# Progressive Sequence Matching for ADL Plan Recommendation

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***Abstract*—Activities of Daily Living (ADLs) are indicatives of a person's lifestyle. In particular, daily ADL routines closely relate to a person's well-being. With the objective of promoting active lifestyles, this paper presents an agent system that provides recommendations of suitable ADL plans (i.e., selected ADL sequences) to individual users based on the more active lifestyles of the others. Specifically, we develop a set of quantitative measures, named wellness scores, spanning the evaluation across the physical, cognitive, emotion, and social aspects based on his or her ADL routines. Then we propose an ADL sequence learning model, named Recommendation ADL ART, or RADLART, which proactively recommends healthier choices of activities based on the learnt associations among the user profiles, ADL sequence, and wellness scores. For empirical evaluation, extensive simulations have been conducted to assess the improvement in wellness scores for synthetic users with different acceptance rates of the provided recommendations. Experiments on real users further show that recommendations given by RADLART are generally more acceptable by the users because it takes into considerations of both the user profiles and the performed activities.**

## I. Introduction

Activities of daily living (ADLs) [1] [2], as commonly used in the healthcare field, refer to the daily self-care activities performed by an individual in his or her place of residence, outdoor, or both. ADLs are usually used to measure the functional status of a person, particularly for elderly, children, and disabled people. There are two subcategories of ADLs. Basic ADLs (BADLs) [1] refer to the daily activities that people do to maintain their well-being, such as feeding themselves, bathing, dressing, etc. Instrumental ADLs (IADLs) [2] [3] are not necessary for fundamental functions, but they help an individual to live independently in a community. Examples of IADLs include shopping, social activity, and financial management. Generally speaking, ADLs are indicatives of potential mental and physical issues, especially for the elderly and the disabled people, whose cognition, mobility, and social capabilities generally deteriorate over time. Some issues faced by the elderly are reflected in their ADLs. For example, if an elder person suffers from a joint disease, he or she will gradually develop slower pace and may take a longer time to perform certain ADLs. Monitoring the time and frequency of ADLs together with a sufficient knowledge base on the user profiles can help caregivers to predict the health trend of the elderly and provide advices in advance.

To date, most existing work on human activity recognition [4] [5] [6] [7] and behaviour tracking [8] focus on activity recognition and tracking without considering them in entirety. In a person's daily life, the order and duration of ADLs are important. Specifically, ADLs happen in a consecutive order form an ADL sequence [9] [10]. There is a need for intelligent agents to learn the ADL sequence patterns, e.g., day-long patterns for better helping the elderly in managing their ADLs. On the other hand, when talking about activity recommendation, people typically refer to either physical activity recommendation [11] or location based casual activity recommendation [12]. These works are in specific activity domains. In this work, we focus on ADLs and we aim to recommend ADLs in sequences, e.g., activity plans, to the elderly. The recommendation of suitable ADL plans to the elderly will hopefully benefit them towards a better life.

In our prior work, ADLART [13] incorporates fusion ART (Adaptive Resonance Theory) [14] to learn ADL sequence patterns. In this paper, we propose a recommendation agent, named Recommendation ADL ART, or RADLART, which extends the functionalities of ADLART and provides recommendations based on the learnt knowledge. Generally, RADLART uses user's profile and partial ADL sequence to find similar daily ADL routines in the knowledge base. Then, among the selected daily ADL routines, based on the ADL wellness assessment module, RADLART chooses the one with the best wellness score for recommendation. Experiments are conducted to test RADLART under different parameter settings. The results show RADLART can indeed improve the wellness scores of the elderly.

The rest of this paper is organized as follows. Section II discusses the issues and challenges in ADL recommendation. Section III introduces the ground work of RADLART, specifically, fusion ART and ADLART. Section IV presents the RADLART model, including the design of the input fields. Section V illustrates the recommendation mechanism of RADLART. Section VI shows the experimental results and discusses the performance of RADLART. Finally, Section VII concludes with a discussion of the limitations and propose the future work.

## II. Issues and Challenges

In this section, we discuss some important issues that have to be considered in designing an activity plan recommendation agent.

First of all, to generate an activity plan recommendation, a quantitative measure of the wellness score is required to provide a multi-modal assessment of a person's health status. Holistically, wellness is multifaceted involving the physical, cognitive, emotional, and social wellness. However, a majority number of existing wellness assessment or recommendation systems only focus on a single aspect, such as physical [15] or social [16]. Although there are systems that promote more than one health aspects [17], to the best of our knowledge, there is none that assesses or recommends based on considerations in all four aspects.

