Design of a Rule-Based and ADL Analysis System to Support Care of the Elderly

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Abstract. Medical advances have allowed people to live longer and this has presented different challenges to support them to keep living independently at home. The COVID-19 pandemic has affected the situation with less care staff and resources available for the elderly, which have also been spending more time at their homes without external contact. Elderly people are typically looked after by formal (professional carers) and informal (relatives and friends) carers. The work of carers has been increasingly supported using technologies for communication and wellbeing monitoring of Activities of Daily Living (ADLs) that elderly people perform in order to detect abnormal events that could negatively affect their well-being. This paper presents the design of a rule-based and ADL analysis system that takes data from different sensors as input and presents a number of visualisations in a dashboard as output. The dashboard is as user friendly as possible for both formal and informal carers of elderly people. It is intended that the proposed system can identify both immediate problems, but also trends and deviations from the individual's norm, or that of a comparable cohort, which indicate the opportunity for pro-active care. This research has been done in collaboration with the Kraydel company, whose staff supported with ideas and with the commercial needs to be considered in the solution design presented in this paper.

Keywords: Activity recognition · Activities of Daily Living · Sensors

1 Introduction

Enabling elderly people to live independent lives safe and well in their own homes is a key challenge of our age. This need has been amplified by the COVID-19 pandemic and the need for the elderly (and other vulnerable) people to shield themselves from external contacts. The gradual affordability and widespread use of technologies for communication and for wellbeing monitoring have supported the work of formal (professional

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carers) and informal (relatives and friends) carers of elderly people. It is of particular interest to monitor the Activities of Daily Living (ADLs) that elderly people perform to detect abnormal events that could negatively affect their wellbeing and send notifications to their carers to act promptly. In addition, care is slowly pivoting towards a model of preventive rather than reactive action, and that is only possible if we have reliable information on people's physical and mental well-being and any trends which suggest an intervention is required.

This paper presents the design of a rule-based and ADL analysis system that takes data from different sensors as input and presents a number of visualisations in a dashboard as output. The dashboard is intended to be as user friendly as possible for both formal and informal carers of elderly people. It is intended that the proposed system can identify both immediate problems, but also trends and deviations from the individual's norm, or that of a comparable cohort, which indicate the opportunity for pro-active care. The solution design presented is the output of a project collaboration with the Kraydel company, whose staff supported with ideas and with the commercial needs to consider for this solution. Kraydel has developed a hub with onboard sensors to be deployed within the home. Kraydel's hub has integration with third party sensors such as motion, smart plugs, and room temperature, and also biomedical devices such as blood-pressure cuffs, pulse-oximeters, clinical thermometers and weighing scales. Kraydel have also developed a proof-of-concept event processing engine that demonstrates some of the principles necessary for identifying ADLs and which was used as foundation of the event processing engine presented in this paper.

The remainder of the paper is organised as follows. Section 2 presents the related work on the motivation for the use of Smart Homes and different types of approaches. Section 3 describes the type of data and the dataset considered. Section 4 introduces the rule syntax approach used. Section 5 explains an event processing engine that uses rules to detect that an ADL has occurred. Section 6 presents a dashboard user interface in which the inferred ADLs are visualised. Finally, Sect. 7 presents conclusions and future work.

2 Related Work

This section presents the related work in two areas: (i) the motivation for the use of Smart Homes, and (ii) different types of Smart Home approaches (knowledge-driven, data-driven, and hybrid).

2.1 Motivation for Smart Home Research

The World Health Organisation (WHO) have recently stated concerns regarding the ageing population, expressing that "In 2019, the number of people aged 60 years and older was 1 billion, and this number will increase to 2.1 billion by 2050" [1]. Health decline of the ageing population through disability and the development of chronic illnesses has had an adverse impact upon the continually increasing healthcare costs, in addition to increasing the strain upon healthcare providers due to staff deficiencies [2]. Thus, an alternative cost-effective care provision is required.

The concept of "ageing in place" has emerged due to the concerns outlined, which aims to support the ageing population through enabling them to live independently for longer within their own homes, thus increasing their quality of life [2]. According to [3], a large majority of the ageing population are reluctant to reside in dedicated care facilities, therefore the progression of supportive measures are required to maintain independent living within their own homes.

