Rule-Based Detection of Health-related Problems of People with Dementia from Lifestyle Wearables: The support2LIVE Approach

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Abstract— **In this paper we describe a rule-based framework for the detection of Health-related Problems of people with dementia, developed in the support2LIVE project. The framework combines a novel ontology for lifestyle data (steps, sleep duration and heart rate measurements) and Health-related Problem representation, a framework for IoT data collection from sensors, a Knowledge Ingestion component that links the data through meaningful relationships and a novel set of SPARQL Inferencing Notation (SPIN) Rules to infer problems from these data. Both the ontology and the rule set are designed based on clinical expert knowledge in the field of dementia. More specifically, lifestyle data is acquired from wearable devices available in the market, making the system affordable and convenient. A model based on Semantic Web technology, OWL (Web Ontology Language), is used to formally represent and integrate sensor measurements, promoting interoperability with other models and data exchange. SPIN rules offer the benefit of simplicity and flexibility as opposed to other rule representations in the domain. Our framework handles the incoming IoT data from the sensors with the use of suitable APIs and contains a Knowledge Ingestion component that transforms the received data to semantic knowledge in the form of RDFs. Finally, a clinician dashboard visualizes results to allow decision making, as shown in proof-of-concept scenarios from real participants in the support2LIVE pilots.**

Keywords- Ontology; Event Detection; Semantic Web; SPIN; Reasoning; Rule-Based Systems; Dementia.

I. INTRODUCTION

As the world population is rapidly aging, people living with dementia globally amount to 50 million in 2019 and are expected to triple to 150 million by 2050 [2]. Yet there is no silver bullet for dementia, such as a pharmacological solution. Only holistic and objective information about a patient's health status can drive tailored interventions to alleviate the ailments and slow down the progression of the disease. However, this imposes a huge burden to informal caregivers and healthcare professionals to manually monitor lifestyle, and Health-related Problems such as movement, sleep and stress.

Lifestyle sensors are a promising and affordable solution to objectively, continuously and affordably monitor patients, but a framework to map and extract clinical Health-related problems is needed. The acquisition of knowledge from continuous and heterogeneous data flows is a prerequisite for Internet of Things (IoT) applications [2][3][4]. Semantic technologies provide integrated tools and methods for representing data and producing new Knowledge from them. Smart environments are increasingly encountering in healthcare technologies at home in actions that create better living conditions for older people by using IoT technologies, such as Active and Healthy Ageing (AHA) and Ambient Assisted Living (AAL). In this context, human activity recognition plays a main role [4], because it could be considered as a starting point to facilitate assistance and care for people with dementia. Due to the nature of human behavior, it is necessary to manage the time and adhere to the spatial restrictions. In doing so, semantic technologies enable expressive reasoning over health data, allowing clinical decision support to be realized. Ontologies are used to describe the context elements of interest (e.g., persons, events, activities, location, time), their pertinent logical associations [6], as well as the background knowledge required to infer additional context information.

In this paper, we propose a Semantic framework for Health-related Problem detection that combines ontologies and SPARQL Inferencing Notation (SPIN) Rules [7]. Ontologies are used to provide the common vocabulary for representing activity related contextual information, whereas SPIN rules derive high-level activity interpretations. SPIN is used as a standardized declarative language able to address the limitations of the standard OWL Semantic Web technologies mentioned previously. More specifically, the temporal relations among activities are handled by SPARQL functions, whereas the derivation of new composite activities exploits the native capabilities of SPARQL to update the underlying activity model.

The SPIN language was chosen to implement this system because it combines concepts from object-oriented languages, query languages, and rule-based systems to describe the behavior of objects on the web of data and the Internet of Things [8]. In addition, it makes the rules accessible and easy to maintain, extend and share. A suitable Reasoner tool, such as the SPIN Application Programming Interface (API), can extract the extra information generated by the rules and reuse it, for example, in executing a SPARQL query, thus generating new knowledge. These rules apply using SPARQL CONSTRUCT or SPARQL UPDATE requests (INSERT and DELETE). SPIN standards also make it possible to define such rules in higher level domain specific languages, so that rule designers do not have to work directly with SPARQL.