In addition, most existing wellness assessment systems developed by the healthcare experts are based on the interview analyses of surveys or questionnaires periodically [18]. However, to promote active interactions and to provide real-time recommendations, it is necessary to assess the elder user's wellness at any time during the day based on the recognized activities [19]. Moreover, we should always allow users to self-report so as to augment the autonomously recognized activities. As such, the wellness scores in each individual quotient can be assigned according to the recognized and the self-reported ADLs. The activity recommendation module should then use the aggregated score across various quotients to suggest a healthier or more active ADL sequence to the user.

Beside the computation of wellness scores, the preference of users towards the recommendation is another issue. If the users do not accept the recommendations, the recommendation system will have less usefulness in real situations. This is one of the common problems faced by the traditional recommendation agents which simply compare the candidate activities with other activities to find the one with the highest score. More specifically, there is lack of a way for the agent to persuade the elderly people to really take the proposed activity. The Fogg Behavior Model [20] states that for a behavior to occur, three elements must converge at the same moment, namely motivation, ability, and trigger. In elderly activity selection, a high wellness score of a ADL sequence poses as the motivation, the collaboratively learnt association between the profiles and the ADL sequences assures the user's ability, and the recommendation serves as the trigger.

One more issue regarding activity recommendation is that most people have some scheduled activities during the day. In such cases, how to take these scheduled activities into consideration is crucial to the success of the recommendation systems. If not, the user will be reluctant to accept the recommendation.

## III. PRELIMINARIES

In this section, we review the preliminary work that provide the foundations to our recommendation system. First, we define the related domain concepts, namely ADL, ADL sequence, ADL routine, and ADL plan. Then, we look at the family of fusion ART networks. Particularly, we go into details of an ADL sequence learning fusion ART model, named ADLART.

### A. *Definition of Related Terms*

Before presenting the recommendation agent, we define the domain terms used in this paper.

**Activities of Daily Living (ADLs)** refer to the daily activities performed by an individual in his or her place of residence [1]. ADLs, such as grooming, shower, breakfast, watching TV, housework, and exercise, are the basic elements that build up everyone's daily life.

**Definition 1:** An **ADL sequence**, $S$, refers to an ordered set of ADLs. Formally, we can write

$$\mathbf{S} = (\mathbf{A_1}, \mathbf{A_2}, ..., \mathbf{A_n}) \tag{1}$$

and

$$A_i = < a_i, s_i, e_i > \text{ for i = 1, ... , n,} \tag{2}$$

where $a_i$ denotes the activity ID, $s_i$ denotes the activity starting time, $e_i$ denotes the activity ending time, and $n$ denotes the total number of identified ADLs.

Three elements are of great importance in ADL sequences, namely 1) the set of ADLs, 2) the occurrence time of each ADL, and 3) the duration of each ADL. The set of ADLs defines the contents of the ADL sequence, and the set is largely depended on the different applications. The occurrence time represents the order of ADLs. The duration of ADLs has different influence (e.g., wellness value). For example, exercise for ten minutes is different from exercise for two hours.

**Definition 2:** An **ADL routine** refers to an ADL sequence that describes a person's ADLs in a day.

A routine can be viewed as a template that may tolerate certain level of variations in the ADL order, occurrence time, and duration. Though not covered in our current work, people may have different ADL routines for different types of days [13].

**Definition 3:** An **ADL plan** refers to a selected ADL sequence recommended for a person to follow.

ADL plans usually come together with a set of selection criteria which recommend the ADL sequence. The aim of our proposed recommendation agent is to suggest ADL plans according to the ADL sequences already performed by the user in the day, and hopefully after the acceptance of the ADL plan recommendation, the user will end the day with a higher wellness value compared against that of the day following his or her original ADL daily routine.

### B. *Fusion ART*

Various models of ART and their supervised learning versions are used in the pattern analysis and recognition tasks. Within the family of ART models, there is a group of networks known as Fusion ART [14] or multi-channel adaptive resonance associative map (multi-channel ARAM) [21], which formulates cognitive codes associating multi-modal patterns across multiple input channels. Fusion ART models can also be used for reinforcement learning. For example, a three channel fusion ART called FALCON is described in [22] [23] [24].

Based on the architecture of a typical fusion ART model (see Fig. 1), the dynamics of fusion ART are summarized as follows.

**Input Fields:** Let $F_1^k$ denote the input field that holds the input patterns of channel $k$.

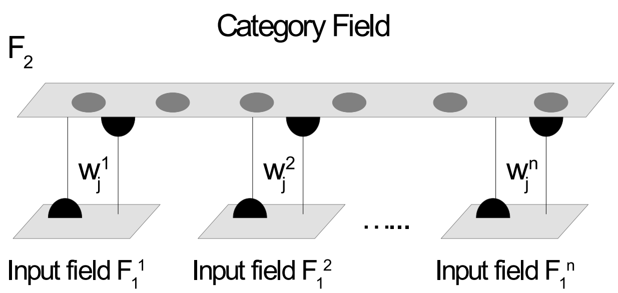


Fig. 1. The generic fusion ART architecture.

