for the issues commonly handled by persons with dementia. The reminder system with our proposed model has notifications at every available time step and is capable of being dynamic so that if the user can respond to notifications correctly, the time will be optimized, and the number of notifications sent can be minimized. This is overcome several problems of users with dementia such as forgetting something (eating, taking medication, events) including forgetting newly learned information, improper execution time that makes them forget about the activity they are doing, ignoring notifications with various influencing factors (for example, they are far from the location of the phone), stress remembering the activities to be carried out, multi-routine plans, and difficulty in setting fixed rules for each individual. However, we acknowledge that the reminder system for dementia users has a number of additional problems that must be addressed, such as dementia-friendly design (simple, flexible, recognizable), information related to activities to be completed, and external support for setting the reminder.

4.6 Conclusions

In this paper, the reminder will notify each time step available before the scheduled time so that people with prospective memory failure that directly impacts daily life, such as dementia, do not forget the activities they will do or ask their caregivers or family repeatedly. Because one notification on the schedule may not be enough for them, on the contrary, too many notifications can have the effect of being a nuisance. It is also used so that people with dementia do not experience stress to remember the activities they will do and overcome difficulties in setting fixed rules for each individual because they have varied life behaviors. Furthermore, the timing of our idea is dynamic, meaning that if the user responds appropriately to notification, the system will optimize the time such that the number of notifications issued is decreased.

The main contribution of this research is that we have a different initial definition of the reinforcement learning process generally for time optimization. Here we make the state as a combination of the time and the possible response of the user so that the system can remind the user before the time scheduled about the activities to be carried out and prepare the required items. The purpose of modelling using reinforcement learning is to get the best time and number of notifications to notify the users. With this model, we can observe the user's response from time to time and estimate the time and future actions. Reinforcement learning can work well to optimize the time for each user response by balancing exploration and exploitation.

In our experiment, we randomly generated user responses because the user's response might be unpredictable, especially for people with dementia. In addition, we show user responses based on dataset from existing research, and it can be seen that the optimal timing is easy to obtain if the user response is constant but different if the user response is very random. Other than that, more experiments carried out will make the agent learn more so that the choice of action to send notifications or remain silent, and optimization of time to send notifications can be better.

第 5 章

Notifications for Forecasted Activity

5.1 Introduction

In today's fast-paced world, it is essential to manage time efficiently to maintain a balance between work and personal life. The use of technology can play a crucial role in managing our daily activities, and one such technology is the notification system that provides reminders for upcoming tasks. However, the effectiveness of the notification system depends on the timing of the reminders, and it can be challenging to identify the optimal time for notification, especially for activities in the future.

In daily lives, some people frequently struggle with time management [92], such as prioritizing tasks, time for study, short breaks, cleaning the house, or meeting with friends, because if they focus too much on one or two things, they often forget other activities that must also be completed to achieve life balance, which can also affect their health. Technologies are developed to support their daily life, work, study, or research, such as personal web libraries [167], Tiimo [197], T-BOT and Q-BOT [197, 212]. But people with very busy schedules, such as nurses, caregivers, or people with problems of cognitive, loss of memory, or dementia [76] can forget the schedule that has been arranged, a reminder system is required in this area [77, 250, 221, 274].

A reminder system is a great way to stay organized and on top of tasks. This can aid in remembering essential information so that it is not forgotten. Through the use of reminders, it is possible to facilitate the recollection of vital information. Some reminder systems notify tasks based on a predetermined time and then send notifications according to this plan [77]. People can set their own reminder system according to their preferences, but they cannot be aware of impending activities; many things can occur outside of their schedule due to busyness[82], stress[95], perspective memory[21]; therefore, schedule alterations can occur[49], rendering pre-set reminders ineffective. Planned activities may be affected by alterations in the schedule. In some cases, this may be normal, but in others, it will be a problem, and work interruptions may cause people to forget about upcoming obligations.

To solve this problem, instead of changing the schedule, we propose a different approach, which is to forecast future activities. Forecasting has been the subject of research in various fields, such as health informatics [243, 179, 9], human-computer interaction [153, 90], and artificial intelligence [276, 79]. The aim of these studies is to develop methods for predicting upcoming activities, events, monitoring, or accidents. For example, a forecasting system for water quality monitoring for aquaculture [256], large-scale wastewater surveillance, or managing milk production on dairy cows [61]. Several techniques have been proposed for forecasting, such as machine learning, probabilistic modeling, and rule-based systems [79].

In daily activities using forecasting, we can inform people of upcoming activities so that they do not need to change their schedules. This means they can complete the task a bit quicker, a bit later, or all at once. For example, if there is a meeting at 1 p.m. and he also needs to take medication at 1 p.m., then there is no need to change the schedule because the duration of taking the medication is brief. However, the time required to send forecasted results still continues to be an issue for the approach. In other studies, forecasting results are sent when forecasting results are obtained or depending on thresholds [256, 224, 52, 9, 147, 138, 59], while others create a separate schedule for sending forecast results [3, 61, 31, 45, 138, 155]. As an example of weather information for farmers, the system will send a push notification whenever the readings fall below the threshold [256, 240]. In the case of daily activities, it is essential to consider user engagement as the recipient of the information, which means whether the user or the target has actually received the information or not. This is a challenge that must be resolved because if we send when the predicted activity result is received, people may forget about the activity due to factors such as perspective memory symptoms; if we send according to the start time of the forecasted activity, people may not necessarily like it at that time due to their busy schedules, which becomes a challenge. Therefore, in this paper, we are motivated to optimize forecasted activity notifications that consider multiple time alternatives for notifications.

In our work, we present two approaches aimed at optimizing the notification time in activity recognition systems. The first approach is called FaTi. FaTi is notification optimization for forecasted activity with reinforcement learning. This approach focuses on notifying users based on the generated start time of the forecasted activity. However, instead of notifying users directly at the start time, we propose to provide alternative notification times in advance. The second approach is called FaPTi. FaPTi is notification optimization for forecasted activity with probabilistic and reinforcement learning. In this approach, provide alternative notification times in advance. However, we calculate the probability of the activity that needs to be done and needs notification before optimizing the time with reinforcement learning. By considering these factors, we are working to further enhance the effectiveness of the notification system. Both approaches offer strategies to improve the timing of notifications in activity recognition systems. By providing users with alternative notification times and considering the probability of activity occurrence, we intend to optimize the user experience and ensure that important activities are not overlooked or forgotten.

Our approach is based on a machine learning algorithm that uses historical data to predict future activities and then sends the appropriate notifications based on the probability and optimal timing. The approach also evaluates the impact of the notifications on user activity and provides feedback to the user. In addition to examining the effects of activities with low probability on forecasted activities.

Method comparisons were performed on the evaluation results of our proposed method with the baseline method for performance measures and probability levels for forecasted activities, and we also observed the characteristics of forecasted activities with low probability. The results show that the FAPTi and FaTi methods are superior to the baseline method, the percentage of positive responses and the response rate have a significant effect on the low probability of forecasted activity; and activities such as dressing up, daily chores, shopping, brushing teeth, taking a bath, working, snack, lunch, short time breaks, drinking, others, and walking have higher positive response values compared to response rates, while activities such as sleeping, learning at home, breakfast, dinner, biking, cleaning, and laundry have better response rates than positive response percentages.

5.2 Materials and Methods

The section on Materials and Methods provides an overview of the process used in this study to collect data and develop a model. This section is divided into two subsections: Model Development and System Architecture.

5.2.1 Model Development

In this section, we introduce the FaTi and FaPTi methods, designed to optimize forecasted activity notifications in daily life. The FaTi method utilizes the random forest algorithm for forecasting and reinforcement learning for time optimization. Figure 5.1 provides an overview of the FaTi method.

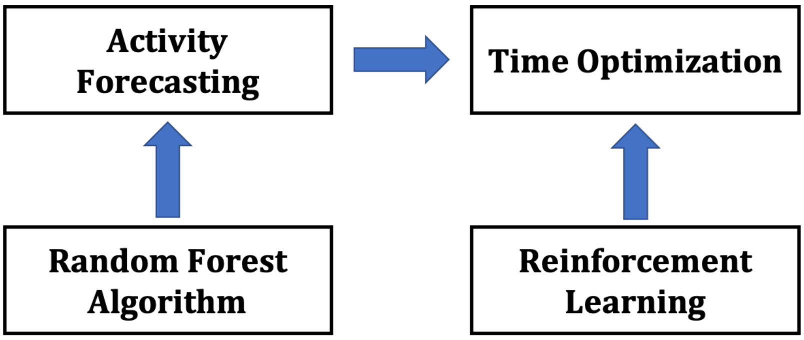


図 5.1: Proposed method (FaTi) overview. Notification optimization for forecasted activity with reinforcement learning.

The FaPTi method incorporates the random forest algorithm for forecasting, Bayes' theorem for probabilistic analysis, and reinforcement learning for time optimization. Figure 5.2 illustrates the overview of the FaPTi method.

The FaTi method in this study utilizes reinforcement learning to assign the optimal notification time for forecasted activities, while the FaPTi method incorporates probability

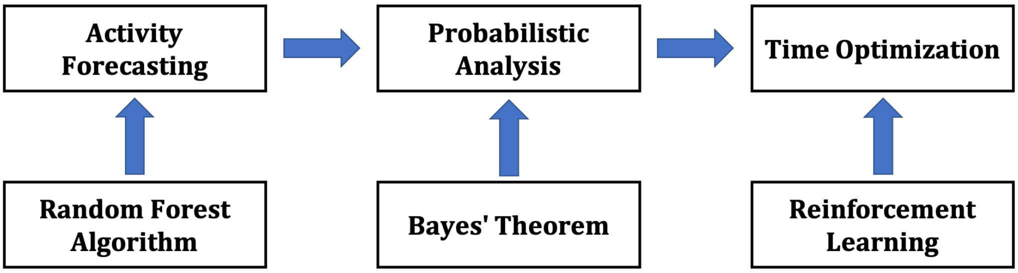


図 5.2: Proposed method (FaPTi) overview. Notification optimization for forecasted activity with probabilistic and reinforcement learning.

calculations before applying reinforcement learning, allowing the determination of the likelihood for an activity must be performed and that notification is required.

In this study, Bayes' theorem as a formula to calculate conditional probabilities is used because this enables us to make informed decisions about whether to send a notification, to optimize the notification delivery for activities from forecasted that require user attention. Bayes' theorem is a fundamental concept in probability theory that allows us to update the probability of an event occurring based on new information or evidence. It is derived from conditional probability, which is the probability of an event occurring given that another event has occurred. In Bayes' theorem, the conditional probability of an event (such as the probability of a user needing to do an activity given that a notification is needed) is calculated using prior knowledge (such as the probability of a notification being needed) as well as the likelihood of observing the event (such as the probability of a user needing to do the activity). *(P(FA—NF))* with the prior probability of a user needing to carry out the activity *(P(NF))* and dividing it by the prior probability of a notification being needed *(P(FA))*. Mathematically, the probability calculation is as follows:

$$P(NF|FA) = \frac{P(FA|NF) \times P(NF))}{P(FA)} \tag{5.1}$$

- *NF*: User needs to do the activity
- *FA*: User needs the notification

To determine levels of activity that need to be done and need notifications, we set thresholds. The threshold value is obtained from calculating the mean probability value of activities that need to be done and need notification for each user. The resulting value of the probability is compared to the threshold value to determine the probability level of a user needing to do the activity and the notification is needed. When the probability value is less than the threshold, the level is low. Nevertheless, if not, the level is high. The high and low levels of these probabilities will be put into a state of reinforcement learning as a product of time, input, and level (the FaPTi method).

In our proposed approach (FaTi and FaPTi methods), the user cannot set the time according to his/her wishes like most reminder systems [67], but the system will remind the user based on the estimated results and before the time of activity is executed because the future events or disturbances are unpredictable, while the system will learn from the user's activity behavior. We set the reminder time from the furthest distance to activity time. Our system will choose the action for the user, if the action is silent, then the user's response is automatically no response; however, if the action is notified, then the user is prompted to respond by selecting one of the options that appear on the notification, such as NOW, LATER, or DISMISS. A NOW response indicates the user approves of the time and will prompt them to begin the activity immediately. A response from LATER indicates that the user appreciates the reminder time but will complete the activity later. A DISMISS response indicates that the user did not wish to be reminded at the current time. If the user does not select the option within five minutes due to negligence or another reason, our system determines that the user chose no response. After receiving a response from users, we optimize the timing of subsequent notifications based on each user's response.

In the part of reinforcement learning, the system acts as the agent while the smartphone serves as the environment. The agent is responsible for observing the user's context to determine whether to send a notification or remain silent. When the notification appears, the user can either NOW, LATER, or DISMISS it, and the response is then used by the agent to assign a reward. This process is aimed at maximizing the accumulated future reward discount, which is done using the Q-learning algorithm. The relationship between the agent and the environment is such that the agent makes observations to get a representation of the environment, which is referred to as the state. Based on the state, the agent takes actions that are determined by its policies. The environment then moves from the current state to the next state and returns a reward. The q-learning algorithm is a type of reinforcement learning that enables the agent to learn from the actions it takes. The algorithm updates the policy of the agent by evaluating the actions taken and their associated rewards. In this way, the agent can improve its performance over time. The method proposed in this paper aims to optimize notifications by providing the user with multiple alternative times for forecasted activities, thereby minimizing the chances of missing important activities.

In the reinforcement learning algorithm utilized by the FaTi method, the state is the product of time and input specified by the Equation (5.5).

$$T = \{60, 50, 40, 30, 20, 10, 0\} \tag{5.2}$$

$$X = \{NOW, LATER, DISMISS\} \tag{5.3}$$

$$P = \{HIGH, LOW\} \tag{5.4}$$

$$S = T \times X \tag{5.5}$$

In contrast, for the FaPTi method, we add the probability level to the state, transforming it into the product of time, input, and level defined in Equation (5.6).

$$S = T \times X \times P \tag{5.6}$$

T means notification sending time, it is set before the activity time until it is equal to the activity time, the longest time is six minutes before the activity, and the shortest time is the same as the activity time. Each time has a difference of ten minutes. Table 5.1 shows the time features of our approach. X is the possible response that will be selected by the user, we show the input features in Table 5.2. The level is the probability level of the activity that needs to be done or not and whether notification is needed or not which has been defined previously, for the explanation of the level features we show in Table 5.3.

表 5.1: Time Feature

Time (T)	**Description**
60	60 minutes before the activity time
50	50 minutes before the activity time
40	40 minutes before the activity time
30	30 minutes before the activity time
20	20 minutes before the activity time
10	10 minutes before the activity time
0	the activity time

表 5.2: Input Feature

Input (X)	**Description**
NOW	Users like notifications at this time, and they will do the activity now.
LATER	Users like notifications at this time, but they will do this activity later.
DISMISS	Users do not like notifications at this time, regardless of whether they will do this activity or not.