Smart home research involving ambient intelligence and the development of assistive technologies has emerged to tackle the specified concerns, with Ambient Assisted Living (AAL) transpiring as one technology-focused approach to support independent living amongst the ageing population. For example, these technologies may monitor an inhabitant's movements within the home and may detect health decline or abnormal behaviours through activity tracking, which may indicate a health or behavioural problem that requires intervention. ADLs are often monitored in smart homes to ascertain the status of health and wellbeing of inhabitants [4]. During an assessment, an inhabitant's independence is observed and evaluated to ensure they have adequate cognitive and physical capabilities to perform basic activities, such as maintaining personal hygiene, dressing, preparing meals and taking medication. An inhabitant must be capable of performing ADLs independently to ensure they can safely live and function in their home environment [5, 6].

Several technologies exist and can be deployed within smart homes to track the movements of inhabitants and automatically recognise activities performed. These are commonly categorised as either vision-based or sensor-based activity recognition approaches [7]. Vision-based approaches, such as the deployment of video cameras, often raise privacy concerns which restrict their adoption. For example, according to [8], a large majority of the ageing population express privacy concerns with vision-based approaches and therefore are reluctant to their installation. Instead, sensor-based approaches are often preferred to eliminate privacy issues within health and wellbeing application areas. These can be body-worn sensors such as smart watches, or environmentally deployed sensors such as Passive Infrared (PIR) sensors, contact switches, vibration, pressure, temperature/light/humidity or Radio-Frequency Identification (RFID) sensors, which can unobtrusively monitor smart home inhabitants [8].

2.2 Knowledge-Driven vs Data-Driven Approach

Sensor-based activity recognition is generally categorised as either knowledge-driven or data-driven [9]. Data-driven approaches require large-scale datasets and the application of data mining and machine learning methods to learn activity models [10], whereas knowledge-driven approaches build activity models through exploiting rich prior knowledge within the focused domain [11]. Data-driven approaches are able to handle temporal information and uncertainty, and this may be deemed beneficial, however their successful implementation relies upon the use of large-scale datasets and reusability concerns have emerged as the learnt models may underperform when applied to a range of users [10]. Another concern that continues to challenge the successful implementation of data-driven approaches is the widely-acknowledged shortage in publicly available, accurately annotated and high-quality datasets [12]. In a study conducted by [13], a data-driven approach was designed and implemented to monitor the health and wellbeing of an elderly smart home inhabitant through detecting both normal and abnormal behaviours whilst performing ADLs. The proposed framework was able to analyse and process environmental sensor data, which were subsequently classified as either normal or abnormal ADLs using the k-Nearest Neighbour (kNN) algorithm. Considering instances of abnormal ADLs, the system generated alerts to notify care providers, in addition to generating a detailed report of the detected behaviour sent via email. The proposed system appeared promising, with the researchers indicating that experiments with real-time data streams were required to further evaluate the effectiveness of the proposed system.

The acknowledged concerns pertaining to data-driven techniques are overcome through the alternative application of knowledge-driven approaches, for example, they eliminate reusability concerns as knowledge-driven approaches generate generic models which can apply to a range of users. Nevertheless, these models are weaker at handling temporal information and uncertainty [11], and they are often weaker in dealing with complex activities due to providing insufficient human knowledge to capture their fine-grained components. Instead, human knowledge is commonly provided upon simplistic activities involving only the fundamental steps required to complete each activity. In a recently conducted study [14], a knowledge-driven solution to activity recognition was developed which combined elements of both static and recurrent models. A smart home inhabitant's behaviour was monitored through implementing a rule-based method which resembled a Finite State Machine (FSM). The developed method involved defining both "signature" sensors, i.e. those that only activated during one particular activity, and "descriptive" sensors, i.e. those that were consistently activated within multiple activities. ADL recognition was performed through detecting activity sequences within binary sensor event streams using the developed FSM-based method, followed by manually adjusting the designed rules based on the training data. Results demonstrated the effectiveness of the developed method; however, researchers stated the general applicability of their method was poor. Another recent study [15], proposed a knowledge-driven activity profiling technique based on training data. The defined activity profiles were used to induce additional features, i.e. fingerprinting, to help distinguish activities performed by smart home residents. A fingerprint vector was defined per activity which held distinguishing sensor events. The windowed training data was then augmented by incorporating the profiled features, for example if a particular window contained two distinguishing sensor events defined within an activity profile, the activity associated with those sensor events was chosen. Experimental results demonstrated the success of the proposed method in comparison to benchmarked techniques.

