A situation-driven framework for relearning of activities of daily living in smart home environments

Oluwafemi Richard Oyeleke
Iowa State University

Follow this and additional works at: https://lib.dr.iastate.edu/etd

Recommended Citation

This Dissertation is brought to you for free and open access by the Iowa State University Capstones, Theses and Dissertations at Iowa State University Digital Repository. It has been accepted for inclusion in Graduate Theses and Dissertations by an authorized administrator of Iowa State University Digital Repository. For more information, please contact digirep@iastate.edu.
A situation-driven framework for relearning of activities of daily living in smart home environments

by

Oluwafemi Richard Oyeleke

A dissertation submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Computer Science

Program of Study Committee:
Carl K. Chang, Major Professor
Jennifer Margrett
Simanta Mitra
Jin Tian
Ying Cai

The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University
Ames, Iowa
2020

Copyright © Oluwafemi Richard Oyeleke, 2020. All rights reserved.
DEDICATION

This doctoral dissertation is dedicated to God almighty who sustained me throughout my doctoral program despite all the obstacles I encountered during my studies. But for His grace, I would not have accomplished this feat.

I am also dedicating this dissertation to my pearl, my mother, Mrs. Elizabeth Folashade Oyeleke, who has been my greatest pillar of support. I am super proud and blessed to have her as my mother, and I am immensely grateful for her unflinching support, encouragements, and unrelenting resolve to pray for me always, especially in my trying times.
TABLE OF CONTENTS

ACKNOWLEDGMENTS ........................................................................................................................................... v

ABSTRACT ............................................................................................................................................................. vii

CHAPTER 1. INTRODUCTION ............................................................................................................................ 1
  1.1 Research Motivation .................................................................................................................................... 4
  1.2 Research Objectives .................................................................................................................................... 4
  1.3 Definition of Terms ........................................................................................................................................ 5

CHAPTER 2. BACKGROUND AND RELATED WORK ......................................................................................... 6
  2.1 Activities of Daily Living (ADLs) ................................................................................................................. 6
  2.2 Activity Recognition ...................................................................................................................................... 7
  2.3 Types of Activity Recognition .................................................................................................................... 7
    2.3.1 Single-User Activity Recognition ......................................................................................................... 7
    2.3.2 Multi-User Activity Recognition ......................................................................................................... 8
    2.3.3 Group Activity Recognition ................................................................................................................... 8
  2.4 Techniques for Activity or Goal Recognition ............................................................................................... 8
    2.4.1 Logic-Based Reasoning ......................................................................................................................... 8
    2.4.2 Probabilistic Reasoning ....................................................................................................................... 9
    2.4.3 Data Mining-Based Inference ............................................................................................................... 9
    2.4.4 GPS-Based Inference .......................................................................................................................... 10
  2.5 Cognitive Disorders in Older Adults .......................................................................................................... 10
  2.6 Nudging Behavior Change among Aging Adults with Cognitive Impairment ............................................. 11
  2.7 Clinical Approaches to Supporting Seniors with Cognitive Impairments .................................................... 12
  2.8 Smart Home Environment (SH) and Its Application for Aging Adults’ Care ............................................ 12

CHAPTER 3. PROPOSED METHOD AND CASE STUDY ..................................................................................... 18
  3.1 Situation-Centered Goal Relearning Framework ......................................................................................... 18
  3.2 Overview of The Framework ..................................................................................................................... 20
    3.2.1 Human Observations and Preprocessing of IADLs Datasets from Smart Home .............................. 22
    3.2.2 LSTM-Based Goal Inference Unit ....................................................................................................... 26
    3.2.3 Situ-Context Generator Unit ............................................................................................................... 29
3.2.4 Goal Reinforcement Unit .................................................................................................................. 34
3.3 Case Study ................................................................................................................................................. 48
3.3.1 Implementation Toolkits for Experiments .......................................................................................... 50
3.3.2 Experimental Procedures for Goal Inference in IADLS Datasets Using LSTM ............................. 52
3.3.3 Experimental Procedures for Feature Selection .................................................................................. 54
3.3.4 Experimental Procedures for Goal Reinforcement Unit .................................................................. 56

CHAPTER 4. SITU-SAFE: A SITUATION-DRIVEN SAFETY MODEL FOR RISK MITIGATION IN IADLS ............................................................................................................................ 61
4.1 State of The Art......................................................................................................................................... 61
4.2 An Overview of the Proposed Method .................................................................................................... 63
4.2.1 Situ-Safe: A Situation-Centered Safety Model for Risk Mitigation .............................................. 65
4.2.2 Reasoning about sequences in Linear Temporal Logic (LTL) ......................................................... 74
   4.2.2.1 Problem Scenario .......................................................................................................................... 75
   4.2.2.2 Learning Priority Action using Gradient Boosted Feature Importance .................................. 77
4.4 Case Study Results .................................................................................................................................. 79

CHAPTER 5. DISCUSSION AND EVALUATION ......................................................................................... 84
5.1 Discussion.................................................................................................................................................. 84
5.2 Evaluation ................................................................................................................................................ 87

CHAPTER 6. CONCLUSION AND FUTURE WORK .................................................................................. 90
6.1 Conclusion ............................................................................................................................................... 90
6.2 Future work ............................................................................................................................................. 92

REFERENCES ............................................................................................................................................... 93
ACKNOWLEDGMENTS

I would like to extend my profound gratitude to my advisor Professor Carl K. Chang who chaired my doctoral program of study committee, and my committee members, Drs. Jennifer Margrett, Simanta Mitra, Jin Tian, and Ying Cai, for their guidance and support throughout the course of this research.

Specifically, I am immensely grateful to Dr. Jennifer Margrett for her invaluable suggestions and feedback during completion of this dissertation. I am also deeply indebted to Drs. Simanta Mitra and Jin Tian for their constructive criticisms, invaluable advice, and suggestions that valuable for the completion of this work. Also, many thanks to Dr. Ying Cai for his valuable suggestions and advice.

In addition, my utmost appreciation goes to my advisor Prof. Carl K. Chang for giving me the opportunity to join his research group, his guidance, and invaluable suggestions through the course of completing this work.

I would also like to express my deepest appreciation to Pastor Adetoyese David Taiwo and Mrs. Nike Oyedemi for their unflinching support, guidance, encouragements, and prayers toward the successful completion of my doctoral studies. Also, I am deeply indebted to Jonathan Compton, who is the senior research analyst at Iowa State University for offering me a graduate assistantship position that allowed me to work with him on several projects including student’s enrollment, retention, and success projects. I learnt and acquired valuable skillsets during my time working with him on these projects. I also would like to thank Mrs. Kate Ayomide Ariwodola for her moral support, encouragements, and prayers toward the completion of my doctoral studies. Many thanks to Prof. John Stanford for his prayers and encouragements.
Finally, I would like to express my heartfelt gratitude to my friends in Ames especially Matthew and Leigh Randall for always hosting me on thanksgiving day celebrations, G. P. and Nancy Foote, Tony and Jan Luttrell for their prayers, moral support and encouragements, and my siblings, Abosede Peggy Oyeleke and Ayodeji Alfred Oyeleke for their love and encouragements.
ABSTRACT

Activities of Daily Living (ADLs) are sine qua non for self-care and improved quality of life. Self-efficacy is major challenge for seniors with early-stage dementia (ED) when performing daily living activities. ED causes deterioration of cognitive functions and thus impacts aging adults’ functioning initiative and performance of instrumental activities of daily living (IADLs). Generally, IADLs requires certain skills in both planning and execution and may involve sequence of steps for aging adults to accomplish their goals. These intricate procedures in IADLs potentially predispose older adults to safety-critical situations with life-threatening consequences. A safety-critical situation is a state or event that potentially constitutes a risk with life-threatening injuries or accidents.

To address this problem, a situation-driven framework for relearning of daily living activities in smart home environment is proposed. The framework is composed of three (3) major units namely: a) goal inference unit – leverages a deep learning model to infer human goal in a smart home, b) situation-context generator – responsible for risk mitigation in IADLs, and c) a recommendation unit – to support decision making of aging adults in safety-critical situations.

The proposed framework was validated against IADLs dataset collected from a smart home research prototype and the results obtained are promising.
CHAPTER 1. INTRODUCTION

Ambient assisted living (AAL) is an emerging and burgeoning multidisciplinary field that aims to leverage information and communication technologies in a person’s activities of daily living (ADLs) to ensure they continue to live independently and safe for improved quality of life (QoL) [1][2][8]. AAL such as smart home environments are retrofitted with various sensors such as pressure sensor, appliance status sensor, light sensor, motion sensor, door contact, etc. [4][5][9]. These are useful for understanding human behavior and activity recognition by analyzing stream of observation data from sensors to infer the goal (otherwise referred to as activity) or the mental state of the person being observed [1][5][6]. Smart home sensors can detect and recognize actions, activity, and situations, and thus be able to support older adult and potentially alleviate the burden of care partners and cost of healthcare [2][3][7].

Smart home sensors provide very basic information—for instance, a stove status sensor would indicate an activity around the stove, and kitchen door contact sensor may indicate that the person being observed is in the kitchen, but with no further insight into the person’s goal or actual activity which otherwise can be inferred [1]. Prominent statistical modeling methods such as Hidden Markov Model (HMM) and conditional random field (CRF) have been employed in the past with the following drawbacks reported: a) HMM—struggles to predict goals with similar observation sequences and do not adequately capture long-term context dependencies due to the Markov assumption (i.e., next state is dependent only upon the current state) [10, 11], b) CRF—takes long-term context dependencies into account unlike HMMs by computing the joint probability of the entire sequence of labels given the observation sequence, however, it can be difficult to train and re-train the model when new observation sequence becomes available for labeling [42]. More so, in situations where sensors fail and lead to missing observation data, the
prediction performance of CRF model is impacted [12]. To overcome these problems, a deep learning model known as Long short-term memory (LSTM) is employed since their recurrent connections can in general store representation of past input events which makes it effective in modeling long term dependencies in observation sequences. More so, LSTM model performance can be optimized with recurrent dropout regularization [13][43][95].

Furthermore, safety is another important metric for evaluating the success of smart home environments [2, 18]. From literature, existing solutions for safety of seniors during activities of daily living in smart home follow two main approaches: a) behavior deviation detection (BDD) and b) smart space partitioning (SSP) [1][5][6][19][97]. These approaches focus only on risks associated with ADLs at coarse-grained level. For example, BDD technique focuses on the degree of similarity and dissimilarity of normal activity observation to abnormal activity observation, thus, a deviation from the normal activity state if detected is thus considered risky [97]. The main drawback of this approach is overgeneralization. In other words, a deviation may not necessarily a risk (e.g., leaving the cupboard opened) and such scenario may constitute hypersensitivity of warning alert (or interference if intervention is offered by a resident care partner) which could overwhelm the senior living in the smart home. SPP technique on the other hand, partitions the smart home space into functional (e.g., bathroom, kitchen, etc.) or risky area and non-functional (e.g. bedroom) or non-risky area continuously monitors senior’s activities in the smart home. If a resident stays too long in the functional area which violates its safety requirement, an alert is triggered, and notification is sent to care partner for possible intervention [19]. The drawback of this approach is that it has the tendency to overestimate the ability of the person performing the IADLs. For example, the senior may exit the functional area within the time expected but may
forget to turn-off the stove, thus, predisposing the resident to fire-accident which could be life-threatening.

Considering that instrumental activities of daily living (IADLs) involve more intricate activities consisting of different skills that requires sequence of action, awareness and direction needed towards achieving the intended goal [24], and the impact of early-stage dementia (ED) on the memory of seniors which causes episode of uncertainty or forgetfulness [23, 24], BDD and SSP thus neglect the need to assess the ability of seniors to perform IADLs independently [6, 22, 23]. Summarily, both BDD and SPP techniques limit the potential of AAL to just detection accidents and emergencies and seniors still rely on intervention of care partners especially when in safety-critical situation [28][29].

However, temporal logic (TL) have been employed in specifying safety properties in safety-critical systems due to its convenient vocabulary for expression of temporal specifications and behavior required of a system [123][125][126]. In order words, it allows for specification of sequence or relative order of events and therefore suitable for risk analysis, accident, and risk mitigation from temporal data [123][127][128][129].

To address these problems and to provide appropriate response to seniors in their ADLs, there is need to understand the user’s context and incorporate anticipatory capability into smart home environment [1][22]. This therefore calls for an interdisciplinary approach that not only uses specific activities of daily living measures to assess IADL functioning of seniors at fine-grained level (i.e., an activity of preparing a hot chocolate may involve a sequence of actions including “fill-kettle-with-water” -> “turn-on-the-stove” -> “grab-glass-cup”, etc.) but also help mitigate these risks [24]. Therefore, in this study, I proposed a situation-centered framework for relearning of activities of daily living in Smart Home Environments. The framework is primarily composed
of three (3) major units namely: a) goal inference unit – employed a deep learning algorithm that leverages regularization technique for improved goal inference in a smart home, b) situation-context generator – consists of an automaton-based activity model for goal path identification, risk assessment model and safety requirements checker for goal path as defined by temporal logic-based rules, to better represent user’s context with capability to anticipate risky situations thus enabling timely response and c) a recommendation unit – a situ-learning agent (SLA) to guide the decision making of resident of a smart home in safety-critical situations.

1.1 Research Motivation

Activities of daily living are sine qua non for self-care and improved QoL. Older adults with ED are potentially predisposed to life-threatening injuries and accidents when performing activities of daily living especially with IADLs due to decline in their cognitive ability and this calls for concern [23][24][30][31][32]. The ability of smart home environments in characterizing user’s situation, anticipating safety-critical situations and improved predictive power of smart home environments may lead to timely and appropriate response thus mitigating these life-threatening injuries that seniors are predisposed to in the IADLs.

1.2 Research Objectives

The objectives of this research include the following:

1. To investigate the predictive performance of LSTM model in inferring human goal in a dynamic environment such as the smart home.

2. To investigate the effectiveness of a linear temporal logic-based safety reasoning model for risk mitigation in instrumental activities of daily living.
3. To investigate the applicability of agent models to support aging adults with early-stage dementia in decision-making in their instrumental activities of daily living in smart home environments.

1.3 Definition of Terms

- **Activity** – consist of a set of tasks, some needs to be executed in sequence. For example, a person may desire to eat: Task 1 – Go to the kitchen; Task 2 – get the silverware; Task 3 – grab foodstuff; Task 4 - cook the food; Task 5... [14].

- **Task** – each task requires some actions to be performed to complete. For example, Task 1 requires: “open-kitchen-door”, “close-kitchen-door” [17].

- **Safety critical task** – is a task that if a person is unable / fails to perform at given time instant could constitute a risk with potential for adverse effects [15].

- **Situation** – is a three-tuple \(<M, B, E>_t\) that characterizes the mental state of a user at a time instant \(t\), where \(M\) is the user's hidden mental state, \(B\) represents the behavior context (i.e., set of user's actions towards a goal), and \(E\) is the environmental context values [16].

- **Intention** – is a temporal sequence of situations to achieve a goal. More formally, Intention can be expressed as an action-laden sequence, \(I = <Sit_1, Sit_2, ... Sit_n>\), such that \(Sit_1\) is the goal-triggering situation and \(Sit_n\) is the goal-satisfying situation [16].

- **Hazard** – refers to a system (object) state that will cause an accident (or a loss event) if other conditions exist in the system's environment [17].

- **Risk** – is the degree of a hazard level together with (1) probability that the hazard will lead to an accident and (2) hazard exposure or duration [17].

- **Safety** – is insusceptibility to accident or losses [17].
CHAPTER 2. BACKGROUND AND RELATED WORK

2.1 Activities of Daily Living (ADLs)

Activities of Daily living (ADLs) are sine qua non for self-care and improved quality of life (QoL). ADL is an important tool used for assessing older adults’ ability to navigate daily life and achieve required objectives; this type of assessment can be particularly helpful when considering persons with dementia [45]. In other words, ADLs reveals the functional capacity of a senior with respect to his/her goal at any given time instance [46]. Generally, activities of daily living can be categorized into two types:

- Basic ADLs: include dressing, bathing, and feeding, etc. [47, 48]
- Instrumental Activities of Daily Living (IADLs): refer to self-care tasks but are learned, requires complex thinking and organizational skills such as meal preparation, laundry, shopping, etc. [24].

In addition, ADLs can also be classified based on the mode of execution and/or the number of people carrying out the activity. The three main classes that exist are vis a vis:

- Single activity – an activity that has been completely executed or performed before a new one is initiated.
- Interleaved activity – refers to an activity which is being performed while a new activity is initiated at the same time; and
- Multi-occupancy activity – This type of activity involves several people (i.e., two or more people performing activities concurrently) [9].
2.2 Activity Recognition

Activity recognition refers to the process of observing a user through sensing of his/her interaction in an ongoing activity within an environment, modeling the activity to enhance the analysis of observation data streams from sensors and leveraging relevant algorithms to infer the goal (activity being performed) of the observed user [32, 33, 34]. Activity recognition is an invaluable technology that is applicable to many human-centered related problem areas such as senior care giving and healthcare; it enhances smart environments to render activity aware services to users [33, 35]. The continuous monitoring of ADLs and recognition of deviations from previous patterns is essential for the assessment of an older adult’s ability to live independently in their home environment and in early detection of impending critical situations [30].