表 5.3: Level Feature

Level (P)	**Description**
high	the probability value is higher than the threshold
low	the probability value is lower than the threshold

The reward function shows maps of the state-action pairs to return the corresponding reward value for a given state, defined in Equation (5.9)

$$A = \{NOTIFY, SILENT\} \tag{5.7}$$

$$R = \{+1, -1, 0\} \tag{5.8}$$

$$r : S \times A \rightarrow R \tag{5.9}$$

For the state transition function, we take the current state and action as input and return the next state. Mathematically, it can be represented as:

$$\delta : S \times A \rightarrow S \tag{5.10}$$

For the policy function, we take the current state as input and return the action to be taken. Mathematically, it can be represented as:

$$\pi(s) = a \tag{5.11}$$

Using the Q-Learning algorithm, the following steps are taken to calculate the q values to be updated in the q table:

1. Initialize, for all $S_t \in$ S; $A_t \in$ A; t = 0.
2. Start with S_0
3. At time step t, choose action $A_t = argmax_{(a \in A)}$ Q(S_t,a), ϵ-greedy is applied
4. Apply action A_t
5. Observe reward $R_{(\mathrm{t+1})}$ and get into the next state $S_{(\mathrm{t+1})}$
6. Update the Q-value function:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_{(t+1)} + \gamma max_{(a \in A)} Q(S_{(t+1)}, a) - Q(S_t, A_t)) \tag{5.12}$$

7. Set t = t + 1 and repeat from step 3

5.2.2 System Architecture

In our system, we use smartphones for data collection and apply the proposed method. Due to the expectation of self-labeling, participants are required to select an activity from a selection in our *FonLog*[108] app by clicking on a smartphone before and after performing the activity. Using this *FonLog* app, we have successfully recorded data with self-labeled in previous study[108]. On the notification side, we have two options for users, the notification response on the banner or the dialog form on *FonLog*. When a user responds to one of the forms, the other forms will also disappear. This is useful for user convenience in responding to notifications. Estimated results or forecasted activity will appear for four hours for each activity class, two hours before the activity time and two hours after the activity time. This is useful for facilitating participants in labeling. If the activity to be carried out is the same as the estimated result, they can click this menu then the start and finish time will be recorded automatically, but they can still modify it if there is a slight difference from the actual time. Figure 6.2 illustrates the user interface for *FonLog*.

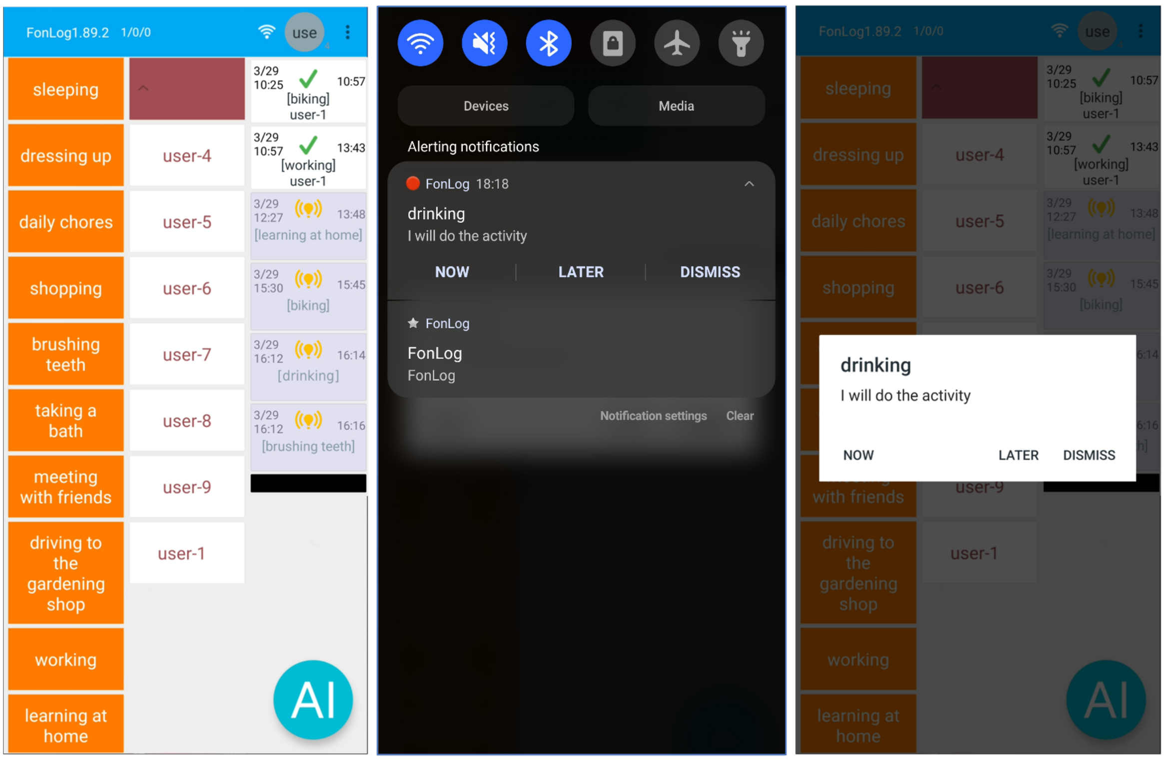


図 5.3: *FonLog* user interface.

For the method used, all processes are done on the server side, so it does not make the smartphone performance heavy. In this way, an internet connection is required for incoming and outgoing data. Internet connectivity is essential for the device to function correctly. The data collected by devices need to be processed and analyzed in real time, which requires a stable and high-speed internet connection. The availability of internet connectivity is one of the crucial elements in implementing the Internet of Things (IoT)[22, 93]. In daily activities, participants may be located anywhere, we cannot guarantee that they will always be in a location with a reliable internet connection. Therefore, it is necessary to formulate a plan for internet connection issues. In our system, data is transmitted from the server to the user's smartphone. When the user labels or responds to notifications, user-side data will be temporarily stored on the smartphone's internal storage. The data will then be transferred to the cloud server when an Internet connection is established. This system also ensures that there is not an excessive amount of data on the local storage by automatically deleting data that has been effectively uploaded to the cloud. This cloud server performs data processing tasks. Even though we use a cloud-based system, our system is not entirely reliant on the internet network; therefore, it can continue to function normally even if there are connection issues. In order to communicate, control, connect, and exchange data with other devices while still connected to the internet, an object must be embedded with technology such as sensors and software.

5.3 Experimental Evaluation

The Experimental Evaluation section provides a summary of the data description and evaluation. The subsections of this section are Data Collection and Evaluation Method.

5.3.1 Data Collection

In this study, we used two datasets to evaluate our method, the EngagementService dataset [97] and we collect data in the field. Data were collected from 24 activities from six participants who used smartphone devices that had the *FonLog* application installed. To determine the initial activity, nineteen activities were taken from the activity list to improve mobile health receptivity by employing environmental data and machine learning [238], then we distributed the initial activity list to the participants and asked them about their daily activities that were not included in the initial activity, then we received five additional activities from the participants. We show the activity information in Table 5.4.

表 5.4: Activity Types

Activity Name	**Source**
preparing to go to bed	[238]
sleeping	[238]
dressing up	[238]
daily chores	[238]
shopping	[238]
brushing teeth	[238]
taking a bath	[238]
meeting with friends	[238]
driving to the gardening shop	[238]
working	[238]
learning at home	[238]
mini-job	[238]
breakfast	[238]
snack	[238]
lunch	[238]
dinner	[238]
short time breaks	[238]
drinking	[238]
biking	Survey from the participants
washing dishes	Survey from the participants
cleaning	Survey from the participants
laundry	Survey from the participants
walking	Survey from the participants
other	[238]

Forecasting is the process of predicting future activity based on past data, whereas, in reinforcement learning, agents learn from the environment, as described in Section 5.2.1.

Therefore, in implementing the system, we first collect the initial data for three days. In this initial data collection, the proposed method has not been implemented. We set on the first day, no reminders were sent to participants. Participants were instructed to select an activity from the list in *FonLog*, click the start recording button when they were about to perform the activity, and then click the stop recording button when they had completed the activity. On the second day, the reminders begin to operate, but not based on the forecasted activity but on the actual activity from the previous day. Notifications are generated randomly; to select an action in the form of notify or silent, seven-time options will be chosen at random if the action is notified. For recording still follow the rules on the first day. On the third day, notifications for reminders were generated randomly based on the second day's activities, and participants recorded the same activities as on the first and second days. From the information gathered in the initial data collection, activity forecasting, probabilistic, and reinforcement learning are implemented. We implemented the proposed method and the baseline method for nine days. At this stage, the reminder data no longer comes from the previous day but from the forecasted activity results. The time required to send the notification will be determined by time optimization utilizing reinforcement learning for the baseline method and probability calculations followed by time optimization utilizing reinforcement learning for the proposed method. We limit the notification time that appears on the participant's smartphone to five minutes. If the user does not respond within five minutes, notifications on banners and dialog forms will automatically disappear. This is intended to prevent the user from receiving unnecessary notifications that could be distracting. Additionally, if there are too many unread notifications, it will be difficult for users to view them one by one.

In addition to conducting direct experiments, this paper also leverages data collected by previous researchers from the EngagementService dataset. The EngagementService dataset comprises various details such as CreationTime, AutoApprovalDelayInSeconds, Expiration, AcceptTime, SubmitTime, AutoApprovalTime, ApprovalTime, RejectionTime, RequesterFeedback, WorkTimeInSeconds, Input.content, Input.hour, Input.minute, Input.day, Input.motion, Input.location, Input.last_notification_time, Answer.sentiment. However, we will only use information from Input.content, Input.hour, Input.minute, Input.day, Input.motion, Input.last_notification_time, and Answer.sentiment, as user responses. Our simulations will center around seven activities, namely biking, bus, walking, train, stationary, driving, and running. These activities will be employed to assess the system's performance and gather responses. To ensure diverse data, we will involve five subjects to extract responses from the available dataset. By selectively utilizing the relevant data fields and activities, we aim to derive valuable insights and evaluate the effectiveness of our system in user engagement analysis. By incorporating data from the EngagementService dataset and conducting our own experiments, we can gain a comprehensive understanding of the factors influencing user engagement across different activity types.

5.3.2 Evaluation Method

The comparison of the baseline, FaTi, and FaPTi methods was conducted to assess the feasibility of our proposed method. The baseline method involved random notification delivery at seven available time alternatives, ranging from sixty minutes before the forecasted activity time to the same time as the forecasted activity. Random notification delivery was chosen as the baseline because no previous method provided optimization of notification timing for forecasted activities with multiple time options. This means that notification delivery for forecasted results in various fields of study [224, 52, 9, 147, 138] was solely based on a single-time forecasted result or employed different scheduling for notification delivery times [3, 240]. We performed the simulation in which the activity dan responses are collected from EngagementService dataset [97] and the dataset from the implementation of the system as described in Section 5.2.2 and 5.3.1, this is intended to test our method's efficacy in user-dependent scenarios. We compare the results of the FaTi and FaPTi methods using both datasets.

Three performance measures as criteria are defined in this paper: percentage of positive responses, user response rate, and response duration. With the percentage of positive responses, we can measure the proportion of user responses that are positive or favorable. It indicates how well the notification method is able to elicit a desired response from the users. A higher percentage of positive responses signifies that the users are actively engaging with the notifications and finding them useful. For example, if a notification is sent to remind users to complete a task, a high percentage of positive responses would indicate that the users are acknowledging the reminder and will take appropriate action. For user response rate, this metric represents the rate at which users respond to the notifications they receive. It measures the level of user engagement and interaction with the notifications. A higher response rate implies that the users are more actively involved and attentive to the notifications. It indicates the effectiveness of the notification method in capturing the users' attention and motivating them to respond. A low response rate may suggest that the notifications are being ignored or overlooked by the users. Response duration is useful for measuring the duration of time it takes for users to respond to the notifications. It represents the speed or efficiency of the user's response. A shorter response duration indicates that the users are promptly attending to the notifications and taking action. It reflects the effectiveness of the notification method in prompting timely responses from the users. On the other hand, a longer response duration may indicate delays or inefficiencies in the users' engagement with the notifications.

By considering these three performance measures, a comprehensive evaluation of the notification methods can be obtained. Each metric provides unique insights into different aspects of the notification system's performance. The percentage of positive responses assesses the impact and effectiveness of the notifications in eliciting desired user actions. The user response rate indicates the level of user engagement and attentiveness. The response duration measures the efficiency of the user's response. Together, these metrics help in understanding the overall effectiveness, user engagement, and efficiency of the notification methods in optimizing the delivery of forecasted activities.

In this investigation, the positive response came from the NOW and LATER responses. The positive response is used for each dataset. The positive response is defined as follows:

$$\frac{RN + RL}{RN + RL + RD} \times 100 \tag{5.13}$$

- RN: the number of activities which is response is now
- RL: the number of activities which is response is later
- RD: the number of activities which is response is dismiss

Then, we determine the user response rate. The user response rate is defined as follows:

$$\frac{NR}{TN} \times 100 \tag{5.14}$$

- NR: the number of user responses to the notification
- TN: total number of notifications sent

Response duration refers to the length of time it takes for the user to respond to a particular stimulus or request. In this context, response duration can refer to the time it takes for a user to respond to a notification. This can include the time it takes to read and comprehend the message, as well as the time it takes to physically respond, such as by clicking a button. In the field of human-computer interaction, response duration is an important metric to consider when designing interfaces and systems. Long response durations can lead to frustration and decreased user satisfaction, while short response durations can enhance the user experience. The response duration is defined as follows:

$$duration = RT - NT \tag{5.15}$$

- RT: the time when the user responds to a notification for each activity.
- NT: the length of time for which the notification appears on the user's smartphone screen for each activity.

In the context of forecasting, it processes data from label information and time for each activity class, where time includes start and finish time. This allows for the provision of future activity information with the time duration to be generated. The label information is used as the target variable, while the start and finish time are used as features. The data will be split into three parts, training data, testing data, and validation data. Cross-validation is a technique used to evaluate the performance of the model, this is important to ensuring its generalizability to new data. In these approaches (FaTi and FaPTi methods), a leave-one-day-out cross-validation approach is used, where one day of data is set aside for validation, and the remaining data is used for training and testing. This approach ensures that the model is tested on data that it has not seen before, allowing for an accurate evaluation of its performance.

5.4 Results

In this section, we present the results of our study following our approach discussed above. The performance of our approach was evaluated based on the percentage of positive responses, user response rate, and response duration. To investigate the impact of integrating probabilistic and reinforcement learning techniques in optimizing the timing of notifications for forecasted activities, we illustrate the performance measurements for the EngagementService dataset in Figure 5.4, while Figure 5.5 presents the results of the experiment dataset.

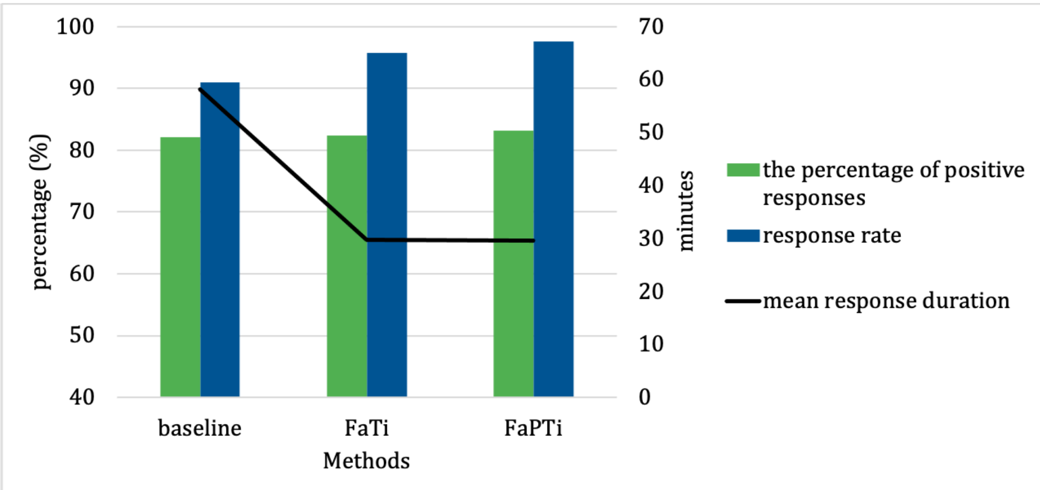


図 5.4: The Performance Measures Comparison From EngagementService Dataset. Positive response and response rate are displayed in percentage (%). Response duration is displayed in minutes.