Recently, hybrid approaches have emerged which integrate both knowledge-driven and data-driven techniques to overcome the acknowledged limitations of each technique. For example, hybrid approaches are able to adjust and learn user preferences continuously, rather than generating static models. A promising hybrid method developed in [16] produced an Intelligent Decision Support System for dementia care. The proposed system involved two levels of decision making i.e. short-term and long-term. Short-Term Decision Making (STDM) was performed to raise alerts for abnormally detected ADLs, whereas Long-Term Decision Making (LTDM) supported decisions upon the rate of progression in the occupant's developmental stage of dementia. The STDM framework integrated data-driven decision making to learn abnormal behaviours and their associated alerts (low, high or emergency), and knowledge-driven rule-based decision making. Experimental results demonstrated the success of the proposed system in terms of classification accuracies obtained in comparison to the benchmarked methods.

Although hybrid methods have appeared promising recently, it was decided to develop a knowledge-driven, rule-based approach within this project due to the acknowledged limitations of data-driven methods. Particularly, the identified shortage of large-scale, accurately annotated datasets. The availability of domain knowledge provided by project partners has further motivated the exploration of a knowledge-driven approach.

3 ADL Dataset Considered

Given that changes in circumstances resulted in an inability to generate specific data for this study, external smart home data was used to evaluate the system. The data comprised of similar sensors and ADLs that were originally considered.

3.1 UCAmI

The chosen dataset was generated by researchers within the UJAmI smart lab over a period of 10 days. The smart lab, presented in Fig. 1, comprised five areas: an entrance, a kitchen, a living room and a bedroom merged with a bathroom. A single male inhabitant performed 24 ADLs whilst manually annotating the dataset during typical morning, afternoon and evening time routines. The recorded activities included: take medication, prepare breakfast, prepare lunch, prepare dinner, breakfast, lunch, dinner, eat a snack. watch tv, enter smart lab, leave smart lab, play a videogame, relax on the sofa, leave smart lab, visitor to smart lab, put waste in the bin, wash hands, brush teeth, use the toilet, wash dishes, put washing in the machine, work at the table, dressing, go to bed, and finally, wake up. A range of binary sensors were deployed throughout the smart lab comprising 4 PIR motion sensors, 24 contact switches and 2 pressure sensors. Pressure sensors were located within the sofa and the bed, contact switches were attached to, or integrated within, various objects and doors, and the PIR motion sensors were located within the main areas of the smart lab i.e., the kitchen, bedroom, bathroom and living area to detect movement.

It was decided to focus initially upon a small subset of ADLs as some were deemed relatively less integral and Kraydel currently had no available sensors to distinguish the following ADLs: wash dishes, laundry, washing hands and housekeeping/cleaning. Consequently, those ADLs were removed. The enter/leave home ADLs were also removed as the only available sensor, i.e., the motion sensor located in the hallway, currently provided insufficient information in distinguishing whether an inhabitant had entered or left the home. Finally, the resting/relax ADL was removed as the motion sensor within the Kraydel hub or the infra-red sensor in the living room could only determine that an inhabitant was in the living area, which was deemed insufficient in distinguishing this ADL. It was discussed that an additional sensor, for example a pressure sensor in the sofa, would provide more detailed information to distinguish the relaxing/resting ADL. Consequently, the ADL subset chosen for this project included the get up, go to bed, prepare meal, visitor, watch TV and use toilet activities.

