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Situation-centered goal reinforcement of activities of daily living in smart home environments

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Abstract

Older adults with early-stage dementia (ED) can experience confusion or lack clarity when performing routine activities of daily living (ADLs). These circumstances predispose the older adult to safety-critical and often risky situations. A safety-critical risky situation is one that constitutes a hazard. To support independent living, a sensor-laden smart environment can be employed to mitigate such hazards. In this paper, we propose a situation-centered goal reinforcement framework that supports older adults with ED in their decision making, and guides them through their ADL in order to fulfill their goal or intention and avoid hazards. First, we employ an LSTM (Long Short-Term Memory) model to infer the current goal of the resident, using their previously observed normal ADL patterns. Secondly, we identify potentially risky situations in their currently observed goal path. We then incorporate a situ-learning agent (SLA) that helps an inhabitant to make the right decision, thus preventing adverse events while guiding her through the task sequence that leads to her goal state. In addition, we use a naïve agent to simulate episodes of confusion similar to those that might be experienced by older adults with ED. We validated our method against an open-source dementia dataset (Quesada et al., 2015) by considering four types of ADLs as case studies. We achieved an accuracy of 90.1% for our goal inference model, higher than the accuracies reported by related studies. We also reported other metrics including precision, recall and f1-score for goal inference model. Finally, SLA's action recommendations relevance was evaluated accordingly.

KEYWORDS

activities of daily living, goal reinforcement, learning agent, situation, smart environment

1 | INTRODUCTION

The ability of an older adult to perform his or her activities of daily living (ADLs) represents his functional capacity (Ghayvat, Mukhopadhyay, Shenjie, Chouhan, & Chen, 2018). ADL is a tool used to assess the older adults' abilities to navigate daily life and achieve needed objectives; this type of assessment can be particularly helpful when considering the context of cognitive impairment (Zhang, Song, & Xue, 2008). Cognitive impairment can result in reduced ability to carry out ADLs (Pfeiffer, Sanchez, & Skeie, 2016; Zhang, McClean, & Scotney, 2012). Inability to perform ADLs may further complicate overall health or expose older adults to risks that could be life threatening or lead to other losses and, increase the need for care and, ultimately the cost of healthcare. These types of circumstances have spur research on ambient assisted living otherwise known as smart home system. One of the primary objectives of smart home technologies/ambient assisted living (AAL) is to improve the experience and quality of life of aging adults, but also ensure safety when performing ADLs (Davis et al., 2017; Pal, Funilkul, Charoenkitkarn, & Kanthamanon, 2018). Generally, in the presence of older adults, AAL refers to technologically laden environments that are sensitive and responsive to their needs, and can provide support to maintain a healthy and independent lifestyle (Hossain, Parra, & Alamri, 2015). AAL can potentially reduce the cost of healthcare and alleviate the burden of care partners (Fahim, Fatima, Lee, & Lee, 2012).

Early-stage dementia (ED) can cause trouble with memory, thus could cause a person to experience: i) difficulty with completion of routine tasks or planning steps to accomplish tasks, ii) disorientation – deterioration in one's ability to navigate a familiar directions or stepwise procedures, iii) short-term changes in memory – may forget why they are at a particular place or what they intended to do at a given time, and iv) poor judgement – affects a person's ability to make the right decisions (Bowen, 1997; Qassem, Tadros, & Moore, 2014; Robinson, Tang, & Taylor, 2015) These changes in memory consequently impact a person's ability, disrupts daily life and exposes them to risks, especially when they are unable to make appropriate decisions during ADLs. ADLs are composition of activity sequences, and each activity is composition of sequence of tasks. Some tasks are referred to as safety-critical tasks because they may constitute a risk. For instance, consider a situation in which an older adult is motivated to prepare a meal because she is hungry; she may forget (i.e., not able to navigate the whole sequence of tasks due to forgetfulness) to "turn off" the stove after the meal has been prepared or may forget to "turn-off" the water tap. Each of the two missed tasks (i.e., not turning-off the stove and the tap) in the activity sequence of preparing a meal could constitute risks to the life of the older adult if he does not get prompt assistance to reverse or prevent the hazardous state or situation. A 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 (Leveson, 2001). For instance, cooking appliances were reported to account for half of all fire-related injuries (Thompson, Galeab, & Hulseb, 2018), and these were due to inappropriate human behaviors. Also, wet floors could cause one to trip or fall, and this has been identified as a major cause of injury for aging adults (Kau, 2015) and ranks as the fifth leading cause of death in older adults (Kannus, Sievänen, Palvanen, Järvinen, & Parkkari, 2005).

In recognition of risky situations facing people with dementia on the daily basis, most AAL systems are able to detect accidents and emergencies by analyzing sensor data and employing suitable algorithms in human activity recognition (HAR; Davis et al., 2017; Zdravevski et al., 2017). Some researchers have been working to improve the effectiveness of ambient intelligence (AmI) for smart homes, while focusing on recognizing activities of interest and providing help to guide an older adult through her ADLs. However, challenges still exist in many of these solutions as they lack a robust model that properly situates the human cognition which basically influences the person to act (representing his or her goal at that time) into the HAR embedded within smart environments. We therefore argue that for a smart home to fully achieve its objectives of "independent living and ensuring safety" of inhabitants while performing an ADL, AmI must not only be able to detect accidents, but should also be able to anticipate actions or tasks that if when performed at a given time could lead to hazardous state, and also provide support that prevents the inhabitant from executing decisions that could constitute a risk. Thus, the capacity to valuate interfaces between components of a system as well as determine the effects of interacting components are desirable attributes in AAL to ensure safety. Although, some work has been conducted to improve the effectiveness of ambient intelligence (AmI) smart homes, it has primarily focused on activity recognition and providing help to guide an older adult through his/her ADLs. Based on our extensive review, less attention has been paid to incorporating automated planning of ADLs, activity sequence generation, and "on-the-fly" intelligent decision support into smart homes. This is important because an activity is a made up of a sequence of tasks, hence, may be intricate for an older adult with cognitive impairment especially when they need perform the tasks in a particular order or stepwise manner to reach their goal for an intended ADL. These limitations also account for why a good number of HARs in smart homes still rely on the intervention of care partners in guiding an older adult through completing an activity in order to reach a goal. Thus, the goal of ambient assisted living, which is "to design technological solutions that promote independent living" (Davis et al., 2017) and reduce or possibly remove burden from care partners is not achieved (Fahim et al., 2012). Secondly, existing HARs do not anticipate the future context of an older adult when performing the sequence of tasks in an ADL. This is so, because, in following through with the sequence of tasks that describes an activity, at some point in the sequence, an older adult with ED may lack clarity or forget the next action to be taken, thus, are unable to complete the tasks with the goal ultimately unfulfilled. Such a situation could constitute a risk. To grant HARs the capability to anticipate, we need new ways to incorporate a genuine "human-always-in-the-loop" model into the activity recognition system (Chang, 2018), that can infer the intention or goal of the inhabitant at a given time, automate the goal plan, generate the corresponding tasks sequence leading to the goal, and enable evaluation of the effect of interaction among the components (i.e., humans, devices and the sensor laden environment). This approach can ensure that safety is treated as emergent property of the smart home system rather than just being a component property.

Therefore, we propose a situation-centered goal reinforcement framework that is: 1) able to infer the intention of a resident in smart home, consequently 2) generates an automated plan of relevant activity to be performed by an inhabitant, and 3) is able to evaluate interaction among the smart home components and recommends the appropriate sequence of tasks that leads toward goal state "on-the-fly". These elements ensure that the inhabitant is able to perform the tasks sequence which leads to the goal state in an independent and safe manner.

2 | BACKGROUND AND RELATED WORK

2.1 | Smart Environments

Smart environments are sensor-laden settings capable of monitoring, identifying their residents and the activities being performed, as well as reacting to their needs (Synnott, Nugent, & Jeffers, 2015). A smart home is an intelligent space that is primarily designed to improve the experience and quality of life of its residents via human-centered applications in order to help adults age-in-place, and also to promote independent living by providing prompts on how to complete their intended ADLs at a given time instance (Davis et al., 2017; Quesada et al., 2015; Saives, Pianon, & Faraut, 2015). This technology can provide support to older adults, especially those with cognitive diseases (e.g., dementia) who may not be able to complete an ADL at a given time due to loss of judgment or episode of confusion (Helal et al., 2003). Smart homes possess the capability for human activity recognition (HAR) and detection of resident the goals via observation of actions performed and other environmental conditions captured by relevant sensor values or signals (Quesada et al., 2015)

A major study conducted by (Saives et al., 2015) focused on improving the independence of residents with specific health conditions via continuous monitoring of disease progression as characterized by changes in lifestyle via the recognition of activities performed by the resident. In order to achieve residents' goals, the researchers used a two-pronged approach. First a sequence mining method was employed to identify the most frequent patterns that characterized the activities of the resident. Consequently, an extended finite automaton was used to model the activities identified. Secondly, the requirements from medical personnel monitoring the resident were modeled by building an additional automaton based on a set of recognizable activities. The system was able to accept activity events and identify any anomaly from behavior based on defined residuals. Saives and colleagues relied on one assumption in detecting a deviation from resident's behavior, namely that the healthcare personnel has a pre-designed list of textual requirements (e.g., 3 meals a day) used as benchmark to verify if the inhabitant was in good health or not. While valuable in some instances, this type of reactive approach can be disadvantageous in other contexts. In the case of ED, ADLs may seem complex and a detected deviation or anomaly may pose a threat to the well-being of the inhabitant since the system was not designed to preempt the anomalous behavior of the inhabitant. In this paper, we argue that a true human-centered system should be able to infer the intention of inhabitant by analyzing minimal sets of behavior and context values at any given time and also preempt any abnormal activities that may compromise the safety of the resident.

(Amirjavid, Bouzouane, & Bouchard, 2013) designed an anomalies recognition and assistance provision system based on a fuzzy temporal data-driven technique. In their work, each activity is defined as a fuzzy conceptual structure represented as a hierarchy of concepts in smart homes. 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. By calculating the distance of an observed activity to the normal world, inference can be made for possible anomalies. If an anomaly exists, the system dutifully reacts to restore the smart home to normal state. However, one limitation in the work conducted is that the system would depend on help from a person to accomplish the plans and actions to restore the home to a normal state when an anomaly is detected. Moreover, in this example emphasis is placed on the system state with no intervention towards helping the resident in reaching their goal state.