By comparing our approach with the baseline method, we were able to assess the superiority of the FAPTi and FaTi methods in terms of their notification relevance and effectiveness. From the EngagementService dataset (Figure 5.4), the difference in the percentage of positive responses is not too significant, but the advantages of our approach are evident in the response rate and response duration. Meanwhile, from our experiment (Figure 5.5), the difference between all performance measurements was very clear, even for the response rate, the FaTi method was 25.26% superior to the baseline method, and the FaPTi method was 27.15% superior to the baseline method. The findings from this

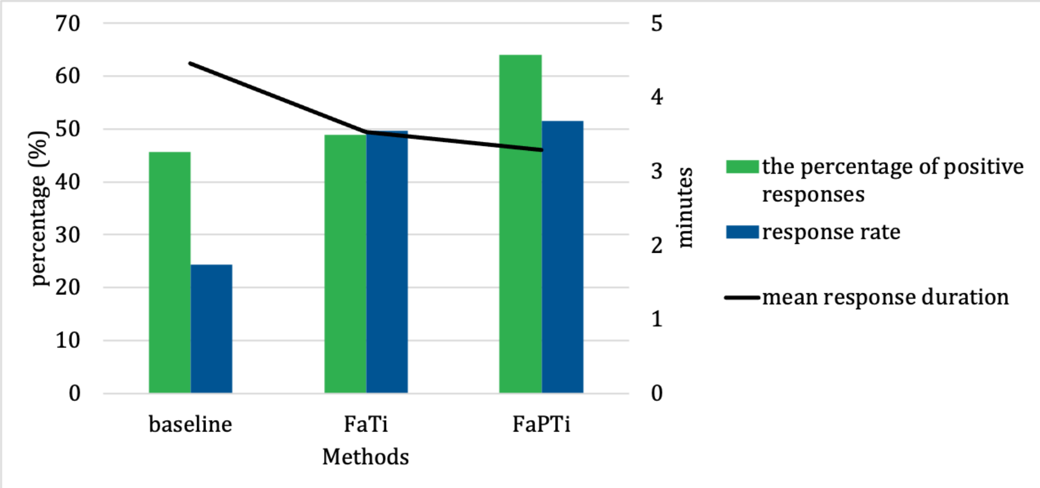


図 5.5: The Performance Measures Comparison From Our Experiment. Positive response and response rate are displayed in percentage (%). Response duration is displayed in minutes. We set the duration for notifications to appear on the smartphone screen to 5 minutes.

comparison serve as compelling evidence for the efficacy of our proposed approach in optimizing forecasted activity notifications. The inclusion of the baseline method in the study allowed us to establish a benchmark and provide a meaningful point of reference for evaluating the performance of our methods. By surpassing the performance of the baseline method, our approach demonstrates its potential to enhance the precision and reliability of notification time, ultimately leading to improved user experiences and outcomes.

In Figure 5.6 and Figure 5.7 we highlight the comparison of probability levels for forecasted activities to see the influence of each scoring criterion on the high and low probability. Through Figure 5.6 we observe the probability level for the forecasted activity from the simulation using the EngagementService dataset. The simulation results reveal significant differences compared to the baseline method, the percentage of positive responses has the lowest value of 27.88% with the difference between high probability and low probability reaching 29.26%, and the difference in response rate is 11.55%, while the average response time has a difference of 3.85 minutes. On the other hand, through the FaTi and FaPTi method approaches, the low probability level still has a good response for each evaluation criteria. For example, in the FaPTi method, the difference between high

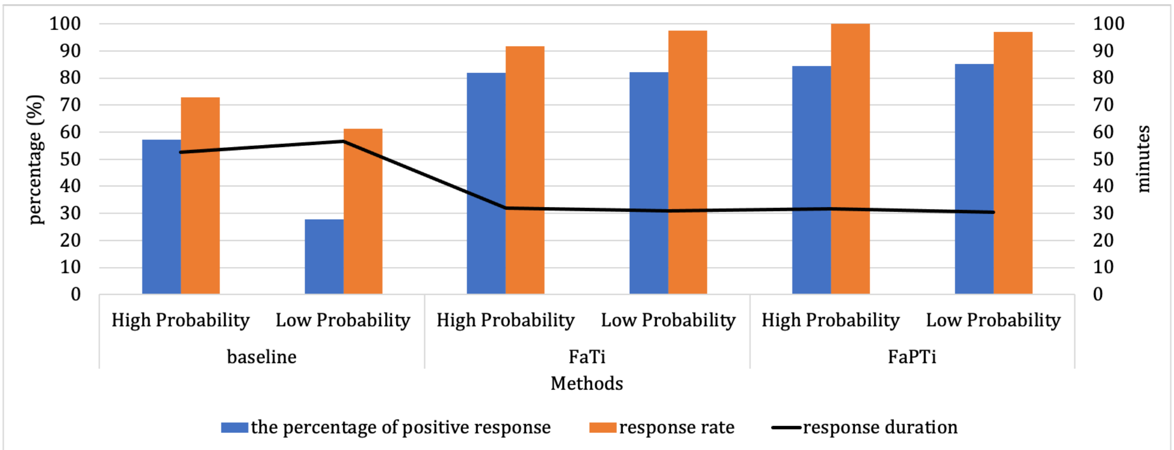


図 5.6: Probability Levels Comparison of Forecasted Activity From EngagementService Dataset. The lowest low probability value is found in the baseline method with a significant gap in the percentage of positive responses and response rate.

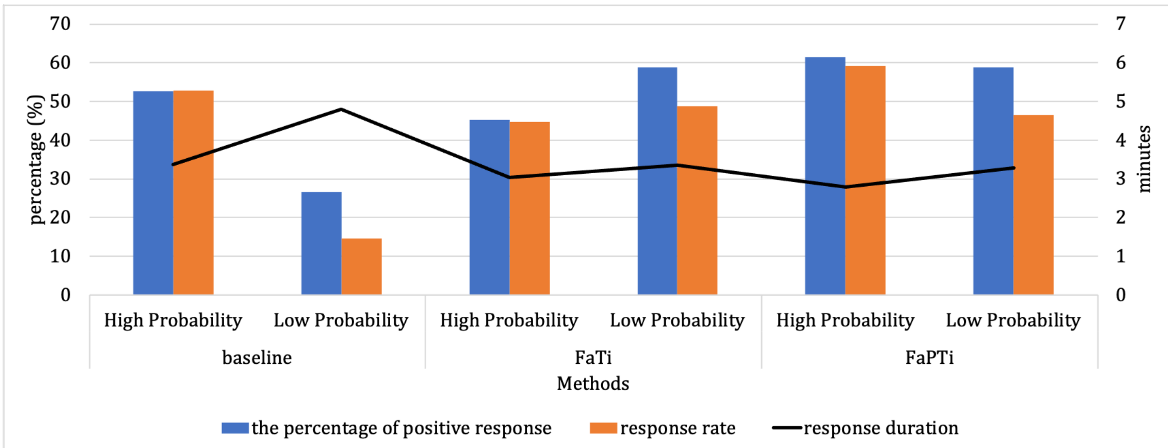


図 5.7: Probability Levels Comparison of Forecasted Activity From Our Experiment. The lowest low probability value is found in the baseline method. The FaPTi method is superior to the baseline and FaTi methods.

and low probability levels of activities predicted is only 2.98%. Additionally, the response rate for low probabilities in the FaTi method is better than that for high probabilities, with a margin of 5.65%.

To further analyze our findings, we conducted an observation of the system implementation in the field, as depicted in Figure 5.7. In Figure 5.7 we highlight the comparison of probability levels for forecasted activities from our experiments. In the baseline method, there is a noticeable gap between high and low-probability activity types in terms of performance measures. In particular, the performance measures for low probability activities show a significant decrease compared to high probability activities with 25.96% for the percentage of positive responses and 38.21% for the response rate, while the mean response time is 1.44 minutes. However, when using the FaTi method, we observed an improvement in the performance measures for low-probability activities. Surprisingly, the performance measures for activities with high probabilities showed a decrease in this case, with a decrease of 13.52% for the percentage of positive responses and 4.01% for the response rate. On the other hand, the FaPTi method yielded positive results by enhancing performance measures for both high and low probability of forecasted activities, indicating that high probabilities maintained good performance while enabling favorable responses for low probabilities as well. This indicates that FaPTi effectively addresses the observed gap between the baseline and FaTi approaches, leading to improved recognition and notification of activities across a wider range of forecasted activity. Through these observations, we can see that the implementation of methods can influence the low probability of forecasted activities. Furthermore, the percentage of positive responses and response rate also play a role in determining the low probability of forecasted activities, while response duration has a relatively minor impact.

Regarding our previous observations, the FaPTi method outperforms the baseline and FaTi methods in terms of performance evaluation and probability levels. Therefore, in this part, we focus on the FaPTi method to examine the differences among forecasted activity with low probabilities, as illustrated in Figure 5.8.

Each activity exhibits distinct characteristics. Activities such as dressing up, daily chores, shopping, brushing teeth, taking a bath, working, snacks, lunch, short time breaks, drinking, other, and walking have higher positive response values compared to response rates. On the other hand, activities such as sleeping, learning at home, breakfast, dinner, biking, cleaning, and laundry have better response rates than positive response percentages. For activities like daily chores, shopping, snack, short time breaks, other, and walking, users have higher positive response values but very low response rates. This indicates

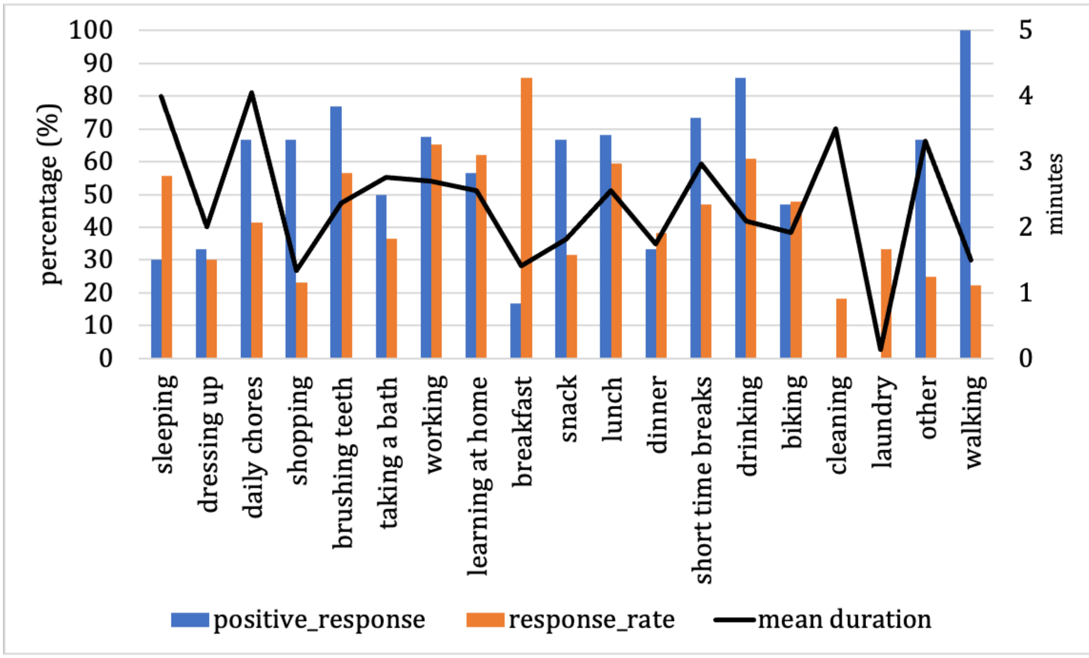


図 5.8: Characteristics of forecasted activity for low probability from our experimental dataset with the FaPTi method.

that for these activities, users choose to respond to notifications at their preferred times and ignore notifications they do not find appealing. Ignoring notifications implies that users have responded at the expected time and consider responding at a different time unnecessary. Activities like sleeping and breakfast have relatively high response rates but low positive responses, suggesting that users do not prefer the notification timing for these forecasted activities. For activities such as dressing up, taking a bath, dinner, biking, cleaning, and laundry, although some activities have higher positive response percentages than response rates, both the positive response percentages and response rates are relatively low, with no positive responses recorded for cleaning and laundry. This suggests that users do not have much time to respond to notifications for these activities. On the other hand, activities such as brushing teeth, working, learning at home, lunch, and drinking exhibit good positive response percentages and response rates, despite being forecasted with low probabilities.

On another note, the mean response duration had the longest value at 4 minutes, and the fastest response at 0.13 minutes. This indicates that the time limitation for notifications displayed on smartphones is still relevant to users. However, this may impact the low response rate, implying that after five minutes, the notification will not appear on the smartphone screen, leading the system to assume no response from the user. Nevertheless, this approach can reduce notification fatigue for users.

In summary, the FaPTi method demonstrates varying response patterns for different activity types with low probabilities. Some activities show higher positive response percentages, while others have better response rates. The duration of responses tends to fall within a reasonable range, highlighting the relevance of the time limitation for notifications on smartphones. This finding underscores the importance of considering users' preferences and behaviors when optimizing the timing of forecasted activity notifications.

5.5 Discussion

This study aims to optimize the timing of notifications for forecasted activities by considering multiple alternative time options. We propose two approaches as our contributions to this paper, the FaTI and FaPTi methods. The effectiveness and relevance of notifications are measured through three performance evaluations: the percentage of positive responses, response rate, and response duration, with two different datasets (EngagementService and our experiment) as explained in Section 5.3.1. To assess the efficacy of our proposed approaches in optimizing notification of forecasted activity, the comparison was made with the baseline method.

By evaluating both datasets, we can the integration of probabilistic and reinforcement learning techniques, specifically in the methods FaPTi (with probabilistic considerations) and FaTi (without probabilistic considerations), optimize the timing of notifications for forecasted activities. Regarding the results of the comparison of methods described in Section 5.4, significant differences were observed in response duration between our proposed approaches and the baseline method in the EngagementService dataset, but there were no substantial differences in terms of the percentage of positive responses and response rate. However, in the field experiment, clear distinctions were observed in all three performance evaluations. Both of our proposed approaches outperformed the baseline method, with a percentage of positive responses of 3.29% and a response rate of 25.26% for the

FaTi method, and a percentage of positive responses of 18.38% and a response rate of 27.15% for the FaPTi method. However, the response durations were not significantly different, with 0.93 minutes for the FaTi method and 1.17 minutes for the FaPTi method. Overall, the FaPTi method exhibited superiority over the FaTi method and the baseline method across all performance measurements and datasets. This indicates that the comparison between our proposed approaches and the baseline method not only validates the effectiveness of our methods but also underscores the importance of integrating advanced techniques such as probabilistic and reinforcement learning in notification optimization for forecasted activity.

To understand the factors have an impact on the low probability of activity that needs to be done or not, and notifications needed or not, our study examined the comparison of probability levels of forecasted activity in both datasets to understand the factors influencing the low probability of activities needing to be done or not, and the need for notifications. From the results of the comparison, the percentage of positive responses and response rate played a role in the low probability of activities, while response duration did not significantly impact the low probability of forecasted activities. Furthermore, our observations demonstrated that the application of the methods could also influence the low probability of forecasted activities, as seen in the substantial disparity between high and low probabilities when applying the baseline method. Additionally, in Figure 5.8 we can also see that low probability can affect the low response rate or percentage of positive responses. However, by selecting the appropriate timing for sending notifications to users, they still have the opportunity to respond to notifications at their preferred time, even though the busyness of future activities is unpredictable. This implies that a low probability for activities that need to be done or not, and need notifications or not, does not imply complete neglect of reminding users, as these activities may not be necessary for the current day but will be needed in the future.