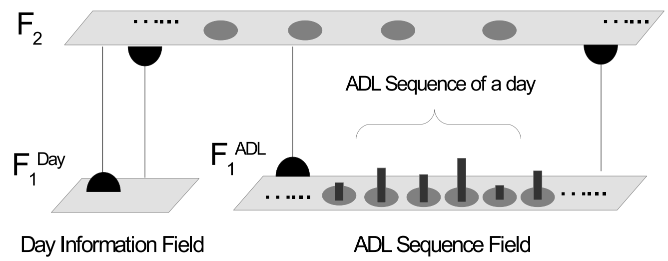


Fig. 2. The ADLART network model.

**Input Vectors:** Let $\mathbf{I}^k$ = $(I_1^k, I_2^k, ..., I_n^k)$, where $I_i^k \in [0,1]$, denote the input vector of channel *k*, for *k* = *1,...,n*.

**Category Field:** Let $F_i$, where $i > 1$, indicate the category field. In the standard multi-channel ART, there is only one category field $F_2$.

**Activity Vectors:** Let $\mathbf{x}^k$ denote the activity vector for input field $F_1^k$, and $\mathbf{y}$ = $(y_1, y_2, ..., y_m)$ denote the activity vector of $F_2$. Initially, $\mathbf{x}^k$ = $\mathbf{I}^k$ for $k = 1, 2, ..., n$.

**Weight Vectors:** Let $\mathbf{w}_j^k$ denote the weight vector associated with the *j*th node in $F_2$ for learning the input patterns in $F_1^k$. Initially, $F_2$ contains only one uncommitted node with the weight vectors containing all 1s.

**Parameters:** Each field's dynamics are determined by the choice parameters $\alpha^k \geq 0$, learning rate parameters $\beta^k \in [0,1]$, contribution parameters $\gamma^k \in [0,1]$, and vigilance parameters $\rho^k \in [0,1]$.

**Code Activation:** Given the activity vectors $x^1, x^2, ..., x^k$, for each $F_2$ node *j*, the choice function $T_j$ is computed follows:

$$T_j = \sum_{k=1}^{n} \gamma^k \frac{|\mathbf{x}^k \wedge \mathbf{w}_j^k|}{\alpha^k + |\mathbf{w}_j^k|}, \tag{3}$$

where the fuzzy AND operator $\wedge$ is defined by $(\mathbf{p} \wedge \mathbf{q})_i \equiv min(p_i, q_i)$ and the norm $|.|$ is defined by $|\mathbf{p}| \equiv \sum_i p_i$ for vectors $\mathbf{p}$ and $\mathbf{q}$.

**Code Competition:** The $F_2$ node with the highest choice function value is identified by the code competition process. The winner is indexed at *J* where $T_J = max\{T_j$ : for all $F_2$ node j$\}$. When a category choice is made at node *J*, $y_J$ = 1 and $y_j$ = 0, $\forall j \neq J$. This indicates a winner-take-all strategy.

**Template Matching:** After code competition, the template matching process takes place to check if resonance occurs. For each channel *k*, the match function is given as follows:

$$m_J^k = \frac{|\mathbf{x}^k \wedge \mathbf{w}_J^k|}{|\mathbf{x}^k|} \geq \rho^k. \tag{4}$$

The template matching value of the chosen node *J* is checked to see whether it meets the vigilance criterion. If any of the vigilance constraints is violated, mismatch reset occurs by setting the choice function $T_J$ to 0 for the duration of the input presentation. The search process will keep selecting other $F_2$ nodes until resonance occurs. If the uncommitted node in $F_2$ is identified as the winner, after learning it becomes committed and a new uncommitted node is created and added in $F_2$.

**Template Learning:** Once a node *J* is selected for learning, in each channel *k*, the weight vector is updated by the learning rule shown as follows:

$$\mathbf{w}_J^{k(new)} = (1 - \beta^k)\mathbf{w}_J^{k(old)} + \beta^k(\mathbf{x}^k \wedge \mathbf{w}_J^{k(old)}). \tag{5}$$

Fusion ART network consists of multiple input fields and a category field. This makes fusion ART structures flexible to solve a wide range of problems. As the weight parameter $\mathbf{w}$ could be updated with single input pattern presentations, the fusion ART architecture is capable of online learning. Another important feature of fusion ART is when no learnt node is matched, the network could autonomously use the uncommitted node to represent the new pattern. This feature makes fusion ART structure self-organizing.