In related work conducted (Lam et al., 2015), a SmartMind was developed to track and monitor the activity of persons with Alzheimer's disease. This system is based on calibrating the smart space into safe or unsafe regions. The resident is expected to perform ADLs in the safe region. When the resident suddenly moves outside the boundary of a safe space or region to perform an activity, an alert is triggered to send a notification to relative care partner for possible intervention. While a trigger is one of the key components required to influence human behavior, it is important to ensure that an appropriate trigger is issued depending on the situation of the inhabitant at a given time instance. It should be noted that, even when the person stays in a safe region when an activity is being performed, the safety of the individual is likely to be compromised when a task in an activity is left unfinished due to an episode of memory loss or confusion. For example, a hazard exists when a person forgets to "turn off" the stove after meal is prepared. As such, the system might not trigger an alert, nor send a notification to the person's care partner of such impending danger.

(Karakostas et al., 2015) proposed the use of a three-layer architecture to compose a sensor-based system to assist individuals with mild cognitive impairment (MCI) through their activities of daily living. The architecture consists of a hardware (i.e., sensors and devices), middleware and an application layer. The middleware consists of modules that aid the abstractions of each device and consequently renders a universal homogenous interface for the application layer. ADLs are monitored and detected through the data generated by the sensors that can be accessed and visualized through a graphical user interface. For instance, the number of times a person opens the refrigerator or completes the tasks to prepare for meals can be captured by the system with timestamps, and the care partners can be informed. To help the person with dementia, a care partner can write down a plan or the sequence of tasks to be followed in order to complete the activity of meal preparation according to the person's daily routine. One of the few limitations of this method is that, it still relies on help from the caregivers to the older adult. In such a setting, the ultimate goal of ambient assisted living (AAL) to promote independent living and not to encroach the privacy of the smart home resident cannot be readily fulfilled. More so, suppose during the course of performing an activity, the resident suddenly experiences an episode of confusion or loss of judgment, this implies that the written down plan might not be helpful since the resident lacks the ability to complete the activity at that instance. Further, the requirement that resident may have to memorize the procedures for the performance such activity could subject him to undue cognitive load. Also, even though the person is being monitored and tracked in real-time, the system lacks the ability to render the required "on-the-fly" assistance when an episode of confusion appears. In addition, from an economic viewpoint, this method is expensive given the additional cost incurred from the services rendered by the caregivers.

One assumption that is common to the aforementioned works is that human will naturally act to satisfy a need or goal. (Bardis, 1974) described 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". However, persons with ED often experiences difficulty in reaching their goal due to decline in their cognitive ability leading to episode of confusion or loss of judgment. Cognition enables us to *understand and predict our behavior, in other words, it is* a mental activity that involves processing of information such that the information is used to make appropriate decisions devoid of risks (Jhangiani & Tarry, 2014). In Situ (Chang, Jiang, Ming, & Oyama, 2009) observable human actions and behaviors influence changes in context values, and these represent a snapshot of a human mental state otherwise known as "desire". Hence, it is believed that human desire can be inferred from their observable actions or behavior as well as their environmental context (Dong, Yang, & Chang, 2013). More so, (Fogg, 2009) asserts that a person could only realize a target behavior if he satisfies three conditions: (1) has ample motivation, (2) possesses the ability to perform the behavior and (3) must not lack the appropriate trigger to perform the behavior. Furthermore, in effecting positive change in human behavior to ensure that they actualize their goal, understanding how people translate goals into actions is important; control theory thus provides for an effective technique called "implementation intentions" for goal pursuit (Simons, 2016).

2.2 | Techniques for Goal Inference and Behavior Simulation

Inferring human goal state or intention is of great interest to researchers in the human-centered computing community, especially those focusing on ambient assisted living (AAL). Most related research has employed statistical modelling techniques, including Hidden Markov Model (HMM; Yordanova, 2011). Although, some research has established the relationship between HMM and the theory of mind (Kelley et al., 2012), it has a number of limitations. First, a system based on HMM alone will struggle to predict intentions in situations where two or more activities on which it was trained to recognize are similar, and with no contextual information provided (Kelley et al., 2012). Second, HMM predictions are poor in situations that are commonplace as observed in its use to encode low-level actions in perspective-making model. Third, (Xie, Yang, Chang, & Liu, 2017) noted that HMM lacks the characteristics to represent the causal relations that exist among actions, context values and goal transitions. Further, goal transitions in HMM have stationary probabilities that do not mirror the reality, as a change in the human goal state relies on current context values.

Another type of statistical modeling technique used for structured prediction problems is known as Conditional Random Field (CRF). In recent times, CRF model has been employed extensively in the areas of speech recognition, natural language processing and image processing (Fang, Kodamana, Huang, & Sammaknejad, 2018). It is a probabilistic graphical model that uses feature functions to model the dependency relations among the variables (Fang et al., 2018; Sutton & McCallum, 2012). CRF is considered superior to HMM not just because it takes context into account in prediction of sequences but also its ability to establish the relations that exist among the actions, context values as well as the goals in its model (Xie et al., 2017). It however has its own drawbacks, especially when it relates to missing data. Missing data is synonymous with sensor failures at one time or another during an activity sequence in a smart home environment (Fang et al., 2018). Handling of missing data of noises due to sensor failures by CRF model might lead to biased estimation of parameters. In addition, a CRF model is highly computationally complex, hence, it is difficult to re-train the model when newer data become available (Fang et al., 2018).

In more recent research, a recurrent neural network (RNN) called Long Short-Term Memory (LSTM) has been employed in predicting the goal or intention of traffic users in an uncertain and dynamic environment involving autonomous vehicle and autonomous driving. For example, (Kim, Kang, & Kim, 2017) developed an LSTM data-driven prediction framework that analyzes the temporal behavior to predict the future trajectory of surrounding vehicles; this is aimed towards the planning of path and avoidance of collision in order to make autonomous driving a success. Similarly, (Patel, Griffin, Kusano, & Corso, 2018) proposed an LSTM-based framework for predicting the future categorical driving intention of surrounding vehicles for lane changes on the highway. This is to guarantee a high degree of safety maneuvers by autonomous vehicles while avoiding other surrounding vehicles on the road during an emergency such as sensor failure (Patel et al., 2018). The choice of LSTM as the modeling paradigm for this work is due to the following reasons. First, smart and internet of things-based environments often stream and generate high volume of data (i.e., big data) in real-time (Peng & Lin, 2016), thus the need for a robust modeling technique suitable for handing sequential data in smart environments. LSTM has a cell called memory which enables it to remember information for long period even when it is trained to learn sequential patterns or multi-class classification sequence problems over big data (Bai, Kolter, & Koltun, 2018). It is also well-suited for learning long-term context or dependencies among observations, handles varying length of observation sequence, and is able to identify the features that are germane to a variety of changes in data (Kim et al., 2017; Lipton, Kale, & Wetzel, 2016). LSTM is known to demonstrate greater efficacy in learning arbitrary functions of the missing data and observations compared to other linear predictive models (Lipton et al., 2016). It is also important to state that LSTM like other predictive models, has its limitations, a major one being that it requires significant hardware resources due to its memory bandwidth requirement (Bai et al., 2018).

Another key part of our work is – simulation of human behavior with respect to their situation (i.e., cognitive or mental state) when performing an ADL. Simulation of human behavior is age-old and has been employed in several human-centered research since the 1950s (Starbuck, 1983). For instance, in the work of (Miehling, Krüger, & Wartzack, 2013), they identified physical mock-up as the simplest form of simulating human-product interactions. (Jager & Mosler, 2007) also posit that "Behavioral determinants and processes as identified in social-scientific theory may be formalized in simulated agents to obtain a better understanding of man–environment interactions and of policy measures aimed at managing these interactions". In their work, they identified human behaviors that qualify for simulation, including decision-making processes, needs, and social learning processes which adequately characterize the manifold choice processes in behavior selection, motivation to perform behavior, as well as retention of both positive and negative experiences after the performance of a behavior. Agent-based models are useful to study emergent behavior in a social system, and are able to deal with uncertainty especially when both the goal and decision interaction are known (Hassan, Salgado, & Pavon, 2008; Vermeulen & Pyka, 2016). Uncertainty in sequential decision making is the absence of information on the choices. In other words, it is the lack of probability distributions of the results of actions (Vermeulen & Pyka, 2016).

2.3 | Influencing Goal-oriented Behavior Change in a Smart Home Environment

In order ensure that people with early-stage dementia are able to successfully navigate through the sequence of tasks that leads to their goal, there is need to support individuals especially when they experience episode of confusion or not able to remember the next appropriate task in an activity sequence. According to nudge theory, people's behavior can be directed towards a target goal through positive reinforcement which is very effective in influencing their motives, incentives and decision making (Sleek, 2013). Reinforcement learning, based on application of artificial intelligence-based systems is a concept that is based on interaction with the environment, and experience; it helps to constrain an agent's behavior to appropriate choices in situation of uncertainty (Leonettia, Locchi, & Stone, 2016). Artificial intelligence-based systems are able to take decisions that have significant impact on humans while taking their goals and desires into consideration (Abel, MacGlashan, & Littman, 2016).

(Phua, Lee, Smith, & Gayler, 2010) proposed an erroneous-plan recognition system (EPR) that detects a sequence of activities that deviates from an ADL. They employed the concept of activity probability and reward in reinforcement learning to infer if a detected activity is erroneous or not. Also, (Hassan & Atieh, 2014) proposed a reinforcement learning-based action prediction in smart home that learns the change in user's behavior using the human action on devices as feedback.

To address limitations posed by previous models, the current study uses a two-pronged approach in reinforcing human goals in the case ADL performance. First, a plan is generated that defines the paths leading to the goal state. To achieve this, we employed an automaton to model the human goal as a sequence of tasks. The aim is to further simplify a seemingly complex activity into smaller subtasks for the smart home resident. This concept is consistent with control theory that characterizes how people translate their goals into actions. Second, we employ a reinforcement learning-based agent that leverages persuasive factors included in Fogg's behavior model (FBM) in nudging goal-directed smart home resident behaviors toward completing his or her desired ADL.