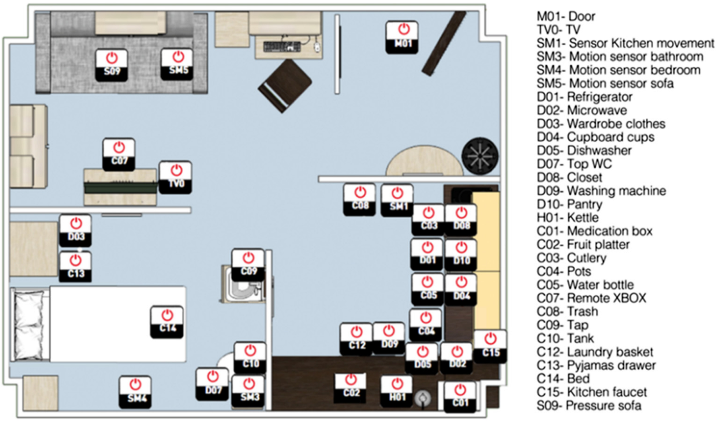


Fig. 1. Location of binary sensors in the UJAmI smart lab

3.2 Dataset Preparation

All activity instances and sensor activations pertaining to the following ADLs were removed from the UCAmI dataset: wash dishes, laundry and washing hands, which involved sensors C09, D03, C13. As for the enter/leave home and resting/relax ADLs, the data for these activities was retained by merging them with others. For example, instances of enter/leave home were relabelled as visitor to efficiently use the available data, in addition to also including synthetic data to represent a binary doorbell activation. The pressure sensor located on the sofa (S09) was also retained within the dataset to provide additional information in distinguishing the watching TV ADL.

The data was then further reduced to remove any additional sensors that the UCAmI dataset contained which did not emulate the Kraydel environment. For example, to recognise the prepare meal ADL, both Kraydel and UCAmI have microwave (D02) and kettle (H01) sensors available, however the UCAmI dataset has an additional 15 kitchen sensors which were removed, including a trash sensor (C08), kitchen motion (SM1), cutlery (C03), closet (D08), refrigerator (D01), pantry (D10), water bottle (C05), cups cupboard (D04), pots (C04), washing machine (D09), laundry basket (C12), dishwasher (D05), kitchen faucet (C15), medication box (C01) and fruit platter (C02). The remaining redundant sensors chosen for removal included the Xbox remote (C07) and a motion sensor at the sofa (SM5) as these were not required to distinguish the chosen subset of ADLs. Finally, the UCAmI dataset was collected over 10 non-consecutive days in 2017, therefore the timestamps were updated and gaps in the data were removed to simulate data collection over 10 consecutive days.

Note that over time additional sensors will become available and it is intended for the approach presented in this paper to be extensible and handle both signature sensors and ADLs detectable through correlation of information from multiple sensors.

4 Rules Syntax

ADLs are used to monitor inhabitants within a smart home. They can be useful in assessing the wellbeing of the inhabitant and their ability to live independently in their own home. The project identified 6 core ADLs that an individual needs to be able to carry out in order for the person to be deemed capable of living independently. 6 ADLs were created based on the sensor data from the UCAmI dataset: Sleep, Get Up, Prepare Meal, Watching TV, Visitor, and Use Toilet.

The UCAmI sensor dataset was modified so that it contained only sensor events that are needed to trigger one of these 6 ADLs. To trigger an ADL, each rule requires a combination of more than one type of sensor event to occur within a specified time window. The rules are stored in the format shown in Fig. 2, each rule lists a number of key-values that are used by the code to determine if an ADL has occurred. Each of the 6 rules requires a minimum of 2 sensor events to happen within a specified time. This section explains each JSON key-value pair as well as describing how daily time routines are used to detect abnormal behaviour on the part of the inhabitant.

The rules specify the conditions that must be met for an ADL to trigger. An example of the rule for the Sleep ADL is shown in Fig. 2, this ADL is used in conjunction with the ‘Get Up’ ADL to calculate sleep duration. It is expected that this ADL will be triggered at ‘Night’, if it occurs during one of the other 3 routines (Morning, Afternoon, Evening) then the ‘Identified Time Routine’ column on the Dashboard UI will give one of these values this instead of ‘Night’. Caregivers that are monitoring the Dashboard can determine that the inhabitant is not sleeping during the expected time routine, this could indicate physical illness or degradation of their mental state.

```
{
  "name": "Sleep",
  "type": "Sequence",
  "rearm_time": 480,
  "time_window": 600,
  "events": ["EM1_On", "L1_Off"],
  "expected_routine": ["Morning", "Afternoon", "Evening", "Night"],
  "min_values": [0,0,0,1],
  "max_values": [0,0,0,1]
},
```

Fig. 2. JSON format for the Sleep ADL

There are two *‘types’* of rules that can be specified in the JSON rules file, these are Combination and Sequence. If the rule states that it is a ‘Sequence’ rule then the sensor events that it requires must happen in a specific order. The order is determined by the “events” section, in Fig. 2 the EM1_On sensor must occur before the L1_Off sensor otherwise the rule will not be triggered.