2.3 Types of Activity Recognition

As briefly discussed earlier, activity recognition systems can be grouped into three main types:

2.3.1 Single-User Activity Recognition

In single-user activity recognition system, a single user is observed and monitored using wide range of sensing devices over wireless sensor networks. These sensing devices captures the user actions in the form of streams of data that may represent the sequence of events and activity context performed by the user. The stream of activity data is then analyzed using some machine learning algorithms to detect patterns and behavior. In [36], their objective was to recognize three postural activities of a user from accelerometer activity data and five machine-learning algorithms, including Decision Tree (J.48), Naive Bayes (NB), k-Nearest Neighbor (IBK), Support Vector Machine (SMO) and Neural Network (Multilayer perceptron), were compared for their accuracy of the activity detection.
2.3.2 Multi-User Activity Recognition

Activity recognition becomes more challenging as the number of people being observed during carrying out activities increases. In a multi-user activity recognition, wearable sensors can be employed in recognizing the activities and behavioral patterns of multiple people in smart environment. In [37, 38], they investigated the problem associated with recognition of activities of multiple residents who tend to perform activities together using wearable sensors to collect activity data and temporal probabilistic models to model interacting processes.

2.3.3 Group Activity Recognition

The dynamics of group activity recognition is quite different from single, or multi-user activity recognition in that it aim to recognize the behavior or objective of a group working on the same task, or subgroups performing independent tasks in parallel [39, 40]. [41] defines it as “an estimation of the emergent group behavior generated by the states and interactions of individual members obtained through sparse wearable sensor observations of the distributed states and environments of the individual members”. Group activity recognition has real-life application especially in sports, gaming, meetings and social networking, and people management in disaster response [39, 40, 41].

2.4 Techniques for Activity or Goal Recognition

There are various techniques that have been used for inferring human goal. Some of the prominent methods include:

2.4.1 Logic-Based Reasoning

In logic-based reasoning for goal recognition, all logical specifications of observed action sequences are checked. In other words, all possible and consistent goals must be examined.
In [78], they proposed a goal recognizer that observes actions executed by a person and iteratively eliminates inconsistent actions and goals from a graph representation of the domain. This was done by analyzing interactions among the actions, action schemas, and goal schemas in the consistency graphs designed.

2.4.2 Probabilistic Reasoning

More recently, probability theory and statistical learning models like Hidden Markov Model (HMM) and Conditional Random Fields (CRF) are becoming popular and are applied in human-centered computing and ambient assisted living (AAL) research. Goal recognition is one of the areas that these models are being used for reasoning about actions, plans, and goals under uncertainty. Some research for instance, has established the relationship between HMM and the theory of mind but also reported its difficulty to predict goals with similar observation sequences [10, 11].

CRF is considered superior to HMM as it gives better performance in goal recognition [44]. Its reported drawback include the inability to adequately capture context dependencies especially in activity observations with varying length of sequences resulting from missing data and incomplete execution of goal tasks, and the complexity of re-training the model when new observation sequence becomes available for labeling [11, 12, 42].

2.4.3 Data Mining-Based Inference

In [76], they employed data mining approach to infer the goal or activity of a person. This problem was modeled as pattern-based classification problem such that it uses discriminative patterns that the problem of activity recognition is formulated as a pattern-based classification problem. They proposed a data mining approach based on discriminative patterns that characterize
important changes between activities of different classes of data to infer sequential, interleaved, and concurrent activities.

2.4.4 GPS-Based Inference

Zhu and Sheng [77] used GPS-based technique to infer human activity. Their method combines vision-based location information and motion data that is collected from a single inertial sensor worn by the person being observed. The advantages of this method include less observation data required to infer human goal, less obtrusiveness and improved inference accuracy.

2.5 Cognitive Disorders in Older Adults

As people age, they are predisposed to age-related diseases, and cognitive impairment is the most common condition experienced by the aging adult demographics [66, 67]. Common cognitive disorders include:

- **Mild Cognitive Impairment (MCI):** MCI refers to an intermediate mental state between a normal cognitive state and dementia that presents an objective evidence of decline in cognitive function from the past but the person’s activities of daily living remain normal [67, 68, 69].

- **Early-stage Dementia (ED):** In early-stage dementia otherwise known as mild dementia, the decline in the patient’s cognitive functioning has substantial interference with activities of daily living [67, 70].

- **Alzheimer’s disease (AD):** AD is a form of neurodegenerative disorder that is progressive and with characteristic significant impact on patient’s memory, thinking, behavioral, social, and psychological well-being [71, 72].
2.6 Nudging Behavior Change among Aging Adults with Cognitive Impairment

Episodic memory deterioration impacts the everyday tasks performed by seniors with dementia which often leads to incorrect ordering or omission of tasks in goal paths [85, 86]. This misstep most times is due to the inability of the senior to recall the correct order of execution of the goal tasks [94]. It is therefore necessary to provide intervention that supports people with ED to successfully navigate through their daily activity sequences toward satisfying their goal. Behavior change is thus essential for ensuring that people achieve their goal while also ensuing their well-being [61][84].

Nudge theory postulates that human behavior can be guided towards a target goal through positive reinforcement which is very effective in influencing their motives, incentives and decision making [79]. Reinforcement learning (RL) is a useful theory that helps to model how the human brain function with respect to deciding what actions to be taken. Therefore, reinforcement learning is key to influencing behavior change as well as motivation [61][79][84]. RL concept is based on interaction with the environment, context information and experience. This helps to constrain an agent's behavior to appropriate actions to be taken in situation of uncertainty caused by episodic memory deterioration [80].

The importance of artificial intelligence-based models such as RL systems cannot be overemphasized as these models are found to be useful interventions to support decision making that have significant impact on humans while taking their goals and desires into consideration [81]. For example, in [82], authors proposed an erroneous-plan recognition system (EPR) that detects deviations or abnormal activity sequences for a given ADL. The concept of activity probability and reward in reinforcement learning was used to infer if a detected activity is erroneous or not. Similarly, Hassan and Atieh [83] proposed a reinforcement learning-based action prediction in
smart home that learns the changes in a user's behavior using the human action on devices as feedback.

Generally, RL aim to influence a person’s ability to recall (i.e., lower-order mental processes) by using contextual changes to prompt spontaneous responses and to bring about automatic behavior change [61][84][96].

2.7 Clinical Approaches to Supporting Seniors with Cognitive Impairments

Due to deterioration in cognitive functions and loss of autonomy experienced by older adults with cognitive disorders and with no curative measures available, non-pharmacological intervention known as relearning that targets the learning to recover useful IADL skills have been employed in clinical settings to help improve their QoL [73, 74]. Generally, there are three methods of relearning, namely:

- **Trial and Error (TE):** This type of learning method requires the patient to guess the correct answer to a task while he/she learns from any errors or mistakes made [74].

- **Errorless Learning (EL):** This method uses feed forward instruction technique whereby a person is provided cues prior to performing a specific task to prevent mistakes during learning [73, 75].

- **Modeling with Spaced Retrieval (MR):** This technique requires a patient to memorize and reproduce a target task sequence [74, 75].

2.8 Smart Home Environment (SH) and Its Application for Aging Adults’ Care

“Aging in place” for older adult is one of the aims of ambient assisted living (AAL) technologies [30, 31]. AAL including SH is a home environment retrofitted with sensors for monitoring, identifying its residents, activities being carried out, as well as reacting and adapting to their needs [50]. SH is an intelligent environment designed primarily to enhance the experience
and QoL of people through human-centered applications and to support “Aging in place” [9][25][49]. This technology can provide support to older adults, especially those with cognitive diseases (e.g., dementia) who may suffer episodic memory deterioration that impacts the persons’ IADLs functioning initiative and performance due to uncertainty or poor judgment [51]. SH is useful for understanding human behavior and it has the capability to detect activities and infer a person’s goal or mental by analyzing stream of observation data captured by SH sensors [91].

In [49], authors proposed a behavior deviation detection system to enhance the independence of seniors living in smart home through continuous monitoring of their health condition as characterized by changes in lifestyle by analyzing patterns from activities performed by the resident. To ensure that the resident successfully execute tasks toward goal satisfaction, a two-pronged approach was proposed. First, the most frequent patterns that characterized the activities of the resident being observed was identified using a sequence mining algorithm and each activity was modeled using an extended finite automaton. Secondly, an additional automaton using a set of recognizable activities were designed to model the requirements that the resident must satisfy as specified by the medical personnel or care partner monitoring the resident. Thus, behavior deviation system was able to accept activity events as input and detect any anomaly from observed behavior based on defined residuals. The approached used by the authors [49] for detection of deviation relied on the assumption that resident care partner has a pre-designed list of activity requirements (e.g., resident must have 3 meals a day) that is used to check if the health condition or well-being of the resident has deteriorated or not. Although, this may be valuable in some instances, however, it can be disadvantageous in other contexts. For instance, people with Ed may suffer deterioration in their cognitive functions and may find it difficult to successfully complete the sequence of tasks in complex IADLs and such deviation may predispose the senior
living in the smart home to life-threatening accidents since the system was not designed to be reactive rather than being preemptive. It is therefore necessary enhance AAL systems with capabilities to infer human goal by taking behavioral and environmental context into account to enable SH to be able to preempt any abnormal actions that may compromise the safety of the resident.

In [97], authors proposed a behavior deviation detection system known as anomalies recognition and assistance provision system. The system is based on a fuzzy temporal data driven technique. First, a fuzzy conceptual structure was used to define each activity as a hierarchy of concepts in smart home environment. An ongoing activity (i.e., current activity being observed) is represented as the base of the hierarchy while the corresponding normal view of the ongoing activity (otherwise referred to as “normal world generic function”) is at the top of the hierarchy. Thus, a fuzzy symmetrizer is used to compute the degree of similarity and dissimilarity of the current activity to the normal world to infer possible anomalies. If an anomaly exists, the system dutifully reacts to restore the smart home to normal state. The limitations of this method include a) Overgeneralization – it assumes that all deviation detected as an anomaly constitutes a risk. This may not be true in all cases, for example, if the kitchen door is left opened after the resident is done with meal preparation, resident should not be overwhelmed with warning alert about this deviation since it does not necessarily constitute a risk, b) Requires the services of a care partner –Whenever an anomaly is detected, the system still relies on the services of a care partner to guide the senior living in the smart home his or her activities of daily living execution plan and also reverse the anomaly to avert potential risk, and c) System-oriented –emphasis is placed more on the system state rather than taking human mental state into context as well in ensuring the safety of the resident.
Lam et al [19] used a smart space partitioning approach to track the location of resident in the smart home. They developed a SmartMind device that is used to track and monitor the activities performed by an older adult with Alzheimer's disease. The smart home environment was also calibrated into two distinct areas which include functional and non-functional areas. The functional area (e.g., kitchen) is considered a high-risk area such that if a person stays too long in that location an alert is triggered to notify the resident and care partners for intervention to avert potential life-threatening or risky situation. The non-functional area (e.g., bedroom) is considered safe location. Although, an alert or trigger designed to prompt resident can be useful intervention to avert potential accident in their ADLs, it is important to ensure that an appropriate trigger is issued depending on the characterization of residents situation at a given time instance [93]. Another drawback of this approach is that it overestimates the IADLs functioning initiative and performance of the resident. In other words, it assumes that the older adult with AD will correctly execute the goal task before exiting the functional area. However, a senior with AD may forget to perform an important task in a goal path (e.g., he/she may forget to close the water tap) which could predispose the senior to fall accident if he/she slips due to wet floor.

In [87], authors proposed an activity recognition system with a three-layer architecture to assist persons with mild cognitive impairment to navigate their activities of daily living. The system has a hardware that include sensors and smart devices, middleware, and a graphical user interface (GUI) application layer. The middleware has modules that it uses to abstract each of the devices and render a universal homogenous application interface layer. The system monitors and detects ADLs performed by SH resident by leveraging activity data generated by the sensors and these are accessible and can be visualized through the application GUI. For example, the system may detect number of times a person opens the refrigerator or successfully completes the activity
of preparing a meal using timestamps information recorded by the activity sensors and then notifies the responsible care partner. If the care partner determines that an anomaly or deviation exist in activity sequence, the care partner intervenes by writing down the appropriate plan or correct order of execution of the tasks with respect to the detected activity (i.e., prepare a meal). The first limitation of this approach is that it interferes with the desired independence envisaged for seniors in living in smart home environments since the system still requires a care partner to provide assistance to the SH resident to successfully complete his or her activity or goal. More so, a written plan for goal execution may not be an effective intervention for a person with MCI since he or she may suffer episodic memory deterioration that could cause the person to forget the plan provided to him. Further, it can be burdensome to require a person with MCI to memorize the execution plan for an activity as this could lead to undue cognitive load. Also, even though the SH resident is being monitored in real-time, the system does not have the capability to provide appropriate assistance to the resident “on-the-fly” especially in situation that may constitute a potential risk. In addition, from an economic standpoint, this method could be too expensive since the services of a care partner is still required which constitutes an additional cost.

Summarily, the related works described above have the assumption that human will naturally act to satisfy a need or goal. In [88], author characterized need or goal as “sometimes provoked directly by internal processes of a certain kind (viscerogenic, endocrinogenic, thalaminogenic) arising in the course of vital sequences, but, more frequently (when in a state of readiness) by the occurrence of one of a few commonly effective presses”. Persons with ED suffer deterioration in IADLs functioning initiative and performance due to decline in their cognitive ability leading to episode uncertainty and poor decision making. Cognition however helps us to understand and predict human behavior. In other words, it is a mental activity that demands
processing of information which is used consequently to make appropriate decisions devoid of risks [89]. Authors in [90] also asserts that observable human actions and behaviors effect changes in context values, and these characterize a snapshot of a person’s mental state otherwise referred to as human desire. Hence, it is believed that human goal can be inferred from their observable actions or behavior as well as their environmental context [91]. More so, in [93], the author argues that a person must have three attributes to successfully accomplish a target behavior or goal which include: 1) ample motivation to, 2) ability to perform the behavior tasks, and 3) an appropriate trigger to initiate the behavior or goal. In addition, to successfully influence positive change in human behavior toward the satisfaction of a person’s goal, it is important to also understand how people translate goals into actions; control theory thus provides for an effective technique called “Implementation Goals” for goal pursuit [92].
CHAPTER 3. PROPOSED METHOD AND CASE STUDY

3.1 Situation-Centered Goal Relearning Framework

In this study, I propose a Situation-centered goal relearning framework (otherwise referred to as Situation-centered goal reinforcement framework) to assist seniors with early-stage dementia (ED) to successfully navigate their complex instrumental activities of daily living (IADLs) or goal. The framework is a computational model of the concept of human-in-the-loop. It also borrows concepts from social and behavior theories that can be helpful in simulating human-centered systems to better understand human behavior in smart home environments (SH). It is composed of three main components that leverage stream of sensor data to analyze human behavior and infer their goals, detects potential action that may constitute a risk in goal path, and consequently recommend appropriate action to seniors toward satisfying their goal while also mitigating risky situations. Figure 3.1 describes the framework components and how each part interacts together to provide a fully automated intervention to support seniors in their IADLs in SH.

Figure 3.1. Situation-Centered Goal Relearning Framework
An overview of the Situation-centered goal relearning framework, description of its components and their operations are discussed in succeeding sections and subsections. First, the following four assumptions define the scope and context of this study:

- **Assumption 1:** The application domain for this study is a smart home environment (i.e., a home environment retrofitted with various sensors for continuous monitoring of an older adult’s IADLs). The sensors detect human actions and environmental context as they interact with the environment while performing their IADLs. Thus, human goal can be inferred from the stream of data generated in the SH as represented by sensor values.

- **Assumption 2:** The SH has only one resident at any given time. Also, the resident’s normal execution patterns (i.e., observation sequences with no deviation or anomaly in the goal path) of the IADLs or goals prior to being diagnosed of ED are known. Thus, goal execution patterns after the older adult (i.e., current IADLs observation) has been diagnosed of ED are referred to as the non-normal IADLs observation sequences (i.e., abnormal observation sequences) due to deterioration in the IADLs functioning initiative and performance of the older adult living in the SH. Both the normal observation and abnormal observation sequences are stored in the data collection repository of the framework as historical data.

- **Assumption 3:** In the course of execution of a goal by the SH resident, he or she can only perform an action at a time and also must complete the execution of the current goal initiated before a new goal execution begins. In other words, no interleaving is permitted.

- **Assumption 4:** Agent model can be helpful to support seniors with ED to avert risky situations in the performance of their goal [62][65]. Therefore, this can be shown by simulating two interacting agents proposed as follows: situ-learning agent (SLA)
otherwise referred to as the teacher/recommender agent, and a naïve agent that represents an older adult with deteriorated IADLs functioning initiative and performance caused by ED. Episode of uncertainty which is synonymous with deteriorated IADLs functioning initiative and performance is designed for the naïve agent such that different sensors that characterizes the goal being performed are supplied to the naïve agent as possible choices of actions to be taken at a given situation in the goal path. Therefore, given an anomalous goal observation sequence performed by a naïve agent, an SLA can prompt the naïve agent to take the appropriate action using some signals (e.g., penalty/reward, action selection and reward probability vectors) to mitigate risky situation.

3.2 Overview of The Framework

The Situ-centered goal relearning framework is made up of three main components which include:

1.) **Goal Inference Unit**: This is an important component of the framework that is required to enable an older adult with ED get needed help or support with respected to his or her goal. The primary function of this component is to infer or predict the goal being performed by the older adult living in smart home environment. It uses a type of recurrent neural network known as Long short-term memory (LSTM) model to infer the SH resident’s goal by leveraging stream of sensor data stored in the data collection repository generated by the observed resident’s interaction in the SH.

2.) **Situ-Context Generator Unit**: The function of this component is responsible for simplifying the navigation of the complex goal path of observed resident. In other words, once the resident’s goal is inferred by the goal inference unit, the Situ-context generator then provides path awareness to enhance the completion of the resident’s
goal given that episodes of uncertainty may impede goal completion. This component exploits situation analytics combined with feature selection algorithm, pattern matching to detect anomaly in goal path, and situ-context graph to generate an automated plan that characterizes the appropriate path toward satisfying the inferred goal.