2.4 | Activities of Daily Living (ADLs) and Definition of Concepts

Activities of daily living refer to foundational self-care activities that form an essential routine of a person needed to navigate daily life such as cooking, bathing, toileting, dressing and grooming (Feng, Chang, & Ming, 2017; Ohnishi, Kanehira, Kanezaki, & Harada, 2016; Xie et al., 2017). (Oyeleke, Yu & Chang, 2018) define an activity as a set of tasks or events that are performed in sequence or ordered in a stepwise manner towards a goal state. For instance, a person may be hungry and need to engage in an activity of cooking in order to satisfy his hunger (i.e., reach his goal state).

Three categories or classes of activities have been identified (Quesada et al., 2015), vis a vis:

- Single activity – an activity that has been completely executed or performed before a new one is initiated;
- Interleave 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 different activities concurrently).

Definition 1. Activity is a set of tasks or events that are performed in sequence or ordered in a stepwise manner towards a goal state. For example, a person may be hungry and may need to engage in an activity of cooking to satisfy his hunger (i.e., reach his goal state; Oyeleke, Yu & Chang, 2018).

Definition 2. Actions refer to a sequence of tasks that is required to be performed or has already been performed with respect to an activity. For example, an activity of preparing a tea may require a person to take some actions such as: "open-kitchen-door", "open-water-tap" or "turn-on-the-stove" (Oyeleke, Yu & Chang, 2018).

Definition 3. A 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 (Knight, 2002)

Definition 4. A Situation (or Situ) 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 (Chang, 2016).

Definition 5. 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 (Chang, 2016).

Definition 6. A 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 (Leveson, 2001).

Definition 7. 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 (Leveson, 2001).

Definition 8. Safety is insusceptibility to accident or losses (Leveson, 2001).

3 | SITUATION-CENTERED GOAL REINFORCEMENT FRAMEWORK

This work presents an implementation of a computational model of the notion of human-in-the-loop that is able to analyze human behavior, infer their intentions or goals, and provide support on the fly when the person is in safety-critical situations. Our goal is to unify multiple social and behavioral theories that offer useful strategies in creating human-centered systems that would be helpful to people with cognitive impairments living in smart homes. Figure 1 shows the different components of the framework and how they work together towards providing a fully automated intervention or support in accordance with the goal of AAL. In this work, our primary focus is on the aspect of goal or intention reinforcement being supported by the framework.

This section presents, first, an overview of the framework (Section 3.1), and second, a discussion of the various components of the framework in relation to their functionality in subsections of 3.1.

Four assumptions to define the scope of this work:

- **Assumption 1.** The application domain is a smart environment (i.e., a smart home consisting of several sensors deployed in different areas of the environment to capture the interactions between the inhabitant and the environment when an ADL is being performed). Sensor values represent observations of inhabitant's actions and their environmental context from which goals are inferred.
- **Assumption 2.** Only one inhabitant lives in the smart home, and his or her routine of activities of daily living prior being diagnosed of ED are known and do not change, thus, regarded as the normal ADL observations stored as historical data. Hence, ADL

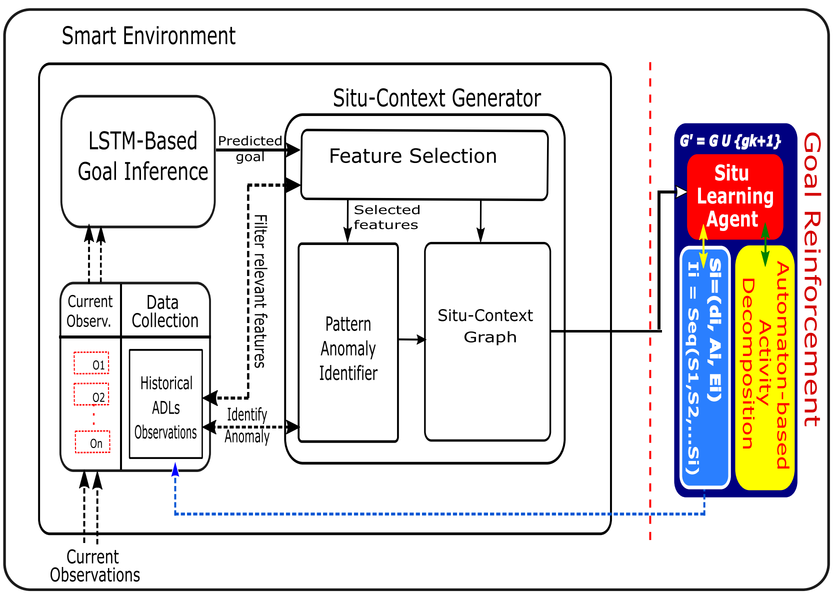

FIGURE 1 Situ-centered Goal Reinforcement Framework

performed after being diagnosed of ED are considered non-normal ADL observations, and are added to the historical data. Although, if the ADL has just begun, we consider it as the beginning of a new (emerging) intention since the inhabitant health is no longer the same.

- **Assumption 3.** The inhabitant only performs a single activity at a time. In other words, an ADL already started must be completed before a new one begins.
- **Assumption 4.** A naïve agent can simulate the behavior of the inhabitant when experiencing episodes of confusion or memory loss. Hence, we say that all required sensors that characterize a given ADL are possible choices that the naïve agent may interact with at that time instant for each situation in the sequence leading to the goal state.

3.1 | Framework Overview

The Situ-centered intention reinforcement framework is based on the extension of our previous work (Oyeleke, Yu & Chang, 2018), which relied on two assumptions: a) a human intention or goal can be inferred, and b) the order or sequence of activities in the path of the inferred goal is known. In this paper, we improve on the previous system by addressing both assumptions with the following two new key components:

1. We propose a goal inference engine that is able to infer the current goal or intention of the resident based on observations obtained from the interacting sensors in the smart home environment. The goal inference engine uses a type of recurrent neural network called long short-term memory (LSTM) for prediction or inferring the human goal (i.e., ADL in this instance).
2. We propose using a situation-context generator to identify activities that are relevant to the inferred goal, and their sequence in the goal path. First, we use the 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 the 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 person performing an ADL and renders timely intervention in safety-critical situations and ensures goal fulfilment, 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 resident livng in the smart home resident. When an abnormal situation emerges, a new goal may have been discovered, and will be added to the goal space if so. i.e. $G' = G \ U \ (gk{+}1)$

3.1.1 | Human Observations and Preparation of Datasets from Smart Home Sensors

Human Observations Dataset

In this work, we use a single activity class dataset consisting of four different ADLs, as represented by the sensor values in the smart home (see Table 1). The dataset relates to "memory abilities and dementia in older adults" generated in a smart home lab with a living room and a kitchen (Quesada et al., 2015). A single person was observed in order to generate four different ADLs, including: "prepare a tea", "prepare a hot chocolate", "drink a glass of water" and "prepare a hot snack". People with early-stage dementia have a tendency to express some abnormality while performing ADLs. This abnormality in ADLs often relates to uncertainty in their decision making due to decline in cognitive ability. An ADL sequence could be termed as abnormal based on the frequency, duration, location and time at which a task(s) or action(s) of the ADL sequence was performed. For instance, people with dementia may forget if they performed a particular a task of their intended ADL sequence or not, hence they may repeat that task several times, or skip such task. Snapshots of a normal and corresponding abnormal sequence of the ADL "Drink a glass of water" are provided in Table 2 and Table 3 below:

Observe in Table 1 that sensor id 'D07' could either be a stove or microwave, however, throughout this work, D07 represents a stove and its values are [ON/OFF]. Similarly, the sensor KT only takes on the values [ON/OFF] throughout this work.

The normal (typical) sequence represents the daily routine of the resident's performance of an ADL (prior to a diagnosis of dementia) towards fulfilling his or her goal. The atypical or abnormal sequence of the corresponding ADL refers to the current observations of the resident (post dementia diagnosis). From the "Abnormal ADL Sequence: Drink A Glass of Water" snapshot shown in Table 3 above, observe that the water sensor "WT1" appears four (4) times instead of twice as shown in Table 2 above for the "Normal ADL Sequence: Drink A Glass of Water". Such repetition of tasks indicates abnormality of the activity sequence. Also, notice that the last value of the water sensor "WT1" in the abnormal sequence was "OPEN" instead of "CLOSE", hence this situation may constitute a risk of a fall due to wet flooring as a result of flooding if the water tap is left opened too long.

TABLE 1 Set of sensors and their attributes (originated from Quesada et al., 2015)

Sensor Id	Name	Sensor values
D01	Sensor detecting interaction with the door of the kitchen.	Has a value of "Open" or "Close"
D02	Sensor detecting interaction with the door of the living room	Has a value of "Open" or "Close"
D03	Sensor identifying the cupboard where cutlery is kept.	Has a value of "Open" or "Close"
D04	Sensor detecting interaction with cupboard where dishes are kept	Has a value of "Open" or "Close"
D05	Sensor detecting interaction with cupboard where glasses and cups are kept	Has a value of "Open" or "Close"
D06	Sensor detecting interaction with the pantry cupboard	Has a value of "Open" or "Close"
D07	Sensor detecting interaction with the stove/microwave	Stove has a value of "On" or "Off" Microwave has a value of "Open" or "Close"
D08	Sensor detecting interaction with the refrigerator	Has a value of "Open" or "Close"
M01	Sensor detecting interaction with the chair	Has a value of "Absent" or "Present"
M02	Sensor detecting interaction with the sofa	Has a value of "Absent" or "Present"
TV	Sensor detecting interaction with the television	Has a value of "On" or "Off"
PH	Sensor detecting interaction with the phone	Has a value of "Pick up" or "Hang up"
WT1	Sensor detecting interaction with the water tap	Has a value of "Open" or "Close"
KT	Sensor detecting interaction with the kettle	Has a value of "On" or "Off", "Absent" or "Present"

TABLE 2 An instance of a normal activity of daily living sequence for "drink a glass of water"