### C. ADLART

The ADLART model [13] (see Fig. 2) is a fusion ART network consisting of two input fields, namely the day information field and the ADL sequence field.

**Day Activity Vector:** Let $\mathbf{S^{Day}}$, where

$$\mathbf{S^{Day}} = (I_1^{Day}, I_2^{Day}, ..., I_{11}^{Day}), \tag{6}$$

denote the activity vector of the day information field, where the boolean value of $I_j^{Day}$ indicates the day information. Altogether, eleven day types are defined including weekdays, weekend, public holiday, sick day, vacation, and special days.

**ADL Sequence Activity Vector:** Let $\mathbf{S^{ADL}}$, where

$$\mathbf{S^{ADL}} = (I_1^{ADL}, I_2^{ADL}, ..., I_n^{ADL}), \tag{7}$$

denote the activity vector of the ADL Sequence field, where the value of $I_i^{ADL} \in [0,1]$ indicates the occurrence time of the $ADL_i$ within the day and *n* is the size of the ADL domain.

To encode the ADL occurrence time, ADLART computes the normalized activation strength as follows:

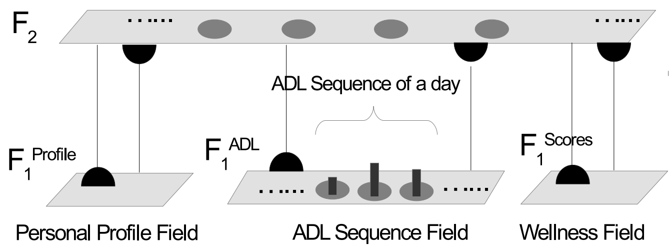


Fig. 3. The RADLART structure.

$$I_i^{ADL} = \frac{t_i}{T_0}, \tag{8}$$

where $t_i$ represents the occurrence time of the day (in minutes) and $T_0$ is the total number of minutes in a day, i.e., 1440. For example, if a person dresses up at 8:00 am, the activation strength value for the dressing up ADL is 8*60/1440 = 0.333 (assuming each day starts at 12 am). By using this representation, the occurrence time of every ADL is encoded into the ADL sequence.

Given the input patterns of the day information and the ADL sequence, ADLART learns the clusters of ADL sequences. Particularly, ADLART can learn a person's typical ADL sequence(s) for a particular type of the day. With this knowledge, ADLART can represent the typical ADL sequence of a particular type of the day and detect possible abnormalities. Conversely, with an ADL sequence input, ADLART can give the day information, such as sick day, holiday, etc.

## IV. RADLART

In this paper, we propose a recommendation model, called Recommendation agent using ADLART (RADLART), which extends ADLART with a profile field and a wellness score field. The RADLART structure is shown in Fig. 3. We use the ADLART's ADL sequence field to model the everyday ADL sequences, use the wellness score field to incorporate the assessment of ADLs, and the profile field to represent various profiles of the elderly. The addition of the profile field is necessary because the elderly generally prefer recommended ADL plans from peer's daily routines. The details of each field are discussed in the following subsections.

### A. ADL Sequence Field

**ADL Sequence Activity Vector:** Let $\mathbf{S^A}$, where

$$\mathbf{S^A} = (I_1^A, I_2^A, ..., I_n^A), \tag{9}$$

denote the activity vector of the ADL Sequence Field. The value of $I_i^A \in [0, 1]$ indicates the order of ADL sequence within the day using Eq. (8), and *n* is the total number of the ADL categories.

We identify a set of 30 ADLs organized into five major categories, namely rest and personal hygiene, meals, housework and exercises, learning, entertainment and social activities. As the activation vector $S^A$ does not contain the activity duration information, ADLs with different lengths of time are encoded separately. For example, "short Catnap" and "long Catnap" are differentiated by whether the catnap is within one hour. Moreover, because always giving the same score to the same activity occurred at different times of the day is not appropriate for certain ADLs, we treat those ADLs as different events if they happen at different times. For example, having a meal in the evening could be either "Dinner" or "Supper" depending on the exact occurrence time. Furthermore, for physical activities, we use three different types of ADLs to represent exercise with different levels of intensity. The full list of our selected ADLs are listed as follows:

**Rest and personal hygiene category** includes "Wake Up", "Wake Up Late", "Personal Hygiene", "Toilet", "Grooming", "Morning Shower", "Evening Shower", "Short Catnap", and "Long Catnap".