3.) **Goal Reinforcement Unit** – This unit of the framework is designed to mitigate the loss of independence in seniors with ED. In many smart home applications, an older adult with deteriorated cognitive functions depends on the services of resident care partner to successfully perform his or her IADLs and this [49][74][97]. Therefore, an agent-based recommender to support senior’s decision-making during episodes of uncertainty in goal path is proposed. First, the goal reinforcement unit takes the context of the SH resident into account by decomposing the generated goal path into sequences of situations to enhance the detection of behaviors or actions that may constitute a risk in the goal path. Situ-learning agent (SLA) otherwise known as the teacher/recommender agent can then recommend appropriate action to senior with ED (in this case the naïve agent) to avert potential risky or safety-critical situations in the goal path. Notice that both the normal observation and the abnormal observation sequences stored in data collection repository for a given goal is visible to goal reinforcement unit of the framework. Therefore, when an abnormal situation emerges, a new goal may have been uncovered, and this will be added to the goal space if so, i.e., $G' = G U \{g_{k+1}\}$. 
3.2.1 Human Observations and Preprocessing of IADLs Datasets from Smart Home

a) Human Observations Datasets Description

This study leverages “memory abilities and dementia in older adults” IADLs datasets of an observed single user in a smart home lab with a living room and a kitchen [9]. The smart home sensors and their corresponding values are summarized in Table 3.1 below. Four different categories of IADLs observation instances of the datasets were considered and these include: “prepare tea”, “prepare a hot chocolate”, “drink a glass of water”, and “prepare a hot snack”. Each category of the IADLs observation instances consisted of both normal and abnormal observation instances. Abnormal observation instances are anomalous observation sequences (i.e., with missed tasks or deviations in the goal path) due to deterioration in IADLs initiative and performance. Anomaly in observation sequences could be due to repetition, ordering, and time duration of a task or action performed. For example, a senior with ED may experience deterioration in cognitive function that could cause him or her to forget to “turn-off” the stove after cooking, “switch on” the kettle before filling it with water, etc. A descriptive snapshot of an instance of a normal and abnormal sequence for IADLs category “Drink a glass of water” is shown in Table 3.2 and Table 3.3 below:
Table 3.1. Description of The Sensors in The Smart Home Lab (Culled from [9])

<table>
<thead>
<tr>
<th>Sensor Id</th>
<th>Function</th>
<th>Sensor Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>D01</td>
<td>Senses interaction with the kitchen door</td>
<td>“Open” or “Close”</td>
</tr>
<tr>
<td>D02</td>
<td>Senses interaction with the living room door</td>
<td>“Open” or “Close”</td>
</tr>
<tr>
<td>D03</td>
<td>Senses interaction with cutlery cupboard</td>
<td>“Open” or “Close”</td>
</tr>
<tr>
<td>D04</td>
<td>Senses interaction with dishes cupboard</td>
<td>“Open” or “Close”</td>
</tr>
<tr>
<td>D05</td>
<td>Senses interaction with cups / glasses cupboard</td>
<td>“Open” or “Close”</td>
</tr>
<tr>
<td>D06</td>
<td>Senses interaction with the pantry cupboard</td>
<td>“Open” or “Close”</td>
</tr>
<tr>
<td>D07</td>
<td>Senses interaction with the stove / microwave</td>
<td>“On” or “Off”</td>
</tr>
<tr>
<td></td>
<td></td>
<td>“Open” or “Close”</td>
</tr>
<tr>
<td>D08</td>
<td>Senses interaction with the refrigerator</td>
<td>“Open” or “Close”</td>
</tr>
<tr>
<td>M01</td>
<td>Senses interaction with the chair</td>
<td>“Absent” or “Present”</td>
</tr>
<tr>
<td>M02</td>
<td>Senses interaction with the sofa</td>
<td>“Absent” or “Present”</td>
</tr>
<tr>
<td>TV</td>
<td>Senses interaction with the television</td>
<td>“On” or “Off”</td>
</tr>
<tr>
<td>PH</td>
<td>Senses interaction with the phone</td>
<td>“Pick up” or “Hang up”</td>
</tr>
<tr>
<td>WT1</td>
<td>Senses interaction with the water tap</td>
<td>“Open” or “Close”</td>
</tr>
<tr>
<td>KT</td>
<td>Senses interaction with the kettle</td>
<td>“On” or “Off”, “Absent” or “Present”</td>
</tr>
</tbody>
</table>
Observe from Table 3.1 that ‘D07’ can either be a stove or microwave sensor. However, throughout this work, D07 will represent a stove sensor with corresponding value “ON / OFF”. Also, KT sensor will only take either value “ON / OFF”.

Table 3.2. A Snapshot of Normal Observation Sequence for IADLs “Drink A Glass of Water”

<table>
<thead>
<tr>
<th>Date Time</th>
<th>Event</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015-02-20 18:22:32</td>
<td>D01 CLOSE Begin_1</td>
</tr>
<tr>
<td>2015-02-20 18:22:46</td>
<td>D01 OPEN</td>
</tr>
<tr>
<td>2015-02-20 18:22:53</td>
<td>D01 CLOSE</td>
</tr>
<tr>
<td>2015-02-20 18:23:07</td>
<td>D05 OPEN</td>
</tr>
<tr>
<td>2015-02-20 18:23:20</td>
<td>D05 CLOSE</td>
</tr>
<tr>
<td>2015-02-20 18:23:27</td>
<td>WT1 OPEN</td>
</tr>
<tr>
<td>2015-02-20 18:23:36</td>
<td>WT1 CLOSE</td>
</tr>
<tr>
<td>2015-02-20 18:24:35</td>
<td>D01 OPEN</td>
</tr>
<tr>
<td>2015-02-20 18:24:41</td>
<td>D01 CLOSE End_1</td>
</tr>
</tbody>
</table>

Table 3.3. A Snapshot of Abnormal Observation Sequence for IADLs “Drink A Glass of Water”

<table>
<thead>
<tr>
<th>Date Time</th>
<th>Event</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015-02-21 18:25:37</td>
<td>D01 OPEN Begin_1</td>
</tr>
<tr>
<td>2015-02-21 18:22:43</td>
<td>D01 CLOSE</td>
</tr>
<tr>
<td>2015-02-21 18:22:49</td>
<td>D05 OPEN</td>
</tr>
<tr>
<td>2015-02-21 18:22:54</td>
<td>D05 CLOSE</td>
</tr>
<tr>
<td>2015-02-21 18:25:58</td>
<td>WT1 OPEN</td>
</tr>
<tr>
<td>2015-02-21 18:26:03</td>
<td>WT1 CLOSE</td>
</tr>
<tr>
<td>2015-02-21 18:26:11</td>
<td>WT1 OPEN</td>
</tr>
<tr>
<td>2015-02-21 18:26:17</td>
<td>WT1 OPEN</td>
</tr>
<tr>
<td>2015-02-21 18:26:39</td>
<td>D01 OPEN End_1</td>
</tr>
</tbody>
</table>

Observe from Table 3.3 that the water tap sensor “WT1” indicated that the smart home resident the water tap “OPEN” and forgets to “CLOSE” it at the end of the activity. This anomaly may constitute a potential risk of slip or fall accident if the water tap is left opened for too long and causing the kitchen floor to get wet. Also notice that the “WT1” sensor indicated that the resident repeated the water tap task twice (i.e., [WT1 OPEN → WT1 CLOSE] and [WT1 OPEN → WT1 OPEN]) instead of once (i.e., [WT1 OPEN → WT1 CLOSE]) as shown in Table 3.2. Such repetition sometimes can be due to deterioration in IADLs functioning initiative and performance thus may constitute a deviation as it could extend the normal duration of the activity.
b) Datasets Preprocessing

Data preprocessing or preparation is an important but tedious process that involves the transformation of raw data (e.g., generated IADLs sensor data) into a format that can be used to train machine learning models optimally [101]. More so, it can be difficult to figure out how to prepare sequential data into training set for LSTM model, hence, quality of the representation of the data observation instances is crucial to performance of the model [102]. The “memory abilities and dementia in older adults” IADLs datasets used for this study consisted of four different categories of IADLs observation instances of the datasets: “prepare tea”, “prepare a hot chocolate”, “drink a glass of water”, and “prepare a hot snack”. Therefore, the first objective is to infer or predict the goal that a senior with ED living in smart home is wanting to accomplish given an instance of abnormal observation sequence generated by the resident and collection of historical IADLs observation sequences stored in the data collection repository. To put it simply, the intent is to determine which of the four different IADLs category the does the current (abnormal) observation sequence generated by the resident belongs to so that an appropriate intervention can be provided to him or her to ensure the completion or satisfaction of the goal. This problem is thus formulated as a multiclass classification problem.

The following steps summarize the process of preparation of the datasets:

1.) Generally, deep learning algorithms such as LSTM model performs well when fed with large-labeled data as training sets (or inputs) [108]. Due to the small size of the four categories of the IADLs observation instances from the original “memory abilities and dementia in older adults” datasets, more synthetic (i.e., normal and abnormal) instances were generated such that it follows the description of each of the four category of IADLs observation sequences. Therefore, a total of 5370 instances of IADLs observation
sequences (i.e., include observations from original dataset and those generated) were preprocessed.

2.) Snapshots of normal and abnormal observations for each IADLs category is then transformed or represented as a sequence of text. For example, a snapshot of IADLs “Drink a glass of water” is represented as follows:

\[ \text{begin, door_c, door_o, door_c, glasses-cupboard_o, glasses-cupboard_c, water_o, water_c, door_o, door_c, end} \]

Notice that sensors with values “open” or “close” are denoted by the suffix indicator “o” or “c” respectively.

In order to take care of the variability in length of the abnormal ADL sequences to the corresponding normal ADL sequences, we employed the pad_sequences() function provided in the Keras deep learning library [107] to pad the variable length sequences to the same length.

iii. To infer or predict the new goal, the LSTM-based goal unit was fed with the training datasets and their corresponding labels. We then introduced a new test sequence to which the trained model assigned labels (i.e., ADL sequence instances for the given single activity).

3.2.2 LSTM-Based Goal Inference Unit

A. LSTM Structure for Sequence Modeling

The goal inference unit of the proposed framework leverages a type of recurrent neural network (RNN) architecture called LSTM algorithm to infer or predict the goal of an aging adult in smart home environment. LSTM (shown in Figure 3.2) is designed to overcome the vanishing and exploding gradient problem that is characteristic of RNN and it is well-suited for modeling sequence related problems due to its capability to exploit temporal information in sequential data
with arbitrary length by mapping the input sequence to the output labels iteratively [95, 109]. More so, its characteristic recurrent connections enable it to store past events which makes it effective in modeling long term dependencies and context [43]. Each block of LSTM has 3 main gates that include forget gate, input gate and output gate, and a cell state otherwise referred to as memory with which it stores past input data. The forget gate is responsible for controlling how much of the old information in the memory should be forgotten (i.e., if the memory state is set to 0, it means that the information in the memory state is discarded, and 1 means that the information should be kept). The input gate decides whether the memory cell should be updated while the output gate controls what information of the current cell state is made visible.

![A Block of LSTM](image)

**Figure 3.2.** A Block of LSTM.

Given a cell state \( c_t \) at the current time step \( t \), the cell state \( c_t \) can thus be updated by the recursive equations as follows:

\[
i_t = \sigma (w_{xi}x_t + w_{hi}h_{t-1} + b_i)
\]  

(i)
\[ f_t = \sigma(w_{xf}x_t + w_{hf}h_{t-1} + b_f) \]  
\[ o_t = \sigma(w_{xo}x_t + w_{ho}h_{t-1} + b_o) \]  
\[ g_t = \tanh(w_{xc}x_t + w_{hc}h_{t-1} + b_c) \]  
\[ c_t = f_t \odot c_{t-1} + i_t \odot g_t \]  
\[ h_t = o_t \odot \tanh(c_t) \]

Where \( w_{xi}, w_{hi}, w_{xf}, w_{hf}, w_{xo}, w_{ho}, w_{xc}, w_{hc} \) denote the weight matrices that connect two different units, while \( b_i, b_f, b_o, b_c \) denote the bias terms, and \( h_t = x \odot y \) denotes element-wise product operator. \( i_t \) is the input gate vector, \( f_t \) denotes the forget gate, \( o_t \) is the output gate vector, \( g_t \) is the state update vector, and \( h_t \) is the output hidden state vector. Also

\[ \sigma(x) = \frac{1}{1+e^{-x}} \] is the sigmoid function.

It is important to note that the behavior of the gate control is data driven (i.e., learned from data). Also, an additional output network is added to the hidden state \( h_t \), this enables us to extract the information relevant to the given problem [56, 95, 109]. For example, since our case study is formulated as a multi-class classification problem, to obtain the prediction class scores for a total of \( J \) classes at a time step \( t \), a softmax layer comprising of the linear transformation is added on top of the last LSTM layer \( L \) to estimate the posterior probability \( p_j \) of the \( j \)-th class as follows:

\[ p_j = \text{softmax}(h^L_t) = \frac{\exp(u^T_j h^L_t + b_j)}{\sum_{j' \in J} \exp(u^T_{j'} h^L_t + b_{j'})} \]

Where \( b_j \) and \( u_j \) are the corresponding bias term and the weight vector of the \( j \)-th class.
B. Methodology for Training of LSTM

The smart home sensors capture each event of an ADL sequence that defines the goal of the resident of the smart home, thus, the goal path or sequence data can be collected over a long-term period. From the goal path history for all $N$ ADLs (i.e., $N$ is equal to the four different ADLs classes used as our case study), ADL data were extracted and combined to generate the training data. The training data containing the goal path of the resident representing each ADLs is then used to train the LSTM. We, therefore, formulate the goal prediction problem as a multi-class classification problem. Given an ADL sequence as input, LSTM automatically maps the input sequence $\left( x^{(1)}, x^{(2)}, \ldots, x^{(m)} \right)$ to output labels $\left( y^{(1)}, y^{(2)}, \ldots, y^{(m)} \right)$ (i.e., the IADLs class labels). We employ one hot encoding to generate the label. For instance,

$$y^{(i)} \text{ is one of } \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix} \text{ which indicates the class or label of the current goal (e.g., prepare a tea) of the resident.}$$

3.2.3 Situ-Context Generator Unit

In general, ambient assisted living technologies such as smart environments are designed with several sensors that enable the continuous monitoring of its residents’ activities of daily living. As a result, streaming and generation of high volume of data (i.e., big data) in real-time are
often associated with smart home environments [59]. Given that aging adults with early-stage dementia may suffer deterioration in their cognitive initiative and performance of IADLs, it is crucial for AAL to provide intervention or support that enhances easy navigation or simplifies the path toward the completion of their inferred goal. Thus, situ-context generator is an important component of the proposed framework that consisted of three sub-units which include feature selection, pattern anomaly identifier, and situ-context graph. These sub-units are interdependent and the descriptions of the functionality of each sub-unit is discussed in succeeding paragraphs.

a) Feature Selection: The situ-context generator uses feature selection technique to identify relevant sensors associated with tasks sensing along the inferred goal path. In other words, it is used for path identification by filtering out relevant features (i.e., sensors associated with detection of tasks that must be performed by the smart home resident in order to successfully satisfy his or her predicted inferred goal by the LSTM-based goal inference unit) from collection of historical IADLs observation sequences stored in the data collection repository. To accomplish this, the numeric dataset representation of the IADLs observation sequences was used as described in [9]. The numeric representation indicates the frequency of each task sensor-values that appeared in an observation sequence detected in smart home environment. For example, the goal path for a normal observation sequence may involve the following sequence of sensor-values: begin, D01-open, D01-close, WT1-open, WT1-close, end. Notice that the sensor ‘D01’ appeared twice in the goal path or sequence, hence, the corresponding numeric representation is recorded as value 2, and sensor WT1 has the value 2. Table 3.4 below represents a snapshot of the numeric format for activity “Drink a glass of water”. In addition, each of the IADLs observation sequences were assigned with corresponding class labels. For example, an IADLs observation that is
normal is assigned the class label “N_ob” while an abnormal observation sequence was assigned with the class label “A_ob” for all observation sequences belonging to each of the four categories of IADLs considered in this study. Table 3.4 is a snapshot of the preprocessed numeric representation of an IADLs category “Drink a glass of water” for the historical observation datasets.