Normal sequence for activity "drink a glass of water"	
2015-02-20 18:22:32	**D01 CLOSE Begin_1**
2015-02-20 18:22:46	D01 OPEN
2015-02-20 18:22:53	D01 CLOSE
2015-02-20 18:23:07	D05 OPEN
2015-02-20 18:23:20	D05 CLOSE
2015-02-20 18:23:27	WT1 OPEN
2015-02-20 18:23:36	WT1 CLOSE
2015-02-20 18:24:35	D01 OPEN
2015-02-20 18:24:41	D01 CLOSE End_1

TABLE 3 An instance of an abnormal activity of daily living sequence for "drink a glass of water"

Abnormal sequence for activity "drink a glass of water"	
2015-02-21 18:25:37	**D01 OPEN Begin_1**
2015-02-21 18:22:43	D01 CLOSE
2015-02-21 18:22:49	D05 OPEN
2015-02-21 18:22:54	D05 CLOSE
2015-02-21 18:25:58	WT1 OPEN
2015-02-21 18:26:03	WT1 CLOSE
2015-02-21 18:26:11	WT1 OPEN
2015-02-21 18:26:17	WT1 OPEN
2015-02-21 18:26:39	D01 OPEN End_1

Dataset Management

The order of tasks in ADL sequences, as well as their geo spatial information, are essential to understand the everyday life of older adults living in smart home environments and easily and reliably detect any change or abnormality in daily life patterns. In this work, we employ LSTM to infer or predict the current or new goal of older adults performing ADLs. With these data, we specifically want to predict to which of the four ADLs, an observed new ADL sequence (i.e., abnormal ADL sequence) belongs to, so that we can ultimately guide the older adult through the completion of his or her goal.

Our training dataset was prepared as follows:

i. Typically, LSTM performs well when it is fed with large dataset. Due to the small number of observation sequences generated in (Quesada et al., 2015) for each of the four single activity classes considered (i.e., “prepare a tea”, “prepare a hot chocolate”, “drink a glass of water” and “prepare a hot snack”), we generated more instances of the ADL data for all for classes of the single activity such that it follows the description of the single activity dataset sensor observation sequences for both the normal and abnormal ADL observations. A total of 5370 observation sequences were used for our experiment.

ii. We then represent each normal and abnormal ADL observation snapshot belonging to each of the four single activity classes considered (i.e., “prepare a tea”, “prepare a hot chocolate”, “drink a glass of water” and “prepare a hot snack”) as a text sequence. For example, the “Normal ADL Sequence: Drink A Glass Of Water” is represented as:
begin, door_c, door_o, door_c, glasses-cupboard_o, glasses-cupboard_c, water_o, water_c, door_o, door_c, end
(note that the letter suffix “o” and “c” indicates the sensor values i.e. open or close). Also, the corresponding class or category labels for each ADL observation sequence are assigned as follows: prepare a tea as “t”, drink a glass of water as “w”, prepare a hot snack as “s”, and prepare a hot chocolate as “c” (see url to “ADLs dataset” in reference section).
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 (Chollet, 2015) 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).

3.1.2 | Goal Inference Engine

A. LSTM Structure for Sequence Modeling

The goal inference engine simply uses LSTM for its prediction. LSTM has the potential to exploit temporal information of sequential data with arbitrary length by recursively mapping the input sequence to the output labels with hidden units as shown in Figure 2 (Hochreiter & Schmidhuber, 1997; Wu, Jiang, Wang, Ye, & Xue, 2016). Unlike the recurrent neural network (RNN), LSTM overcomes the vanishing and exploding gradient problem. LSTM is able to store the state vector representing a snapshot of the sequence of the past input data using its memory called “cell”. The cell's current state is updated in consonant with the input, output, and previous state of the cell. The LSTM also has a “forget gate”, a control mechanism that enables the network to discard or forget past state in the memory or know when to update its state based on new information. Suppose that c_t represents the state of the memory cell at the current time step t. Thus, c_t will be updated by the recursive equations as follows:

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

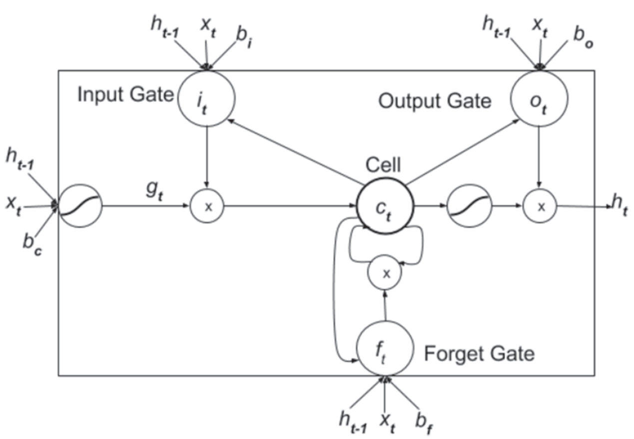

FIGURE 2 The basic structure of an LSTM unit.

$$f_t = \sigma(w_{xf}x_t + w_{hf}h_{t-1} + b_f) \tag{2}$$

$$o_t = \sigma(w_{xo}x_t + w_{ho}h_{t-1} + b_o) \tag{3}$$

$$g_t = tanh(w_{xc}x_t + w_{hc}h_{t-1} + b_c) \tag{4}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \tag{5}$$

$$h_t = o_t \odot \tanh(c_t) \tag{6}$$

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

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad \text{is the sigmoid function.} \tag{7}$$

Observe that network can discard or forget the information c_{t-1} that is stored in the cell for a given the configuration f_t = [0, … 0]. Also, the flow of information from the input to the output, can be controlled by the input gate i_t and the output gate f_t. 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 (Kim et al., 2017**)**. For example, since our case study is formulated as a multi-class classification problem (see Figure 3), 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 of is added on top of the last LSTM layer L to estimate the posterior probability p_j of the j-th class as follows:

$$p_j = softmax\left(h_t^L\right) = \frac{\exp\left(u_j^T h_t^L + b_j\right)}{\sum_{j' \in j} \exp\left(u_{j'}^T h_t^L + b_{j'}\right)} \tag{8}$$

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 ($x^{(1)}$, $x^{(2)}$, …, $x^{(m)}$) to output labels ($y^{(1)}$, $y^{(2)}$, …, $y^{(m)}$) (i.e., the ADLs class labels). We employ one hot encoding to generate the label. For instance, $y^{(i)}$ is one of $\begin{pmatrix}1\\0\\0\\0\end{pmatrix}, \begin{pmatrix}0\\1\\0\\0\end{pmatrix}, \begin{pmatrix}0\\0\\1\\0\end{pmatrix}, \begin{pmatrix}0\\0\\0\\1\end{pmatrix}$ which indicates the class or label of the current goal or intention (e.g., prepare a tea) of the resident.

In order to optimize the network parameters, we employ an efficient Adam gradient descent optimizer with a logarithmic loss function, known as "*categorical_crossentropy*" in Keras, as well as a dropout and a recurrent dropout regularizer of 0.5 each, respectively. We used a dense LSTM layer with 64 neurons in the hidden layer, 4 neuron in the output layer with a softmax activation function. We used batch size of 64, 7 epochs and embedding dimension size of 128.

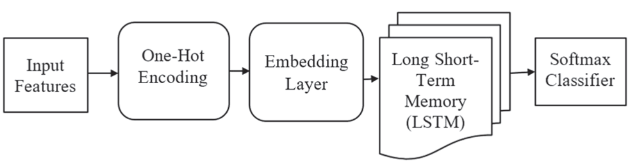

FIGURE 3 The goal inference LSTM architecture with softmax classifier

3.1.3 | Situation-Context Generator

Generally, smart environments may involve several sensors that monitor activities of daily living. This, consequently leads to streaming and generation of high volume of data (i.e., big data) in real-time (Peng & Lin, 2016). In order to successfully support people with early-stage dementia through ADLs, there is need to simplify the path that leads to completion of their goals. Hence, the situ-context generator is a critical component of our framework. The Situ-context generator is a cluster of three sub-units namely: feature selection, pattern anomaly identifier and situ-context graph. These sub-units are interdependent. We thus provide descriptions of each sub-units in succeeding paragraph.

a. **Feature Selection**: To generate a simplified path corresponding to the desired goal state, inferred or predicted by the LSTM-based goal inference unit, there is need to identify or filter the relevant features (i.e. sensors that needs to be interacted with by the resident in order to fulfil the predicted goal) from the historical ADLs observations. To achieve this, first, our ADLs datasets were represented in numeric form as described in (Quesada et al., 2015). Next, we added class labels to distinguish between "normal" (N_ob) from the "abnormal" observation (A_ob) class for each category of ADLs considered in this work. The numeric representation is done by indicating the number of times a sensor-value appears in an observation sequence for each sensor in the smart home environment. For example, consider the normal observation sequence for a given ADL: begin, D01-open, D01-close, WT1-open, WT1-close, end. Since sensor 'D01' appears twice in the sequence, then we say D01 has the value 2, and also sensor WT1 has the value 2. Table 4 below represents a snapshot of the numeric format for activity "Drink a glass of water".

Second, we applied chi-squared (χ^2) statistical test on the ADLs observations, which measures or determines the absence of independence between the features in the class (Meesad, Boonrawd, & Nuipian, 2011). Our aim is to select the features whose occurrence shows dependence on the occurrence of the class (with respect to the predicted goal). In other words, we use the χ^2 statistical test to select K best features for each of the four categories of ADLs observations. χ^2 is defined as:

$$\chi^2 = \sum_{k=1}^{n} \frac{(A_k - E_k)^2}{E_k} \tag{9}$$

Where:

A – is the observed frequency, i.e number of observations of class

E – is the expected frequency, i.e.number of expected observations of class

b. **Pattern Anomaly Identifier (PAI)**

The pattern anomaly identifier leverages the "difflib" module in python, for contiguous subsequence matching when comparing pairs of sequences. This PAI calls the module to compares the pattern of a normal observation sequence for a predicted goal with that of current observation (abnormal observation sequence) to identify the anomaly in the current observation sequence. Then, the subsequence with the anomaly (incorrect choice of action) is identified in the abnormal observation, thus ensuring a resident gets appropriate support or recommendation on action to be taken in such a situation that could constitutes a risk. Figure 4 below show an instance of anomaly identified for an abnormal observation sequence of drink a glass of water.