Our case study showed the observed results of each activity for a low probability of activity predicted by the FaPTi method for our experiment to understand the difference between activity on user engagement for low probability of forecasted activity. The intention behind this selection was that the FaPTi method had proven to be superior to FaTi and the baseline method. Additionally, our choice of a dataset for the experiment was motivated by the fact that individuals have varying levels of busyness each day, and daily activities may not be performed every day. Therefore, this aspect became our focus in analyzing field data. Some activities showed a high percentage of positive responses, such as daily chores, shopping, snack, short time breaks, others, and walking. This indicates that users require reminders for these activities despite the low probability of forecasted activities. However, they are not always in front of their smartphone screens, resulting in the dismissal of notifications at other times when they are about to engage in or are currently performing activities. On the other hand, activities such as brushing teeth, working, learning at home, lunch, and drinking exhibited similar levels of positive response percentage and response rate, indicating that the system effectively learns and understands user behavior for these activities. In contrast, for activities such as cleaning and laundry, the system still needs to understand user behavior to determine the optimal notification delivery time due to the low percentage of positive responses and response rate. Thus, this study was able to demonstrate the characteristics of activities in user engagement with a low probability of forecasted activities.

In this work, we are unaware of the number of notifications users receive from various applications on their smartphones because the influx of notifications can lead users to ignore them more frequently. Although we have limited the appearance time of notifications on users' smartphone screens to avoid notification overload, we cannot control notifications from other applications. Examining the number of notifications that appear on smartphones at specific times can provide better insights to enhance user engagement.

We hope that our proposed method and research findings will prevent individuals from missing out on future activities. Our system is designed to be dynamic, so if users can respond to notifications correctly, the timing will be optimized to facilitate users' self-improvement and achieve a balance between important tasks and planned activities. Furthermore, in the future, this information contributes to improving data collection in research involving human activities.

5.6 Conclusions

In this study, notifications are sent as reminders for upcoming activities, ensuring that individuals with prospective memory issues or busy schedules do not miss important tasks due to a lack of timely reminders. With timely notifications for future activities, users can better plan their tasks and improve productivity. In situations where unexpected activities arise, users can manage their activities more effectively and allocate the necessary time to complete urgent tasks. This helps avoid time wastage and allows users to stay focused on essential activities. Furthermore, by receiving relevant notifications, users feel informed and actively engaged in their activities. They can feel supported and assisted in their daily activities, regardless of whether the activities are planned or unplanned. This can enhance user satisfaction with the user experience of applications or systems that provide effective notifications.

The main contribution of this paper is providing time optimization in the delivery of notifications for predicted activities through two approaches: the FaTi and FaPTi methods. We offer multiple time options for each predicted activity. The FaTi method contributes to optimizing the time among the available options directly for the forecasted activities. The FaPTi method contributes by considering the probability of activity being necessary and requiring a notification based on the predicted activities before the notification timing optimization process takes place. We incorporate the state as a combination of time, the possible response of the user, and the probability level for an activity that needs to be done and needs notification, allowing the system to notify the user before the forecasted activity time. With the FaTi and FaPTi methods, it is possible to observe user responses over time and predict future timing and actions. By harmonizing exploration and exploitation, reinforcement learning can optimize the time of each user response.

Our proposed methods, FaTi and FaPTi, contribute to the field of activity recognition by offering innovative techniques to enhance notification timing, ultimately improving the usability and effectiveness of activity recognition systems.

Future work will focus on addressing activities with more complex problems such as in healthcare facilities, as the activities of medical staff, such as nurses, can vary on a daily basis. Additionally, the challenges of shift scheduling, including morning, afternoon, evening, and night shifts, pose further complications for individual scheduling. The varying shift assignments can disrupt their routine activities, adding to the complexity of the problem. To address these challenges, a larger dataset will be required, while ensuring that the data collection process does not interfere with the performance of medical staff.

第 6 章

Deploying Intelligent Technology in Healthcare Institution

6.1 Improving Complex Nurse Care Activity Recognition

6.1.1 Introduction

Recent developments in the smartphone industry, electronic devices and fitness trackers have contributed to increasing research works centered on Human Activity Recognition. Different sensors, wearable devices and mobile applications are generally used to obtain data regarding activities of daily life (ADL) including sedentary behaviour, postural transitions, and dynamic behaviour [161] to routine activities done by office workers or nurses [108]. The application of Machine Learning and Deep Learning algorithms allowed researchers to grasp action, interaction and motion patterns from an individual or group of people. The focus of activity recognition varies from simple activities such as walking, standing, and sitting to complex activities performed by medical staff to assist patients in hospitals.

With the increasing aging population, activities by the elderly, caregivers and nurses are being further studied to improve care delivery. HAR serves as an assistive tool to improve elderly life support, monitoring both cognitive and physical functions [64]. Nurse activities are studied with the wearable approach where users carry the sensors with them as they perform any activity [106][108]. However, challenges on data collection due to environmental factors and noise especially in the hospital setting still limits researches on HAR. To overcome these challenges, various types of sensors are integrated in the data collection from inirtial, physiological, to environmental sensors. Accelerometer is the most prevalent sensor used for activity recognition and oftentimes deployed together with other sensors such as body temperature sensors, compasses, electromyography, electrocardiograph, gyroscopes, magnetometers, barometric pressure sensors, and oximetry sensors [64].

A survey on the challenges and potential of barometric sensors for human activity tracking pointed out altitude, climate, and air velocity as common factors considered in the integration [157] of the device in data gathering. Even so, HAR researchers found solutions to these limitations and used various barometric pressure sensors to distinguish sitting and standing activities [161], predict driving behaviour [98], and locating floor level of users [94] considering elevation changes. Barometric sensors can detect any pressure or temperature changes. Additional information from barometric sensor overcomes inter-patient variability of kinematic patterns which often limits the performance of initial sensors in detecting transitions between different activities and postures [162].

Barometric pressure sensor can be useful for complex activity recognition. However, using barometric pressure sensors for nursing activities in hospitals is a challenge because to identify nurse activities we need to get the pressure value from the care movement without being influenced by other factors. While the barometric sensor will capture every change in movement, temperature and wind in the environment might affect the pressure reading.

In this study, we integrated sensors in a hospital to collect data for activity recognition and obtain nursing records without interfering with nursing activities. Our research aims to extract features from the barometric pressure sensor and Quuppa sensors for activity classifiers. We examine the relationship between timestamp extensions and pressure features. We introduce features specific to the barometric pressure sensor to explore how the pressure feature works well for nursing activities in the real world and compare it with data collected from the lab. We show the characteristics of the pressure feature, such as identifying activity classes, which can be improved when we use the barometric pressure sensor. With timestamp extension, we investigate which pressure feature works better when we extend the label of complex nurse care activity recognition.

6.1.2 Method

In this section, we describe the system architecture, data collection, model data, and integrating nursing care records with activity recognition.

Data Collection

The data was gathered from 4,544 activity labels from 15 nurses at Nagoya University Hospital using three devices: a barometric pressure sensor, a Quuppa sensor, and a smartphone. Participants are required to bring a barometric pressure sensor placed in a chest pocket and a personal mobile disinfectant that is equipped with a Quuppa sensor, including IoT, hanging around their waist as shown in Figure 6.1. When nurses went into an SICU room, they used gel to clean their hands and then performed the activity.

図 6.1: Nurse using Fonlog with disinfectant on waist and the barometric pressure sensor on pocket

Because we expected self-labeling, participants were asked to choose the activity from the list in our app (Fonlog) by click or voice using a smartphone before and after doing the activity. The Fonlog user interface navigated by users is shown in Figure 6.2. The objective is to classify activities into one of the thirty-three activities performed as listed in Table 6.1. The data gathering overview is shown in Figure 6.3.

表 6.1: Activity Classes

Activity Group	Activity Name
Patient care	Observation, Clean Care (help patients such as with bathing or wiping the body), Nutritional Dietary Care (help patients such as making healthy recipes), Excretion Assistance (Provide excretion assistance according to the condition of the person being treated), Suction (perform care such as clearing the airway), Circulatory Care (perform care such as blood circulation), Posture Change (Changing the position of the patient), Movement Support (support for patient movement), Family Support (Help for the patient's family), Rehabilitation / recreation, Care For Other Patients
Medical assistance	Injection Support, Dosage (Prescribe and administer medicine to patients), Treatment Support, X-Ray Support, Blood Gas Measurement, Drug Management, Other Medical Assistance
Environmental arrangement	Indoor Environmental, Cleaning The Room, Other Environment Maintenance, Compatible With Medical Devices

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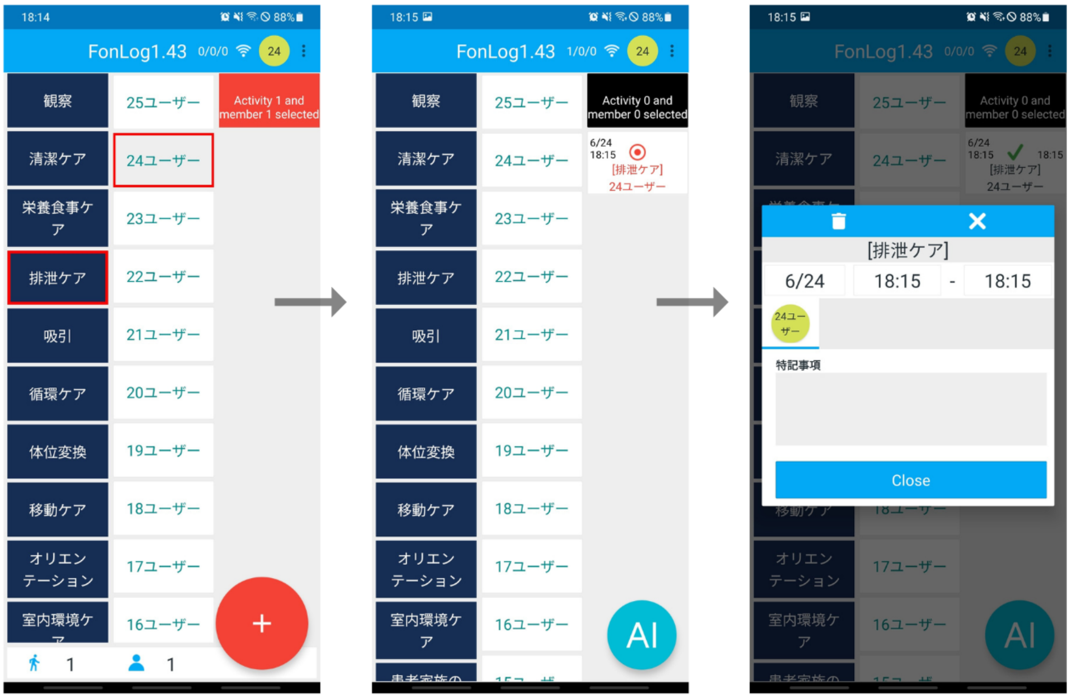

図 6.2: Fonlog user interface used by nurses during data gathering

表 6.1 – continued from previous page

Activity Group	Activity Name
Documentation / communication	PC Record, Handwriting Record, Conference (a meeting held at a nursing or medical facility), Patient Information Gathering, Report To Doctor, Transfer Matter (ongoing work transfer), Information Sharing, Operational Coordination, Other Records, Report or Contact, Committee Activities, Nursing Staff Guidance

System Architecture

Quuppa locator was installed on the ceiling of the hospital. It was used to record the address of a barometric pressure and Quuppa sensors for each nurse. When the air pressure changes, the locator in the SICU (Surgical Intensive Care Unit) room can record location

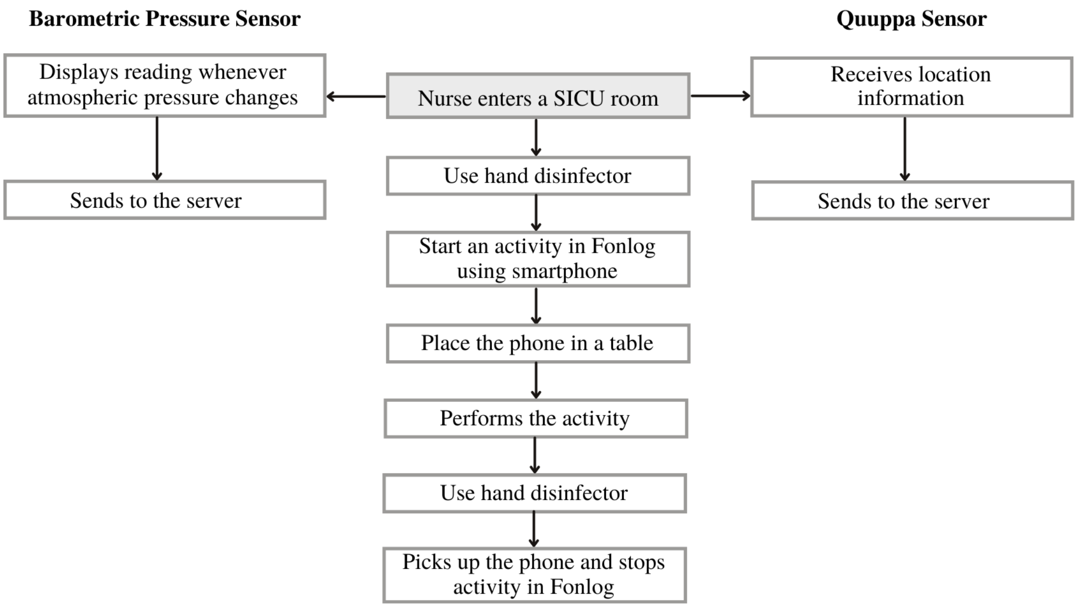

図 6.3: Overview of Data gathering set-up

information and send the data to the Quuppa server. The Quuppa server is located in the hospital, so internet connection disruptions have no effect on data gathering. With a strong connection, the data is sent from the local server to the cloud server. In the same way as for data labels, we temporarily store data on the smartphone's internal storage before transferring it to a cloud server when connected to the internet. This system also makes sure that there is not too much data in the internal storage because data that has been successfully sent to the cloud will be deleted automatically. Data processing is done on this cloud server. Although we use a cloud system, the system we propose does not depend entirely on the internet network, which means that our system can still work well even if there are problems with the connection. This is very important in the implementation of IoT because using IoT, an object is embedded with technologies such as sensors and software with the aim of communicating, controlling, connecting, and exchanging data with other devices while still connected to the internet.

6.1.3 Preprocessing

Preprocessing was performed to address clock synchronization and incorrect timestamps. In our experiment, we used three devices, so synchronization was necessary. Using a barometric pressure sensor, the dimensions of the data set we use are timestamp, device name, and pressure value in Pascal units. The dimensions of the data obtained from the Quuppa sensor are timestamp, device name, position (X and Y), and area. The device name should match the device used by each nurse. The pressure value in Pascal units and positioning on the X and Y axis of the Quuppa sensor are the values assigned to the classification model. Instead of the clocks synchronizing directly from three devices, we chose to split the Quuppa and barometric pressure sensors first, but still based on self-labeling by the user using the smartphone. This approach can avoid the error occurring in one device affecting all the data collected if three devices were synchronized. Furthermore, this allows us to compare the evaluation results with and without the barometric pressure sensor. In our combination, we separate the Quuppa feature synchronization with the labeling time of the smartphone and the pressure feature from the labeling time. We then set the basic variables for activity, start time, end time, and user identity. After that, the results of synchronization between Quuppa features and pressure features are merged based on basic variables. In this way, a missing value at a certain moment in one sensor will not affect the sensor value at the same moment in the other device. Another preprocessing technique done is extending the activity label time, as one of the risks of self-labeling that needs to be considered is incorrect time[108]. Therefore, we alter each activity's label to be wider than the recorded segment with some of the alternative times described in Section 6.1.3. This is applied before the start time or after the end time, or both.