The *“rearm_time”* is the amount of time in seconds that must have elapsed before the ADL can be triggered again. If the Sleep ADL is detected, it can only be detected again after 480 s or 8 min. The UCAmI dataset initially had multiple sensor events going Off and On at the same Date and Time, this generated multiple ADLs of the same type when in fact only 1 ADL had occurred. The re-arm time feature was created to mitigate this, the dataset was eventually modified to remove all duplicate instances. However, this feature could be useful when using real-time sensors especially pressure sensors as they may give erroneous data.

The "time_window" value is used in conjunction with the current sensor event's date and time to find other sensor events. When a sensor event is read in, an initial check is performed against the rules file to see if this event matches the final sensor event in any of the rules *"events"* section. If any of the 6 rules' final *"event"* match the current sensor event then that rule is flagged for a further check. That rule's time window value is subtracted from the current sensor event's time to create a historic time window, the first event is then searched for within this window. In Fig. 2 the final sensor event that the Sleep Rule requires is L1_Off (Light turned off), if this L1_Off event is read in from the sensor events file, the code then searches for the first event EM1_On (Mattress pressure sensor on) in the sensor data.

The *"events"* section consists of 2 or more sensor events, all must occur within the stated time window. If the rule is a Sequence rule then the events must occur in the order listed, a Combination rule only requires all specified events to occur.

The expected routine lists all 4 times of day (Morning, Afternoon, Evening, Night), the number of times the ADL is expected to occur for each is listed in Min Values and Max Values. In Fig. 2, the Min and Max Values for sleep is 1 for the Night routine, it is not expected to occur more than once or during the other 3 routines.

It is important to be able to detect what is considered to be normal and abnormal behaviour as this can indicate a decline in physical health or a cognitive decline. The *"expected_routine"* is used to keep track of when the ADLs are activated and whether this is in keeping with the individual's normal routine or if it is an abnormal behaviour and perhaps a cause for concern and further investigation. The Dashboard UI was designed so that the routine time frames are customizable for an individual, this helps to ensure that the detection of abnormal behaviour is more accurate for each individual user.

5 Event Processing Engine

In this part, the main objective was to develop an event processing engine that could receive sensor events and recognize ADLs by using a rule-based system. The event processing engine was developed using Python, the web application was created using Flask. This section explains how the event processing engine uses the rules to detect that an ADL has occurred.

The UCAmI dataset is evaluated against a set of rules to check if an activity has taken place. When each line of the dataset is read in, the code performs a preliminary check to determine if the current sensor event matches any of the rule's events. All rules that require that particular sensor event are then added to a dataframe for potential matches. The code iterates through each rule and calculates the historic time window by subtracting the rule's *'time_window'* value from the current sensor event's time. The events that occurred within this window are compared to each of the potential rules' other required events. If a match occurs, then the ADL is added to a list of Detected ADLs and displayed on the web application Dashboard.

The two Rule 'types' are Combination and Sequence rules, the event checking code differs for each, with the sequence check code being more complex. A Sequence rule can only be activated if the sensor events occur in the order stated in the rule's events list. A Combination rule does not require the events to happen in a specific order, only that they both occur within the time window. The rationale behind the Sequence rule is that logically certain sensor events should take place before other events. In the case of the Get Up ADL, the bedside lamp (L1_On) must be in the On state before the mattress (EM1_Off) sensor is in the Off state. Note that this is just an example of a sequence rule and some conditions might change based on the individual's habits and routines. The Sequence check only performs the time window check if the current sensor event matches the final event in the rule's event list. This ensures that if the other rule event(s) are discovered within the time window they will have happened before the current event.

A broken or missing event ADL check was created to keep track of ADLs that are partially activated but not completed. This could give a Caregiver or Clinician some insight into the inhabitant's behaviour, if key ADLs such as 'Prepare Meal' are started but not finished then this is flagged on the Dashboard. When either the Combination or Sequence check methods are called, both methods perform a further check to look for broken Combination/Sequence events. A Broken Combi/Sequence ADL is when a sensor event matches a rule but the other events the rule requires do not occur. To detect that a broken ADL has occurred, the Combination and Sequence check methods add any sensor events to a list of potential broken ADLs. The list is also checked when the methods are called, and any event that has since been used to trigger an ADL is removed from the broken ADL list.