Notice that water tap (water_o) highlighted with the plus sign "+" was not closed for the activity sequence.

TABLE 4 Numeric representation of observation sequence for activity "drink a glass of water"

D01	D01	D03	D04	D05	D06	D07	D08	KT1	M01	M02	TV	PH	WT1	CLASS
5	0	0	0	2	0	0	0	0	0	0	0	0	2	N_ob
5	0	0	0	2	0	0	0	0	0	0	0	0	0	N_ob
4	0	0	0	2	0	0	0	0	0	0	0	0	3	A_ob
4	0	0	0	1	0	0	0	0	0	0	0	0	3	A_ob
4	0	0	0	2	0	0	0	0	0	0	0	0	3	A_ob

FIGURE 4 Instance of anomaly identified for abnormal sequence of activity "Drink a glass of water"

c. **Situ-Context Graph (SG):** is a graphical presentation of inferred human intention as a sequence of situations from observation data generated by the sensor networks in a smart home. Unlike the work of (Badea & Olaru, 2016) 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 5 is an example of an SG of inferred intention 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 intention 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 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.

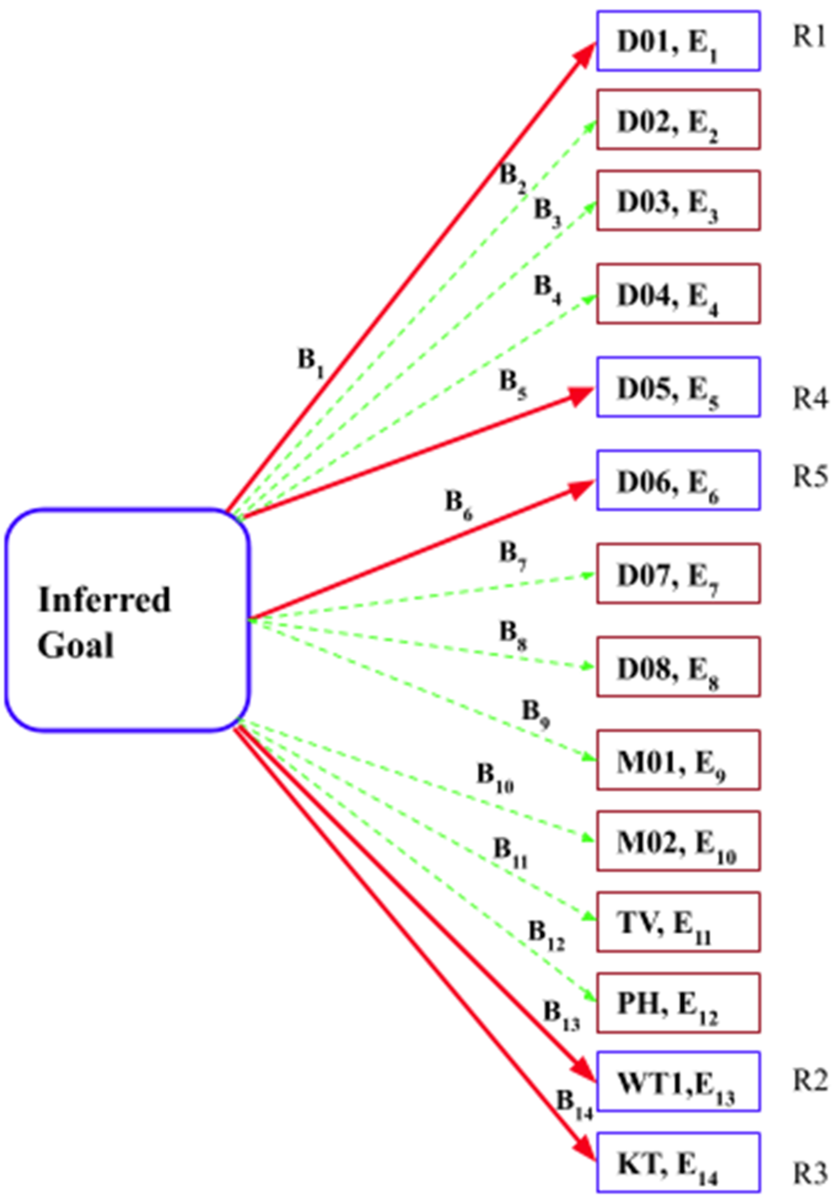

FIGURE 5 Situ-context graph of inferred goal_1 (see goal id_1 definition Table 9)

3.1.4 | Goal Reinforcement in ADL

Persuasive design techniques have been employed in several technological applications or solutions aimed at nudging change in a person's behavior towards a target behavior. Although, several persuasive technologies models have shown promise especially in area where the aim is to incite a behavior (Fogg, 2009), understanding the factors that may halt a target behavior as well as how people translate their goals into actions (Simons, 2016) would be of great significance and critical for their successes in AmI related fields. To achieve the aforementioned, we adopt persuasive design strategies based on the Fogg behavior model (FBM) combined with techniques borrowed from control theory in building a situation (situ) learning agent that will aid the reinforcement of human intention in the course of their activities of daily living to ensure that they attain their goal.

This work focuses on people with early-stage dementia. This category of people often experiences either an episode of confusion or memory loss, and consequently, disrupts their daily life. Confusion is a change in mental abilities causing lack of clarity (Kirkpatrick, 2013). A person in such a state have difficulty with thinking (Helal et al., 2003) and will lack sufficient ability to perform the sequences of tasks in his ADL that will lead to his goal at that time instant. Although, a person may have sufficient motivation (intrinsic in this case) to satisfy his or her goal, the lack of clarity will halt the target behavior from happening, hence, could put the inhabitant of a smart home in a safety critical situation. To ensure that the target behavior happens, a trigger comes handy in nudging the person off state of confusion in enabling him to perform the appropriate tasks sequences that lead to a goal. FBM identifies a type of trigger called "facilitator" as an effective tool that makes a target behavior to happen or easier to do provided the person has a high motivation.

For example, the intention of a smart home resident at a particular time may be to "prepare a tea", in this case, the resident could be said to be sufficiently motivated to satisfy his goal since the motivation is intrinsic (i.e., prompted either to pleasure himself or satisfy his hunger at that time instant). Moreover, to fulfil his intention, he must perform a sequence of activities that defines the scenario path toward goal completion. Supposing at some point in the performance of the activities he experiences an episode of confusion, it then implies that he no longer have sufficient ability to complete the sequence in order to reach his goal. Consequently, the target behavior or intention is halted, and could constitute a risk (e.g., leaving the stove turned "ON" and not remembering to turn it "OFF" due to lack of clarity). FBM also notes that "simplicity" is a key factor to increasing human ability that would cause a target behavior to happen, reason being that if performing an activity sequence that leads to goal completion causes us to think hard, it becomes intricate to do in a situation of confusion. We therefore incorporate into our framework the idea of "implementation intentions" – a behavior change technique used in control theory for activity planning or decomposition to ensure goal completion (Simons, 2016). We discuss in details implementation and operations of goal reinforcement components in the framework in the next section.

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

By implementation intentions, we mean further decomposition of an activity sequence that represents the path towards fulfilment of an ADL goal into its corresponding actionable sub-processes or task sequences that lead toward the fulfilment of the same goal. This decomposition is important as it enables the situ-learning agent (SLA) to have a better reading or bigger picture of the component steps or procedures involved in fulfilling the intended goal. Consequently, SLA is able to anticipate what tasks in the sequence may constitute safety-critical tasks when a wrong action is taken, therefore, the SLA is able to provide support to the inhabitant by recommending the appropriate action to be taken when a person is unable to make the right decision. To achieve this, we leverage on the potency of automata as a tool for pattern recognition. For each inferred intention or goal, a corresponding automaton is generated to model the activity plan produced by the SG and it is further decomposed into a sequence of task. Basically, task sequences are constructed by using the possible values of the interacting activity sensors that describe the inferred intention as discussed in section 3.3.3b. Figures 6, 7, 8 and 9 shows the possible transition scenarios that the naïve agent could go through when performing each of the four ADLs category.

For example, consider Figure 6 above, an automaton state diagram, that models the decomposition of activity sequence defining the goal id_1 into corresponding tasks sequences. It consists of five states with the labels: D01, WT1, KT, D05 and D06. D01 is the start state and the accept state (i.e., end of the activity), hence indicated by a double circle. The arrows going from one state to another are called Situ-transitions (or simply transitions). The inputs to automaton are the sets of actions/tasks that needs to be performed by an inhabitant in each of the situations in the goal path.

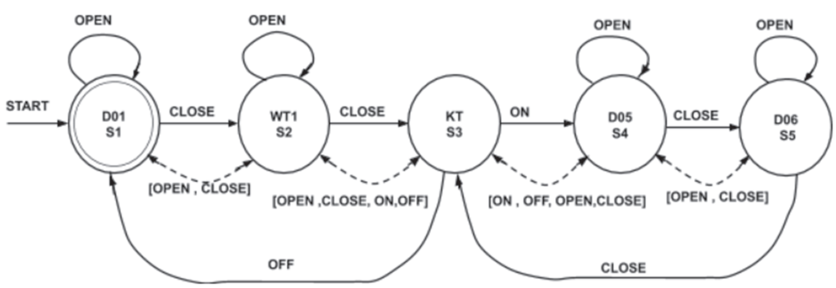

FIGURE 6 Automaton state diagram modeling the decomposition of inferred goal id_1 (see goal id_1 definition Table 9).