Feature Extraction

From our experiment, we got the pressure value in units of Pascal and the position on the X and Y axis from the Quuppa sensor. To maximize data usage, a sliding window for data segmentation is applied. In this paper, we perform sliding windows with a one-minute duration without overlapping. The features extracted are mean, standard deviation (STD), maximum, minimum, maximum-minimum, summation, variance, skewness, and kurtosis. We also include in the feature vector the spending time of each user when performing activities at a certain hour since change in time due to temperature fluctuation can affect the value of the barometric pressure sensor. For each sample, we use 30 features with the barometric pressure sensor and 21 features without the barometric pressure sensor.

Evaluation Method

Random forest is used for classification. To maintain the imbalance among activity classes in the dataset, we limit the data samples to no more than 3.000 for each activity, as well as other activity classes, and then combine them. The model is then evaluated using cross-validation, with activity data on one day used as test data, and the other day is used for training. Validation of both training and testing followed. This flow is repeated for all the available days. Both accuracy and F1 score were measured to assess the model. The evaluation results in terms of accuracy and F1 scores are shown in Table 6.2.

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表 6.2: Accuracy and F1 Score with and without barometric pressure sensors

	with		without	
Activity	Accuracy	F1 Score	Accuracy	F1 Score
Observation	0.98	0.98	0.95	0.94
Clean Care	0.94	0.92	0.91	0.88
Nutritional Dietary Care	0.88	0.72	0.82	0.48
Excretion Assistance	0.93	0.84	0.84	0.58
Suction	0.97	0.92	0.9	0.74
Circulatory Care	0.86	0.9	0.96	0.96
Posture Change	0.97	0.92	0.82	0.78
Movement Support	0.66	0.4	0.75	0.46
Indoor Environmental Care	0.83	0.7	0.81	0.52
Family Support	0.91	0.78	0.87	0.3
Rehabilitation / recreation	0.77	0.52	0.75	0.14
Dosage	0.9	0.76	0.87	0.6

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表 6.2 – continued from previous page

	with		without	
Activity	Accuracy	F1 Score	Accuracy	F1 Score
Care For Other Patients	0.92	0.86	0.88	0.72
Injection Support	0.82	0.82	0.83	0.8
Treatment Support	0.9	0.86	0.85	0.72
X-Ray Support	0.83	0.54	0.9	0.64
Blood Gas Measurement	0.93	0.88	0.89	0.76
Drug Management	0.75	0.74	0.91	0.92
Other Medical Assistance	0.83	0.72	0.74	0.4
Cleaning The Room	0.89	0.72	0.82	0.46
Other Environment Maintenance	0.9	0.86	0.79	0.62
Compatible With Medical Devices	0.7	0.24	0.78	0.2
PC Record	0.95	0.96	0.86	0.86
Handwriting Record	0.9	0.58	0.84	0.6
Conference	0.93	0.88	0.92	0.76
Patient Information Gathering	0.96	0.94	0.91	0.8
Report To Doctor	0.88	0.66	0.89	0.7
Transfer Matter	0.92	0.9	0.93	0.88
Information Sharing	0.92	0.82	0.81	0.58
Operational Coordination	0.97	0.98	0.94	0.98
Other Records, Report or Contact	0.7	0.16	0.89	0.74
Committee Activities	0.8	0.6	0.8	0.5
Nursing Staff Guidance	0.95	0.6	0.92	0.64

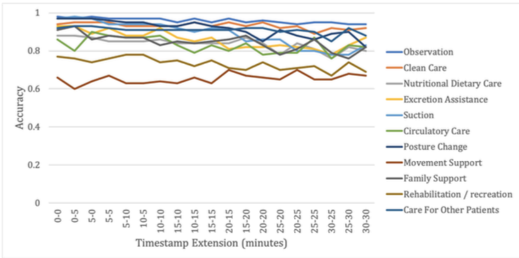
The same method is used to test the performance with and without the barometric pressure sensor. If the values for both metrics are greater, they indicate that the model can be able to classify observations into classes. Accuracy is the most intuitive performance measure, which only displays the observed ratio that is as expected. The F1 score, which accounts for both false positives and false negatives, is the weighted average of precision and recall.

Timestamp Extension

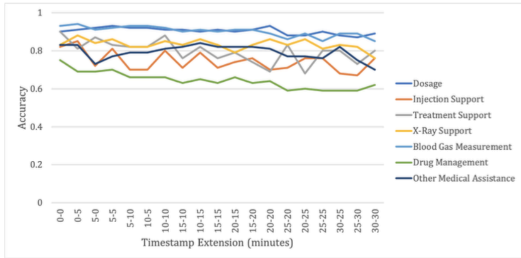
In real-life data collection, obtaining accurate labels is a challenging task. In our experiment, we asked nurses to do self-label. Self-labeling basically refers to the process of gaining confidence in oneself. Therefore, it is unavoidable to rely on nurses to provide labels. With this method, timestamp accuracy becomes a challenge. Nurses need to input an activity label before or after they perform the activity. This can happen too soon or too late, so that the inserted timestamp might be erroneous compared to that of the actual activity. Therefore, to overcome this problem, we need to use several methods to extend the timestamp.

From our observations, the smallest average duration of activity is four minutes, but many activities are recorded for less than that. The presence of such a short duration motivated us to investigate the extension of the timestamp to improve the accuracy of activity recognition. In this section, we focus on the value with the barometric pressure sensor because the barometric pressure sensor has better accuracy than without the barometric pressure sensor, but the extension with other sensors is also shown in Figure 6.8 and explained in Section 6.1.4.

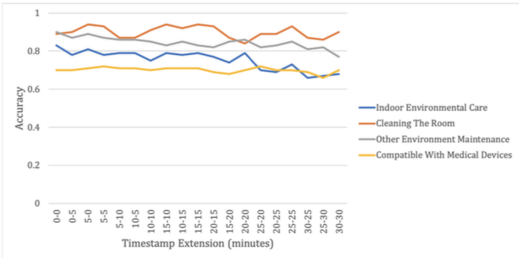
For the timestamp extension, we initially added the time sequentially, starting from 5 minutes before, 5 minutes after, and up to 30 minutes before and after. Figure 6.4 shows the accuracy of each activity when the extension is carried out, and Figure 6.5 shows the F1 score for each activity. From Figure 6.4 and Figure 6.5, we can see that there are different peaks for different activity classes, such as movement support activity have peak accuracy at 20 minutes before and 15 minutes after extension, while circulatory care has accuracy peaks at 5 minutes before. For the F1 score, excretion assistance has a peak of 10 minutes before and after, while nutritional dietary care has a peak of 15 minutes before



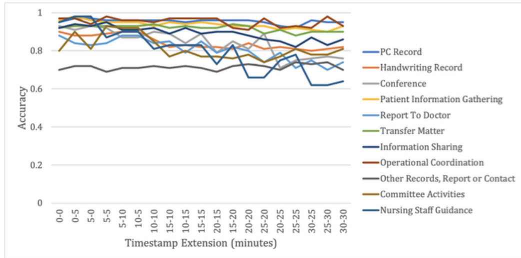
(a) Patient care



(b) Medical assistance



(c) Environmental arrangement



(d) Documentation / communication

図 6.4: Accuracy with timestamp extension of labels for each activity class

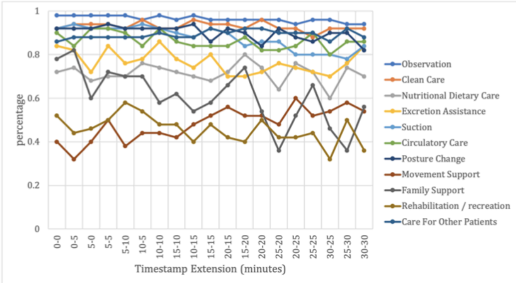
and 20 minutes after. This indicates that each activity has a different impact at each time, so it is necessary to consider an extension of time based on the type of activity the nurses do. In addition, for each time the extension is added, the overlap also increases (Figure 6.6). Therefore, we take another method to find better results. We make the timestamp extension more flexible, the first approach by taking into account the time each user spends on certain activities, then adding the average time each user spends on the short duration, and the second approach is to change the short time by the average time the user spends. We assume the following conditions for the flexible timestamp extension approach:

$$T1: \text{ if } xi < \frac{\sum x}{n} \text{ then } \frac{(\frac{\sum x}{n})}{2} \text{ else } xi$$

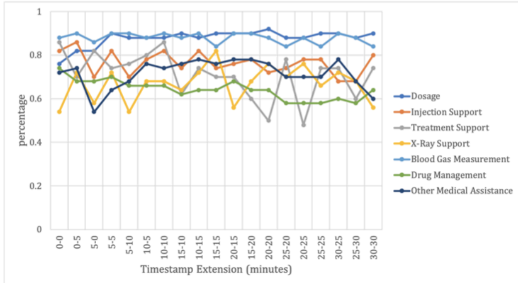
$$T2: \text{ if } xi < \frac{\sum x}{n} \text{ then } \frac{(\frac{\sum x}{n}) - (xi)}{2} \text{ else } xi$$

where *T1* and *T2* are the flexible timestamp extension, x is the duration of each user on a particular activity, xi is the current duration, and n is the number of samples.

Using this method, the impact of feature pressure increases even for all features, and the overlap for the second approximation (T2) can be reduced from the sequential extension of timestamp, but in the first approximation (T1) the overlap is getting bigger, we show it in Figure 6.7.

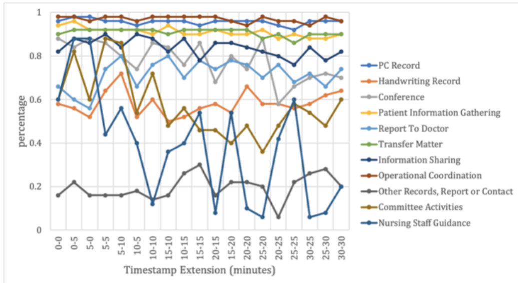


(a) Patient care



(b) Medical assistance

(c) Environmental arrangement



(d) Documentation / communication

図 6.5: F1 score with timestamp extension of labels for each activity class

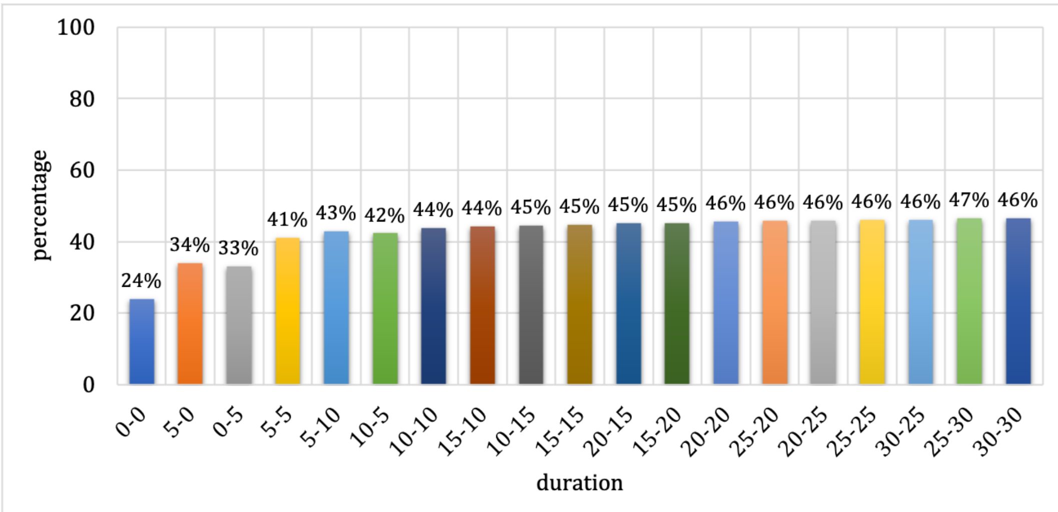


図 6.6: Percentage of Overlapping

Relationship Between Timestamps Extension and Pressure Features

When using a barometric pressure sensor, not only body movement but also the speed of movement and body high and low states will affect sensor readings. Therefore, investigating the relationship between timestamp extension and pressure features needs to be explored. By calculating scores for each feature, we can determine which features' at-

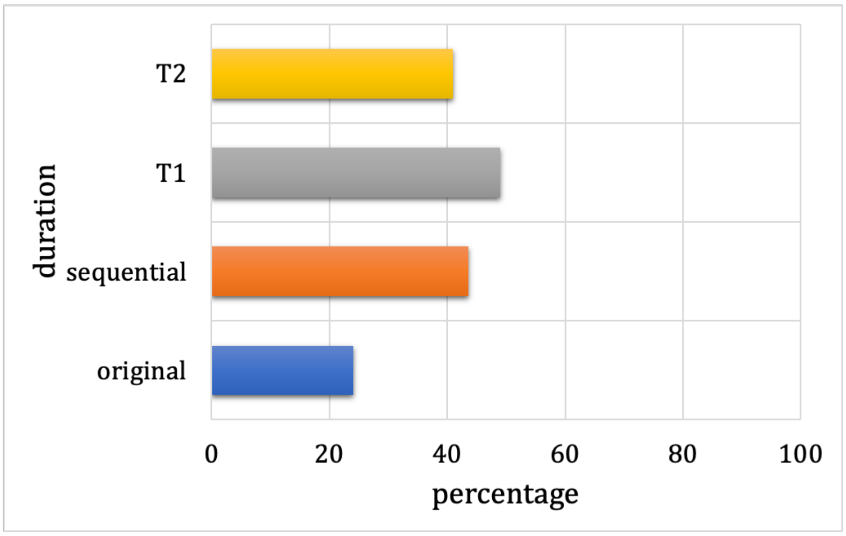


図 6.7: Percentage of overlapping for flexible timestamp extensions

original: original label duration; sequential: the sequential extension of timestamp; T1: the flexible timestamp extension with add the short duration; T2: the flexible timestamp extension with change the short duration.

tributes are most associated with the model's predictions. A higher score indicates that the specific feature will have a greater impact on the model, which is used to predict a certain variable. To get the scores for each feature, in this paper, we use mean-decrease accuracy. This technique uses the mean decrease in accuracy to calculate the feature importance of permuted out-of-bag samples. Based on the score of the feature importance shown in Figure 6.9, we thoroughly investigated the nursing care record data. We found the pressure feature worked better when we extended the label compared to other sensors (see Figure 6.8), especially in nursing activities.

6.1.4 Result

In this paper, we identified activity classes that can improve activity recognition for complex nursing care. In Table 6.2, we show the accuracy of activity recognition. We can see with a barometric pressure sensor that the number of activities as much as 73% of 33 activity classes better such as Observation, Clean Care, Nutritional Dietary Care, Excretion Assistance, Suction, Posture Change, Indoor Environmental Care, Family Support, Rehabilitation, Dosage, Care For Other Patients, Treatment Support, Blood Gas Measurement, Other Medical Assistance, Cleaning The Room, Other Environment Maintenance, PC Record, Handwriting Record, Conference, Patient Information Gathering, Information Sharing, Operational Coordination, Nursing Staff Guidance. Even activity of posture change can improve very much by up to 15%, the reason is the barometric pressure sensor not only affects the large movements but also the subtles movements of the human body, which means that when the posture changes, the human or body position does not change, but the speed of movement during the activity will be affected. Meanwhile, activity classes such as Circulatory Care, Movement Support, Injection Support, X-Ray Support, Drug Management, Compatible With Medical Devices, Report To Doctor, Transfer Matter, Other Records, Report or Contact are better without a barometric pressure sensor. In addition to body motion and speed movement, the height of the body when carrying out activities can impact the sensor readings. This makes the barometric pressure sensor become important in recognizing complex activities, especially in nursing care. The average accuracy for nurse activities without a barometric pressure sensor is 85%, while the accuracy of activity recognition by entering the pressure sensor value increases by 3% to 88%. In addition, with the barometric pressure sensor, the macro F1 score is 75%, and 66% without the barometric pressure sensor. F1 scores increase for 24 activities, but it decrease for several records.