In [1], we presented our SPIN/SPARQL rules for health problem detection and tested them in real data coming from sensors. In this paper, we expand our framework to include components such as the IoT data collection, which collects the data coming from various sensors with the use of APIS, the Knowledge Ingestion component, which "translates" the collected data to RDF triples and the visualization dashboard, which can be used by clinicians to monitor their patients

The approach is employed in support2LIVE [9], a project which aims to integrate wearable devices and smartphone apps to support timely assessment and intervention of elders in the spectrum of dementia. A proof-of-concept scenario on how visualizations of the detected problems aids clinical decision making is demonstrated using real-world data from the project's pilot deployments in Thessaloniki, Greece.

The rest of the paper is organized as follows. Section II presents related work in the domain of ontology-based reasoning architectures in the Healthcare field. Section III describes the proposed System architecture that combines OWL ontologies and SPARQL rules in order to derive high-level activity interpretations. Section IV presents the use case scenario that evaluates the proposed architecture. Finally, Section V provides our conclusions and proposed future work.

II. RELATED WORK

In previous related studies, Semantic Web technologies have been used to represent knowledge from home healthcare systems. Related projects incorporating these technologies are KnowSense [10], COSAR [11], ACTIVAGE [12], Dem@Care [13], Faber [6], and FallRisk [14]. Table 1 summarizes the Aim of these Projects and the Methodology of semantic technology used respectively.

Table 1 - Related Work

Project	Year	Aim	Methodology
KnowSense	2015	Activity Recognition in Healthcare system	Description Logic Reasoning, (DL) for activity detection and SPARQL queries to extract clinical problems
COSAR	2011	Activity Recognition in in context-aware environments	Ontological reasoning is also combined with statistics
ACTIVAGE	2017	Development of Smart Living solutions for active and healthy aging	Interoperable Ontologies, rule-based reasoning
Dem@Care	2015	Supporting independent life for elderly people with dementia	Interoperable Ontologies, Rules, Reasoning
FABER	2015	Detect abnormal behaviors for medical applications	Simple reasoning on an ontology
FallRisk	2015	Detect falls of elderly in smart homes	Semantic Reasoning techniques

KnowSense supports monitoring of the activities of elderly people with dementia in controlled and diffused environments. Semantic Web technologies, such as OWL 2, are widely used in KnowSense in order to display sensor and specific application observations, as well as to implement solutions for identifying activities and identifying problems in everyday life activities (Instrumental Activities of Daily Living, IADLs) with the aim of clinical evaluation, in various stages of dementia. Description (Logic Reasoning, DL) reasoning for activity detection and SPARQL questions are used to extract clinical problems. On the other hand, the semantic techniques that KnowSense uses cannot be easily extended and re-used.

COSAR provides a solution based on the use of ontologies and ontological reasoning combined with statistical conclusions. Simple patient activities are identified by statistical methods, such as selecting the most likely method compared to others. Ontological reasoning is also combined with statistics to identify complex activities that cannot be apparent only by statistical methods.

ACTIVAGE is a large-scale pilot project, which aims to develop Smart Living solutions that positively affect active and healthy aging. The ACTIVAGE IoT Ecosystem Suite (AIOTES) project, is a set of techniques, tools and methodologies (rule-based reasoning, interoperable ontologies, etc.) that increases semantic interoperability at different levels between heterogeneous IoT platforms. The approach uses different mechanisms of reasoning that can improve the understanding of patients' heterogeneous data and help generate new knowledge by providing services to end users.

Dem@Care provides a complete system consisting of heterogeneous sensors, designed to support independent living for the elderly with dementia or similar health problems. This approach incorporates a heterogeneous set of detection methods and technologies, including video, audio, in addition to normal, environmental and other measurements. Semantic technologies (e.g., rule-based reasoning) are used to process and analyze sensor data according to user requirements. This leads to feedback and decision support, which is communicated to end users through appropriately designed user interfaces. A variety of clinical scenarios and environments are supported, from short-term trials in hospital settings to long-term monitoring and support of daily living at home, for independent living.