**Meal category** includes "Breakfast", "Lunch", "Brunch", "Afternoon Tea", "Dinner", and "Supper". As aforementioned, the classification of ADLs for meals is sensitive to the occurrence time.

**Entertainment and social activities category** includes "Outdoor Social", "Indoor Social", "Watch TV", "Board Game", "Video Game", "Short use of computer", and "Long use of computer". Note that "On computer" includes many activities on computer including Internet surfing, reading articles, managing photos, etc., but excludes playing computer games which is classified as "Video Game".

**Housework and exercise category** includes "Light House Work", "Heavy House Work", "Light Exercise", "Exercise", and "Heavy Exercise" . As aforementioned, we use three types of ADLs to represent exercises with different levels of intensity.

**Learning category** includes "Reading", "Writing", and "Working".

Please note that, similar to ADLART [13], RADLART is also limited in the ADL representation. Specifically, ADLs are represented with the starting time only and the duration information has not yet been captured. Consequently, RADLART cannot handle the interleaving ADLs and the multiple occurrences of the same ADLs.

### B. Profile Field

The profile field is incorporated in RADLART with the view that the ADL plan recommended from people with similar profiles is more acceptable to the user.

**Profile Activity Vector:** Let $\mathbf{S^P}$, where

$$\mathbf{S^P} = (a, g, s), \tag{10}$$

denote the activity vector of the profile field, where $a, g$, and $s$ indicate the encoded age, gender, and fitness level of a person, respectively.

To encode the age of the elderly, we use $a = (Age - 50)/50$, assuming the elderly are aged between 50 to 100 years old. We use the boolean variable $g$ to represent gender, where

TABLE I. WELLNESS SCORES OF ADLS IN FOUR QUOTIENTS

| ADL | Physical | Cognitive | Emotional | Social |
|---|---|---|---|---|
| Wake Up 1 | 0 | 0 | +10 | 0 |
| Wake Up 2 | 0 | -5 | +5 | 0 |
| Hygiene | +1 | +5 | +2 | 0 |
| Toilet | 0 | +5 | +2 | 0 |
| Grooming | 0 | +5 | +2 | 0 |
| Morning Shower | +2 | +5 | +3 | 0 |
| Evening Shower | +2 | +5 | +3 | 0 |
| Short Catnap | -10 | 0 | +5 | 0 |
| Long Catnap | -20 | 0 | +10 | 0 |
| Breakfast | +2 | +5 | +1 | 0 |
| Lunch | 0 | +5 | +1 | 0 |
| Brunch | 0 | +3 | +1 | 0 |
| Afternoon Tea | 0 | +3 | +1 | 0 |
| Dinner | 0 | +5 | +1 | 0 |
| Supper | -2 | +3 | +2 | 0 |
| Watching TV | -3 | +2 | 0 | -2 |
| Board Game | -3 | +2 | 0 | +10 |
| Video Game | -3 | +2 | 0 | 0 |
| Short use of computer | -5 | +2 | +2 | +2 |
| Long use of computer | -10 | +4 | +5 | +5 |
| Outside Social | +5 | 0 | +2 | +15 |
| Indoor Social | +2 | 0 | +4 | +15 |
| Light House work | +10 | +3 | -5 | -2 |
| Heavy House work | +20 | +5 | -10 | -4 |
| Light Exercise | +10 | 0 | +2 | +2 |
| Exercise | +20 | 0 | -2 | +4 |
| Heavy Exercise | +30 | 0 | -6 | +2 |
| Reading | -3 | +5 | +5 | +3 |
| Writing | -3 | +10 | +5 | +5 |
| Working | -5 | +10 | -10 | +10 |

male is encoded as 1, while female as 0. For the fitness level, we assign fitness values using BMI categories [25] [26] [27]. There are five discrete levels of $s$: 0 (Severe thinness, BMI $< 16$), 0.25 (Underweight, $16 \leq$ BMI $< 18.5$), 0.5 (Normal range, $18.5 \leq$ BMI $< 25.0$), 0.75 (Overweight, $25 \leq$ BMI $< 30$), and 1 (Obese, BMI $\geq 30$).

### C. Wellness Score Field

There are various ways to compute wellness scores from a sequence of activities. In our approach, we assume every elderly begins the day with a wellness score of 50 (median value of the interval [0, 100]). Each performed activity introduces a change in the wellness score in the four respective aspects.

**Wellness Score Activity Vector:** Let $\mathbf{S^W}$, where

$$\mathbf{S^W} = (I^P, I^C, I^E, I^S), \tag{11}$$

denote the activity vector of the wellness score field, where $I^P, I^C, I^E$, and $I^S$ are the wellness scores in the physical, cognitive, emotion, and social quotients, respectively.