We take a closer look into the results after changing or adding timestamps that came before and/or after the label timestamp. Overlapping occurs more often when we modify or prolong the timestamp when the start and finish times are increased, the percentage of overlap is shown in Figure 6.6. In order to manage label overlap across activities, activity recognition is carried out as one vs rest to reduce the amount of overlapping data. For each activity class, the accuracy is shown in Figure 6.4 while altering the label timestamp extension sequentially, and the F1 score is shown in Figure 6.5 when conducting the similar approach successively. We grouped the activities into four categories based on the work the nurse did to make it easy to see a comparison. In each category, both accuracy and F1-score reach a peak at different times for each activity. Movement Support in the patient care category has the highest accuracy when adding 20-minutes-before and 15-minutes-

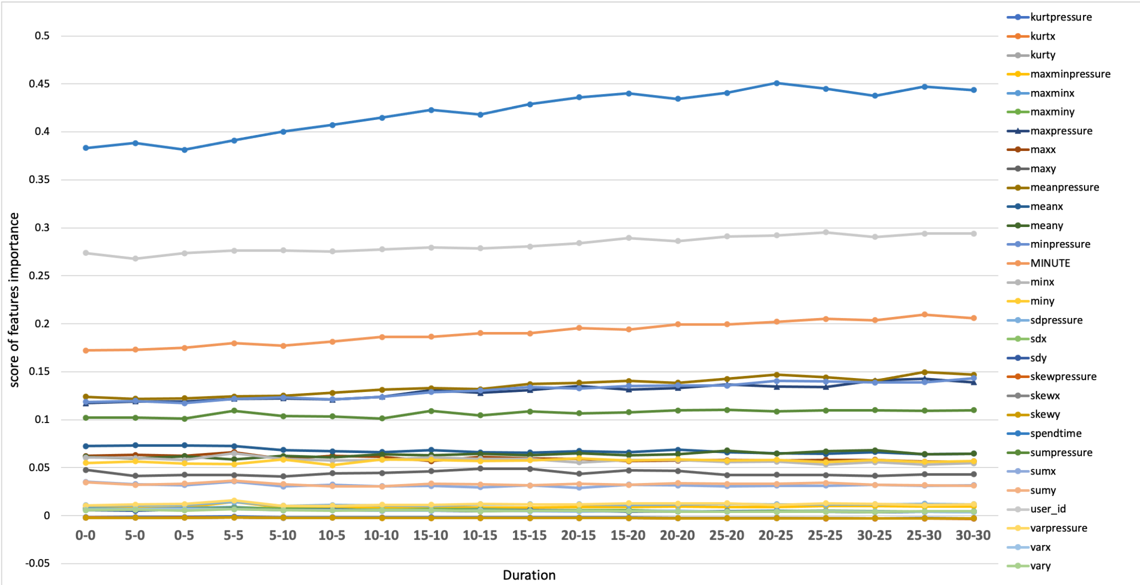
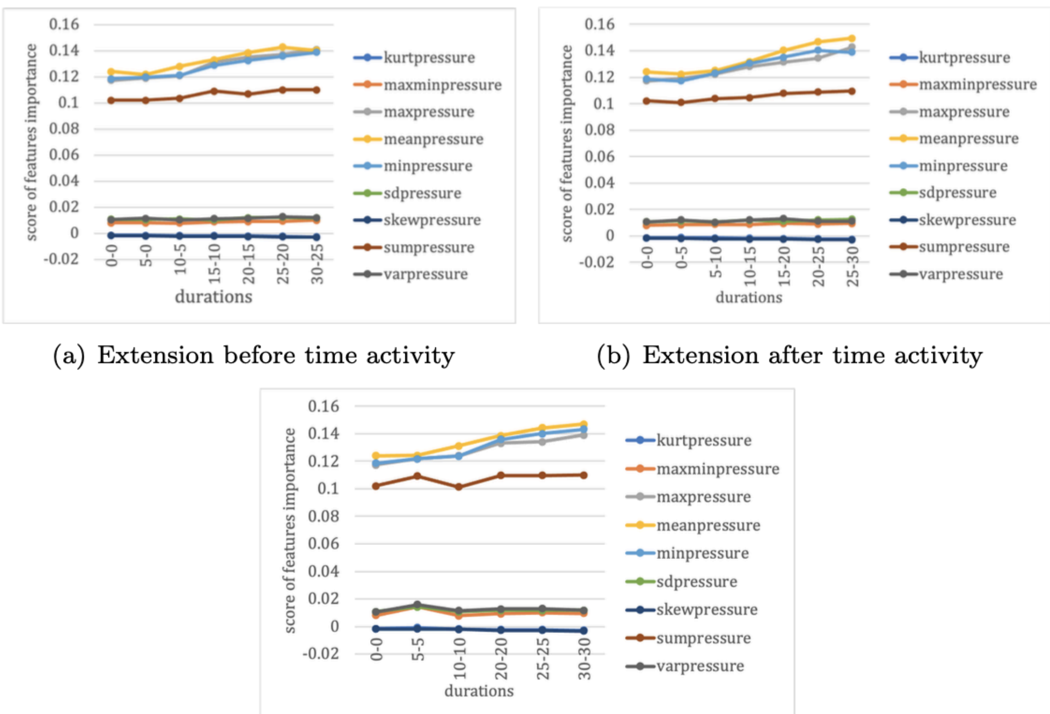


図 6.8: Correlation between Timestamp Extensions and All Features

after the label timestamp, while Committee Activities for the documentation category have a similar trend when extending the label timestamp by 5-minutes-before and after. However, Drug Management in the medical assistance category and Indoor Environmental Care in the environmental arrangement category perform better without extension. In terms of F1-score, for example, Movement Support achieves the highest value when a 20-minute-before and 25-minute-after label timestamp extension is applied; Compatible With Medical Devices exhibits similar trends with a 30-minute before and after label timestamp extension; and Drug Management performs better without an extension. Accuracy and F1-score for flexible timestamp extension can be seen in Table 6.3. These findings point to the need of taking into account extending the length of the various label times for each activity.

We also investigated the relationship between timestamp extension and pressure features. By computing scores for each feature, we can discover which feature has the most influence on the model's predictions. A feature will have a bigger impact on the model used to predict a certain variable if it receives a higher score. In Figure 6.8 we show the correlation between timestamp extensions and features for all features.

Specifically for the barometric pressure sensor feature shown in Figure 6.9, when we extended 5 minutes before the activity time, the number of features increased by 66.7%, an extension of 5 minutes after gave an impact of 55.6% the number of features that experienced an increase, and an extension of 10 minutes (5 minutes before and after) had an impact on all features (the accuracy of all features increases), including from the 5-minute extension before or after, which means the 10-minute extension has a larger effect on the model. In addition, after an extension of 10 minutes (5 minutes before and after) to 60 minutes (30 minutes before and after) there are 2 features that do not show any improvement, namely skewness and kurtosis. Overall, timestamp extension has a greater impact on pressure features with 83.3% features can improve their performance, but the highest values are different for each features and time.



(a) Extension before time activity

(b) Extension after time activity

(c) Extension before and after time activity

図 6.9: Correlation between Timestamp Extensions and Pressure Features

However, certain activities, like Committee Activities, get benefit most from extensions when the more flexible timestamp extension is determined by considering the average duration. Both the accuracy and F1-score of the second approach (T2) are much higher than those of the first approach (T1). This result can be seen in Table 6.3. The impact of flexible timestamp extensions on all features (100% number of features) increased, as reflected in Figure 6.10, which indicates that the extension has a greater influence on the model. These findings demonstrate that the feature is more significantly affected over time when each user's behavior is differentiated at extended timestamps. This occurs because the barometric pressure sensor affects variations in weather, altitude, and movement speed in addition to the user's movement.

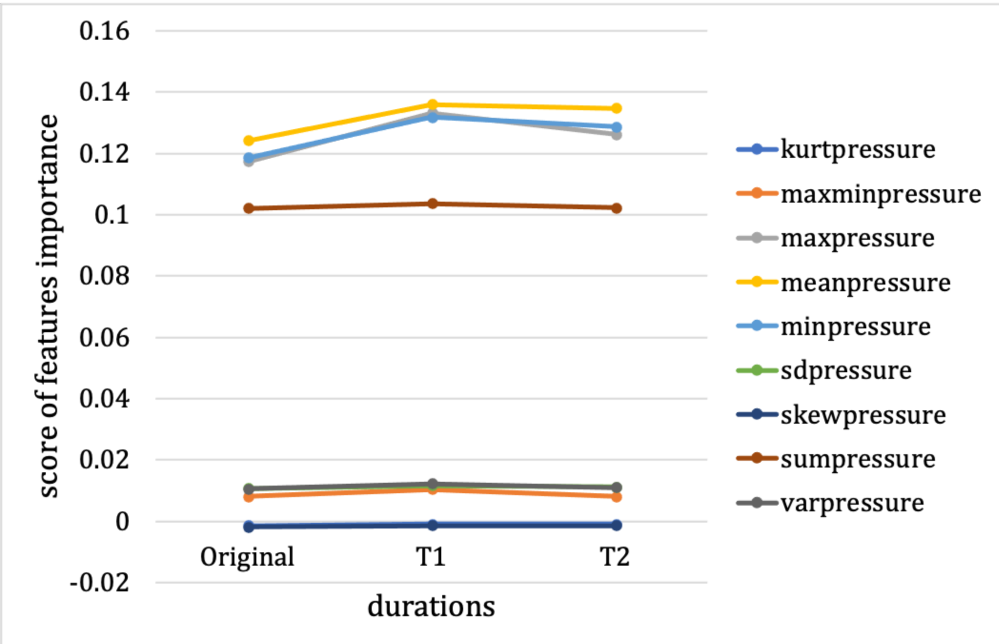


図 6.10: Correlation between Flexible Timestamp Extensions and Pressure Features

表 6.3: Accuracy and F1 Score of the pressure feature with flexible timestamp extension

	Accuracy			F1 Score		
Activity	Ori	T1	T2	Ori	T1	T2
Observation	0.98	0.96	0.96	0.98	0.96	0.96
Clean Care	0.94	0.91	0.96	0.92	0.92	0.96
Nutritional Dietary Care	0.88	0.85	0.86	0.72	0.68	0.7
Excretion Assistance	0.93	0.9	0.92	0.84	0.78	0.8
Suction	0.97	0.95	0.96	0.92	0.88	0.9

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表 6.3 – continued from previous page

	Accuracy			F1 Score		
Activity	Ori	T1	T2	Ori	T1	T2
Circulatory Care	0.86	0.69	0.85	0.9	0.76	0.9
Posture Change	0.97	0.94	0.96	0.92	0.88	0.9
Movement Support	0.66	0.77	0.71	0.4	0.72	0.6
Family Support	0.91	0.81	0.93	0.78	0.46	0.74
Rehabilitation / recreation	0.77	0.78	0.78	0.52	0.58	0.4
Care For Other Patients	0.92	0.91	0.93	0.86	0.86	0.84
Dosage	0.9	0.9	0.9	0.76	0.82	0.8
Injection Support	0.82	0.73	0.78	0.82	0.74	0.74
Treatment Support	0.9	0.75	0.91	0.86	0.72	0.9
X-Ray Support	0.83	0.82	0.89	0.54	0.58	0.74
Blood Gas Measurement	0.93	0.89	0.9	0.88	0.84	0.84
Drug Management	0.75	0.7	0.76	0.74	0.74	0.78
Other Medical Assistance	0.83	0.81	0.87	0.72	0.78	0.8
Indoor Environmental Care	0.83	0.8	0.88	0.7	0.74	0.84
Cleaning The Room	0.89	0.92	0.94	0.72	0.82	0.88
Other Environment Maintenance	0.9	0.83	0.87	0.86	0.82	0.86
Compatible With Medical Devices	0.7	0.74	0.75	0.24	0.54	0.54
PC Record	0.95	0.94	0.94	0.96	0.94	0.94
Handwriting Record	0.9	0.86	0.87	0.58	0.54	0.48
Conference	0.93	0.89	0.91	0.88	0.86	0.86
Patient Information Gathering	0.96	0.93	0.95	0.94	0.9	0.92
Report To Doctor	0.88	0.84	0.95	0.66	0.68	0.86
Transfer Matter	0.92	0.91	0.91	0.9	0.88	0.88
Information Sharing	0.92	0.92	0.94	0.82	0.86	0.88
Operational Coordination	0.97	0.9	0.78	0.98	0.94	0.84
Other Records, Report or Contact	0.7	0.67	0.88	0.16	0.24	0.76

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表 6.3 – continued from previous page

	Accuracy			F1 Score		
Activity	Ori	T1	T2	Ori	T1	T2
Committee Activities	0.8	0.82	0.88	0.6	0.66	0.76
Nursing Staff Guidance	0.95	0.96	0.97	0.6	0.66	0.7

Ori: original duration; T1: the flexible timestamp extension with add the short duration; T2: the flexible timestamp extension with change the short duration.

6.1.5 Discussion

As a result of the evaluation, we demonstrate the performance of the classification for activity recognition, and our proposed method can improve activity recognition for several activity classes in real-life using the pressure sensor that has environmental disturbances to identify user activities. We evaluate complex activities in nurses rather than simple activities. This becomes one of the challenges when we use pressure sensors. Accuracy and F1 score improved well with the pressure sensor. Random forest achieved the highest accuracy of 98%, and the F1 score was also 98%, with a better number of activities as much as 73% of 33 activities compared to that without a barometric pressure sensor. In addition, when we conducted experiments in our lab with fewer activities, there were two activities that had accuracy below 50% while in real life with uncertain conditions, the lowest accuracy was only 66%. This shows that the pressure feature works well in real life for complex nurse care activity recognition.

Our experiment applies self-labeling for label collection, which can reduce the high cost of third-party observers. We provide a timestamp solution to ensure the adequacy of sensor data and if the time participants input the activity label is different from the actual activity. Timestamp extension is another challenge in study using barometric pressure sensors because not only body movements but also outliers impact the reading, such as changes in altitude, temperature, and weather [161][162]. Therefore, various approaches as described in Section 6.1.3 have been shown for modifying the timestamp, performing sequential extensions and paying attention to the time each nurse spends doing activities.

Compared to the Quuppa feature, over time the pressure feature has a bigger impact than the Quuppa feature, that means the pressure feature works better when we extend the label timestamp. This information can be helpful for timestamp solutions when working with barometric pressure sensors.

On the other hand, we also provide the results of an investigation into the relationship between timestamp extension and pressure features so that it can be considered for nursing care activities using barometric pressure sensors. Timestamp extension has a greater impact on pressure features, especially in flexible extensions, which can have an impact over time, but the highest values are different for each feature and time. The pressure feature that works well when we extend the label is meanpressure. Because the identification of body movement using a barometric pressure sensor also affects the altitude and speed of movement, which will be different every day and every time, the meanpressure feature works better than other features.

We realized that in the current work, we did not explore the target patients of the nursing care activities and the objects used, which may also affect the accuracy. For example, the same nursing care activities but with different positions of the patient for example, lying on the mattress or sitting in a chair [161] will affect the barometric pressure sensor because of the different height of the state. This system can also be used in other fields or other activities, but paying attention to building environment is important because the same activity on different floors [94][260] will provide different barometric pressure sensor readings. And it needs to be understood that it will be very difficult if we recognize complex activities performed in outdoor environment [98][161] without a reference sensor.

6.1.6 Conclusions

In this paper, our method integrates the barometric pressure sensor and Quuppa data into the activity classifier and proposed timestamp extension for the inaccurate labels. Using this method, we contributed to the investigation of complex nurse care activity recognition that can exhibit several characteristics of pressure features, such as identifying activity classes that can improve when we use barometric pressure sensors and investigating the relationship of pressure features with the modification of label durations, which is often required in complex and realistic applications. This provides insight into the impact of extended label timestamps on the barometric pressure sensor with multiple time alternatives.