Secondly, feature selection based on filter method given by chi-squared ($\chi^2$) statistical test is then applied to the preprocessed dataset for selection of sensors associated with detection of tasks relevant to the completion of the inferred goal. $\chi^2$ simply measures the absence of independence between the features in the corresponding class label [98]. In other words, it is used for the selection of features (sensors) whose occurrence is dependent on the occurrence of the class label (i.e., relative to the inferred goal). Thus, K best features to be selected for each of the four categories of IADLs observation sequences using the $\chi^2$ statistical test can be specified to identify the sensors or features relevant to the goal path. $\chi^2$ is defined as:

$$\chi^2 = \sum_{k=1}^{n} \frac{(A_k - E_k)^2}{E_k}$$  \hspace{1cm} (ix)

Where:

$A$ – is the observed frequency, i.e number of observations of class
b) Pattern Anomaly Identifier (PAI)

PAI is the second sub-unit of the situ-context generator component of the framework. It is designed to detect anomaly in a goal path or IADLs observation sequence. PAI utilizes a python programming language pattern module called “difflib” that is used for contiguous subsequence matching when comparing pairs of observation sequences. In other words, the PAI module performs a pattern matching operation to compare the normal observation sequence for an inferred goal to the corresponding abnormal observation sequence that is currently being observed to detect any risky behavior or actions in the goal path. A detection of anomaly in the goal path ensures that the aging adult performing the IADLs gets appropriate intervention or recommendation on the choice of action to be taken to mitigate potentially risky situation. Figure 3.4 below indicates an instance of a detected anomaly from abnormal observation sequence of an activity “drink a glass of water”
Notice that water tap (water_o) highlighted with the plus sign “+” was not closed for the activity sequence.

c) **Situ-Context Graph (SG):** is a graphical presentation of inferred human goal as a sequence of situations from observation data generated by the sensor networks in a smart home. Unlike the work of [99] that generates context graph by mapping just the relevant attributes of the activities performed to edges of a graph to define a human context, situ-context graph pre-establishes the plan or procedure that leads to the goal path by identifying subsets of sensor networks that will be interacted with in the performance of the ADL. Figure 3.5 is an example of an SG of inferred goal of a resident who would like to “prepare a tea”. In SG, both the rounded rectangle and non-rounded rectangles are the nodes and they represent concepts, while both the solid and dashed arrows are the edges and represent relationships between concepts. Concepts here may refer to either the human goal or each of the activity sensors in the smart home. The non-rounded nodes also store relevant information such as environmental context (location, time, sensor status and order). The relationships (i.e., edges with labels $B_n$ where $n = 1\ldots j$) on the other hand, define the behavioral contexts (actions) of the inhabitant. Also, note that the nodes connected by the red solid edges define the path that leads to the goal state. This essentially helps to reduce the intricacies of the resident engaging in tasks that are not relevant (i.e., the nodes connected by the green dashed edges) to the satisfaction of their goal at a given time instant. In addition, notice that the nodes also hold the environmental context variables $E_m$ (where $m = 1\ldots k$) that captures relevant context information with respect to the ongoing activities in the environment. The variable $R_h$ (where $h=1\ldots d$) signifies the ranking of the ordering or transition with respect to the task sensors that must be interacted with in the goal path.
3.2.4 Goal Reinforcement Unit

This main objectives of the goal reinforcement unit of the framework are to assist aging adult with decision-making in their IADLs on the appropriate actions to be taken to mitigate potentially risky behavior in the goal path that may constitute an accident in the smart home environment and also to mitigate aging adults’ dependence (i.e., prevent the loss of independence).
on care partner to successfully perform their activities of daily living. Basically, the goal reinforcement unit uses an agent model that takes the context of an observed aging adult performing an IADL into account and then uses persuasive technique (i.e., triggers) to provide recommendation to mitigate a risky behavior in an inferred goal path.

Several human centered applications have employed persuasive techniques to nudge behavior change toward a target behavior. For example, in [93], authors used a persuasive technology to incite a desired behavior. Nonetheless, understanding the factors that may halt a target behavior and how people especially aging adults translate their goals into actions would be of great importance and critical to the success ambient assisted living applications and the field of ambient intelligence [92]. Hence, the goal reinforcement unit follows Fogg’s behavior model (FBM) persuasive design strategies that also combine techniques from control theory in designing of Situ-learning agent that acts as a recommender or teaching agent for decision support to ensure that the smart home resident successfully completes (satisfy) his or her goal.

As mention earlier, this study focuses on people with early-stage dementia. In other words, this category of persons suffers from deterioration in cognitive initiative and performance of IADLs that may cause episodes of confusion or uncertainty that often interferes with their daily life. Confusion is often due to a change in a person’s mental abilities that causes lack of clarity [100]. An aging adult in such a state have difficulty with thinking and will have limited ability to successfully navigate or execute the sequence of tasks required to satisfy his or her goal at that time instant [51]. Despite the possibility that the aging adult may have sufficient motivation (i.e, intrinsic in this case) to satisfy his or her goal, an episode of uncertainty or lack of clarity will impede the fulfilment the target behavior, hence, could predispose the aging adult to a risky or safety critical situation in the smart home environment. To forestall such situation and ensure that
the target behavior happens, a trigger may prove to be useful in nudging the person off state of uncertainty or confusion to enable him to successfully execute the sequence of tasks toward the fulfilment of the inferred goal. In FBM a type of trigger known as “facilitator” is considered an effective tool that ensures that a target behavior comes to fruition by simplifying the set of tasks as long as the person involved has a high level of motivation [93].

For example, given that goal of a person living in a smart home at a particular time is an IADLs of “preparing tea”, therefore, it suffices to say that the person is sufficiently motivated to satisfy his goal because motivation is intrinsic in this case (i.e., he is prompted by either his self-gratification or the need to satisfy his hunger at that time instant). Besides, the person must the sequence of tasks that lead to the goal satisfaction. Suppose that at some point in the course of performance of the activity he experiences an episode of uncertainty with regard to the activity tasks sequence, it therefore implies that the smart home resident no longer possesses sufficient ability required to successfully execute the sequence of tasks toward satisfying his goal. Hence, it suffices to infer that the target behavior or goal has been impeded and this could predispose the aging adult living in the smart home to a risky situation (e.g., stove left on and unattended for too long due episode of uncertainty or forgetfulness). FBM also asserts that simplifying a goal into its subtask increases a person’s ability to accomplish a target behavior, this is because if the approach to performing the goal forces the person performing the activity to think hard, it may lead to cognitive overload and the activity thus become too difficult especially when episode of uncertainty sets it. Therefore, this notion of “goal decomposition” is incorporated into the goal reinforcement component of the framework using automaton for planning of the goal subtasks to enhance early identification of risky situations in the IADL observation sequence [92]. Description
of the functionality and implementation of the goal reinforcement component are discussed in the succeeding paragraphs.

**A. Implementation Goals – Automaton-based Activity Decomposition**

This is an activity modeling step that enhances the detection of anomaly in a goal path. In other words, it refers to the decomposition of IADLs observation sequence into its corresponding actionable sub-processes or task sequences that lead toward the goal satisfaction. This decomposition is essential as it provides the situ-learning agent (SLA) with more context information with respect to the component steps or procedures that must be performed toward the fulfilment of the goal. Hence, SLA can anticipate actions that may constitute a risk or safety critical task and consequently recommend appropriate actions to mitigate a potential risky situation when the smart home resident suffers episode of uncertainty due to deterioration in his or her IADLs cognitive initiative and performance. The activity modeling technique used is based on the efficacy and robustness of automata which has been widely used in many pattern recognition and activity modeling applications [33, 34]. Thus, an automaton activity decomposition of the activity plan presented by SG into sequence of tasks corresponding to each inferred goal can be generated as shown in Figures 3.6, 3.7, 3.8, and 3.9. Each automaton state diagram shows the possible transition choices or path that can be undertaken by the naïve agent (i.e., the agent simulating possible interaction of an aging adult with deteriorated IADLs cognitive initiative and performance) in the course of carrying out each of the four IADLs. Essentially, the task sequences involved in each of the goal path are constructed by using the possible values of the interacting activity sensors that describe the inferred goal as discussed in the succeeding paragraphs.
Figure 3.6. Automaton State Diagram Modeling the Decomposition of an Inferred Goal Label “Prepare tea”

Figure 3.7. Automaton State Diagram Modeling the Decomposition of an Inferred Goal Label “Prepare hot chocolate”.
Figure 3.8. Automaton State Diagram Modeling the Decomposition of an Inferred Goal Label “Drink a glass of water”

Figure 3.9. Automaton State Diagram Modeling the Decomposition of an Inferred Goal Label “Prepare hot snack”

For illustration, Figure 3.6 above depicts an automaton state diagram that models the decomposition of IADLs state sequence that characterizes the goal identified as “prepare tea” into its corresponding sub-tasks sequence. The goal path involves five main states with the following
corresponding states labels: D01, WT1, KT, D05, and D06. D01 depicts the start state and the accept state (i.e., end state of the activity), hence denoted with by the concentric circles. The transitions from one state to another indicated by the arrows are referred to as situ-transitions (or simply transitions). The inputs to the automaton are the sets of actions / tasks that must be performed by the resident of the smart home in each of the states or situations defining the goal path. The output on the other hand, represents either the accept state (i.e., when the goal is successfully completed or has been satisfied) or reject state (i.e., when the goal was not successfully completed or has not been satisfied). Also notice from the automaton state diagram in Figure 3.6 that it is made up of two distinct transition arrows (i.e., solid and dash arrows). The part of automaton state diagram with the solid transition arrows only represents a finite automaton (FA) model of the goal execution by an aging adult who does not suffer from deteriorated IADLs cognitive initiative and performance caused by ED, while the part of the automaton state diagram that consisted of both the solid and dash transition (the dash arrows are bi-directional) arrows represents a nondeterministic finite automaton (NFA) model of the goal execution by an aging adult with deteriorated IADLs cognitive initiative and performance (see Table 3.5). Therefore, the NFA can be used to simulate or depict episodes of uncertainty or poor decision-making triggered by deteriorated cognitive initiative and performance that may could predispose a person to life-threatening injuries or accidents in course of performing an IADLs.

In addition, each of the five states has state labels that correspond to $S_1$, $S_2$, $S_3$, $S_4$, and $S_5$, respectively. The state labels are referred to as a sequence of situations that characterizes an intention path $I= <S_1, S_2, S_3, S_4, S_5>$, in other words, goal can be inferred from intention path. Each of the situations represents an activity that is made up of subtasks in the goal path. For example, situation $S_1$ describes an activity D01 that is composed of two main subtasks vis a vi: “OPEN” and
“CLOSE” tasks. Therefore, the equivalent tasks sequence for the same goal may be characterized as follows:

\[[S_1\text{OPEN} \rightarrow S_1\text{CLOSE}] \rightarrow [S_2\text{OPEN} \rightarrow S_2\text{CLOSE}] \rightarrow [S_3\text{ON}] \rightarrow [S_4\text{OPEN} \rightarrow S_4\text{CLOSE}] \rightarrow [S_5\text{OPEN} \rightarrow S_5\text{CLOSE}] \rightarrow [S_3\text{OFF}]\]

Table 3.5. Nondeterministic Finite Automaton State Transition Table Indicating Episodes of Uncertainty for the Goal Label “Prepare tea”

<table>
<thead>
<tr>
<th></th>
<th>OPEN</th>
<th>CLOSE</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>S_1</td>
<td>S_1, S_2</td>
<td>S_2, S_1</td>
<td>n / a</td>
<td>n / a</td>
</tr>
<tr>
<td>S_2</td>
<td>S_2, S_1, S_3</td>
<td>S_3, S_2, S_1</td>
<td>n / a</td>
<td>n / a</td>
</tr>
<tr>
<td>S_3</td>
<td>n / a</td>
<td>n / a</td>
<td>S_4, S_2</td>
<td>S_1, S_2, S_4</td>
</tr>
<tr>
<td>S_4</td>
<td>S_4, S_3, S_5</td>
<td>S_5, S_4, S_3</td>
<td>n / a</td>
<td>n / a</td>
</tr>
<tr>
<td>S_5</td>
<td>S_5, S_4</td>
<td>S_3, S_4</td>
<td>n / a</td>
<td>n / a</td>
</tr>
</tbody>
</table>

Table 3.6. Finite Automaton State Transition Table the Normal Transition Steps or Task Sequence for the Goal Label “Prepare tea”

<table>
<thead>
<tr>
<th></th>
<th>OPEN</th>
<th>CLOSE</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>S_1</td>
<td>S_1</td>
<td>S_2</td>
<td>n / a</td>
<td>n / a</td>
</tr>
<tr>
<td>S_2</td>
<td>S_2</td>
<td>S_3</td>
<td>n / a</td>
<td>n / a</td>
</tr>
<tr>
<td>S_3</td>
<td>n / a</td>
<td>n / a</td>
<td>S_4</td>
<td>S_1</td>
</tr>
<tr>
<td>S_4</td>
<td>S_4</td>
<td>S_5</td>
<td>n / a</td>
<td>n / a</td>
</tr>
<tr>
<td>S_5</td>
<td>S_5</td>
<td>S_3</td>
<td>n / a</td>
<td>n / a</td>
</tr>
</tbody>
</table>

Table 3.6 depicts the normal transition steps or task sequences toward the satisfaction of the goal “Prepare tea” given that the person does not suffer episode of uncertainty or confusion that. The transition steps involves the person moving from one situation or state to another to satisfy his or her goal based on the task / action that needs to be performed in each of the situation sequence as detected by the sensors associated with each of the states. When the person performing the activity is in state S_1 and he or she performs an action OPEN on the kitchen door, he will gain entry into the kitchen but will remain in S_1 (this time he will be at the rear of the door). If the action OPEN taken in S_1 is then succeeded by an action of CLOSE, he will move to state S_2. Similarly,
when in S₂ and an action OPEN is performed, it is expected that he stays in S₂ because moving to the next state S₃ may constitute a risky state leading to slip or fall accident (flooded kitchen or wet floor) if he forgets to close the water tap and it is left opened for too long (indicated by the values in the cell intersecting state S₂ and action OPEN in Table 3.5) [100]. Hence, the appropriate action to be taken before transiting to state S₃ is a CLOSE action. When in S₃ and an action ON is performed, he will move to S₄. However, suppose that the person experiences an episode of forgetfulness or lacks clarity on the next appropriate action to be taken, he may decide to move to S₂, and afterward to S₁, and eventually exits the kitchen as represented by the values in the cell intersecting row S₃ and column ON in Table 3.5. Such scenario may constitute a hazardous state if the water in the kettle eventually dries up and the stove is not turned OFF; this may lead to a fire outbreak in the smart home which could be life threatening. In state S₄, if the person performs an action OPEN, he will remain in state S₄ until that is succeeded by an action CLOSE before moving to S₅. Similarly, if in S₅, and an action OPEN is performed, he will need to perform an action CLOSE to transit to S₃. Finally, when in S₃, an OFF action must be performed to transit to S₁, at which point we say that the goal has been satisfied. Note that the cells with “n/a” values indicate that the actions are not applicable to the corresponding situations.

B. Situ-Learning Agent (SLA)

In sequential decision-making, uncertainty arises often due to the dearth of information on the choices (now or in the future) or the probability distributions of outcomes of actions [65]. Agent-based models can be very useful in such situations as they possess the requisite intelligence to cope with uncertainty when they are aware of the goal and the decisions interaction [62, 65]. Hence, agent-models can transform goals into action tasks [103]. This attribute is largely
responsible for their wide application in several human-centered research especially in studying and understanding emergent behaviors in social systems.

The main objective here is to support an older adult with deteriorated IADLs cognitive initiative and performance with decision-making especially in safety-critical situations (i.e., a situation that could compromise safety of the smart home resident when critical task or step is missed during the performance of an IADLs e.g., forgetting to turn-off the stove) when he or she suffers episode of forgetfulness or lacks clarity on how to successfully navigate the goal path. Thus, a situ learning agent is proposed that can anticipate the risk associated with the action taken by the smart home resident in a goal path, and consequently recommends an appropriate action to mitigate a potential risk to ensure that the goal is satisfied or fulfilled. First, SLA uses the concept of Situ – a cluster of probabilistic inference models to characterize the human situation or a person’s mental state over time [16] (Situ architecture is shown in Figure 3.10). Secondly, though SLA is an adaptation of a type of reinforcement learning systems otherwise referred to as learning automata or model learning [63, 64, 156] that is known to be efficient for modeling situations in an environment characterized by uncertainty, an additional attribute or learning heuristic was introduced. Some application areas of model learning based reinforcement learning systems include environments with incomplete knowledge or uncertainty (e.g., episode of uncertainty or confusion expressed by person with deteriorated cognitive initiative to perform an IADLs), as well as for the understanding of embedded control software [63, 64]. Thus, this type of agent can recommend appropriate actions by pursuing or learning actions currently perceived to be optimal among possible set of actions or choices provided in a probabilistic environmental context [104].
A second agent called naïve agent was also contrived to simulate deteriorated IADLs cognitive initiative in a person with ED who may suffer episodes of uncertainty when performing IADLs. The aim is to show how SLA can offer support for decision-making by recommending appropriate action to the naïve agent in situations of uncertainty to ensure that the naïve agent successfully satisfy its goal.
The SLA possesses the following attributes defined by four parameters \( <M, B, E, Q> \).

\( M \) is a vector defined by two-tuple \( <P(t), \hat{D}(t)> \), it keeps track of the human desire (i.e., the naïve agent’s) in situation or state \( S \) for goal \( G \). \( P(t) \) is an action selection probability vector, such that \( p_i(t) \) is the probability that an \( i \)\textsuperscript{th} action will be taken by the naïve agent in a state or situation \( s_i \). Note that \( \sum_i^n p_i = 1 \). \( B \) is a set of possible actions (i.e., \( r \) actions) that the naïve agent can choose from, that may satisfy \( s_i \) in goal path \( G \). An action chosen or taken is represented as \( \alpha(t) = \alpha_i \).

Also, \( \alpha(t) \in B \) for all \( t \) and \( E \) is a set \( <R, D> \). Suppose \( R = \beta(t) \), where \( R \) is the reward or penalty for an action taken in situation \( S_i \). An action is rewarded with a point value of 1 if it is the appropriate choice, otherwise it is penalized with a value 0 (i.e., \( R = \{1, 0\} \)). In other words, \( \beta(t) \)
is the response from the environment. \( \hat{D} \) is a set \{\( d_1, d_2, ..., d_r \)\}. \( d_i(t) \) is the probability that an action \( \alpha_i \) will be rewarded.