Table I lists all the ADLs that are used in all our experiments and their effects on the different quotients. Because the list of ADLs is not exhaustive in real life and their effects to the different quotients have not been analyzed quantitatively in the literature, Table I presents an illustration on how the listed major ADLs (introduced in Section IV-A) can be assessed as the assignments of wellness scores. Although all the scores are assigned manually, they generally reflect the respective expert knowledge in their respective fields. Specifically, the physical scores are determined based on how ADLs affect the physical activeness of the elderly. For example, different intensity levels of exercise directly affects their physical well-being [18]. Moreover, house work is considered as a healthy activity for the elderly [18], but all activities associated with a relatively long time of stationary motion during day time (such as lying, sitting, and standing) affect the physical aspect negatively. The cognitive capability of the elderly can be generally assessed by whether they can remember the necessary information correctly and whether they can perform the ADL successfully. Therefore, we assign positive scores (relatively small numbers due to high frequency of occurrences) to the performed ADLs. It is hard to determine how most ADLs affect the emotional well-being of the elderly, unless the insights or the outcomes of the events are known. Among all the selected ADLs in the emotional quotient, we assign the highest positive scores to wake up in the morning according to [28] and long catnap (because on common sense, it is refreshing). Among all the listed ADLs, the two obvious social events are assigned with the highest positive scores in the social quotient. “Working” and “Board Game” are also assigned with high positive scores, because in our definition, “Board Game” refers to the traditional board game played head to head.

In the wellness score field, only the values of four quotients are stored. They will be used to compute an overall wellness score by RADLART in a later phase. The details of the computation are given in the next section.

TABLE II. THE MAJOR PHASES OF THE RECOMMENDATION AGENT

| Phase | Details |
|---|---|
| Training Phase | System training by data including profile, ADL sequence, and four wellness quotients' values |
| Sequence Selection | Select $m$ ADL sequence categories that have the closest initial part to the input ADL sequence $\mathbf{S^A}$. |
| Recommendation | Among the selected $m$ ADL sequence categories, recommend the ADL sequence with the maximum wellness ranking function $F(\mathbf{S_i^W})$ value (see Eq. (12)). |

## V. RADLART RECOMMENDATION MECHANISM

Using the three data fields described in Section IV, RADLART could learn the elderly's ADL sequence patterns from the training data. With this learnt knowledge, RADLART is able to give recommendations to the elderly. In the recommendation mechanism, RADLART first takes the ADLs performed by the elder user and his or her scheduled future ADLs as the input ADL sequence. Then, RADLART tries to select a number of entries in the knowledge base that match both the user profile and the input ADL sequence. In the matching process of ADL sequence, RADLART only looks at the specific subset of ADLs which is in the input ADL sequence. Therefore, we name this process *partial matching*. The selected ADL sequence categories will be ranked based on corresponding wellness scores and the best candidate will be used for recommendation. The overall mechanism is summarized in Table II and the details are further elaborated in the following subsections.

### A. ADL Sequence Learning

In this learning phase, RADLART takes the training data which contain the ADL daily routines of the elderly with different profiles and the wellness scores of the four quotients. For each data entry, RADLART tries to classify them into existing categories. If successful, the weight vector of the existing category is updated according to the new input entry (see Eq. (5)). If not, RADLART creates a new category for that input entry. After this training phase, RADLART will possess a knowledge base that contains various categories of user profiles, ADL routines, and wellness scores of the four quotients.

### B. ADL Sequence Selection

The mechanism of ADL sequence selection is summarised in Algorithm 1. Given a set of ADLs that the elder user has performed, RADLART recommends a sequence of ADLs for the remaining part of the day with the objective of maximizing the overall daily wellness score. Instead of recommending the ADLs with the highest wellness score, RADLART, however, takes consideration of the already performed ADLs. Based on these and the possibly scheduled future ADLs, RADLART searches the knowledge base using partial matching and selects $m$ categories that, at this point of the day, have ADL sequences closely similar to the given ADL sequence of the user. Subsequently, RADLART chooses one of the best wellness scores from the selected $m$ categories for recommendation. The matching of partial ADL sequence is only based on those presented ADLs that have been performed or scheduled.

### C. Score Ranking and Recommendation

Most existing wellness assessment systems developed by the experts are based on the interview analyses of surveys or questionnaires periodically [18]. However, to initiate more frequent interactions and to provide more real-time recommendations, RADLART is able to assess the elder user's wellness score at any time during the day based on the recognized activities [19].

The wellness scores in each individual quotient can be assigned according to the respective ADLs recognized or self-reported. The activity recommendation module uses the aggregated score to suggest a healthier or more active ADL sequence to the user. After selecting $m$ candidates in the $F_2$ layer, the next step is to choose one from them according to the ranking function, $F(m)$.