Even with self-labeling, our system is successful in gathering data on nursing activities without sacrificing the quality of the user's work. Although we have used almost the same method in previous experiences using smartphones, employing three devices at once is a challenge in field experiments we try to solve. In this paper, we have compiled the findings from our experience working in hospitals. The findings demonstrate that even though the barometric pressure sensor is influenced by outlier factors, identification accuracy can still be depended upon and may even increase when compared to utilizing merely a Quuppa sensor. Moreover, our study's findings show that flexible time has a beneficial impact on the overall pressure sensor feature.

Future studies will focus on identifying workplace mental health issues that may impact the quantity and quality of nursing care. Staff who are assigned to the appropriate tasks at the appropriate times and who have a good mentality on life will undoubtedly perform better at work, of course, supported by good teamwork as well. We want to study physically demanding activities such as big movements that can cause stress.

6.2 Care Forecast and Tracing System

6.2.1 Introduction

In Japan [283], an ageing society, the number of elderly people in need of nursing care is increasing year by year [278]. However, there is a shortage of caregivers [279], and there is an increasing need to compensate for the shortage of caregivers by improving the efficiency of care. In order to solve this problem, research [277, 282, 285, 284, 286] has been conducted to develop robots and IT systems to assist caregivers in their work.

In this chapter, we develop a system that collects action record data and provides feedback based on the data in nursing care facilities, aiming at improving the efficiency of nursing care work. This system is linked to the nursing care record system and collects nursing care records and sensor data. The system also provides feedback to caregivers through notifications to the mobile application for care records. This notification system creates a machine learning model that predicts the future using the collected data, and includes a notification function that notifies the caregivers of the predicted results.

As a result, this system enables the transmission of feedback and the collection of caregiver behavior data before and after the feedback is given, making it possible to verify the effectiveness of the notification. In addition, the system can be optimized in terms of notification timing and frequency and can be linked to various future prediction models in the nursing care field.

6.2.2 Requirement Definition

This chapter defines the requirements for the care forecasting and tracing developed in this paper. In this paper, we develop a system that creates care records, predicts the future based on the collected care record data, and has a notification function of the prediction results as a feedback function for caregivers. The feedback function includes a dashboard for visualization of the data, in addition to the notification function. The care record data recorded by caregivers is acquired via API and visualized in real-time as much as possible. However, this paper mainly describes the notification function.

This system is developed by adding functions based on the mobile application FonLog [109, 281], which was developed in a previous study. The function for creating care records has been completed in the previous studies [109, 281]. For the prediction function for the collected care record data, a machine learning model for future prediction is installed on the server based on the prediction of future care action times [109], future prediction of care record contents [121], prediction of elimination times [280] and analysis of mood fluctuations [261] conducted in the previous study. Notification of the prediction results to caregivers is achieved by sending notifications to servers and mobile applications using Firebase. Table 6.4 lists the requirements.

The requirements are classified into four categories according to their contents: UI, function, notification, and optimization. Requirements 1-3 are requirements related to UI (user interface) and refer to the mobile application screen. Requirements 4 - 9 refer to settings that should be able to be changed on the server side as a system. Requirements 10

- 12 refer to the settings that should be changeable on the mobile app side of the system. Requirements 13 - 15 refer to the settings that should be optimized for the notification function among the configurable requirements.

6.2.3 Systems Design

This chapter describes the design of the care forecasting and tracing system developed in this paper. The overall data flow is explained and then the design of each function is described.

System Architecture

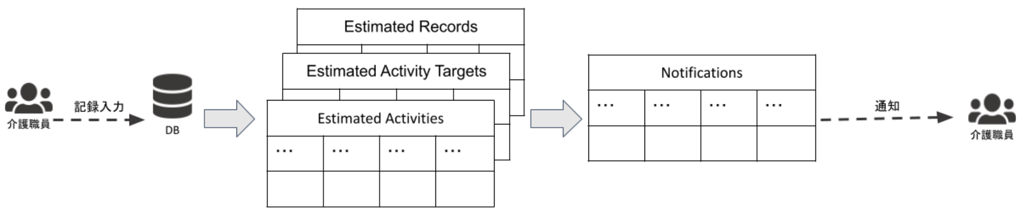


図 6.11: Data flow throughout the system. The caregiver enters the care record via the mobile app. These care records are saved in a database. Using this care record data, machine learning is used to predict the future. The estimation results are saved in database tables such as estimated activities. The stored estimation results are then used to generate notifications for caregivers, which are saved in the Notifications database table. The stored notifications are sent to the caregivers when it is time to send them.

The overall configuration of the system is described. Figure 6.11 shows the data flow of the entire system. The caregivers record care record data from the mobile app. The recorded care record data is stored in a database. Using this care record data, machine learning is performed to predict the future. The estimation results are stored in database tables such as estimated activities. The stored estimation results are then used to generate notifications for caregivers, which are stored in the Notifications database table. At the same time, settings such as which carer to send the notification to and at what time, as well as the notification message to be displayed are also generated. The stored notifications are sent to the caregivers at the time of transmission.

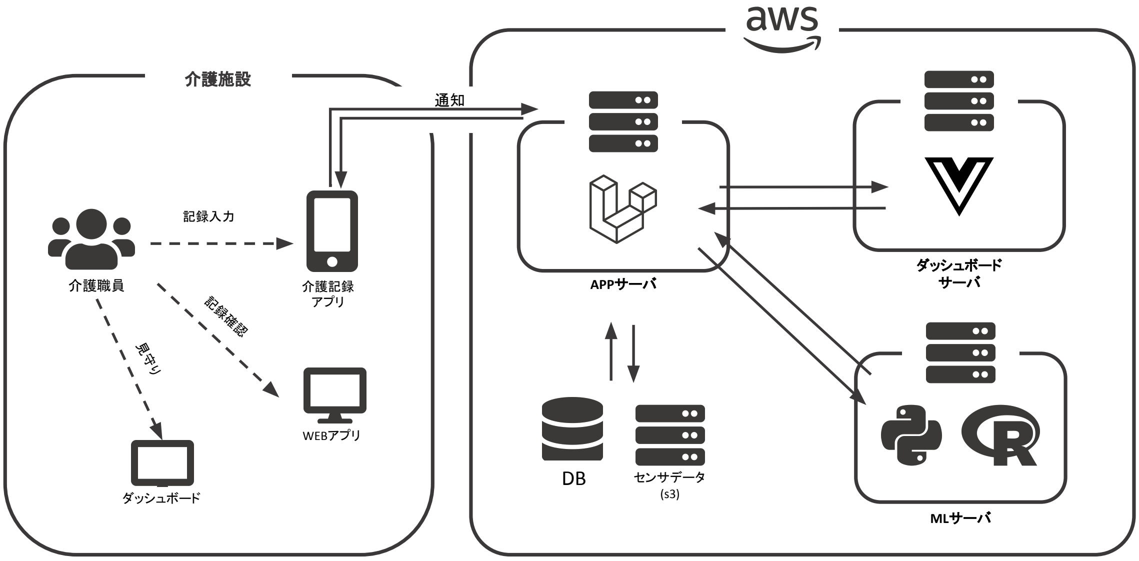


図 6.12: The server configuration of the system is shown. A mobile app, a web app, and a web dashboard for care records are used in nursing homes. The mobile app and web app for care records is FonLog, which has already been developed in a previous study. The web dashboard is a data visualization system. The ML server makes future predictions based on the collected care record data.

Figure 6.12 shows the server configuration of the system. A mobile app for care records, a web app, and a web dashboard is used in the nursing home. The mobile app for care records and the WEB app are FonLog, which have already been developed in previous research. The mobile app is used to input care records, and the WEB app is used to modify data from PCs and register new residents. The WEB dashboard is a data visualization system.

There are three main servers: the APP (Application) server, the dashboard server, and the ML (Machine Learning) server. The APP server is the back-end of the mobile app for care records and has functions for sending user information and other data via APIs and storing the input care records in a database.

In this paper, we additionally develop functions for storing future prediction results and generating and sending notifications to the APP server. This APP server is also responsible for the API for sending data for visualization to the dashboard server. The dashboard server is responsible for the web page for data visualization. However, the dashboard server basically does not need a database, because the acquisition of care record data and login authentication are all performed from the APP server via the API. The ML server obtains care record data from the APP server via API and sensor data from S3. There is a machine learning model made in R or Python in the ML server, which makes future predictions based on the acquired care record data and sensor data. In this paper, no additional development is carried out and the prediction model developed in the previous study [109, 120] is used. All prediction results are stored in the DB via the APP server.

Care Records

In this paper, the care record data is regarded as a caregiver's action record. This is because care record data contains information such as the type of action, the time of day, and which resident the action was performed on.

The collection function of caregiver record data is already in FonLog. The care record data is entered using the mobile app for care records and stored on the APP server.

Future Prediction

This section describes a function for generating notifications to caregivers based on future prediction results. This function can be divided into two main parts: "machine learning of future predictions" and "notification generation".

In machine learning for predicting the future, machine learning is used to predict the future based on care record data. The model makes predictions and stores the results in a database. In the "Generating notifications" section, the model selects which information from the future prediction results to be notified and generates notifications. By separating the future prediction and the generation of notifications, it is possible to select and notify only important and effective data from the prediction results.

Machine Learning for Future Prediction.

In this section, we describe the machine learning model for future prediction. In this paper, we assume that the machine learning models developed in our previous research for the future prediction of nursing care action times [109], future prediction of the contents of nursing care records [121], prediction of defecation times [280], and future prediction are installed on a server.

The predicted data are stored in the Estimated table (Estimated Activities, Estimated Activity Targets, Estimated Records). This is developed because the care record data is stored in three database tables called Activities (Activities, Activity Targets, and Records) so that the care record data and the care record prediction result data are stored in the same data structure. The data structure of the care record data and the data of the care record prediction results are stored in the same data structure.

This method of storing prediction results can also be used in models from other studies. For example, Saito et al. [214] predicts the time of excretion. By storing the excretion time predicted by this model and the caregiver's Estimated table, it is possible to notify the prediction results.

Notification Generation

In this section, a notification is generated from the result of the future prediction made in section 6.2.3. The notification includes the ID of the Estimated table, the title to be displayed, the message, the notification time, the notification user ID, and others. The generated notifications are stored in the Notifications table. Notifications are generated based on a template called the Notification Templates table. In this Notification Template, the content of the message and the number of notifications are set for each behavior type and caregiver. This makes it possible to change the number of notifications and the content of messages by caregivers. This notification table also stores information that is not machine-learned predictions but that we want to feed back to the caregivers, such as the information on the patient's hand-offs.

By generating and storing Estimated Results and Notifications separately, only the most important information can be carefully selected for feedback, and the data structure allows optimization of message contents, notification frequency, and notification time according to the type of behavior and caregiver.

There are several studies that optimize the number of notifications and notification times. There is a lot of research aimed at preventing forgetting and improving efficiency by prompting users to perform activities based on notifications [221]. There are several methods for determining the timing of notifications, such as optimization based on pre-set appointments Citepollack2003autominder or based on sensing such as heart rate [71]. However, too many notifications can interfere with the concentration of work [71]. Therefore, it is important to learn from observed user behavior and adjust the notification process according to the situation [172]. To this end, there are several studies that aim to optimize the notification timing. For example, systems that provide multiple times to send notifications in order to learn each user's behavior [77], and studies that set optimal times [84, 77], which confuse the user [97], which learns about interruptions and finds the appropriate time to send notifications. In our system, we would like to incorporate such an optimization mechanism in the notification generation part.

Feedback

In this section, we describe the feedback functions for caregivers. The feedback functions include sending notifications to the caregivers' mobile phones and a web dashboard. In addition, we also develop an attendance management function for the case where we want to notify caregivers who are currently working.

Work Timetable Management

This timetable management function is used to determine which caregivers are to be notified. Caregivers record the start and finish of their workday in advance. In our previous study [109], estimated which caregiver will do which work on the next day. Although it is possible to use this estimation instead of the attendance control function, we decided to implement the attendance control function in this study because of the problem of inaccurate notifications if the accuracy of the estimation is low.

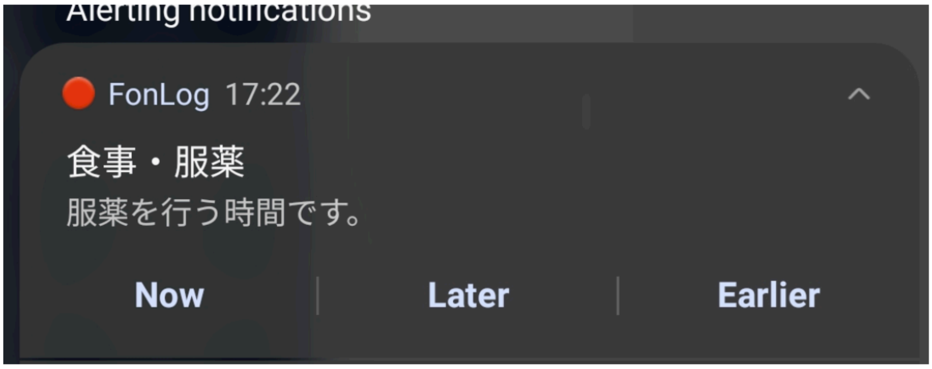
When caregivers arrive and leave work, they press the "Arrive" and "Leave" buttons from the web page. This allows the system to know which caregivers are currently working.

The system can be set to send notifications only to caregivers who are currently working.

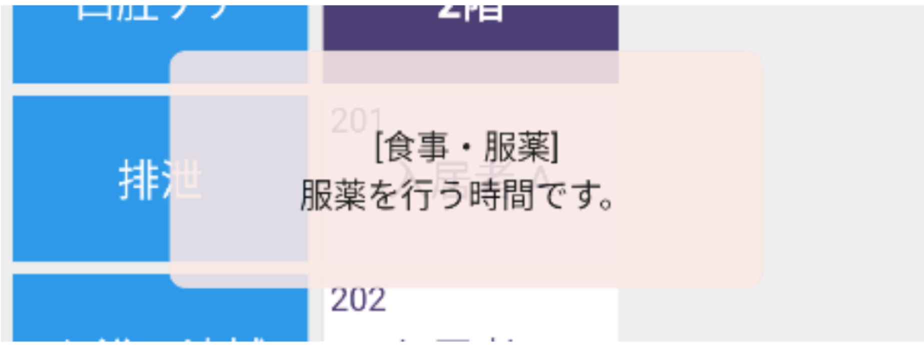
Notification

In this system, we have two types of notifications displayed in smartphone applications. Notification (1) is a notification displayed in the Android notification center. Notification (2) is a notification that appears when you want to open an app, as shown in Figure 6.13. In notification (1), a button is displayed as in the notification message, and the time when the button is clicked and which button is clicked is stored. The number and type of buttons can be adjusted, and currently two types of buttons, "now" and "later", are planned to be displayed. If the "now" button is clicked, no re-notification is shown, and if the "later" button is clicked, a notification will be generated again. In notification (2), the information is only displayed and the time when it is displayed is saved.

Notifications to the web dashboard are in the form of the most recent notification. The buttons "now" and "later" are displayed with the notification. When each button is clicked, the behavior is the same as that of the mobile application.



(a) Notification (1) : Android Notification



(b) Notification (2) : Notification with Toast

図 6.13: Notifications in the smartphone app

Estimated Results

The predicted activity is displayed in the mobile app. In figure 6.14, the predicted activity is also displayed, and the estimated results are shown as gray buttons. As shown in this figure, the predicted activity is displayed as a gray button. By clicking this gray button, the activity type and the target patient are selected, and if the prediction is wrong, the prediction can be edited here. As in the case of inputting a general nursing care record, you can create a nursing care record based on the estimated behaviors by pressing the "decision" button. The predicted behavior is displayed as a gray button for a certain period of time, after which it automatically disappears.