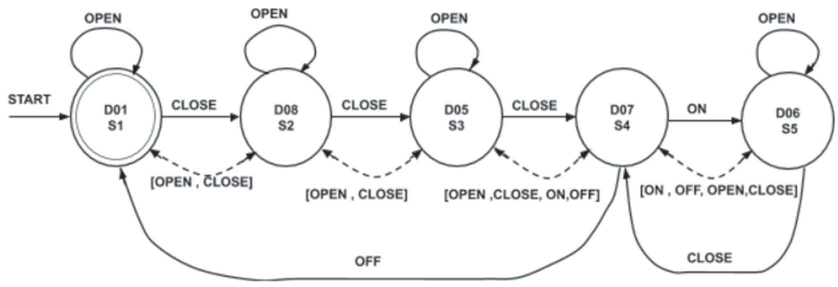

FIGURE 7 Automaton state diagram modeling the decomposition of inferred goal id_2

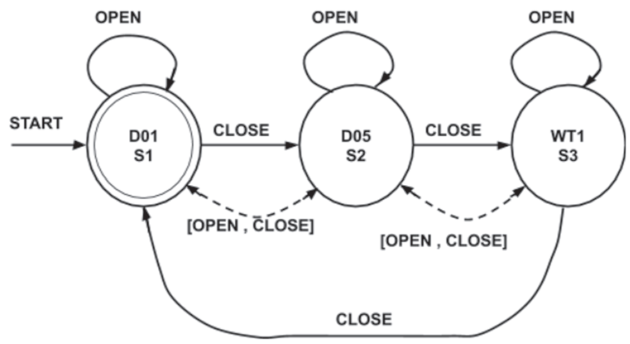

FIGURE 8 Automaton state diagram modeling the decomposition of inferred goal id_3

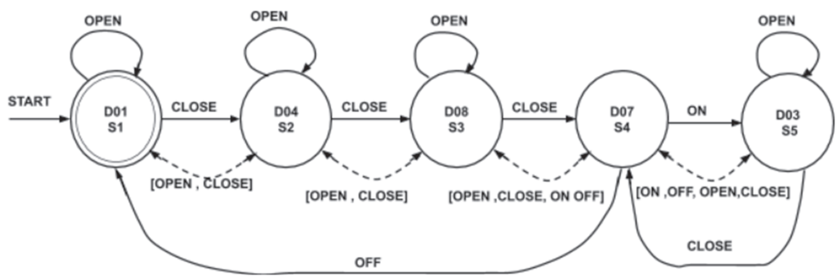

FIGURE 9 Automaton state diagram modeling the decomposition of inferred goal id_4

The output is either accept state (i.e., the goal has been fulfilled) or reject (i.e., goal was not fulfilled). Observe that the automaton is made up of two distinct transition arrows; solid and dash. The state diagram with the solid transitions only – indicates a finite automaton (FA) model of the goal execution by an inhabitant who does not suffer from ED, while the state diagram consisting of both solid and dash transition arrows, represents a nondeterministic finite automaton (NFA) model of the goal execution by an inhabitant diagnosed with ED (see Table 5). Also note that we use the NFA to simulate or depict episodes of poor judgements or decision making that could constitute a risk to life. The dash arrows are bi-directional.

In addition, notice that each of the five states has labels corresponding to S1, S2, S3, S4 and S5, respectively, which refer to the situations sequence defined as <S1, S2, S3, S4, S5> = I. Each situation also corresponds to an activity composed of subtasks. For instance, Situation S1 describes the activity D01, and it is composed of two subtasks vis a vi; OPEN/CLOSE tasks. Therefore, the equivalent tasks sequence for the same goal is given as:

$$[S1\_OPEN \rightarrow S1\_CLOSE] \rightarrow [S2\_OPEN \rightarrow S2\_CLOSE] \rightarrow [S3\_ON] \rightarrow [S4\_OPEN \rightarrow S4\_CLOSE] \rightarrow [S5\_OPEN \rightarrow S5\_CLOSE] \rightarrow [S3\_OFF]$$

TABLE 5 A nondeterministic finite automaton state transition table showing episodes of confusion goal id_1

	OPEN	CLOSE	ON	OFF
S1	S1, S2	S2, S1	n/a	n/a
S2	S2, S1, S3	S3, S2, S1	n/a	n/a
S3	n/a	n/a	S4, S2	S1, S2, S4
S4	S4, S3, S5	S5, S4, S3	n/a	n/a
S5	S5, S4	S3, S4	n/a	n/a

TABLE 6 Finite automaton state transition table showing normal task sequence for goal id_1

	OPEN	CLOSE	ON	OFF
S1	S1	S2	n/a	n/a
S2	S2	S3	n/a	n/a
S3	n/a	n/a	S4	S1
S4	S4	S5	n/a	n/a
S5	S5	S3	n/a	n/a

Table 6 describes the normal or required task sequence that leads to goal id_1 for an inhabitant without ED. The inhabitant moves from situation to situation to satisfy his or her goal depending on the task/action he/she performs which is recognized by the sensor corresponding to that situation. Table 6 depicts the normal transition sequence to satisfy goal_1. When in S1 state and performing action OPEN on the kitchen door the inhabitant enters the kitchen and remains in S1 (this time at the rear of the door). If she performs a next action of CLOSE on the door she moves to state S2. Similarly when in S2 and performs an OPEN action she stays in S2 because moving to S3 risks flooding the kitchen if the she forgets (as represented by the values in the cell intersecting state S2 and action OPEN in Table 5) to close the water tap hence constitutes a risky state (e.g. inhabitant may slip due to wet floor) (Belli, 2001) . Therefore he must perform a CLOSE action before moving to S3. In the state S3 if action ON is performed he moves to S4. However if inhabitant experiences episode of forgetfulness or lacks clarity on what she wants to/should do next may transit to S2 and next to S1 and exit the kitchen as depicted by the values in the cell intersecting row S3 and column ON in Table 5. This scenario may constitute a hazard if the water in the kettle dries up and the stove is not turned OFF; it could cause fire outbreak which poses threat to life. Inhabitant remains in state S4 when she performs action OPEN and transits to S5 when performs a CLOSE action. Similarly she remains in S5 when she performs action OPEN but will transit to S3 when he performs a CLOSE. Finally in state S3 he must perform an OFF action at which point we say that the goal is satisfied. Note that n/a implies that the action is not applicable to that situation.

B. **Situ Learning Agent (SLA)**

Uncertainty in sequential decision making is the lack of information on the options (now or in the future) or on the probability distributions of outcomes of actions (Vermeulen & Pyka, 2016). Agent-based models are useful to study emergent behavior in a social system, as these models possess the intelligence to cope with uncertainty when aware of the goal and decisions interaction (Hassan et al., 2008; Vermeulen & Pyka, 2016). As a result, these models are able to transform goals into action tasks (Chen, Li, Chen, & Wen, 2011).

Our aim here is to be able to support a person with early-stage dementia in making the right decision 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 when performing ADLs e.g. forgetting to turn-off the stove) when he or she forgets or lacks clarity. Thus, we propose a situ learning agent (SLA) that can anticipate the action taken by human and its consequence, and consequently ensure that the right action is taking towards satisfy the goal. 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 (Chang, 2016). Figure 10 describes the Situ architecture. Secondly, though SLA is an adaptation of a type of reinforcement learning systems called model learning or learning automata (Vaandrager, 2017; Zhang, Granmo, & Oommen, 2012), that is known to be efficient in environment with uncertainty, we also introduced additional attribute for heuristic. Model learning based reinforcement learning systems have been reported to be efficient in an environment with incomplete knowledge or uncertainty (such as a state of confusion in persons with ED), as well as for the understanding of embedded control software (Oommen & Hashem, 2010; Vaandrager, 2017). Thus, the system is able to take decisions in situations of uncertainty by learning the best action out of a set of actions provided in a probabilistic environmental context (Narendra & Thathachar, 1974).

We also contrive a second agent called naïve agent to simulate episode of uncertainty in person with ED when performing ADLs. The aim is to show how SLA recommends or guides the naïve agent in making the right decision (Figure 11 above shows SLA's and naive agent interaction with the activity sensor environment).

The SLA has the following attributes defined by four parameters <*M*,*B*,*E*,*Q*>. *M* is a vector defined by two-tuple $< P(t), \widehat{D}(t) >$, it keeps track of the human desire (i.e. the naïve agent) 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 i *th* action will be taken by the naïve agent in state or situation s_i. Note that $\sum_i^n pi = 1$. *B* is a set of r actions that the naïve agent can choose from, which may satisfy s_i in goal G' . Note that the action chosen/taken is denoted as $\alpha(t) = \alpha_i$. Also, $\alpha(t) \in B$, for all t. *E* is a set <*R*, *D*>. Suppose $R = \beta(t)$, where *R* is the reward or penalty for an action taken in situation *S*1. An action is rewarded with a point value of 1 if it is the appropriate choice, otherwise it is penalized (i.e., $R = \{1, 0\}$). In other words, $\beta(t)$ is the response from the environment. $\widehat{D}$ is a set $\{d_1, d_2, \ldots, d_r\}$. $d_i(t)$ is the probability that an action α_i will be rewarded.

We also assume that the SLA uses a 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