It is also assumed that the SLA uses a contrived heuristic \( Q \) (otherwise referred to as trigger), to identify the safety-critical state \( s_i \), and then, and the computes the best choice of action \( \alpha(t) \) from among \( B \) for the naïve agent. It is based on its knowledge of an action priority vector \( H \) generated by the environment, such that, it prioritizes the best action (correct choice of action) for the state with the anomaly higher than other action choices for that state. In other words, each action is assigned a value \( h_i \), where \( h_i \) for the best \( \alpha_i \) is maximal. Hence, apart from attribute \( Q \), naïve agent has other attributes as SLA. Algorithm 1 below shows coordination of the of the SLA and naïve agent for choosing an action \( \alpha_i \) for \( s_i \) in the goal path \( G \). Note that in this dissertation, \( G \) is used to denote both goal and goal path. That is, a goal path \( G \) is a path leading to the goal \( G \).

**Algorithm 1: A SLA, Naïve Agent Coordination Algorithm**

**Input**: an evenly matched reward probability vector \( \hat{D}(t) \), action probability vector \( P(t) \), action priority vector \( H \), and Situation Sequence \( S \), such that \( \hat{d}_i \) for \( \alpha_i \) is not optimal at situation \( s_i \) for goal path \( G \)

**Output**: an optimal \( \alpha_i \) whose \( \hat{d}_i \) is maximum, and \( p_i \) is also maximum at situation \( s_i \) in goal path \( G \)

**Initialization**:

1. Add input states or situation sequence for goal \( G \);
2. Initialize action priority \( H \) vector
3. \( p_i(t) = 1/w \), Such that \( w \) is the number of action choices that naïve agent can choose from at \( s_i \).
4. \( \hat{d}_i(t) = 1/2 \)
5. Set \( x_i = y_i = 0 \).

**Method**:

**For** \( t = 1 \) to \( K \) \( Do \)

1. Naïve agent choose an action \( \alpha(t) \) randomly according to the action selection probability vector \( P(t) \). Given that \( \alpha(t) = \alpha_i \).
2. Update $x_i(t)$ and $y_i(t)$ using the Bayesian attribute of the conjugate distributions, in accordance with the response or feedback from the environment:

3. Set $x_i = y_i = 0$.

   If $R(t) = 1$ Then $x_i(t) = x_i(t - 1) + 1; y_i(t) = y_i(t - 1)$
   Else $x_i(t) = x_i(t - 1); y_i(t) = y_i(t - 1) + 1$

4. For each action $i$, determine the upper 95% reward probability bound of $d_{i}(t)$ as:

   $$\int_{0}^{d_{i}(t)} v^{(x_{i}-1)} (1 - v)^{(y_{i}-1)} dv$$

   $$\int_{0}^{1} u^{(x_{i}-1)} (1 - u)^{(y_{i}-1)} du = 0.95$$

5. Use the linear discretized rule defined below to update the action probability vector $P(t + 1)$:

   If $R(t) = 0$ Then
   $$p_n(t + 1) = \max(p_n(t) - \delta, 0), n \neq m$$
   $$p_m(t + 1) = 1 - \sum_{n \neq m} p_j(t + 1)$$
   Else
   $$P(t + 1) = P(t)$$

   **End:**

   where:

   * $G$: is the predicted goal which has a defined path or situation sequence

   * $s_i$: is the $i$th situation or state of the observed situation sequence defining the goal path of $G$

   * $\alpha$: is the action chosen by the naive agent

   * $H$: is the action selection priority vector generated by the environment, where $h_i$ assigned to the optimal $\alpha_i$ is maximum.

   * $x_i, y_i$: are the Beta distribution's two positive parameters for action $i$. 

---

**SLA:** On naive agent's choice in step 1, run $Q$ to determine the best $\alpha(t)$ for $s_i$ as:

$$\max(H)$$
\( p_i \) is the \( i \)th item of \( P \) (i.e., the action selection probability vector)

\( \hat{d}_i \) is the \( i \)th item of the Bayesian estimates vector \( \hat{D} \), which is derived by the 95% upper bound of cumulative distribution function (cdf) of the corresponding Beta distribution.

\( m \) indicates the index of the element of the reward probability estimates \( \hat{D} \) that is the maximum.

\( R \) is the reward or penalty from the environment for an action taken.

\( \alpha \) is a value that represents the minimum step size. It is chosen randomly from the range (0, 1).

### 3.3 Case Study

The case study used in dissertation is based on the “memory abilities and dementia in older adults” IADLs datasets of an observed single user in a smart home lab [9]. The smart home lab has a living room and a kitchen. Table 3.1 above gives a description of the sensors in the smart home and the functions. IADLs observation instances datasets for four categories of IADLs were considered namely: “prepare tea”, “prepare a hot chocolate”, “drink a glass of water”, and “prepare a hot snack”. Each category of the IADLs observation instances consisted of both normal and abnormal observation instances. Abnormal observation instances are anomalous observation sequences (i.e., with missed tasks or deviations in the goal path) due to deterioration in IADLs initiative and performance. A description of normal instances of normal IADLs observation sequences is presented in Table 3.7 below.
Table 3.7. Description of Instances of Normal IADLs Observation Sequences

<table>
<thead>
<tr>
<th>ID</th>
<th>IADLs / Goal</th>
<th>Description of Instances of Normal IADLs Observation Sequences</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Prepare a tea</td>
<td>1) enter the kitchen, 2) fetch some water into the kettle, 3) turn kettle on, 4) get the cup from the glasses cupboard, 5) get tea bag from the pantry cupboard, 6) put the tea bag into the cup, 7) pour some hot water from the kettle into the cup</td>
</tr>
<tr>
<td>2</td>
<td>Prepare a hot chocolate</td>
<td>1) enter the kitchen, 2) take milk from the fridge, 3) take a cup from the glasses cupboard, 4) pour milk into the cup, 5) heat it on the stove, 6) take the chocolate from the pantry cupboard, 7) puts some chocolate into the cup</td>
</tr>
<tr>
<td>3</td>
<td>Drink a glass of water</td>
<td>1) enter the kitchen, 2) take a cup from the glasses cupboard, 3) fill the cup with water from the tap</td>
</tr>
<tr>
<td>4</td>
<td>Prepare hot snack</td>
<td>1) enter into the kitchen, 2) get a plate from the serving plate cupboard, 3) collect the food from the fridge, 4) cook the food on the stove, 5) get the silverware from the cutlery cupboard</td>
</tr>
</tbody>
</table>

Also, Table 3.8 below highlights the sensors involved in the performance of each of the IADLs and characterizes the normal execution plan of an observed user (i.e., interaction benchmarks) without deteriorated cognitive initiative to perform IADLs from historical observation datasets. Although, the order of the sensors is not absolute as human behaviors are dynamic. In addition, ‘A’ indicates that a sensor is applicable or involved in an IADLs while ‘NA’ implies that the sensor is not applicable or not required. ‘O’ implies that it is optional. But for this experiment, we consider ‘O’ as not required.
3.3.1 Implementation Toolkits for Experiments

For the rest of this chapter except otherwise stated, the implementation toolkits used for this case study include:

a) Anaconda Individual Edition (AIE): AIE formerly known as anaconda distribution, is an open-source platform that provides an easy-to-use environment to perform Python data science, artificial intelligence, and machine learning related projects on a single machine. It offers users with thousands of machine learning and deep learning open-source packages and libraries that can be accessed through its cloud-based repository. AIE is an adaptable framework that provides the utilities to develop, distribute, install, update, and manage software in a cross-platform approach. Due to its open source conda, it allows users to
easily manage multiple data environments that can be maintained and run independently without interfering with each other. Therefore, it is an effective tool for building machine learning models as it also supports best Python packages built by the open-source community, including scikit-learn

b) **Keras:** This is an API that is mainly used for specifying and training differentiable programs that are found to be useful in many scientific computing and artificial intelligence projects [105, 158]. In other words, it is an open-source deep neural network library that supports easy productization of convolution neural networks, recurrent neural networks, and or a combination of both models [158, 159]. Keras is also a multi-backend and multi-platform API and it runs seamlessly on central processing unit (CPU) and graphics processing unit (GPU).

c) **Theano:** This is a Python library that compiles mathematical expressions such as multi-dimensional arrays (i.e. matrix-valued expressions) into machine language that runs efficiently on CPU and GPU architectures [160, 161]. Theano has been widely used for implementations of expressions related to machine learning with neural networks because it is fast and efficient. Thus, in this study, Theano is used as backend for my experiment’s environmental setup [160, 161].

d) **Scikit-learn:** Scikit-learn also known as sklearn is a free Python module that integrates a wide range of machine learning algorithms used for supervised and unsupervised learning problems. It is implemented in such a way that it interoperates seamlessly with the Python scientific and numerical libraries (i.e., SciPy and NumPy) [162, 163, 164].

e) **Python:** Python is the programming language used for the code implementation. It is a high-level, object-oriented, interpreted, and general-purpose programming language that
strongly emphasizes code readability [166]. It has become increasingly popular choice for algorithmic development, machine learning, data science because of its robust scientific libraries that enhances productivity and performance [165, 166].

3.3.2. Experimental Procedures for Goal Inference in IADLs Datasets Using LSTM

To investigate the efficacy of the LSTM model for inferring human goal in smart home environments based on the goal inference unit of the proposed framework, an experiment was conducted by building an LSTM model that is fed with the preprocessed IADLs observations datasets discussed in section 3.2.1b as inputs. First, the datasets were split into train and test sets in the ratio 30 to 70, respectively. Also, to optimize the LSTM networks parameters, an efficient Adam gradient descent optimizer with a logarithmic loss function, known as “categorical_crossentropy” in Keras was applied. Further, both dropout and recurrent dropout regularization were applied at the rate of 0.5, respectively. The model also uses a dense LSTM layer with 64 neurons in the hidden layer and 4 neurons in the output layer with a softmax activation function. The batch size specified is 64, an epoch value of 7, and an embedding dimension size of 128. In addition, two variants of the LSTM model were evaluated and compared to examine the impact of recurrent dropout on their predictive performance.

Summarily, a person’s goal can be inferred by feeding an instance of an abnormal IADLs observation sequence into the optimally trained model such that the output of the LSTM model will be assigned the appropriate or corresponding class label (e.g., prepare tea). The results obtained are shown in Table 3.9 and Table 3.10, respectively.
Table 3.9. LSTM Model Predictive Performance on Each of The IADLs Categories

<table>
<thead>
<tr>
<th>Inferred Goal Id</th>
<th>Inferred Goal</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Prepare tea</td>
<td>72.0%</td>
<td>100.0%</td>
<td>84.0%</td>
</tr>
<tr>
<td>2</td>
<td>Prepare a hot chocolate</td>
<td>100.0%</td>
<td>60.0%</td>
<td>75.0%</td>
</tr>
<tr>
<td>3</td>
<td>Drink a glass of water</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
<tr>
<td>4</td>
<td>Prepare hot snack</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Table 3.10. Results of LSTM Models Predictive Performances

<table>
<thead>
<tr>
<th>LSTM Models</th>
<th>Accuracy</th>
<th>Mean Precision</th>
<th>Mean Recall</th>
<th>Mean F1- Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSTM with recurrent dropout</td>
<td>90.1%</td>
<td>90.0%</td>
<td>90.0%</td>
<td>90.0%</td>
</tr>
<tr>
<td>LSTM with no recurrent dropout</td>
<td>73.0%</td>
<td>62.0%</td>
<td>75.0%</td>
<td>66.0%</td>
</tr>
</tbody>
</table>

From the results shown in Table 3.10, the LSTM model with recurrent dropout regularization outperforms the LSTM model without recurrent dropout. This implies that recurrent dropout can improve LSTM model performance significantly, and this can be very useful in dynamic environments such as the smart home where context information or dependencies may be missing due to sensor failure and are essential for decision making. In addition, some related work that investigated the application of HMM and CRF were examined for comparison. For example, in [106], authors reported the following accuracy scores: 64.9%, 71.0% and 68.3% for
HMM model prediction performance on observation datasets for morning, afternoon, and evening time, respectively. However, authors in [107] evaluated the predictive performance of four different models that include Naïve Bayesian Classifier (NBC), HMM, Hidden semi-Markov Model (HSMM) and CRF for human activities or goal inference. They reported the following predictive accuracy scores 78.4%, 70.0%, 70.9%, and 81.8% for each of the optimally trained models, respectively. While I acknowledge that the experimental settings for the results obtained by these authors may differ in some aspect, nonetheless, the accuracy score obtained for the optimally trained LSTM model with recurrent dropout reported in Table 3.10 is quite significant and better. In addition, its mean precision, recall, and F1-score also indicated that the LSTM model performed well with predicting goals with similar subsequences. I plan to further investigate the performance of HMM and CRFs models using the same experiment and environment settings that is used for building the LSTM model in this dissertation for a more balanced comparison.

3.3.3. Experimental Procedures for Feature Selection

As discussed earlier in section 3.2.3(a), the situ-context generator uses feature selection algorithm to identify relevant sensors associated with tasks sensing along the inferred goal path. Thus, in this section, a filter-based feature selection algorithm characterized by chi-squared ($\chi^2$) statistical test was implemented and applied to the datasets described in section 3.2.3(a). The filter-based feature selection algorithm measures the absence of independence between the features in the corresponding class label [98]. In other words, it is used for the selection of features (sensors) whose occurrence is dependent on the occurrence of the class label (i.e., relative to the inferred goal). Thus, K best features to be selected for each of the four categories of IADLs observation sequences can be specified to identify the sensors or features relevant to the goal path. The results
obtained for each of the four categories of inferred goals are presented in Tables 3.11, 3.12, 3.13, and 3.14, respectively.

Table 3.11. Selected Features for Inferred Goal Label “Prepare Tea”

<table>
<thead>
<tr>
<th>Selected Features</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>WT1</td>
<td>131.517</td>
</tr>
<tr>
<td>D01</td>
<td>3.317</td>
</tr>
<tr>
<td>D05</td>
<td>0.033</td>
</tr>
<tr>
<td>D06</td>
<td>0.031</td>
</tr>
<tr>
<td>KT</td>
<td>0.025</td>
</tr>
</tbody>
</table>

Table 3.12. Selected Features for Inferred Goal Label “Prepare a Hot Chocolate”

<table>
<thead>
<tr>
<th>Selected Feature</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>D07</td>
<td>189.574</td>
</tr>
<tr>
<td>D08</td>
<td>189.574</td>
</tr>
<tr>
<td>D01</td>
<td>70.157</td>
</tr>
<tr>
<td>D05</td>
<td>0.044</td>
</tr>
<tr>
<td>D06</td>
<td>0.016</td>
</tr>
</tbody>
</table>

Table 3.13. Selected Features for Inferred Goal Label “Drink a Glass of Water”

<table>
<thead>
<tr>
<th>Selected Feature</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>WT1</td>
<td>150.000</td>
</tr>
<tr>
<td>D01</td>
<td>21.543</td>
</tr>
<tr>
<td>D05</td>
<td>0.026</td>
</tr>
</tbody>
</table>
Table 3.14. Selected Features for Inferred Goal Label “Drink a Glass of Water”

<table>
<thead>
<tr>
<th>Selected Feature</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>D07</td>
<td>202.955</td>
</tr>
<tr>
<td>D01</td>
<td>0.036</td>
</tr>
<tr>
<td>D04</td>
<td>0.023</td>
</tr>
<tr>
<td>D08</td>
<td>0.018</td>
</tr>
<tr>
<td>D03</td>
<td>0.012</td>
</tr>
</tbody>
</table>

Tables 3.11, 3.12, 3.13, and 3.14 above presents the relevant features (i.e., task sensors) that the smart home resident is required to interact with toward the satisfaction or fulfilment of his or her inferred goal. The scores suggest that the features selected have significant relationship (i.e., contributes more to the target outcome than the remaining features or sensors present in the smart home environment) for the predicted or inferred goal. Therefore, the feature selection algorithm will discard any feature whose value is zero. This implies that such feature will not be considered in the situ-context graph (as shown in Figure 3.5) for the inferred goal. Therefore, the results obtained emphasizes the plausibility of generation of a pre-planned automated goal path in smart home environments by identifying locations of relevant sensors associated with the detection of corresponding tasks sequences.

3.3.4 Experimental Procedures for Goal Reinforcement Unit

In this experiment, I show how Agent models can be helpful to support aging adults with ED to avert risky situations in the performance of their goal. This is shown by simulating two interacting agents: SLA referred to as the teacher / recommender agent, and a naïve agent that representing a person with deteriorated IADLs cognitive initiative and performance. Give an
anomalous goal sequence performed by a naïve agent, an SLA can provide a cue or recommend appropriate actions to the naïve agent in situations that may constitute a risk.