In the detailed record screen, the predicted details are entered as initial values, and a detailed record can be created based on the predictions.

図 6.14: Mobile app for care records.

6.2.4 Discussion

In this section, we discuss whether the developed system with the requirements and the limitations of this system.

Requirements Verification

For requirements 1-3, the mobile application already follows these requirements. For the web dashboard, requirements 1-2 have not been done yet because interviews with caregivers are required. Requirement 3 for the web dashboard was satisfied by making the system displayable on a tablet device as well.

Requirements 4-7 are satisfied by the ability to customize notifications for each behavior type and caregiver using the Notification Template table. Requirement 8 is satisfied by providing three types of notifications: a notification to the Android notification center, a notification displayed when the Android application is opened, and a notification to the web dashboard. For requirements 9-11, both the mobile application and the web dashboard have a function to modify (add, delete, or update) notifications according to which buttons the caregiver selects in the notification. However, since the contents of editing may differ depending on the type of action, this paper implements only the function of deleting the notification when the OK button is clicked. Requirement 12 can be changed in the Android notification settings. Optimization of requirements 13-15 is realized by separating future prediction and notification generation. However, the algorithm for optimization has not been created yet, and it is necessary to select and develop which algorithm to use in the future.

System Limitations

The mobile application is designed to be used in nursing homes where only some of the rooms are networked. For example, this is a facility where WiFi is available only at the nurses' station. Therefore, the entered care record data are once stored in the mobile terminal and are sent to the server when the terminal is connected to the network. This may cause a loss of real-time data transmission. In addition, the data sent to the server are stored in JSON format on the server and then stored in the database by batch processing at one-minute intervals. In addition, notifications are sent via Firebase when it is time to display notifications, so if there is no network connection at that time, notifications are displayed the next time when the user connects to the network. These factors may cause delays in real-time performance.

In this approach, the machine learning model of periodic future prediction predicts the time at which the action will be taken. Therefore, there is a possibility that there are two different predictions: one made at 8:00 am for the period between 10:00 and 11:00 am, and another made at 9:00 am for the period between 10:00 and 11:00 am. In this case, it is possible to display both predictions, but it is not possible to determine whether only one of the predictions was correct, or whether both were correct but only one of them was used by the caregiver. In other cases, when the caregiver created the record without using the button for the predicted caregiver action displayed in gray, it is not possible to determine whether the prediction was incorrect or whether the prediction was correct but the caregiver did not use the gray button.

For traceability of the notification confirmation process. We store the click time of the button displayed at the same time as the notification as the time when the notification is confirmed. However, there is currently no way to record the exact time when a notification is confirmed, as the time when the notification is shown and the time when the button is clicked may differ.

6.2.5 Conclusion

In this work, we develop a system that collects data on caregivers' behavior records and provides feedback based on the data, aiming at improving the efficiency of caregiver work in nursing care facilities. This system is linked to a nursing care record system to collect nursing care records and sensor data and provides feedback to caregivers via notifications to a mobile application for nursing care records. In addition, by collecting caregiver behavior data before and after the feedback as caregiver records, it is possible to verify the effect of the feedback. The feedback is divided into a function for predicting the future using various learning models and a function for generating notifications based on the prediction results, which enables optimization of the notifications.

However, there is a possibility that the time when the notification was confirmed and the time when the confirmation button was clicked is different, which is a limitation of the functionality of this system to strictly track when the notification was confirmed. In addition, although we designed a UI that enables the creation of care records based on the results of behavior prediction, we also found a problem that it is difficult to strictly evaluate whether the predicted results were correctly answered at the time of evaluation.

表 6.4: List of requirements. Classified into four categories: 'UI', 'Functionality', 'Notifications', and 'Optimization'.

No.	Type	Requirements	Related Studies
1	UI	The UI design of the system is simple.	[4, 11, 40]
2	UI	Simple UI structure	[11, 40]
3	UI	The system should be easily portable for the user.	[4]
4	Function	Can choose which caregivers to notify.	
5	Function	Caregivers currently working on the floor can be selected and notified.	
6	Function	Notification can be targeted at user groups.	
7	Function	Notification priorities can be set.	[4]
8	Function	Type of notification can be changed.	[87]
9	Function	Notification can be generated again based on the caregiver's response.	
10	Notification	The time at which the notification is acknowledged is stored.	
11	Notification	Can be stopped when notification is no longer required	[40]
12	Notification	Audible alarms and vibrating notifications are possible.	[33, 78]
13	Optimization	Optimised notifications can be displayed according to the user.	[87]
14	Optimization	Timing of reminders can be adjusted each time.	[1, 78]
15	Optimization	Notification times can be optimized.	[101]

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Discussion and Future Work

This thesis represents a step towards addressing the significant challenges in task management that can effectively support healthcare by exploring and understanding human activities and behaviors using technology to enhance their lives. The work to explore and understand complex and organized human activities has direct implications for the study of technology clarity in the well-being and healthcare domains. In this regard, understanding the time management of human activities to prevent missed activities becomes crucial, as it can widely help avoid stress, depression, performance decline, and individual health issues. Utilizing reminder systems, the contribution of this thesis is to improve task management and care. This thesis introduces numerous methods and frameworks to enhance the comprehension of time-based activities in the fields of mobile computing, mobile health, and activity recognition. The proposed thesis will enhance personal and professional healthcare understanding of reminder systems in daily life.

In this thesis, we propose assistive technology and needs analysis as research instruments for mobile computing studies. In Chapter 3, we provide a needs analysis for a reminder system based on a systematic review. We consider assistive technology for the entire community, starting with the elderly and individuals with dementia. When considering assistive technology for the elderly and individuals with dementia, it is important to consider individual needs and preferences and ensure that the technology is user-friendly, affordable, and accessible to all members of society. Starting with the elderly and individuals with dementia as the focus of assistive technology development reflects a commitment to inclusivity and social justice. These two groups often face specific challenges in their daily lives, and assistive technology can help reduce disparities and provide them with better access to technological benefits. Technology continues to rapidly evolve and can produce beneficial solutions for various segments of society. By starting with individuals with dementia, the development of assistive technology can be expanded to include other groups. The advantages of this technology will create opportunities for everyone to improve their quality of life, regardless of age or health condition. Using the elderly and individuals with dementia as the initial focus of assistive technology development allows for valuable data collection and experiences. Research and discoveries from their interactions with assistive technology can provide better insights and understanding of the needs and challenges faced by these groups. This information can be used for further development and improvement of technology that will benefit all segments of society. Using assistive technology for individuals with dementia as a starting point can help increase awareness and acceptance of this technology on a broader scale. When people see the benefits and positive impact of this technology on vulnerable groups, they are more likely to accept and adopt assistive technology for themselves or other groups. The main recommended assistive technology for a reminder system is a smartphone. With a smartphone, we have a simple configuration, device identification, activity tracking, and portability. This overcomes issues with other devices such as smart carpets, bed sensors, door sensors, or video cameras. To address the needs analysis, the focus is placed on task completion time duration. To support this, data collection on various types of routine activities that may be performed is necessary, as well as considerations for feature extraction techniques for voice recognition and the design of a user-friendly system. We consider the feasibility of end-user requirements when they use the system to function effectively, such as the user's ability to know the most urgent or important event and having a simple reminder design. The system's ability to record user activity is deemed suitable.

For schedule-based reminder systems, we have static and dynamic time. By learning from user behavior, for static time, we need to learn whether we need to notify or not. For a dynamic time, we need to learn when to notify. Striking a balance between notification or non-notification, when, and how many times to notify becomes a challenge that needs to be addressed. In Chapter 4, we present methods that effectively learn the need for notification or non-notification, when, and how much time to notify by considering the balance between exploration and exploitation using reinforcement learning. Considering the balance between exploring new time options and exploiting the learned optimal timing policy can be a challenge addressed in this thesis because the reward function needs to align with the desired objectives of the reminder system, such as maximizing user responsiveness or optimizing the balance between effectiveness and user experience. Our proposed method using reinforcement learning allows the system to learn from user feedback, which is crucial for improving the timing and effectiveness of reminders. By considering the product of time and possible responses as states, the system can capture the temporal relationship between the reminder and the user's response, thus allowing the system to learn the most effective time for each individual. Reminder systems with multiple alternative timing options require dynamic decision-making based on the current context. Our proposed method provides a framework for decision-making that can adapt and update its strategy based on changing conditions and user behavior. By representing the state as the product of time and possible responses, the system can capture the dynamics of user response patterns over time and make informed decisions about when it is appropriate to send reminders. In addition, the system can learn and adapt to individual preferences and response patterns, optimizing the timing of reminders for each user. This personalized approach can improve reminder effectiveness and increase user engagement. Reminder systems need to strike a balance between effectively reminding users and avoiding distraction or insensitivity. Our proposed can help find this balance by learning from user feedback and optimizing the reminder schedule based on the product of time and likely response. This allows the system to adapt to user preferences and adjust reminder times to provide a positive user experience. From experimental tests and feedback, reinforcement learning learns effective strategies for agents. Agents can actively adapt to the environment to optimize timing by maximizing future rewards.

A reminder system for unpredictable activities means reminding about activities that do not have a fixed schedule. Methods for scheduling and rescheduling can be used for activities that do not yet have a schedule. However, the future is unpredictable. Even if we have planned activities and use scheduling or rescheduling methods, there is a possibility that other circumstances may arise, such as forgetfulness, being busy, or disruptions that prevent the planned activities from being carried out. Therefore, to address this challenge, we take an approach of a reminder system for anticipated activities. In anticipated activities, we need to consider whether the activity needs to be performed or not and whether it requires notification or not. In Chapter 4, we propose notification optimization by providing several alternative timings for forecasted activities with and without probabilistic consideration for activities that need to be performed and require notification. It is important to consider various factors when sending notifications to people after getting the results of the forecasted activities. We should not only send notifications when we have gotten the forecast results as future daily activities cannot be predicted. Therefore, it is important to strike a balance between providing useful reminders and avoiding excessive distractions, especially for low-probability activities. In this thesis, we present two approaches that aim to optimize notification timing in activity recognition systems. The first approach is called FaTi. FaTi is a notification optimization for forecasted activity by reinforcement learning. This approach focuses on notifying the user based on the resulting start time of the estimated activity. However, instead of notifying the user directly at the start time, we propose to provide an alternative notification time in advance. The second approach is called FaPTi. FaPTi is a notification optimization for forecasted activity with probabilistic and reinforcement learning. In this approach, provide an alternative notification time in advance. Our research investigates the impact of low probability of estimated activities and optimizing notification time with reinforcement learning. We also show the gap between estimated activities that are useful for self-improvement by people for the balance of important tasks, such as tasks performed as planned and additional tasks to be completed. For the evaluation, we used two datasets: an existing dataset and we collected data in the field with the technology we developed. In the data collection, we had 23 activities from six participants. To evaluate the effectiveness of this approach, we assessed the percentage of positive responses, user response rate, and response duration as performance criteria. Our proposed method provides a more effective way to optimize notifications. By incorporating the probability level of activities that need to be performed and require notifications into the state, we achieve a better response rate than the baseline, with a gain of 27.15%, in addition to other criteria that are also greater by using probabilities.

This thesis applies the proposed system in a realistic setting to demonstrate its capability and feasibility for activity recognition studies. Utilizing technology to record data by leveraging the reminder system for managing activities in complex scenarios such as healthcare facilities poses significant challenges due to the varying activities of medical staff, such as nurses, on a daily basis. Furthermore, scheduling shift challenges, including morning, afternoon, evening, and night shifts, introduce further complications for individual scheduling. Varied shift assignments can disrupt their routine activities, adding complexity to the problem. To address these challenges, a larger dataset is required while ensuring that the data collection process does not disrupt the performance of the medical staff. In Chapter 6, we employed a two-step approach to address the challenges faced by healthcare professionals in healthcare facilities. Firstly, we conducted experiments at Nagoya University Hospital for nursing data recording. Secondly, we developed a system that collected action log data and provided feedback through notifications based on the data obtained from the nursing facility. In the experiments at Nagoya University Hospital, we investigated the recognition of complex nursing activities using barometric pressure sensors and identified several pressure feature characteristics. This included identifying activity classes that could be enhanced when using barometric pressure sensors and exploring the relationship between pressure features and the often-required modifications in label duration in complex and realistic applications. In this experiment, we requested nurses to perform self-labeling using the FonLog application. To address the issue of inaccurate labeling, we proposed a timestamp extension method using sequential and dynamic approaches (T1 and T2). Additionally, we considered how movement speeds within activities influenced barometric pressure sensor readings, aside from body posture or height. The accuracy of activity recognition improved for 24 out of 33 activity classes, with even a 15% increase for posture change activities. This was because the barometric pressure sensor not only captured significant movements but also subtle body movements, making it crucial for recognizing complex activities, particularly in nursing care. We collected real-world data in the hospital setting, and therefore, we introduced an effective system for data collection in activity recognition without disrupting nursing tasks. Using this system, we collected 4,544 activity labels from 15 participants. For the system that collects activity records data and provides feedback through notifications as a reminder system, we propose a system that collects and provides feedback based on activity records data in nursing facilities. The aim is to enhance the efficiency of nursing work. This system collects nursing records and sensor data that work in conjunction with the nursing record system. It also provides feedback to nurses through notifications on their smartphones regarding the nursing records. These notifications include functions that create machine learning models to predict the future using the collected data and inform caregivers about the predicted outcomes. In the feedback generation process, by separating the generation of future predictions from the creation of notification content, we have achieved a structure that allows for the optimization of notification content, timing, and frequency. Additionally, a button is displayed alongside the notification, enabling medical staff to adjust the time when they confirm the feedback and set up notifications again.

In the future, to expand data analysis on the balance between exploring new time options and exploiting optimal time policies, more factors need to be considered for more complex problems, where user activities can be missed despite preventive measures using the reminder system. The impact of missed activities for each activity class needs to be investigated. The methods we propose and the use of the associated reminder system dataset open up future avenues of research. Identifying post-schedule movements to re-notify users if they miss scheduled activities becomes an interesting future endeavor. Additionally, we are also interested in improving the quality and quantity of data recording through the utilization of the reminder system.

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Conclusion

This thesis investigates the improvement of task and care management through the utilization of a reminder system. The following explanation is a summary of each research objective. First, in Chapter 3, we discuss studies related to prospective memory issues, including applications, sensors or systems, methods, and data used in the scope of human activity recognition and the design of relevant everyday routine activity technologies. The main objective of this research is to determine the feasibility of a system that can be used in the analysis and/or prevention of missed activities. Our observational results indicate that smartphones are a suitable choice for delivering unique information to accurately identify objects, and they are convenient to use as reminder technology. We provide an analysis of the requirements for a reminder system in the recognition of daily activities. Second, in Chapter 4, we introduce a system that can effectively learn whether to notify or not, when to notify, and how often to notify, considering the balance between exploring new time options and exploiting optimal time policies learned by aligning the reward function with the desired goals of the reminder system. As a result, the proposed system can optimize timing and adapt to individual personality characteristics to determine the best time for sending notifications about scheduled activities. Third, in Chapter 5, we present a method that can optimize the timing of notification delivery as reminders for predicted activities. The proposed method considers whether an activity needs to be performed or not and whether a notification is necessary or not. The results allow us to understand the characteristics of each activity class, and the proposed method can effectively and appropriately determine the timing of notification delivery to users for predicted activities.

Fourth, in Chapter 6, we provide insights into the application of technology in real-world situations with various wearable devices without significantly disrupting daily operations and performance. The results demonstrate that we successfully recorded data and we can obtain feedback from users as processed information for analytical needs without significantly disturbing day-to-day operations and performance. The discoveries presented in this thesis have broader implications for other research endeavors and systems, as outlined in future studies.

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