**Algorithm 1** Sequence Selection using Partial Matching

```
Initialize counter c = 0
Activate every category j in F_2 by choice function T_j = Σ_{k=1}^{n} γ^k |x^k ∧ w_j^k| / (α^k + w_j^k) according to input vector (S^P, S^A)
while Counter c < m do
    select category J such that T_J = max{T_j : for all F_2 node j}
    set node activation y_J ← 1
    while match function m_J^k = |x^k ∧ w_J^k| / |x^k| < ρ^k (no resonance) do
        deselect and reset J by T_J ← 0, y_J ← 0
        select another node J with T_J = max{T_j : for all F_2 node j}
    end while
    if resonance occurs (routine recognized) then
        put J into the selected category set
        update counter by c++
    end if
end while
```

Please note that, for all-round well-being, it is important to have a balanced set of scores across all the four wellness quotients. In other words, a low score in any quotient is not desirable for wellness recommendation. Compared against arithmetic mean, geometric mean favours balanced set of scores and penalizes low values in any of the four quotients. Therefore, in RADLART, we use the geometric mean formula:

$$\mathbf{F}(\mathbf{m}) = (I^P * I^E * I^S * I^C)^{\frac{1}{4}}, \tag{12}$$

to compute the ranking function.

## VI. Experiments

### A. Methodology

To evaluate the performance of RADLART, we conducted various simulations. In the first set of experiments, we compare the RADLART recommendations with the users' typical daily routines. The second set of experiments simulates a more realistic cases by taking human factor into consideration that we assume users take recommendations with different acceptance rates and they will only follow the recommendation for a predefined period of time.

We construct a simulator to simulate the daily lives of different types of the elderly. The simulator first takes inputs from a set of elderly profiles which represent persons of different ages, genders, and body fitness levels. In the second step, the simulator generates daily routine templates based on the personal profiles with certain level of randomness. These routine templates represent relatively stable ADL sequences on elderly's everyday life. Finally, daily ADL sequence instances are generated from the routine template. By following this three-step process, the simulator could generate numerous samples trying to replicate the real situations with certain level of randomness.

### B. RADLART Recommendation

In this set of experiments, we evaluate how well the RADLART agent recommends ADL plans by comparing against the baseline, which refers to the users' typical daily routine. Moreover, we want to see the effect of the recommendations at different times in a day. The inputs of the experiments are a set of simulated data samples of ten users and a typical daily routine of one selected user. In the experiment, at a particular point of day, the agent gives recommendation to the selected user and the user follows all ADLs according to the recommended ADL plan. We then analyze whether there is any improvement in the wellness score.

In the training phase, we input ten profiles into the simulator to generate 100 daily routine templates, and then generate 1000 ADL sequences from these routines. In the testing phase, we input a person's profile and a daily routine template spanning 10 ADL sequence samples. For each sample, we run the recommendation agent with four different settings: 1) no recommendation taken, 2) taken recommendation (following all ADLs in the plan) at 11:00 am, 3) taken the recommendation at 3:00 pm, and 4) taken the recommendation at 6:00 pm. The results are shown in Fig. 4.

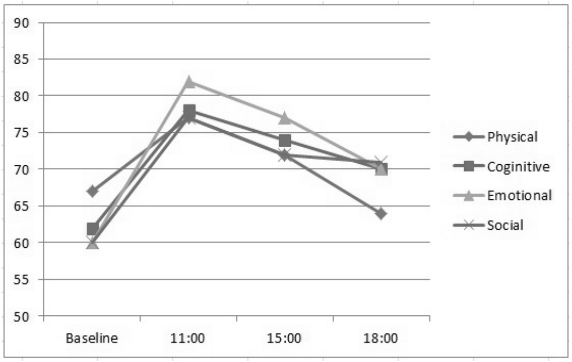


Fig. 4. Wellness scores improvement by following the recommendations of the RADLART agent in different starting times.

Generally speaking, the recommended ADL plan is expected to improve the user's overall wellness scores. In addition, we could observe in Fig. 4 that if the user takes the recommendation earlier in the day, RADLART gives recommendations that have more balanced wellness scores in the four quotients. This may suggest that the geometric mean approach of computing the overall wellness score (see Eq. (12)) provides a balanced recommendation across all the quotients.

### C. Experiments with Different Acceptance Rates

In the second set of experiments, we simulate more realistic scenarios wherein the elderly may not always follow the RADLART recommendations. In other words, the elderly accept recommendations according to different acceptance rates. Moreover, if they have already taken some recommendations, they will switch back to their typical routines after some time. In that case, the agent will continue giving recommendations which hopefully will be accepted according to the acceptance rate.