FABER is a pervasive system designed to detect abnormal behaviors for medical applications. It first computes events and actions from the available context data by using simple reasoning on an ontology. Computed boundaries, actions and events are sent to the knowledge-based inference engine.

In **FallRisk**, the main objective is to detect falls of elderly in smart homes. It relies on a platform that uses multiple learning-based fall detection systems. The results of these systems are filtered and put into an ontology that carries the context knowledge. The knowledge, including contextual information about the user, is then used to refine the fall detection. The strength of this approach, besides the combination of both techniques, is the compatibility with any fall detection technique. However, it solely deals with fall detection.

The above-mentioned systems use semantic rule-based mechanisms and provide solutions for activity and event recognition based on the use of ontologies and ontological reasoning. However, most methods are quite sophisticated and complex to express and to maintain due to rich logic support. For this reason, the SPIN language was selected for this study to create semantic rules. SPIN offers multiple advantages [6] [7]. SPIN rules offer the benefit of simplicity and flexibility as opposed to other rule representations. Moreover, SPIN is based on SPARQL, a well-established query language and protocol, which is supported by numerous engines and databases. Therefore, SPIN rules can be directly executed on the databases and no intermediate engines with communication overhead need to be introduced. Moreover, it has an object-oriented model that leads to better maintainable solutions. Specifically, the SPIN rule engine does not have to check all rules at all times, but instead rules are checked incrementally when new instances of a certain class are inserted (or modified) in the ontology. This leads to better rule execution performance. Furthermore, SPIN is a more promising de-facto industrial standard for the future of combining ontologies and rules, as it builds upon the widespread use of SPARQL.

III. SEMANTIC REASONING APPROACH FOR HEALTH-RELATED PROBLEM DETECTION

This section presents the proposed Semantic System for Health-related Problem detection with the aim of recognizing the activities of people with dementia through the use of different sensors and producing new knowledge by offering new services to end users of the system such as doctors, health professionals and patients. As shown in Figure 2, the raw data are collected by users (i.e., the patients with dementia) using various wearable sensors and smart home sensors. Afterwards, raw data are modeled on Resource Description Framework (RDF) ontologies and stored in the Knowledge Database (GraphDB) for the purpose of creating the System Knowledge Base. Then, the semantic analysis, which will be presented in the next section (Spin Rule Engine, Ontology and Rule reasoner, etc.), processes and interprets the data, enriching the Knowledge Base of the system.

A. *IoT Data Collection*

The data are collected from sensors installed in smart homes as well as from wearables. The sensors track the activities of the users unobtrusively. In that way, participants were able to perform their daily tasks without any external interference. Thus, acquiring data that correspond to everyday tasks without introducing bias in the behavior of the user due to the presence of sensors, our framework would simulate the everyday tasks of the participant at the highest possible level.

The data collected through the available sensors can be classified into three distinct categories. These categories are:

1. Activity of the patient/participant
2. Sleeping behavior
3. Cardiac activity

As far as the activity of the user is concerned, the available sensors can provide measurements listed in Table 2.

Table 2 - Activity Metrics

Metric	Unit
Steps	Amount of steps
Calories	Amount of calories
Distance Covered	Amount of meters covered
Elevation	Amount of meters in height climb
Sedentary Active State	Minutes
Light Active State	Minutes
Fairly Active State	Minutes
Very Active State	Minutes

Regarding the sleep pattern of the user, the data acquired provide records and deliver information listed in Table 3.

Table 3 - Sleep Metrics

Metric	Unit
Duration of sleep	Minutes
Efficiency of sleep	Percentage
Asleep Stage	Minutes
Time to Fall Asleep	Minutes
Awake Stage	Minutes in stage
Light Stage	Minutes in stage
Deep Stage	Minutes in stage
REM Stage	Minutes in stage
Awake Stage Count	Count of stage in session
Light Stage Count	Count of stage in session
Deep Stage Count	Count of stage in session
REM Stage Count	Count of stage in session

Regarding the cardiac activity of the user, the data collected from the available sensors provide the metrics shown in Table 4.