Other health metrics that are included in the analysis are Sleep Duration and Bathroom Frequency, both are displayed on the Dashboard. If the sleep duration is less than 6 h or more than 10 h an alert is created, this is shown in a DataTable on the Dashboard UI. The code requires both a Sleep and Get Up ADL to calculate duration, if Get Up doesn't occur then the sleep duration is not calculated. Future work would include a feature to notify if a Sleep ADL was not followed by a Get Up ADL within a certain amount of time. Another important health indicator is bathroom frequency, excessive visits that deviate from the inhabitant's norm may indicate illness. A daily upper limit is set within the code, when this value is exceeded this is flagged on the dashboard.

6 ADL Dashboard UI

The Dashboard User Interface (UI) was developed using the Python web application framework Flask. This section describes the analysis output presented on the Dashboard. The original UCAmI dataset is from 2017, the dates were changed to 2021 to reduce the amount of scroll back when using the date dropdowns.

6.1 Daily Summaries

The Daily Summaries stacked bar chart in Fig. 3 shows the number of ADLs that were triggered for a given day. The dates are shown on the Y axis, and an ADL frequency count (1, 2, 3…10) is on the X axis. Each day's bar consists of different colours representing different ADLs, the size of each section of the bar visually depicts how many times the ADL occurred that day (X axis count). A dropdown Date Picker allows the user to choose a date range, the bar chart updates according to the range chosen. The legend lists the ADLs, it is clickable and allows the user to remove ADLs from the chart, this is useful as it allows the user to simplify the chart, especially when comparing the same ADL over multiple days.

The stacked bar chart can be further customized with the Routines radio buttons underneath the chart. In Fig. 4, the 'Night' routine is selected, the chart then updates to only show the ADLs that took place during that time range. This feature is a good way of visually comparing the frequency of ADLs for several days, e.g., how many bathroom visits occurred during the night. The chart also includes a hover menu that appears when the mouse hovers over a bar, this lists the ADLs and the count for that day.

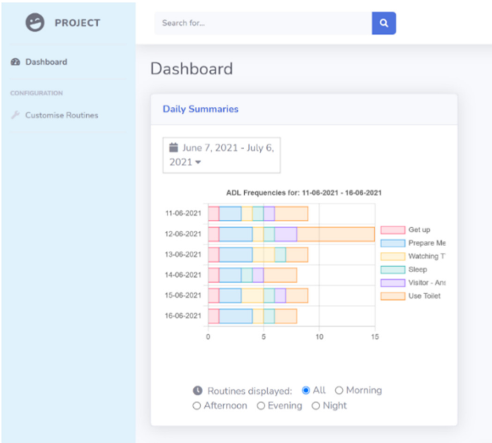


Fig. 3. Stacked Bar chart showing the frequency of all ADLs per day.

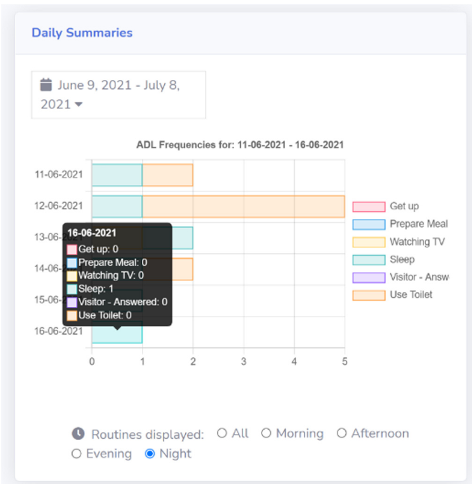
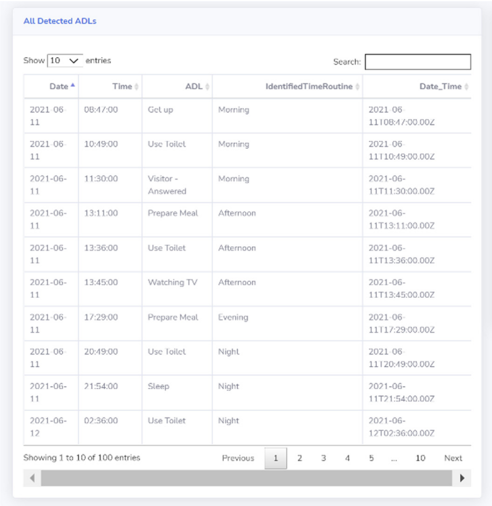


Fig. 4. Stacked Bar chart with Night routine selected.