Table 3.15. Some Safety-critical Situations in The Four IADLs Observation Sequences

<table>
<thead>
<tr>
<th>Normal observation sequence</th>
<th>Abnormal observation sequence</th>
<th>Safety-critical situations</th>
<th>Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>begin, door_o, door_c, water_o, water_c, kettle_on, cupboard_o, cupboard_c, pantry_c, kettle_off, door_c, end</td>
<td>begin, door_o, door_c, water_o, water_c, kettle_on, cupboard_o, cupboard_c, pantry_c, kettle_on, door_c, end</td>
<td>Kettle was not turned “off” at the end of the activity for abnormal observation sequence. Hence, may constitute a risk.</td>
<td>Prepare tea</td>
</tr>
<tr>
<td>begin, door_o, door_c, fridge_o, fridge_c, cupboard_o, cupboard_c, stove_on, pantry_o, pantry_c, stove_off, door_o, door_c, end</td>
<td>begin, door_c, door_o, door_c, fridge_o, fridge_c, cupboard_o, cupboard_c, stove_on, pantry_o, door_o, door_c, end</td>
<td>Stove was not turned “off” at the end of the activity for abnormal observation sequence thereby constituting a risk.</td>
<td>Prepare hot chocolate</td>
</tr>
<tr>
<td>begin, door_c, door_o, door_c, cupboard_o, cupboard_c, water_o, water_c, door_o, door_c, end</td>
<td>begin, door_o, door_c, cupboard_o, cupboard_c, water_o, water_c, water_o, door_o, door_c, end</td>
<td>Water tap was not “closed” at the end of the activity. Hence, may constitute a risk</td>
<td>Drink a glass of water</td>
</tr>
<tr>
<td>begin, door_c, door_o, door_c, dishes-cupboard_o, dishes-cupboard_c, fridge_o, fridge_c, stove_on, cutlery-cupboard_o, cutlery-cupboard_c, stove_off, door_o, door_c, end</td>
<td>begin, door_o, door_c, dishes-cupboard_o, fridge_o, dishes-cupboard_c, fridge_c, stove_on, cutlery-cupboard_o, stove_on, cutlery-cupboard_c, door_o, door_c, end</td>
<td>Stove was not turned “off” at the end of the activity for abnormal observation sequence. Therefore, may constitute a risk.</td>
<td>Prepare hot snack</td>
</tr>
</tbody>
</table>

I demonstrate this by considering instances of all four categories of IADLs observation situations sequences with potential risky situations. Table 3.15 above describes the safety-critical
situations in each of the IADLs observations sequences considered in this experiment. Each safety-critical situation represents a missed task during IADLs, hence the need for SLA to recommend appropriate action to the naïve agent in such situation to avert potential danger that may arise from such anomaly or deviations. The procedure describing this experiment is discussed in the succeeding paragraphs.

First, I ran the simulation experiments to show how SLA can assist with decision-making in smart home environment by recommending appropriate actions to naïve agent its action or behavior may constitute a safety-critical situation that could lead to life-threatening injuries or accident if timely intervention is not provided. Consider a situation <Sit₃> that may constitute a risky or safety-critical situation (e.g., not turning “off” the kettle detected by the kettle sensor i.e., KT) in the goal path characterized by the situation sequence <Sit₁, Sit₂, Sit₃, Sit₄, Sit₅> for IADLs activity label “prepare tea” described in Table 3.15. To simulate an episode of lack of clarity or forgetfulness with respect to the appropriate action to be taken by the naïve agent in such situation, five possible choices of actions (i.e., door_o, water_c, kettle_off, cupboard_c, pantry_c) corresponding to the sensors detecting each of the actions including the missed task for kettle sensor in <Sit₃> and those relating to tasks in both the preceding and succeeding situations to the safety-critical situation would be presented to the naïve agent to choose from. Although, for IADLs activity label “Drink a glass of water” with 3 states given as <Sit₁, Sit₂, Sit₃>, 3 possible choices of actions were presented to the naïve agent. Each of these actions have action selection probabilities and reward probabilities. The action selection probabilities represent the probability of each action (possible choices) being chosen by the naïve agent, while reward probabilities represent the probabilities that the corresponding actions chosen will be rewarded. To avoid biases, both the action probabilities and reward probabilities have equal values at the initialization stage.
Also, note that the sum of the action selection probabilities is approximately equal to 1. Finally, the following assumptions were made:

1. The reward probability represents the motivation of that makes a person for wants to perform a task. It is the probability that if an action \( \alpha(t) \) is taken in \( s_t \), it will be rewarded (i.e., satisfy the goal path)

2. The naïve agent will respond positively to the SLA’s trigger (facilitator) \( Q \), which recommends the best action for state \( s_t \)

The results obtained are shown in Table 3.15 below.

Table 3.16. Results of the Action and Reward Probabilities for Optimal Action

<table>
<thead>
<tr>
<th>Goal ID</th>
<th>Threshold</th>
<th>Action probabilities at initialization</th>
<th>Action probabilities at convergence</th>
<th>Reward probabilities at initialization</th>
<th>Reward probabilities at convergence</th>
<th>Number of Iteration</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.95</td>
<td>0.20, 0.20, 0.20, 0.20</td>
<td>0.01, 0.01, 0.96, 0.01</td>
<td>0.50, 0.50, 0.50, 0.50</td>
<td>0.50, 0.50, 0.99, 0.50</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>0.95</td>
<td>0.20, 0.20, 0.20, 0.20</td>
<td>0.01, 0.01, 0.96, 0.01</td>
<td>0.50, 0.50, 0.50, 0.50</td>
<td>0.50, 0.50, 0.99, 0.50</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>0.95</td>
<td>0.33, 0.33, 0.33</td>
<td>0.02, 0.02, 0.96</td>
<td>0.50, 0.50, 0.50</td>
<td>0.5, 0.50, 0.99</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>0.95</td>
<td>0.20, 0.20, 0.20, 0.20</td>
<td>0.01, 0.01, 0.96, 0.01</td>
<td>0.50, 0.50, 0.50, 0.50</td>
<td>0.50, 0.50, 0.99, 0.50</td>
<td>1</td>
</tr>
</tbody>
</table>

From Table 3.16, at convergence, the action probability corresponding to the appropriate or optimal action (i.e., kettle_off in the case of \(<\text{Sit}_3>\) for IADLs label “Prepare tea”) choice is maximum, and also exceeds the specified threshold of 0.95. Also, its corresponding reward probability is also maximum. Therefore, it suffices to conclude that SLA’s recommendation is
accurate, if the reward probability $d_i(t)$ of the action chosen $\alpha(t)$ is maximum and its action selection probability is also maximum at convergence (i.e., greater than the threshold). The number of iterations corresponds to the number of runs or steps it took the SLA to determine which action is appropriate or optimal in safety-critical situation. Hence, the results show that situ-learning agent has the potential to support decision-making by recommending appropriate action in safety-critical situations detected in a goal path.
CHAPTER 4. SITU-SAFE: A SITUATION-DRIVEN SAFETY MODEL FOR RISK MITIGATION IN IADLS

4.1 State of The Art

The recent surge of interest in the demography of older adults is due to the steep rise in aging adult dependency ratio and an estimated 47 million people living with dementia globally [5, 112]. This category of people is highly predisposed to accidents and injuries in IADLs especially fall and fire accidents which account for 18% to 25% of accidents among the older adults living independently [20, 29, 112]. It has been estimated that 30% of seniors older than 65 years fall each year and 30% die of fire accident in home respectively [112, 113] while it has also been projected that the costs of maintaining seniors in retirement homes would almost double in the next 35 years with a steep drop in the number of caregivers expected [5]. These have provoked the attention of researchers from diverse disciplines to seek efficient solutions that is adaptable to the changing needs and safety of aging adults in their IADLs [18, 28].

The related research or solutions that target safety of seniors with early-stage dementia (ED) in activities of daily living (ADLs) in smart home environments are limited. Our findings from related works show that existing solutions for safety of seniors in smart home environments often address these risks from two main perspectives namely: a) behavior deviation detection (BDD) and b) smart space partitioning (SSP). The main concern with both safety approaches is that they focus on the risks associated with ADLs at coarse-grained level (e.g., “prepare a hot snack”). Considering that instrumental activities of daily living (IADLs) which include more complex activities that typically comprised of different skills which requires sequence of action, awareness and direction needed towards achieving the intended goal [24], and the impact of ED on the memory of seniors which limits their judgment and causes episode of uncertainty or forgetfulness [20, 21], BDD and SSP thus neglect the need to assess the ability of seniors to
perform IADLs independently [5, 22, 23]. These situations predispose seniors to the major risks during IADLs.

For example, authors in [111] and [97] adopted a behavior deviation detection method in their work. Specifically, [97] proposed an anomalies recognition and assistance provision system that relied on fuzzy temporal data-driven approach. They defined each activity as a fuzzy conceptual structure represented as a hierarchy of concepts in smart home environments. Current activity being observed sits at the base while the “normal world generic function,” which represents what the normal world should be like, sits at the top of the hierarchy. Fuzzy symmetrizer is then used to infer any deviation anomaly by computing the similarity degrees of an observed activity to the normal world using fuzzy symmetrizer. However, the drawbacks of this approach include – i) Overgeneralization, since not all behavior deviation may constitute a risk (e.g., leaving the kitchen door opened) thus an intervention to reverse such deviation (either by a resident caregiver or automated assistance) based on the degree of similarity may be overly intrusive and impugn seniors independence, and ii) Underestimation, in other words, a supposed prompt intervention by a resident caregiver to assist the senior in shutting the kitchen door may be considered by senior as an interference rather than intervention if he/she is aware of that the action performed is non-risky. Similarly, [27] developed an automated system that uses a Markov chain model to detect abnormal patterns in the activities of daily living of an aging adult by analyzing the probability distribution of the spatiotemporal data of the activity being performed. This system also suffers similar drawbacks as in [111] and [97].

On the other hand, [22], [19] and [28] employed smart space partitioning methodology to enhance the safety of seniors with ED in smart home environments. In [19], an activity tracking and monitoring system was proposed to detect risky situations and trigger alert that sends
notification to care partner for possible intervention. The overall idea of this approach is to partition the smart home environment into safe and unsafe partitions using Kinect sensors. Thus, if a senior is detected to have stayed too long in the unsafe region of the smart home environment, a notification alert is triggered. One major drawback of this approach is that it overestimates the ability of a senior with dementia to independently perform IADLs in the unsafe region. However, since seniors with ED may suffer episode of uncertainty/forgetfulness during IADLs, there is the tendency for the senior to perform an action that predisposes him/her to a risky situation even he/she leaves exits the unsafe region on time. For example, a senior may forget to “turn-off” the stove after preparing a hot snack and this constitute a risk of fire outbreak if left unattended to for too long.

To summarize, existing systems presented different strategies for risk mitigation in activities of daily living although at coarse-grained level but failed to consider seniors’ ability and awareness to perform an IADL independently. Hence some limitations still exist. This therefore calls for an interdisciplinary approach that not only uses specific activities of daily living measures to assess IADL functioning of seniors [24] at fine-grained level (i.e., an activity of preparing a hot chocolate may involve a sequence of actions including “fill-kettle-with-water” -> “turn-on-the-stove” -> “grab-glass-cup” etc.) but also help mitigate these risks.

4.2 An Overview of the Proposed Method

In Chapter 3 of this study, a Situation-centered goal reinforcement (or relearning) framework which composed mainly of three component units, namely: Goal inference unit, Situation-context generator, and Goal reinforcement unit was proposed in addressing this problem.

1. First, the Goal inference unit employs a deep learning model to infer the goal (intended IADL) a smart home resident is wanting to perform at a given time instance in order to ensure that he/she
gets the appropriate support in case they encounter uncertainty/difficulty with decision making on task completion.

2. The Situ-context generator then identify activities that are relevant to the inferred goal, and their sequence in the goal path. First, it uses feature selection to filter out features (activity sensors) that are not relevant to the satisfaction of a goal. Then, a pattern anomaly identifier unit that leverages a sequence matching module in “python programming tool” for subsequence matching, was used to check for the anomaly in the currently observed situation sequence. A situation-context graph is then used to represent the relevant features to the inferred goal.

3. Goal reinforcement unit – this anticipates the context of the aging adult performing an IADL and renders appropriate intervention in safety-critical situations toward the satisfaction of his/her goal, and ii) Observations from sensor data consist of the collection of data (i.e., both the historical and current ADL observations) which are analyzed to infer the goal of the smart home resident.

To address the risk associated with IADLs functioning of seniors at fine-grained level, a safety model for risky mitigation driven based on systems theory is thus proposed. In systems theory, safety is considered as an emergent property of systems rather than a component property [17]. A system is a set of components or parts that interact toward achieving a specific goal [17]. In other words, systems theory enables the evaluation of the interfaces between the systems components or parts (in the case smart home environments these may include human resident, activity detection sensors’ network and the environment). Hence, the IADLs functioning of an aging adult can be assessed by evaluating the system state at a given instant as characterized the sequence of actions performed and relevant to his/her goal. Therefore, to further enhance the Situation-centered goal relearning framework towards achieving the above objective, the proposed Situ-Safe model for risk in mitigation in the framework’s Situ-context generator component adopts
a three-pronged approach which include: Automaton-based activity modeling, IADL risk assessment and Safety reasoning using linear temporal logic (LTL).

![Smart Environment Diagram]

Figure 4.1. Situ-centered Goal Relearning Framework with The Newly Remodeled Situ-Context Generator Component

4.2.1 Situ-Safe: A Situation-Centered Safety Model for Risk Mitigation

The proposed Situ-Safe remolds the existing safety method of the Situ-context generator in the previously proposed Situ-centered goal relearning framework with the following attributes:

a) **Automaton-based Activity modeling**: Activity modeling is an important element for activity recognition and it further helps to aid residents in sequential activities in smart homes [115, 116, 148]. It allows for the detection of ethereal anomalies or changes in activities that are localized in time and space [117]. Therefore, it is needed to enhance reasoning given real-time streaming sensor data to infer the goal or current activity of the resident in smart home [148]. For instance, it may be important to detect safety-critical situation (or action) within the IADLs currently being undertaken. To achieve this, an
automaton-based activity modeling and pattern recognition is employed which has been used in related work [133, 134]. This tool is helpful especially as it aids detection of potentially risky situations at fine-grained level in goal path.

Table 4.1. Some sensors present in the smart home environment (originated from [9])

<table>
<thead>
<tr>
<th>Sensor Id</th>
<th>Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>D01</td>
<td>Kitchen door sensor</td>
</tr>
<tr>
<td>D02</td>
<td>Living room door sensor</td>
</tr>
<tr>
<td>D03</td>
<td>Cutlery cabinet sensor</td>
</tr>
<tr>
<td>D04</td>
<td>Dishes cabinet sensor</td>
</tr>
<tr>
<td>D05</td>
<td>Cups cabinet or cupboard sensor</td>
</tr>
<tr>
<td>D06</td>
<td>Pantry sensor</td>
</tr>
<tr>
<td>D07</td>
<td>Stove / microwave sensor</td>
</tr>
<tr>
<td>D08</td>
<td>Refrigerator sensor</td>
</tr>
</tbody>
</table>
Figure 4.2 shows the possible transition sequence for the activity of making. The automaton state diagram models the activity decomposition into sequence of actions towards goal satisfaction. It consists of five sensor states with the labels: D01, D08, D05, D07 and D06. D01 indicates the start state (goal triggering state) and the accept state (goal satisfying state) denoted by the concentric circle. The transition from one state to another as indicated by the arrows are referred to as situ-transitions. The inputs to automaton are the sequence his/her goal. The output of the automaton is either an accept state (i.e., the resident successfully satisfied his/her goal) or reject state (i.e., goal was not successfully executed or fulfilled).

Notice that the activity model is composed of two types of arrows: solid and dashed transition arrows. A solid transition arrow alone indicates a finite automaton (FA) model of the goal execution by an older adult without expressing episodes of temporal organization of action sequence error, while state transitions indicated with both solid and dashed arrows imitates a nondeterministic finite automaton (NFA) model of temporal organization of action error in activity execution sequence performed by the senior living
in smart home (see Table 4.2 and Table 4.3). The dash arrows are bi-directional. In addition, notice that each of the five states correspond to the sequence of situations \( S_1, S_2, S_3, S_4 \) and \( S_5 \), formally expressed as \( I = < S_1, S_2, S_3, S_4, S_5, > \). Also, note that each situation or state is a dual action state indicating the fine-grained decomposition of the activity execution tasks sequence. For instance, Situation \( S_1 \) describes the activity task \( D_01 \) with action values “OPEN/CLOSE”.

Table 4.2. An NFA Model Representation of an Instance of Temporal Organization of Action Sequence Error for Activity Label “Prepare a cup of hot chocolate”.

<table>
<thead>
<tr>
<th></th>
<th>OPEN</th>
<th>CLOSE</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>( S_1 )</td>
<td>( S_1, S_2 )</td>
<td>( S_2, S_1 )</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>( S_2 )</td>
<td>( S_2, S_1, S_3 )</td>
<td>( S_3, S_2, S_1 )</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>( S_3 )</td>
<td>( S_3, S_2, S_4 )</td>
<td>( S_4, S_3, S_2 )</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>( S_4 )</td>
<td>n/a</td>
<td>n/a</td>
<td>( S_5, S_4, S_1 )</td>
<td>( S_1, S_3, S_5 )</td>
</tr>
<tr>
<td>( S_5 )</td>
<td>( S_5, S_4 )</td>
<td>( S_4, S_5 )</td>
<td>n/a</td>
<td>n/a</td>
</tr>
</tbody>
</table>

Table 4.3. An FA Model Representation of an Instance of a Normal Activity with no Temporal Organization of Action Sequence Error.