Table 4 - Cardiac Activity Metrics

Metric	Unit
Heart rate	Beats Per Minute
Fat Burn Zone	Minutes in this Zone
Cardio Zone	Minutes in this Zone
Peak Zone	Minutes in this Zone
Out of Range Zone	Minutes in this Zone

The sensor data are communicated on our databases through APIs, in order to be collected and processed properly. In that way, the data are grouped together and can be further processed in order to have sanity checks run on them, assuring the validity of their values before proceeding into the next steps. This procedure ensures that the data process pipeline produces reliable results in each step.

B. *Knowledge Ingestion*

Having acquired all the necessary raw information from all the available sensors, it is imperative to translate the raw data into meaningful representations. This procedure is called Knowledge Ingestion (KI) and is of crucial importance because it links the data through meaningful relationships, that are human understandable. These representations will act as a knowledge base, upon which more sophisticated and complicated relations will be built, thus providing semantic data logical relationships as well as acting as a logic base for further reasoning.

The translation process from raw information to linked data representations, i.e., representations that provide “meaning”, is realized through the creation of RDF (Resource Description Framework) statements. An RDF statement is composed of three elements, often called a triplet. Through the use of a well-defined syntax, the relation between two different data segments is determined, via the use of a subject, a predicate and an object. The subject and the object elements represent the two different data segments that are going to be linked together, while the predicate element defines robustly the relationship between the two. Thus, each RDF Statement that is created, by using the proper subject, predicate and object, supplies the Knowledge Base (KB) with the correct relationship between the provided data.

The creation of multiple RDF statements that characterize the relationships between the data, leads to an extensive graph that describes all the possible relations between all the available data. Each data segment is represented by a node, and the relationship between two data segments (i.e., nodes) is represented by a node-linking line. An example of an RDF statement that exists in our Knowledge Base is shown in the block of code below.

```
<rdf:Description
rdf:about="http://www.semanticweb.org/ITI/ontologies/2021/2/CARL
#Sleep_2020-05-237"><awake_minutes
xmlns="http://www.semanticweb.org/ITI/ontologies/2021/2/CARL#"
rdf:datatype="http://www.w3.org/2001/XMLSchema#decimal">9
</awake_minutes>
</rdf:Description>
```

The aforementioned example illustrates the way an RDF statement is structured in the Knowledge Base. This representation, written in an XML format, is robustly structured and well-defined, for each of the elements of the triplet that constitute an RDF statement. It can be seen from the input “Sleep_2020_05-237” that the participant has been awake for 9 minutes. The relationship between the subject and the object, that is the integer number 9, is defined by the predicate “awake_minutes”, that signifies the relationship between these two data segments.

The corresponding graph of the aforementioned statement is shown in Figure 1 below.

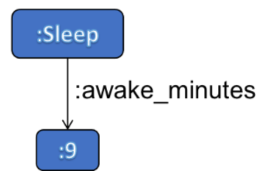

Figure 1 - Graph of an RDF statement in our Knowledge Base

C. *Ontology and Knowledge Base*

The proposed approach is built on top of emerging Semantic Web technologies. We started with the definition of system ontology for representing different elements of a healthcare system. The goal of the ontology creation is the semantic visualization of all concepts related to activity recognition in the healthcare system, as well as the ability to act as a semantic information integration model derived from the system's sensors. A common practice in the development of ontologies is the reuse of existing models, so we relied on already developed and valid ontologies for developing a part of the supporting ontology. The following are an overview of the existing entities used:

- **Dem@Care** [12]: An ontology to represent experimental protocols of diagnostic support and dementia diagnosis in a controlled environment.
- **SSN (Semantic Sensor Network)** [14]: Contains the ontology SOSA (Sensor, Observation, Sampler and Actuator). These ontologies describe semantic sensors, actuators, sampling and their actions. It is a W3C recommendation and OGC application.