6.2 Detected ADLs

The Detected ADL DataTable is shown in Fig. 5, it displays all of the ADLs for the entire dataset. The table includes the following columns – Date, Time, ADL, Identified Time Routine. The number of entries shown can be modified using the dropdown menu in the top right, the default is 10 entries. An ADL search function is included that enables the user to search for and display only the entries for that ADL. The Identified Time Routine gives the general time of day (Morning, Afternoon, Evening, Night) when the ADL occurred, this may be different to when an ADL is expected to occur. When an ADL occurs during a ‘Time Routine’ other than the one in which it is expected to occur, this could indicate a new illness or worsening of an existing condition.


All Detected ADLs

Show 10 entries Search:

Date	Time	ADL	IdentifiedTimeRoutine	Date_Time
2021-06-11	08:47:00	Get up	Morning	2021-06-11T08:47:00.00Z
2021-06-11	10:49:00	Use Toilet	Morning	2021-06-11T10:49:00.00Z
2021-06-11	11:30:00	Visitor - Answered	Morning	2021-06-11T11:30:00.00Z
2021-06-11	13:11:00	Prepare Meal	Afternoon	2021-06-11T13:11:00.00Z
2021-06-11	13:36:00	Use Toilet	Afternoon	2021-06-11T13:36:00.00Z
2021-06-11	13:45:00	Watching TV	Afternoon	2021-06-11T13:45:00.00Z
2021-06-11	17:29:00	Prepare Meal	Evening	2021-06-11T17:29:00.00Z
2021-06-11	20:49:00	Use Toilet	Night	2021-06-11T20:49:00.00Z
2021-06-11	21:54:00	Sleep	Night	2021-06-11T21:54:00.00Z
2021-06-12	02:36:00	Use Toilet	Night	2021-06-12T02:36:00.00Z

Showing 1 to 10 of 100 entries Previous 1 2 3 4 5 ... 10 Next

Fig. 5. Detected ADLs DataTable.

6.3 Daily Summary

The Daily Summary bar chart in Fig. 6 shows all ADLs that occurred on one day, the date can be changed using a dropdown menu. The Y Axis shows frequency count, this is the number of times that the ADL occurred, e.g., Sleep = 1, Prepare Meal = 2 times. The X axis lists the 6 ADLs (Sleep, Get Up, Prepare Meal, Watch TV, Visitor, Use Toilet). This chart is useful if the user wants to quick visual update on the current day as opposed to comparing multiple days and trends.

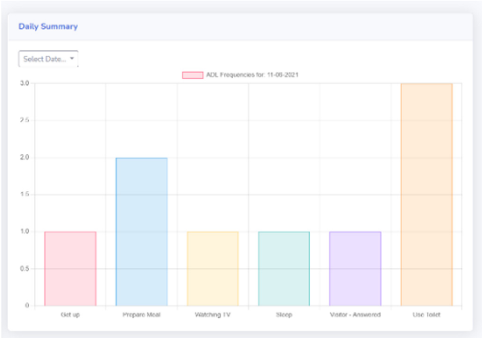


Fig. 6. Daily Summary Bar chart for one day.

6.4 Notification Alerts

This table is an amalgamation of the bathroom frequency and sleep duration alerts. The table is shown in Fig. 7, the columns are – Alert Type, Date, Alert, Information. Alert Type can be either 'Bathroom Alert' or 'Sleep Alert'. The Alert column gives the number of bathroom visits e.g., *"7 bathroom visits today"*, for Sleep it will state the sleep duration e.g. *"You slept for 12:13:00 h"*. The Information column then gives more detail as to why this activity has been flagged as an alert. For the sleep alert, it simply states "Overslept", the rule uses less than 6 and more than 10 h as the cut off values for sleeping too little or too much. The dataset does not include any instances of sleep duration being less than 6 h, so only the overslept alert is displayed. The information section for the bathroom alerts gives the upper limit of expected daily bathroom visits. This upper limit