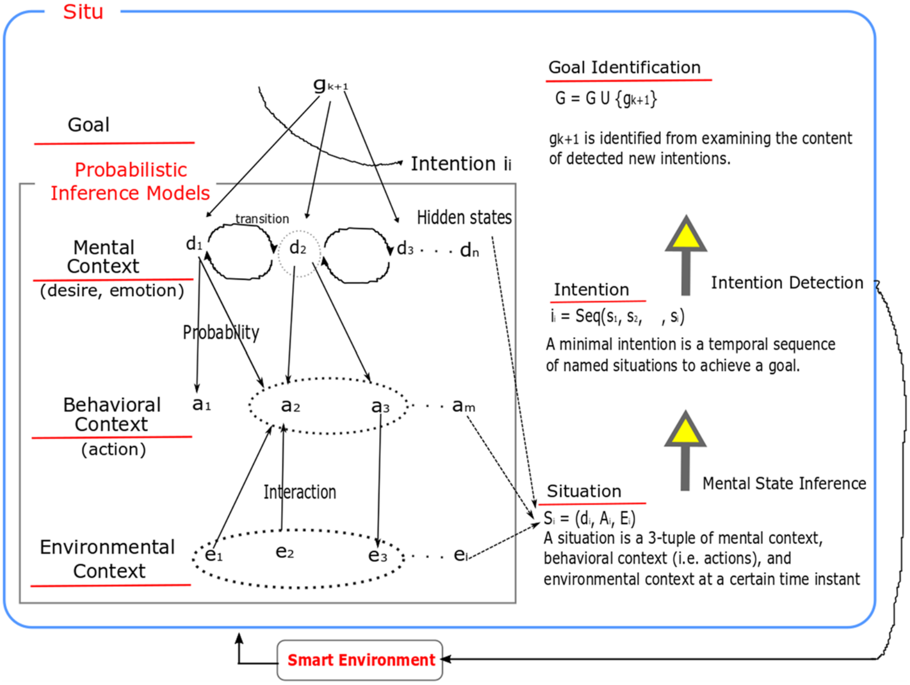

FIGURE 10 Situ architecture

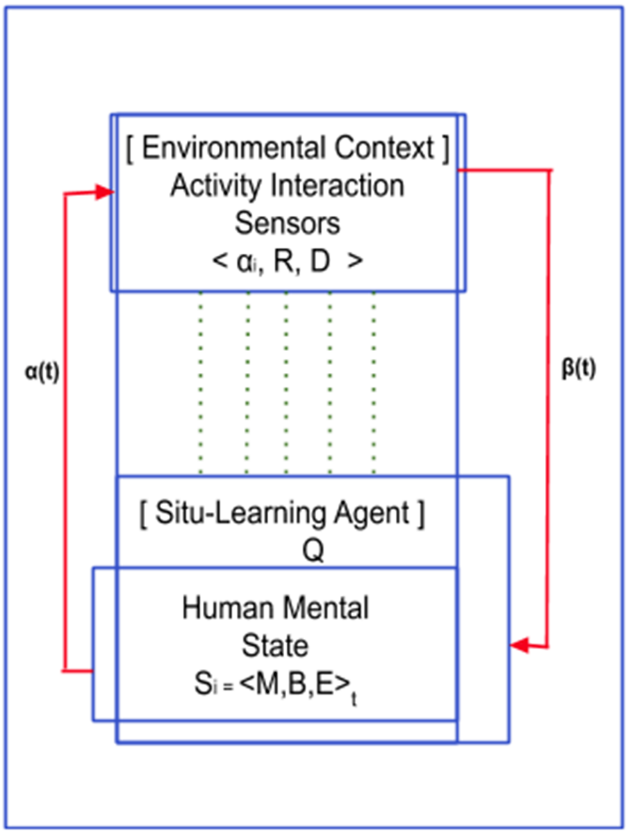

FIGURE 11 SLA, naïve agent and activity sensors interaction

that state. In other words, each action is assigned a value h_i , where h_i for the best α_i is maximal. Note that with the exception of 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 α_i for s_i in the goal path G'.

Algorithm 1 A SLA,Naive Agent Coordination Algorithm

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

Output : an optimal α_i whose $\widehat{d}_i$ 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. $p_i(t) = \frac{1}{w}$, Such that w is the number of action choices that naïve agent can choose from ats $_i$.
4. $\widehat{\mathrm{d}}_\mathrm{i}(\mathrm{t}) = \frac{1}{2}$
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 $\alpha(t) = \alpha_i$.

$$\boxed{\begin{array}{c}\boldsymbol{SLA}{:}On\ naive\ agent's choice\ \ in\ step\ 1, \boldsymbol{Run}\ Q;\ to\ determine\ the\ best\ \alpha(t)\ \text{ for }\ s_i\ as{:}\\ \max(H)\end{array}}$$

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 $R(\mathrm{t}) = 1$ 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 $\widehat{d}_i(t)$ as:

$$\frac{\int_0^{\widehat{d}_i}(t)v^{(x_i-1)}(1\text{-}v)^{(y_i-1)}dv}{\int_0^1 u^{(x_i-1)}(1\text{-}u)^{(y_i-1)}du} = 0.95$$

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 ith situation or state of the observed situation sequence defining the goal path of G'

α: 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 α_i is maximum.

$$x_i,\ y_i: \text{are the Beta distribution's two positive parameters for action i.}$$

$$p_i: \text{is the ith item of P (i.e.the action selection probability vector)}$$

$$\widehat{d}_i: \text{ is the ith item of tbe Bayesian estimates vector } \widehat{D}, \text{ which is derived by the } 95\% \text{upper bound}$$

$$\text{of cumulative distribution function (cdf) of the corresponding Beta distribution}$$

$$m: \text{indicates the index of the element of the reward probability estimates } \widehat{D} \text{ that is the maximum}$$

$$R: \text{is the reward or penalty from the environment for an action taken}$$

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

4 | CASE STUDY

Table 7 below presents a description four instances of single activity ADLs considered in this work (Quesada et al., 2015).

Table 8 highlights the sensors involved in the performance of each of the ADL. We also must emphasize that this represents normal plan or interaction benchmarks for the ADL and as contained in the historical observations of the inhabitant prior being diagnosed with ED. Although, the order of the sensors as presented in the table do not represent necessarily represent the activity sequence for each ADL. In addition, 'A' indicates that a sensor is applicable or involved in an ADL 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.

4.1 | Goal Inference Experiment

A. **Experiment and Results:** In this study, we leveraged both the Theano's and Keras Deep Learning library's implementations of LSTM (Chollet, 2015). To train the LSTM model, we first split the dataset into train and test set. We use 30 percent for training and 70 percent for test. To

TABLE 7 Description of a resident's typical sequence for performing the ADLs

	ADLs	ADL sequence
1	Prepare a tea	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
2	Prepare a hot chocolate	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
3	Drink a glass of water	1) enter into the kitchen, 2) take a cup from the glasses cupboard, 3) fill the cup with water from the tap
4	Prepare hot snack	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

Abbreviation:ADLs, activities of daily living.

TABLE 8 Interacting sensors for each ADL (originated from Quesada et al., 2015)

Id	ADL	D01	D02	D03	D04	D05	D06	D07	D08	M01	D02	TV	PH	WT1	KT
1	Prepare a tea	A	NA	O	NA	A	A	NA	NA	O	NA	NA	NA	A	A
2	Prepare a hot chocolate	A	NA	O	NA	A	A	A	A	O	NA	NA	NA	NA	NA
3	Drink a glass of water	A	NA	NA	NA	A	NA	NA	NA	O	NA	NA	NA	A	NA
4	Prepare hot snack	A	NA	A	A	NA	NA	A	A	O	NA	NA	NA	NA	NA

Abbreviation:ADL, activity of daily living.

infer the goal of the inhabitant, we feed the trained LSTM model with an abnormal observation of a given ADL, which the LSTM is able to predict by assigning it the corresponding class label. We then evaluate the accuracy model. A model accuracy of 90.1% was achieved. In addition, in order to see how well the LSTM model performed on the dataset, we further compute both the precision, recall, and f1-score for each class label as well as the average which summarized in Table 9 below.

Results obtained for precision, recall and f1-score for each ADL class shown in Table 9 indicates that our LSTM-based goal inference model performed very well. Also, 90.1% prediction accuracy was obtained for our model. We further compared our model accuracy with those obtained for both HMM and CRFs in (Lago & Inoue, 2018) and (Ghasemi & Pouyan, 2015) respectively. In (Lago & Inoue, 2018), the ADLs datasets for morning, afternoon and evening were collected separately. They obtained 64.9%, 71.0% and 68.3% as the test accuracies prediction of the HMM model for morning, afternoon and evening datasets respectively. Also, (Ghasemi & Pouyan, 2015) used four different types of model namely; Naïve Bayesian Classifier (NBC), HMM, Hidden semi-Markov Model (HSMM) and CRF to infer human activities or goals. 78.4%, 70.0%, 70.9% and 81.8% were reported as the better results obtained for NBC, HMM, HSMM and CRF respectively. Therefore, our LSTM model outperform all four state of the art models employed in both (Lago & Inoue, 2018) and (Ghasemi & Pouyan, 2015). In addition, the results in Table 9 also show that LSTM can predict goals in a wide range of activities of daily living with a relatively high accuracy, even when these ADLs have similar subsets of situations sequences.

4.2 | Feature Selection Experiment

A. **Experiment and Results:** To implement the univariate selection (Chi-Square feature selection), we leveraged the scikit-learn library which provides us with the SelectKBest class to select the top k features.

Tables 10, 11, 12, and 13 below indicate the relevant features (i.e., the interacting sensors) that the inhabitant is expected to interact with in order to fulfil his or her predicted goal. The scores indicate that features selected have the strongest relationship (i.e. contributes more to the target outcome than the remainder features or sensors present in the smart home environment) with respected to the intended or predicted goal. Hence, features with score of zero are omitted from the table, not used for generation of the corresponding situ-context graph (refer to

TABLE 9 Goal inference experiment results and evaluation metrics

Inferred goal Id	Inferred goal	Precision	Recall	F1 score
1	Prepare a tea	72.0%	100.0%	84.0%
2	Prepare a hot chocolate	100.0%	60.0%	75.0%
3	Drink a glass of water	100.0%	100.0%	100.0%
4	Prepare hot snack	100.0%	100.0%	100.0%
Average		93.0%	90.0%	90.0%

TABLE 10 Selected features for inferred goal id_1

Selected features	Score
WT1	131.517
D01	3.317
D05	0.033
D06	0.031
KT	0.025

TABLE 11 Selected features for inferred goal id_2

Selected features	Score
D07	189.574
D08	189.574
D01	70.157
D05	0.044
D06	0.016

TABLE 12 Selected features for inferred goal id_3

Selected features	Score
WT1	150.000
D01	21.543
D05	0.026

TABLE 13 Selected features for inferred goal id_4

Selected features	Ranking score
D07	202.955
D01	0.036
D04	0.023
D08	0.018
D03	0.012

Figure 5) corresponding to the inferred goal. The results, therefore, show that feature selection amplifies the plausibility of automation of a pre-planned path for an inferred goal in smart home environments, by identifying locations relevant to the sequence of tasks defining the predicted goal state.

4.3 | Goal Reinforcement Experiment

Here, we demonstrate how SLA assists or guides the naïve agent through task completion in safety-critical situation. To do this, we considered instances that may constitute a risk in an ADL situation sequence for all four categories of ADLs. Table 14 below describes the safety-critical situations considered in this experiment. Each safety-critical situation represents a missed task during ADLs, hence the need for SLA to recommend appropriate action to the naïve agent in such situation to avert the danger that may arise.

4.3.1 | Experimental Settings

Our implementation leverages the open-source Anaconda Distribution for Python machine learning and deep learning which provides an easy-to-use environment for scientific Python (SciPy). Thus enabling easy management of libraries, dependencies and environment.