In this experiment, we assume the elderly follow recommendations at different acceptance rates, namely 0% (baseline), 25%, 50%, 75%, and 100%. Moreover, the elderly will always follow the given recommendation for two consecutive hours. After which, the RADLART agent will provide recommendation again. For example, at 8:00 am, the agent gives the following ADL plan: having breakfast at 8:20 am, going light exercise at 8:50 am, and having lunch at 11:20 am. If the elder user accepts the recommendation, his or her routine will be having breakfast at 8:20 am and doing light exercise at 8:50 am as suggested. However he or she will switch back to the typical routine say "house work" at 11:00 am, and he or she will consider the lunch recommendation again at 11:20 am and make a decision on the next ADL according to the acceptance rate.

We conducted the experiments in our simulation environment using different acceptance rates. The result shows that in the designed experiment scenarios, the system helps to improve the elderly's wellness scores. The relationship between the average wellness scores and the different acceptance rates is given in Fig. 5. It is shown that users with higher acceptance rates benefit more from the RADLART recommendation agent.

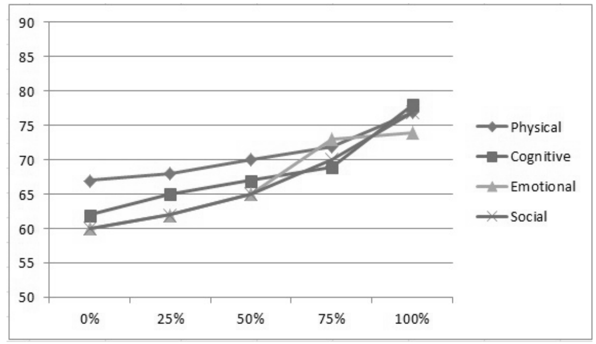


Fig. 5. Wellness scores improvement by following the recommendations of RADLART under different acceptance rates.

TABLE III. PREFERENCES BY REAL ELDERLY

| ADL sequence | preference mean | SD |
|---|---|---|
| Typical Routine | 4.3 | 0.3 |
| RADLART | 3.9 | 0.4 |
| Highest Score ADL | 2.8 | 0.7 |

### D. Experiments on User Preference

One important feature of RADLART is that all the recommendations are generated from the learnt knowledge base of target population. More specifically, the profile field in RADLART ensures the recommended activity source shares the similar profile with the current user. This is expected to increase the ability of the user to perform the recommended activity sequence. Psychology literature show that people are easily influenced by their preferred peers [29]. To evaluate how people might accept the recommendations provided by our RADLART agent, we evaluate its acceptance rate by people.

The experiment consists of two parts. In the first part, we interview subjects for their profiles and typical daily routines. Based on these information, we train the RADLART agent. In the second part, we ask the same subjects about their routines in a particular morning. Then we show them three choices of activity recommendations with the corresponding supporting reasons highlighted for the afternoon: 1) the activities from the typical daily routine model, 2) the activities with the highest wellness scores, and 3) the activities recommended by RADLART (from people with similar profile). For each recommendation choice, we ask the subjects their preferences of the recommendations with the scale from 1 to 5 (where 5 means strongly willing to choose, and 1 means not interested at all).

We conducted the experiment on eight elder Singaporeans. It is shown in Table III that the RADLART recommended ADL plans receive higher preferences than the ADLs with the highest wellness scores, and is close to the preference level of people's typical daily routines.

## VII. CONCLUSION

In this paper, we propose an ADL plan recommendation agent named RADLART, which extends an ADL sequence learning model named ADLART. The key features of RADLART include a partial ADL sequence matching mechanism and an ADL sequence wellness scoring module. In addition, the RADLART recommendation agent uses peer elderly's ADL sequences as the recommendation knowledge base which hopefully is more acceptable to the elderly.

To test the performance of RADLART, we construct a simulator to generate elderly's profiles and ADL sequence samples. Our experiments show that if the elderly accept the recommendations from our RADLART agent, their well-being will much likely improve.

Going forward, RADLART can be further developed in several directions. Such as (1) the current ADL sequence representation cannot qualitatively represent the duration of ADLs, (2) though different fields are used to encode different profiles, currently we have not yet taken the disability information into considerations, and (3) the wellness score computation is currently based on the geometric mean but more sophisticated algorithms may be applied to formulate a multi-objective optimization problem.

## ACKNOWLEDGMENT

This research is supported by the National Research Foundation, Prime Minister's Office, Singapore under its IDM Futures Funding Initiative and administered by the Interactive and Digital Media Programme Office.

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