<table>
<thead>
<tr>
<th></th>
<th>OPEN</th>
<th>CLOSE</th>
<th>ON</th>
<th>OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>( S_1 )</td>
<td>( S_1 )</td>
<td>( S_2 )</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>( S_2 )</td>
<td>( S_2 )</td>
<td>( S_3 )</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>( S_3 )</td>
<td>( S_3 )</td>
<td>( S_4 )</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>( S_4 )</td>
<td>n/a</td>
<td>n/a</td>
<td>( S_5 )</td>
<td>( S_1 )</td>
</tr>
<tr>
<td>( S_5 )</td>
<td>( S_5 )</td>
<td>( S_4 )</td>
<td>n/a</td>
<td>n/a</td>
</tr>
</tbody>
</table>
Table 4.3 describes a scenario where an older adult correctly executed the action sequence transitioning from situation state to another towards the satisfaction of goal of making a cup of hot chocolate. At situation (state) $S_1$, the senior performs an action OPEN on the kitchen door to gain access into the kitchen and on opening the door will remain at the rear of the door at $S_1$. An action CLOSE on the door should lead to transition to $S_2$. Similarly at $S_2$, after an OPEN action is performed, corresponding CLOSE action must be performed before transiting to $S_3$ otherwise leaving the refrigerator door opened for too long could cause damage to the refrigerator and defrost ice could also cause wet floor which could constitute the risk of fall (as shown in Table 4.2 in the cell intersecting $S_2$ and action OPEN) [48]. If at state $S_4$, and an action ON is performed he moves to $S_5$. Suppose that the smart home resident forgets the next action in sequence and moves to $S_1$ to exit as shown by the values of the cell intersecting row $S_4$ and column ON in Table 4.3. This event may constitute a hazardous state that could lead to fire accident which may be life threatening if the stove was not turned OFF. At $S_5$, a CLOSE action should succeed an OPEN action to transit to $S_4$ to turn OFF the stove after which he transits back to $S_1$ to exit the kitchen at which point the goal is satisfied. Note that the cells with “n/a” values imply that the action is not applicable to that situation.

b) Risk Matrix for Assessment of functioning Initiative and performance of Instrumental Activities of Daily Living:

The ability of seniors with ED to perform ADLs and IADLs is reliant on their cognitive abilities, and these activities often require several steps of actions toward an action goal [24, 118]. It is commonplace for these seniors to express compromised ability to perform activities of daily living and episode of uncertainty thus constituting safety
hazards [119]. For example, the temporal position of an action in an activity sequence might be out of order; consider a scenario where a senior intends to make a cup of tea, he/she might turn-on the kettle first before putting water inside it and this may constitute a risk (otherwise referred to as temporal organization of action sequence error) [119]. To address this problem, there is need to assess the risk implication of cognitive deficit expressed by seniors with respect to appliance interactions (actions) leading toward their goal. Therefore, an IADLs risk rating matrix is devised and adapted from two tools: a) the “revised interview for deterioration in daily living activities in dementia 2 (R-IDDD2)” scale for assessing the IADLs functioning initiative and performance of seniors with ED [27] and b) weighted severity of consequence scale used for identifying and evaluating hazards in engineering controls [121]. More formally, risk is defined as follows:

\[
Risk \ Rating = \text{Likelihood of Occurrence (OS)}
\]

\[
\times \text{Severity of Consequence Score (CS)} \quad (x)
\]

Therefore, equation (x) above is leveraged in devising a risk matrix for assessment of risk associated with IADLs functioning initiative and performance of seniors with ED in smart home environment. From equation (x) above, the likelihood of occurrence or occurrence score is based on the R-IDDD2 scale that is used in clinical research settings and validated for assessing functioning initiative and performance of IADLs by seniors with ED [120, 132]. The scale is rated from “0” (never any difficulties) to “4” (always having difficulties) and adapted to provide the likelihood of occurrence as shown below.
Table 4.4. Likelihood of Occurrence Assessment Scale [adapted from 120, 121, 131]

<table>
<thead>
<tr>
<th>Occurrence Score (OS)</th>
<th>Likelihood of Occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rating</td>
<td>R-IDDD2 Score</td>
</tr>
<tr>
<td>Not present</td>
<td>0</td>
</tr>
<tr>
<td>Rare</td>
<td>1</td>
</tr>
<tr>
<td>Possible</td>
<td>2</td>
</tr>
<tr>
<td>Likely</td>
<td>3</td>
</tr>
<tr>
<td>Almost Certain</td>
<td>4</td>
</tr>
</tbody>
</table>

From Table 4.4, the R-IDDD2 score represents the likelihood that a senior has difficulty with or miss the temporal position of an action in an activity. For example, if a senior who in when making a cup of tea always struggles with the temporal position of either to first turn-on the kettle first before putting water inside is rated a “4” implies that it is almost certain he/she will perform the activity sequence out of order. Thus, may be predisposed to the risk of fire accident. If the senior is rated a “0”, it implies that he/she do not struggle with temporal order of the actions required in the goal path.

The weighted scaling for assessment of severity of consequence assigns a disproportionately higher value for the moderate and high Severity of Consequences as shown below [121].

Table 4.5. Weighted Severity of Consequence Assessment Scale [adapted from 121]

<table>
<thead>
<tr>
<th>Consequence Score (CS)</th>
<th>Impact to ...</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rating</td>
<td>Person Safety</td>
</tr>
<tr>
<td>No Risk</td>
<td>1</td>
</tr>
<tr>
<td>Minor</td>
<td>5</td>
</tr>
<tr>
<td>Moderate</td>
<td>10</td>
</tr>
<tr>
<td>High</td>
<td>20</td>
</tr>
</tbody>
</table>
Thus, appropriate levels of action and intervention can be assigned to the higher risk and higher consequence operations [121].

Table 4.6. Risk Matrix for Assessment of IADLs Functioning Initiative and Performance of Aging Adults

<table>
<thead>
<tr>
<th>Likelihood Of Occurrence (OS)</th>
<th>Severity of Consequence (CS)</th>
<th>Impact to Resident’s Safety and Property Damage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CS = 1 No Risk</td>
<td>CS = 5 Minor</td>
</tr>
<tr>
<td></td>
<td>RR = 4 LOW</td>
<td>RR = 20 LOW</td>
</tr>
<tr>
<td>OS = 4</td>
<td>RR = 40 HIGH</td>
<td>RR = 80 CRITICAL</td>
</tr>
<tr>
<td>OS = 3</td>
<td>RR = 3 LOW</td>
<td>RR = 15 MEDIUM</td>
</tr>
<tr>
<td>OS = 2</td>
<td>RR = 10 MEDIUM</td>
<td>RR = 20 LOW</td>
</tr>
<tr>
<td>OS = 1</td>
<td>RR = 5 LOW</td>
<td>RR = 20 HIGH</td>
</tr>
<tr>
<td>OS = 0</td>
<td>RR = 0 Not Applicable</td>
<td></td>
</tr>
</tbody>
</table>

From Table 4.6, the color coded scores may be used for benchmarking actions performed in goal sequence or path as either permissible (non-risky) or safety critical (risky) depending on the severity of risk they pose to the senior resident in smart home. For example, a senior may intend to drink a glass of water and perform the following action sequence to satisfy his/her goal:

\[
\text{begin, kitchen} \rightarrow \text{door}_{\text{open}}, \text{kitchen} \rightarrow \text{door}_{\text{close}}, \text{glasses} \rightarrow \text{cupboard}_{\text{open}}, \ldots, \text{water} \rightarrow \text{tap}_{\text{open}}, \ldots, \text{kitchen} \rightarrow \text{door}_{\text{open}}, \text{kitchen} \rightarrow \text{door}_{\text{close}}, \text{end}
\]

Note from the action sequence that the cupboard door was not closed after it was opened and this deviated from the normal behavior. However, leaving the cupboard door opened may not necessarily constitute a risk hence such deviation maybe permissible thereby lessens the tendency to of overwhelm the senior with too many alerts. Observe also from the action sequence that “water tap” was not closed after it was opened, this deviation
may not be permissible (safety-critical) because it may constitute a potential risk of fall accidents if the floor gets flooded.

c) Temporal Logic Reasoning for Safety Specification

The expressive power of temporal logic has been exploited in some smart home environments research especially for activity recognition. In [139] for instance, they proposed an automated Recognizer of ADLs that is based on temporal logic and model checking to enhance real-time recognition of ADLs in a smart environment. Also, [140] prototyped a HomeTL with a visual editor that allows healthcare providers to create and specify rules that determines the modus operandi of technologies in the smart home environment. This work, however, focuses on safety specification and risk management in activities of daily living at fine-grained level.

Risk management decisions are essential especially in safety-critical situations that seniors are predisposed to when carrying out ADLs and IADLs. Reasoning about the plausible occurrence of undesirable possible impending hazards or accidents demands ways to prevent or mitigate them [123, 124]. Therefore, the ability to effectively model and reason with temporal information is fundamental for risk management in smart home environments [124]. Temporal logic (TL) have been employed in specifying safety properties in safety-critical systems due to its convenient vocabulary for expression of temporal specifications and behavior required of a system [123, 125, 126]. In order words, it allows for specification of sequence or relative order of events and therefore suitable for risk analysis, accident, and risk mitigation from temporal data [127, 128, 129, 132,]. Here, a linear temporal logic (LTL) is employed.
4.2.2 Reasoning about sequences in Linear Temporal Logic (LTL)

LTL formulae over the set of atomic propositions $AP$ are contrived in accordance with the grammar described below [130]:

$$\varphi ::= \text{true} \mid p \mid \neg \varphi \mid \varphi_1 \land \varphi_2 \mid 0 \varphi \mid \varphi_1 \cup \varphi_2$$

where $p \in AP$, $\varphi$ is a formula and

$p$ is an atomic proposition

$0 = "next": \varphi$ is true at the next moment or step

$\cup = "until": \varphi_1$ is true until $\varphi_2$ is true

$\diamond = "eventually": \Phi$ will become true at some point in the future

$\square = "always": \Phi$ is always true

Figure 4.3. LTL Propositions Evaluation Over a Sequence of States [adapted from 130]
4.2.2.1 Problem Scenario

Suppose that the inferred goal of a senior resident in a smart home at a given time instance is to “drink a glass of water”. A prior observation of normal goal path may be composed of three main tasks (i.e., interaction with kitchen-door, cupboard, and water-tap) that is executed in accordance with the action sequence given below:

\[
\begin{align*}
\text{begin, kitchen} & - \text{door}_{\text{open}, \text{kitchen}} - \text{door}_{\text{close}, \text{cupboard}} - \text{cupboard}_{\text{open, close}}, \text{water} \\
& - \text{tap}_{\text{open, water}} - \text{tap}_{\text{close}, \text{kitchen}} - \text{door}_{\text{open, kitchen}} - \text{door}_{\text{close, end}}
\end{align*}
\]

Since ED causes decline in cognitive functioning of seniors, the temporal position of an action in a goal sequence may miss or might be out of order and this deviation may constitute a risk or hazardous state [74, 119].

\[
\begin{align*}
\text{begin, kitchen} & - \text{door}_{\text{open}, \text{kitchen}} - \text{door}_{\text{close, cupboard}} - \text{cupboard}_{\text{open, close}}, \text{water} \\
& - \text{tap}_{\text{open}, \text{..., kitchen}} - \text{door}_{\text{open, kitchen}} - \text{door}_{\text{close, end}}
\end{align*}
\]

To mitigate such risks, an LTL is leveraged to define requirements ensure safe execution and satisfaction of goal as follows:

First, it is assumed that an IADL (goal) path is defined by a finite number \( N > 0 \) of sequential tasks. The tasks each have dual mode actions (i.e., active “ON” and inactive “OFF” states) that are required to be performed in succession (i.e., from goal triggering state to goal satisfaction state). For a given goal path, an active action may assume a priority status if it can constitute a potential risk (otherwise referred to as safety-critical action). Its priority status is rescinded only if changes its states to inactive. If a new action is triggered active while a priority action remains active, the priority action is recommended to change to inactive mode in the
succeeding state. An active action that is not a priority (i.e., does not constitute a risk) may be succeeded by a priority action without it changing state to inactive mode. However, the succeeding priority action must go inactive mode in the next state.

Therefore, an LTL formulation of the safety requirements for tasks execution in goal path as follows: First, let p, q represents task actions. Suppose the set of atomic propositions is given as \{priority_p, active_p\} such that 1 \leq p, q \leq N, where priority_p implies that task action p is a priority action, active_p implies that action p is in active mode. Hence, two desirable safety properties or objectives is given by the formula \(\varphi\):

\[
\varphi = \varphi_1 \land \varphi_2
\]

a) \(\varphi_1\): “A priority action will become inactive in succeeding moment at some time”

\[
\varphi_1 = \Box \left( \land_{1 \leq p, q \leq N} \left( (\text{priority}_p \land \neg \text{priority}_q) \rightarrow \Diamond \text{priority}_p \right) \right)
\]

In other words, the senior resident in smart home must close the “water-tap” after getting glass of water from the tap to avert safety-critical situations or hazardous state.

Observe that the conjunct \(\neg \text{priority}_q\) is required to specify that no other action is active at the same moment priority action priority_p happens. Also, note that priority_p implies that priority_p goes to inactive state.

b) \(\varphi_2\): “In the presence of an active action succeeded by a priority action the priority action will become inactive in succeeding moment at some time”

\[
\varphi_2 = \Box \left( \land_{1 \leq p, q \leq N} \left( (\text{active}_p \land \Diamond \text{priority}_q) \rightarrow \Diamond \text{priority}_q \right) \right)
\]
Here, the objective is to address overgeneralization problem since not all action deviation may constitute a risk. For instance, if \textit{cupboard\textsubscript{open}} action is performed and it is immediately succeeded by action \textit{water – tap\textsubscript{open}}, it should be permitted that action \textit{cupboard\textsubscript{close}} was not performed or missed but action \textit{water – tap\textsubscript{close}} must succeed \textit{water – tap\textsubscript{open}} in the next moment. It is considered that leaving the cupboard door opened may not necessarily constitute a risk, thus, triggering an alert to notify the smart home resident to close the cupboard may be regarded as interference and impede their desired independence.

4.2.2.2 Learning Priority Action using Gradient Boosted Feature Importance

The intent here is to be able to automatically learn or estimate priority action in each goal path which the LTL safety reasoning model $\varphi$ require for its execution. To achieve this, first, the feature importance scoring or ranking attribute of gradient boosted tree algorithm is exploited to automatically learn and estimate if an action (feature) is a priority action from a trained predictive model of a given goal path. Two notable benefits of gradient boosted learning algorithm are fast execution speed and better predictive performance [144, 146, 147].

A gradient boosting algorithm is defined according by the equations below:

$$r_t(u) = H_p \left[ \frac{\delta \lambda (p, f(u))}{\delta f(u)} \right]_{f(u) = f_{t-1}(u)}$$  \hspace{1cm} (1)$$

$$(\sigma_t, \beta_t) = arg \min_{\sigma, \beta} \sum_{i=1}^{M} [ -r_t(u_i) + \gamma k(u_i, \beta) ]^2$$  \hspace{1cm} (2)$$
Where $\delta \lambda (p, f)$ is a loss function, $k(u_i, \beta)$ is a base-learner, and $\{r_t(u_i)\}_{i=1}^M$ represents a negative gradient along the observed data [143, 146].

Secondly, the gradient boosted algorithm is then applied to the numeric datasets (or synthetic datasets) generated from the risk matrix table (shown in Table 4.6). To generate the synthetic dataset for estimation of priority action, a score is assigned to each action-detecting sensor in a goal path based on the risk level according to the risk matrix. For example, an activity “drink a cup of water” has 3 main sensors namely: kitchen door sensor “D01”, cupboard sensor “D05”, and water tap sensor “WT1”. Actions performed on kitchen door (open/close) and cupboard (open/close) are “no-risk” actions, thus, are assigned values corresponding to the “no risk” column label of the risk matrix only. However, if “WT1” is opened and not close, this may constitute a safety-critical tasks, thus, “WT1” is assigned values corresponding to the “severe” column label of the risk matrix. Finally, the last column of the generated synthetic dataset is a binary class label (i.e., takes value 0 or 1) which correspond to the type of deviation in a goal path as represented by either $\varphi_1$ or $\varphi_2$.

Table 4.7. Snapshot of Synthetic Dataset for Activity Label “Drink a cup of water” for Estimation of Priority Actions

<table>
<thead>
<tr>
<th></th>
<th>D01</th>
<th>D05</th>
<th>WT1</th>
<th>Class ($\varphi_1 = 1, \varphi_2 = 0$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>4</td>
<td>1</td>
<td>80</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>2</td>
<td>60</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>3</td>
<td>40</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>4</td>
<td>20</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1</td>
<td>80</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>2</td>
<td>60</td>
<td>1</td>
</tr>
</tbody>
</table>
Note that the number of instances of the synthetic dataset generated for each goal is the same for the corresponding goal in the “memory abilities and dementia in older adults” used as case study. A snapshot of the synthetic dataset generated for an activity (goal) “drink a cup of water” is shown in Table 4.7 above.

4.4 Case Study Results

First, the proposed LTL safety reasoning model was implemented and a synthetic dataset (i.e., from the risk matrix table for assessing IADLs functioning initiative and performance was generated. A gradient boosted algorithm was applied to the synthetic dataset (shown in Table 4.7) to estimate the importance of action (i.e., determine whether an action is priority action or permissible) relative to the goal path, and the outcome is passed onward to the LTL safety reasoning model to identify or flag behaviors that may constitute a risk in goal sequence or path. The proposed LTL safety reasoning model is then validated against “memory abilities and dementia in older adults” dataset, specifically for four (4) types of IADLs including: “prepare tea”, “prepare a hot chocolate”, “drink a cup of water” and “prepare a hot snack”. The dataset was collected from a smart home environment with a living room and a kitchen [9]. Although the “memory abilities and dementia in older adults” dataset consisted of both normal and abnormal observation sequence for the four types of IADLs considered in this work but the objective of this part of the study is only focused on observation sequences with deviation (abnormal action sequence) since the objective is focused on mitigating risky situations).