Notifcation Alerts

Alert Type	Date	Alert	Information
Bathroom Alert	12-06-2021	[7] bathroom visits today	Upper limit is set to a maximum of 5 visits.
Bathroom Alert	20-06-2021	[7] bathroom visits today	Upper limit is set to a maximum of 5 visits.
Sleep Alert	2021-06-12	You slept for 12:13:00 hours	Overslept
Sleep Alert	2021-06-13	You slept for 12:58:00 hours	Overslept
Sleep Alert	2021-06-14	You slept for 11:04:00 hours	Overslept
Sleep Alert	2021-06-15	You slept for 15:41:00 hours	Overslept

Fig. 7. Notification alerts table, this includes sleep and bathroom frequency alerts.

value can be customized for the inhabitant to give a more tailored experience. The actual number of daily visits is displayed in the Alert column.

6.5 Broken ADLs

The tables shown in Fig. 8 display all sensor events that were a partial match for a rule but did not result in an ADL activating, due to the other events needed not occurring in the time window. The tables include the sensor type (L1 is a lamp sensor), the value column indicates whether the sensor was on or off, the status, timestamp data, and the name of the partially triggered ADL rule. The Sequence rules table in Fig. 8(a) lists all ADL rules that require the sensor events to occur in a particular order. The Broken Combination table in Fig. 8(b) displays the sensor events and rule's that do not have to occur in any specific order.

Broken Sequence ADL Events

type	value	status	time	rule
L1	1	L1_On	2021-06-11T21:53:00.00Z	Get up
M01	1	M01_On	2021-06-13T12:16:00.00Z	Visitor - Answered
M01	1	M01_On	2021-06-16T12:43:00.00Z	Visitor - Answered
M01	1	M01_On	2021-06-16T13:05:00.00Z	Visitor - Answered
M01	1	M01_On	2021-06-17T12:23:00.00Z	Visitor - Answered
L1	1	L1_On	2021-06-17T21:36:00.00Z	Get up
EM1	1	EM1_On	2021-06-17T21:38:00.00Z	Sleep
EM1	1	EM1_On	2021-06-22T11:45:00.00Z	Sleep

Broken Combination ADL events

type	value	status	time	rule
D02	1	D02_On	2021-06-11T10:19:00.00Z	Prepare Meal
D02	1	D02_On	2021-06-11T10:21:00.00Z	Prepare Meal
S09	1	S09_On	2021-06-13T13:52:00.00Z	Watching TV
S09	1	S09_On	2021-06-13T13:53:00.00Z	Watching TV
D02	1	D02_On	2021-06-15T12:07:00.00Z	Prepare Meal
D02	1	D02_On	2021-06-15T12:08:00.00Z	Prepare Meal
D02	1	D02_On	2021-06-19T12:15:00.00Z	Prepare Meal
D02	1	D02_On	2021-06-19T12:17:00.00Z	Prepare Meal

Fig. 8. (a) Broken sequence ADL table; (b) Broken combination ADL table.

7 Conclusions and Future Work

This paper presented the design of a rule-based and ADL analysis system that takes data from different sensors as input and presents a number of visualisations in a dashboard as output. The main parts of the system are: (i) a syntax to represent ADL rules, (ii) an event processing engine to process the ADL rules, and (iii) a dashboard user interface that includes a number of visualisations. The solution design presented is the output of a project collaboration with the Kraydel company, whose staff supported with ideas and with the commercial needs to consider for this solution. The project identified 6 core ADLs that an individual needs to be able to carry out for the person to be deemed capable of living independently: sleep, get up, prepare a meal, watch TV, have a visitor, and use toilet. Alternative forms of entertainment can be accommodated.

It was not possible to use real data collected from Kraydel because there was not enough at the time of the development of the system. As an alternative, the UCAmI dataset was used because the types of sensors considered (motion sensors, contact switches and pressure sensors) were the same as those used by Kraydel. Using a dataset collected at a smart lab instead of a dataset from Kraydel comprised by data from real situations did not affect the design presented in this paper. In terms of further data analysis and improvements, using a larger amount of real data collected from Kraydel will help in the development of the event processing engine and its ADL detection accuracy. While the number of sensors considered was determined by the sensors used by Kraydel, the modular design of the system allows adding or removing sensor data as required. Future work will consider the use of data collected from Kraydel and from other datasets to keep testing and improving the system. The use of more data from different sources to improve the functioning of the system and the accuracy in detecting abnormal behaviour will be investigated.

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