TABLE 14 Some safety-critical situations in ADLs observation sequences

Normal observation sequence	Abnormal observation sequence	Safety-critical situations	Class
begin, door_o, door_c, water_o, water_c, kettle_on, glasses-cupboard_o, glasses-cupboard_c, pantry_c, pantry_c, kettle_off, door_c, **end**	**begin**, door_o, door_c, water_o, water_c, kettle_on, glasses-cupboard_o, glasses-cupboard_c, pantry_c, pantry_c, **kettle_on**, door_c, **end**	Kettle was not turned "off" at the end of the activity for abnormal observation sequence. Hence, may constitute a risk.	Prepare a tea
begin, door_o, door_c, fridge_o, fridge_c, glasses-cupboard_o, glasses-cupboard_c, stove_on, pantry_o, pantry_c, stove_off, door_o, door_c, **end**	**begin**, door_c, door_o, door_c, fridge_o, fridge_c, glasses-cupboard_o, glasses-cupboard_c, **stove_on**, pantry_o, door_o, door_c, **end**	Stove was not turned "off" at the end of the activity for abnormal observation sequence thereby constituting a risk.	Prepare a hot chocolate
begin, door_c, door_o, door_c, glasses-cupboard_o, glasses-cupboard_c, water_o, water_c, door_o, door_c, **end**	**begin**, door_o, door_c, glasses-cupboard_o, glasses-cupboard_c, water_o, water_c, **water_o**, door_o, door_c, **end**	Water tap was not "closed" at the end of the activity. Hence, may constitute a risk	Drink a glass of water
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**	**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**	Stove was not turned "off" at the end of the activity for abnormal observation sequence. Therefore may constitute a risk.	Prepare hot snack

Notes. Bolden text indicates the start and endpoint for each ADL sequence. Red text is used to indicate an anomaly or abnormal pattern in the given ADL sequence.

4.3.2 | Experimental Procedure

We then ran the experiments to simulate the performance of the SLA in recommending appropriate actions to naïve agent in each safety-critical situations as follows. Consider the safety-critical situation (i.e. not turning "off" the kettle (KT sensor)) occurring at situation < Sit_3> in situation sequence < Sit_1, Sit_2, Sit_3, Sit_4, Sit_5> for activity "prepare a tea" identified in Table 14. To simulate the lack of clarity or forgetfulness on the appropriate action to be taken by the naïve agent in such situation, we introduced the 5 sensor values including the missed task for kettle sensor in < Sit_3>, and other sensor values relating to tasks in both the preceding and succeeding situations to the safety-critical situation as possible choices (i.e. door_o, water_c, kettle_off, glasses-cupboard_c, pantry_c). Note that since activity "Drink a glass of water" has 3 states given as < Sit_1, Sit_2, Sit_3>., 3 possible actions were used instead. The action probability values represents the probability of each action (possible choices) being chosen by the naïve agent, while reward probabilities represents the probabilities of the each action being rewarded if chosen. At initialization, both action probabilities and reward probabilities are equal to avoid biases. Also, note that the sum of the action probabilities is approximately equal to 1. We reported the values of both reward probabilities for the actions and the action probabilities at initialization and convergence, convergence threshold as well as the number of runs for convergence as shown in the Table 15) below.

This experiment relied on the following assumptions for the results shown in Table 15 above:

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_i, 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_i

From Table 15, at convergence, the action probability corresponding to the appropriate (optimal action i.e. kettle_off in the case of < Sit_3> for activity "Prepare a tea") choice is maximum, and it is greater than the threshold of 0.95. Also, its reward probability is also maximum. Thus, we say 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 which leads to convergence (i.e. exceeds the threshold). The number of iteration is the number of run or step it took the SLA to determine which action is appropriate or optimal in safety-critical situation. Thus, the results show that Situ learning agent (SLA) can recommend appropriate action in safety-critical situations identified in an ADL goal sequence.

5 | DISCUSSION

To our knowledge, this is the first study that has explored an end-to-end (i.e. from prediction of goal or intention, to generation of relevant goal path, and recommendation of appropriate task in risky situations) automated framework to support seniors with early-stage dementia in their activities of daily living. Our specific relevant findings are as follows:

LSTM can infer goals with a relatively high accuracy in a wide range of activities of daily living with similar situations. Further, a number of advantages of LSTM model for goal prediction, especially in dynamic environment like the smart home, were identified that are consistent with past research (Bai et al., 2018; Kim et al., 2017; Lipton et al., 2016; Peng & Lin, 2016).

First, LSTM included the influence of its cell otherwise known as memory on its ability to make predictions in a wide range of situations in ADLs. Its memory is able to retain information over a long period, hence, makes it suitable for learning sequential patterns when trained on multi-class classification sequence problems involving bigdata.

Second, LSTM demonstrates better performance in handling observations with varying sequence length, as well as learning both short and long-term contexts or dependencies when reccurent dropout regularizer is applied, and thus, it is also able to capture long-term relationships among observations (Kim et al., 2017; Lipton et al., 2016). As such, LSTM has advantage over HMM, that is unable to represent relations that exist among actions, context values and goal transitions (Xie et al., 2017), and CRF, that is only able to estimate the probability of the entire sequence by relying on the whole information from the entire sequence observation (Abramson, 2015). In an environment like the smart home where sensors may fail and lead to information loss, CRFs' estimation may be biased (Fang et al., 2018).

TABLE 15 Results of the action and reward probabilities for optimal action

Goal ID	Threshold	Action probabilities at initialization	Action probabilities at convergence	Reward probabilities at initialization	Reward probabilities at convergence	Number of Iteration
1	0.95	0.20, 0.20, 0.20, 0.20, 0.20	0.01, 0.01, 0.96, 0.01, 0.01	0.50, 0.50, 0.50, 0.50, 0.50	0.50, 0.50, 0.99, 0.50, 0.50	1
2	0.95	0.20, 0.20, 0.20, 0.20, 0.20	0.01, 0.01, 0.01, 0.96, 0.01	0.50, 0.50, 0.50, 0.50, 0.50	0.50, 0.50, 0.50, 0.99, 0.50	1
3	0.95	0.33, 0.33, 0.33	0.02, 0.02, 0.96	0.50, 0.50, 0.50	0.5, 0.50, 0.99	1
4	0.95	0.20, 0.20, 0.20, 0.20, 0.20	0.01, 0.01, 0.01, 0.96, 0.01	0.50, 0.50, 0.50, 0.50, 0.50	0.50, 0.50, 0.50, 0.99, 0.50	1

However, the findings from this study also suggest that it can be difficult to tune the LSTM hyperparameters (e.g. epochs, number of neurons, batch size) in order to have an optimally trained model, since there are no hard and fast rules on how to do it. Thus, a systematic exporation of different configurations has to be performed, and this could take hours or days to train. Nonetheless, the Keras deep learning library allows you to save your final optimal LSTM model, hence, when new observation sequence or data becomes available, the saved model can be loaded to make prediction on the new data.

Further, the results obtained from our feature selection experiments also amplifies the plausibility of automation of a pre-planned path relevant to the fulfilment of the inferred goal in smart home environments. The univariate feature selection we employed was able to identify the relevant features or sensors that the person performing an ADL need to interact with in order to fulfil the inferred goal, hence, a simplified goal path is represented. We believe that automated path planning will be very useful in supporting seniors in their ADLs especially those with early-stage dementia. Hence, there is a need to validate the performance of the univariate feature selection method against other existing ones such as the recursive feature elimination, and feature importance technique.

Finally, in our goal reinforcement experiment, we contrived a naïve agent to simulate an episode of forgetfulness or uncertainty during ADLs in person with early-stage dementia. Our findings suggest that our agent model otherwise referred to as Situ learning agent (SLA) is able to recommend appropriate action in a risky situation detected in an ADL goal sequence, thus, averting potential hazards from the performance of ADLs in smart home environments. Thus, this observation shows that our findings also agree with previous research that agent-based models are useful to study emergent behaviors in a social system or an environment with uncertainty such as the smart home (Hassan et al., 2008; Vermeulen & Pyka, 2016;Oommen & Hashem, 2010; Vaandrager, 2017).

6 | THREATS TO VALIDITY

Although, agents have been successfully used to simulate human behavior in many human-centered applications, the proposed framework needs to be applied to real-life, dynamic scenarios to verify its efficacy. More so, it is a general belief that hazardous states cannot be completely eliminated in any system since some hazards are inherent elements of systems. For example, an electrical spark could happen due to high voltage and may lead to fire outbreak.

7 | CONCLUSION AND FUTURE WORK

It is important for an older adult to be able to carry out ADLs 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 ADLs. 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). In this paper, we present a Situation-centered goal reinforcement framework that uses an LSTM-based goal engine to infer the intention/goal of a resident living in smart home and generate an automated plan: by identifying a relevant activity sequence that defines the intention/goal path using a univariate feature selection technique, and we represent the same as situ-context graph. The automated plan is further simplified into a sequence of tasks such that a situation-learning agent is able analyze the goal path, learn, and anticipate actions/tasks that may constitute a risk if the resident fails to execute them appropriately either due to forgetfulness or lack of clarity. The SLA is able to make recommend appropriate actions to the resident (as simulated by naïve agent) to ensure that his or her goal is fulfilled at that time.

In our experiment, we considered four different cases of activities of daily living using a single activity class dataset generated from smart home lab reported (Quesada et al., 2015). First, we used an LSTM inference model to predict the goal of the resident. We further evaluated the performance of the model using metrics including; accuracy, precision, recall and f1-score, and compared our results against other state of the art predictive models. In addition, we incorporate a situ-learning agent to support older adults with ED with decision making, to ensure that they are able to complete their ADL sequences with respect to their goal.

We have been able to show that LSTM can infer goals with a relatively high accuracy in a wide range of activities of daily living, even with similar situations. Further, feature selection can be employed to identify the relevant task with respect to a predicted goal to enable the generation of an automated path in smart home environments. In addition, situ-learning agent show 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 ADL sequence in smart home environments. Overall, the results obtained are quite promising in our opinion. Finally, the scope of this work is currently limited to single activity class, and for our future work, we would extend our Situ-centered intention reinforcement framework to other scenarios of ADLs such as interleave activity.

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