The “memory abilities and dementia in older adults” dataset was preprocessed as shown in Table 4.8 below.
To determine whether an action is a priority action (importance) relative to a goal, a feature selection with gradient boosted feature importance method is used. The model is implemented using XGBoost software library with scikit-learn installed on Anaconda distribution for python machine learning and deep learning environment. First, the SelectFromModel class is used which takes a model and then reconstruct a dataset into a subset with selected features by calling the transform() method on the SelectFromModel instance to consistently select the same features on the training dataset and the test dataset. The class then use a threshold to decide which feature (sensor among the action detecting sensors) to select as a priority task / action. Note that this model is applied to the dataset shown in Table 4.7. The selected priority action is then fed into the LTL safety reasoning model to catch $\varphi_1 \land \varphi_2$ temporal organization of action sequence errors in the corresponding goal instance in the preprocessed IADLs datasets shown in Table 4.8 above.
Table 4.9. Risk Mitigation Accuracy for Situ-safe Safety Model

<table>
<thead>
<tr>
<th>IADLs Category</th>
<th>Number of IADLs sequence instances</th>
<th>Safety Requirement</th>
<th>Test Criteria</th>
<th>Manual verification of violations detection Accuracy</th>
<th>Verifiocation Accuracy with estimated priority action</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prepare tea</td>
<td>Total cases 525 ( \varphi_1 ) cases = 365 ( \varphi_2 ) cases = 160</td>
<td>( \varphi = \varphi_1 \land \varphi_2 )</td>
<td>( Kettle_{on} \rightarrow Kettle_{off} ) ( Kero_{close} \rightarrow Water_{open} \rightarrow Water_{close} )</td>
<td>100%</td>
<td>70.1%</td>
</tr>
<tr>
<td>Prepare a hot chocolate</td>
<td>Total cases 510 ( \varphi_1 ) cases = 321 ( \varphi_2 ) cases = 189</td>
<td>( \varphi = \varphi_1 \land \varphi_2 )</td>
<td>( Stove_{on} \rightarrow Stove_{off} ) ( Cupboard_{close} \rightarrow Stove_{on} \rightarrow Stove_{off} )</td>
<td>100%</td>
<td>68.0%</td>
</tr>
<tr>
<td>Drink a cup of water</td>
<td>Total cases 675 ( \varphi_1 ) cases = 403 ( \varphi_2 ) cases = 272</td>
<td>( \varphi = \varphi_1 \land \varphi_2 )</td>
<td>( Water_{on} \rightarrow Water_{close} ) ( Cupboard_{close} \rightarrow Water_{on} \rightarrow water_{close} )</td>
<td>100%</td>
<td>74.0%</td>
</tr>
<tr>
<td>Prepare a hot snack</td>
<td>Total cases 570 ( \varphi_1 ) cases = 353 ( \varphi_2 ) cases = 217</td>
<td>( \varphi = \varphi_1 \land \varphi_2 )</td>
<td>( Stove_{on} \rightarrow Stove_{off} ) ( D.cupboard_{close} \rightarrow Refrigerator_{open} \rightarrow Refrigerator_{close} )</td>
<td>100%</td>
<td>72.3%</td>
</tr>
</tbody>
</table>

The safety reasoning model given by \( \varphi = \varphi_1 \land \varphi_2 \) evaluated two types of deviations namely: safety-critical task and permissible actions in an activity sequence as reported in Table
Activity IDs 1, 2, 3, and 4 all presented instances of both types of temporal organization of action sequence error (i.e., $\varphi_1$ and $\varphi_2$). First, I manually evaluated the LTL safety reasoning model by running it on all instances of the four goals dataset in Table 4.8 and checking for violations of the set criteria. For instance, for activity “prepare tea” the criteria is to look for a deviation such that an action $Kettle_{on}$ had been performed and $Kettle_{off}$ was not performed (which constitute a risk). The model was able to detect both types of deviations in all four types of goals with an accuracy of 100%. However, since the goal of a smart home environment is to reduce the burden of care partners and to ensure the independence of the senior living in the smart home, thus I used gradient boosted algorithm to first estimate and select priority action with respect to the goal being observed and the outcome is then passed to the LTL safety reasoning model using the same set criteria to detect both types of deviations. 70.1%, 68.0%, 74.0% and 72.3% accuracy were achieved respectively and an average accuracy of 71.1%. This therefore implies that the safety reasoning model can support seniors in focusing and prioritizing their attention on task with higher risk and consequences when carrying out their instrumental activities of daily living to avert hazardous with an accuracy of 71.1%. In addition, I believe the accuracy of the model can be improved with more observation datasets as the accuracy of detection increases with a greater number of instances of the IADLs. More so, the gradient boosted algorithm model can also be optimized by tuning parameters.

Finally, given the potential of the proposed situ-safe model for safety reasoning and automatic identification of risky actions in fine grained IADLs or goal path, it therefore implies that the SLA reasoning capacity for risky mitigation discussed in section 3.2.4 B of chapter 3 will now depend on the situ-safe model risk mitigation. Therefore, the previous assumption for a
contrived heuristic $Q$ that relies on action priority vector $H$ as discussed in section 3.2.4 B for SLA is replaced and upgraded with situ-safe safety model as depicted in Figure 4.4 below.

Figure 4.4. SLA, Naïve agent interaction with LTL Safety Reasoning Model
CHAPTER 5. DISCUSSION AND EVALUATION

5.1 Discussion

To my knowledge, this is the first study that presents an end-to-end automated framework (i.e., from prediction goal prediction, to provision of goal path awareness, to detection of risky behaviors, and action recommendation to mitigate risky event) to support aging adults with early-stage dementia (ED) to successfully carry out their complex instrumental activities of daily living (IADLs). Specific findings from this study are discussed in succeeding paragraphs.

The results obtained as shown in Table 3.10 indicate that an LSTM model can be very useful for can prediction of human goal with a relatively high accuracy even with different goals with similar subsequences. More so, some characteristic advantages of LSTM model for goal prediction in a dynamic environment like the smart home from sequential observations were discovered to be consistent with those found in existing literature [13, 43, 56, 57, 58, 59]. First, LSTM’s cell state (otherwise referred to as memory) and its recurrent connections can retain information over a long period, thus, these attributes make it possible for it to effectively for model and learn long term context dependencies even with IADLs observations with varying length sequences better than both HMM and CRF models [11, 12, 13, 43, 56, 58, 60]. More so, LSTM predictive performance improves significantly when recurrent dropout regularization is applied [13, 43]. Although, an optimally trained LSTM model can be stored and used for future predictions when new observations sequences becomes available, however, due to the evolving nature of human subjects especially if the cognitive functions and wellbeing of an observed aging adult worsen overtime and causing a significant change in his/ her behavior, there will be need to retrain the LSTM model to accommodate the new changes presented in the newly available observation sequences.
Further, the impact of type 1 (false positive) error and type 2 (false negative) error in this domain of application given that both type of errors are significant issues in screening of health conditions and wellbeing [149]. The precision and recall scores obtained (i.e., 93.0% and 90.0% respectively) for the optimally trained LSTM model (i.e., LTSM with recurrent dropout) indicates a low false positive and false negative, although, both type 1 and type 2 errors can create consequential and counterintuitive problems if an observed IADL sequence to be classified is rare and common, respectively [150]. Given that the preprocessed datasets (i.e., labeled datasets) used for this study presents an uneven class distribution, the LSTM model was further evaluated using F1-score which is a weighted average of both precision and recall. An F1-score of 90.0% obtained further show that the optimally trained LSTM model has a low type 1 and type 2 errors.

Another interesting finding relates to the plausibility of path identification for a predicted or inferred goal. From Figure 3.1, the feature selection component leverages univariate feature selection algorithm to filter sensor observations that are relevant to the completion of the predicted goal (results shown in Tables 3.11, 3.12, 3.13, and 3.14). Thus, automated path planning can be very useful to support aging adults who might have trouble with planning an intended activity sequence to ensure that they successfully satisfy their goal. Nonetheless, there is need to further this research and validate the performance of univariate feature selection algorithm against other existing ones such as the recursive feature elimination, and feature importance technique.

Furthermore, this study also attempts to address major concerns that impact the adoption of smart home technologies designed to support older adults which include personal safety, sensitivity to activity and independence of the aging adults living in smart home environment [44,45,46,47]. Existing approaches such as behavior deviation detection (BDD) and smart space portioning (SPP) that have been used to address this problems suffer two main drawbacks
including: a.) overgeneralization — this leads to hypersensitivity of warning alert triggered by the smart home sensors which could overwhelm the resident and b.) overestimation — this is an assumption that the IADLs cognitive initiative and performance of an aging adult is optimal at all time, however, this is not always true since aging adults are prone to temporal organization of actions sequence when performing their IADLs. Hence, SPP may compromise the safety of the aging adult and predispose them to potential life-threatening injuries. In this study, a situation-centered safety model for risk mitigation in IADLs known as Situ-safe was proposed. Situ-safe uses linear temporal logic (LTL) to formulate safety-reasoning model to verify safety requirements in IADLs observation sequences and leverages feature selection with gradient boosting feature importance scores to automatically identify what deviations in an IADLs observation sequence are permissible (i.e., actions that may not constitute a risk) so as to mitigate against hypersensitivity of warning alert and potentially risky behaviors in a goal path. The LTL safety-reasoning model with feature selection gradient boosting feature importance scores was evaluated and an average accuracy of 71.1% was achieved, although, evaluation without feature selection gradient boosting feature importance scores (i.e., with manual assignment of permissible and priority actions) resulted in 100% accuracy. This implies that Situ-safe has the potential to mitigate both the overgeneralization and overestimation problems associated with BDD and SPP respectively with a high accuracy. In other words, Situ-safe can further enhance smart home capability to support aging adult without overwhelming them with unnecessary warning alert while also ensuring their safety. In addition, it is important to state that there may exist complex scenarios where an aging adult may need to decide between two priority actions in a goal path, however, Situ-safe’s capability is currently limited to safety requirements in sequential actions with no branching.
Finally, relearning is a clinical approach used for supporting older adults in correctly executing an intended goal to avert errors [74]. In this study, a situ-learning agent (SLA) was proposed to support decision making with respect to goal of the resident in risky situation. Agent models can be helpful in supporting aging adults with ED in smart home to avert risky situations in their goal path. Therefore, a simulation of two interacting agents that include the SLA which is the teacher/recommender agent and a naïve agent representing an aging adult with deteriorated cognitive initiative and performance of IADLs was shown. From the results obtained in Table …, it was observed that given an anomalous goal observation sequence performed by a naïve agent, SLA pursue actions that are currently perceived to be optimal and then uses signals (i.e. reward/penalty, action selection and reward selection probabilities) to recommend appropriate action for the given anomalous situation in the goal path to the naïve agent. Therefore, this suggests that agent models can support decision making especially under uncertainty by recommending appropriate action toward goal satisfaction. This findings also corroborate those reported in previous research used to study emergent behaviors in a human-centered application domains or environments with uncertainty such as the smart home and agent models were found to be useful to support decision making [62, 63, 64, 65].

5.2 Evaluation

The datasets used in this study was collected from smart home lab with sensor’s network that is composed of mainly contact and pressure sensors [9]. In other words, IADLs observation sequences in the datasets are captured when then sensors detect (senses) touch or interactions with the instruments being used to carry out the activities being performed in the smart home. The drawbacks of these types of sensors is that they lack the capability to adequately capture human context. Social context or social cognition such as affect, mood, and emotions are important
factors that influences the everyday experiences of people with direct and indirect impact on health and behavior and they can be useful in understanding and predicting human behaviors. [89, 151, 152]. However, one way to possibly address this limitation and improve the quality of the datasets is by leveraging Emotiv Epoc+ wireless electroencephalogram (EEG) brain wear device in addition to the touch and pressure sensors in the collection of human observation datasets. Emotive Epoc+ headset is a device with 14 channel mobile EEG that is designed to capture contextual human brain data [154]. Therefore, this can further provide access to qualitative context data that can be monitored, analyzed, visualized, and helps to better understand human context such as excitement, engagement, relaxation, interest, stress, and focus [155]. Also, Microsoft Kinect sensor can prove to be useful and improve the quality of datasets as it can provide three-dimensional context information about people’s activity being monitored (e.g., detection of unusual behaviors or patterns) [153]. Nonetheless, despite the gains that can be made by leveraging these devices, their cost effectiveness must also be considered.

Furthermore, it can be difficult to tune LSTM model hyperparameters (e.g., epoch, number of neurons, batch size, etc.) to achieve an optimally trained model since there are no hard and fast rules for choosing appropriate hyperparameter values. Oftentimes, a systematic approach needs to be devised to explore several configurations of the LSTM model with different hyperparameter values and this could take several hours or days to train. More so, the quality of the preprocessed data that is fed into the model as input also influences the performance of the model prediction.

In addition, it may be argued that cheaper solutions such as using additional sensors that can be programmed to automatically halt an anomalous behavior or actions taken in a goal path (e.g., close water tap if it is not closed) would suffice to mitigate risky situations in smart home. The limitation of this approach include a) dependability — sensors are not entirely dependable and
thus, may fail to when critical condition emerges in a goal path, b) interference — such solution could interfere with the desired level of independence of an older adults especially if he or she, has the capability to execute the intended task, and c) cost effectiveness — Although some sensors can be cheap but some other sensors can be very expensive, hence, this approach could prove costly in the long run.

Finally, although agent models have been used to study and understand emergent behaviors in several human centered applications [62, 65], nonetheless, there is need to validate the efficacy of the proposed situ-learning agent for decision support in a real-life and dynamic scenario with an observed aging adult. Also, it may not always be feasible to come up with improved designs to eliminate risks altogether as it is almost impossible to enumerate all parameters to implement a perfect solution.
CHAPTER 6. CONCLUSION AND FUTURE WORK

6.1 Conclusion

It is important for an older adult to be able to carry out instrumental activities of daily living (IADLs) and live an independent and healthy life while aging in place. However, older adults can suffer from cognitive impairment that affects their ability to make sound judgments. Non-normative cognitive aging (e.g., dementia) affects adults’ ability to cope with or keep track of sequential tasks in IADLs. Failure to take the right decision or complete the tasks of an activity may pose a risk (e.g., forgetting to turn off the stove). These spurred researchers in cross disciplinary fields such as ambient intelligence (AmI), gerontechnology, and computer Science to leverage information and communication technologies (ICT) in the form of assisted living technologies (AAL) (e.g., smart home) for understanding human behavior and recognition of a person’s goal in their daily life to ensure they continue to live independently and safe for improved quality of life [1, 2, 5, 6, 8].

Smart home is a sensor laden environment and its sensors capture very basic information sensors provide very basic information which may be sufficient to recognize a person’s activity at a coarse-grained level but may not provide insight into the person’s goal and/or situation which instead is inferred [1]. Older adults with ED experience episodes of uncertainty (known as temporal organization of action sequence error) especially when engaged with complex instrumental activities of daily living that requires sequence of steps for goal completion, this potentially predisposes them to risk in such fine-grained level activity and may lead to life-threatening injuries and accidents. To address these problems, I propose a situation-driven framework for relearning activities of daily living in smart home environments. The framework is
composed of three main components namely – goal inference unit, situation-context generator, and a recommendation unit.

First, the goal inference unit uses a deep learning model known as long short-term memory (LSTM) to infer a person’s goal in a smart home environment. This model was trained using “memory abilities and dementia in older adults” ADLs datasets collected in a smart home [9] to infer a person’s goal. The model performance was evaluated and compared against other state-of-the-art models and the results showed that my LSTM based goal inference model performed better.

Secondly, safety is a key metric for evaluating the success of smart home environment, therefore, it is important for an older adult to be able to carry out activities of daily living safely while aging in place[18, 53]. Therefore, the situ-context generator component uses a three-pronged approach namely: automaton-based activity modeling, ADLs risk assessment and safety reasoning using linear temporal logic (LTL) to enhance anticipation and mitigation of risk associated with the performance of fine-grained level IADLs by an older adult with early-stage dementia. The safety reasoning model achieved an average accuracy of 71.1% in the detection of temporal organization of action sequence errors that may constitute a potentially hazardous state leading to life-threatening injuries in smart home environment.

Thirdly, anticipation and detection of risky behaviors or situations in a person’s goal path is not enough to mitigate potential risky or hazardous states, there is need to provide support to guide seniors in taking appropriate action to avert potential risk. While this is crucial, it is also necessary to reduce the level of involvement or interference of care partners who might have been assigned to monitor and provide needed support to seniors when in such potentially risky situations. Thus, the objective of the recommendation unit is to provide automated support to seniors by recommending appropriate action to avert a potentially risky state or situation. To
achieve this, we show by simulation two interacting agents—a naïve agent that simulates episode of uncertainty during instrumental activities of daily living and a situation learning agent (SLA) that provides recommendation to the naïve agent to mitigate potentially risk situation. In addition, a situ-learning agent shows potential in supporting older adults when performing ADLs, while mitigating the risk of hazard that may arise from wrong decisions or inappropriate actions taken during the completion of an IADL sequence in smart home environments. Overall, the results obtained were quite promising.

6.2 Future work

My current research has opened many interesting possibilities to the development of efficient and adaptive solutions for assisted living. My previous and current research case studies have so far focused on an end-to-end automated approach to supporting single activity and single user [14, 53]. However, interleaving is a natural phenomenon that people tend to exhibit especially when they initiate parallel goals or activities, I plan to further investigate how parallel goals can be inferred within the context of smart home environment. In addition to that, I also plan to improve upon the safety reasoning model to address risks associated with interleaved actions that may have the same priority level. To address this problem, I intend to explore some properties of branching time temporal logic [54, 55]. Finally, the explicit notion of time was not considered in the safety reasoning model, I also plan to explore explicit time-sensitive risk as part of my future work.
REFERENCES


29. G. Yapici, A. Ö. Kurt, S. Öner, T. Şaşmaz, and R. Buğdaycı, “Determination of the Home Accident Frequency and Related Factors Among the People Older than 65 Years Old Living in Mersin City Center, Turkey,” SAGE Open, vol 9, issue 2, April 1, 2019