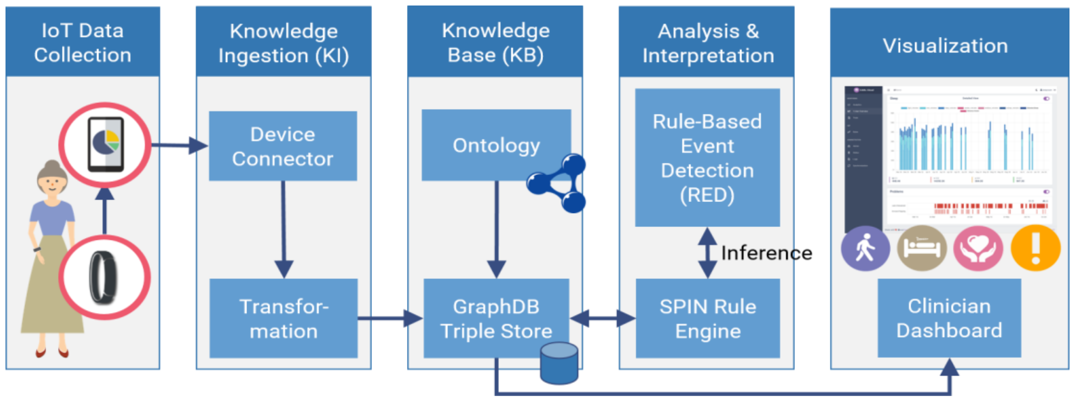

Figure 2 - Architecture of the proposed system

- **SmartHome** [15]: This ontology is an extension of SSN ontology and focuses on the representation of spatial and time aspects of entities included in spaces with devices belonging to the smart home category.

The system's ontology (Figure 3) is expressed in OWL 2 (W3C, 2012), which is a representation language commonly used in the semantic community for entity development shows the hierarchy of entity classes and the hierarchy of its properties. Object attributes are relationships that link classes together, and data attributes link classes to simple values (such as integers, alphanumeric, dates, etc.).

The main classes of ontology are Device, Event, HealthProblem, Person, and Profile. The Device represents the devices of the system. Event is a parent class for different Event-related classes. It has two subclasses Activity and Measurement. Activity contains the information of activities. Measurement includes instances, which represent information of measurements (Calories, Distance, Floor, HeartRate, Movement, Sleep, Steps). The HealthProblem is a parent class for different Health Problem - related classes. It consists of subclasses HeartProblem, MovementProblem, MultiProblem and SleepProblem. The class Person includes instances, which represents the type of Person of the system (Doctor, Patient). Finally, the class Profile includes information from users' profile (Age, Gender, etc.).

After adding Semantic Web technologies to the raw data and modeling them based on the system ontology, "Semantic Data" are stored in a semantic Graph Database, which constitutes the Knowledge Base of our system. For this purpose, we have chosen GraphDB, an enterprise ready Semantic Graph Database, compliant with W3C Standards. Semantic Graph Databases (also called RDF triplestores) provide the core infrastructure for solutions where modelling agility, data integration, relationship exploration and cross-enterprise data publishing and consumption are important. Querying and reasoning are performed over stored RDF graphs with SPARQL language.

Table 5 - A Priori Rule Base of the different semantic rules that describe the modeled activities

	Variables (number)	Rule	Problem
1	Duration in minutes	Time to fall asleep in a day > 180	Insomnia
2	Count of sleep interruptions	Number of interruptions in a day > 10	Restlessness
3	Duration in minutes	Sleep total duration in a day> 480	Too much sleep
4	Duration in minutes	Sleep total duration in a day < 300	Lack of sleep
5	Duration of "Nap" state in minutes	Asleep in Naps > 100 in a day	Increased Napping
6	Occurrence of "Nap" State, Occurance of "Night Sleep" state	Asleep in Naps end time < 2 hours from Sleep start time	Nap close to bedtime
7	Time Asleep / Time in bed	Sleep Efficiency < 85	Bad Quality Sleep
8	Step count, Heart Rate measure, Duration in minutes	Steps < 50 & Heart Rate > 90 (Fat Burn Zone) for duration > 300	Stress or Pain
9	Heart Rate measure	HR < 60	Low Heart Rate
10	Step count, Heart Rate measure, Duration in minutes	Steps <1000 & Heart Rate < 80 for duration > 300	Inactivity
11	Step count, Heart Rate measure, Duration in minutes	Steps < 500 & Heart Rate < 100 for duration > 800	Lack of Movement
12	Step count	Steps < 80	Lack of Exercise

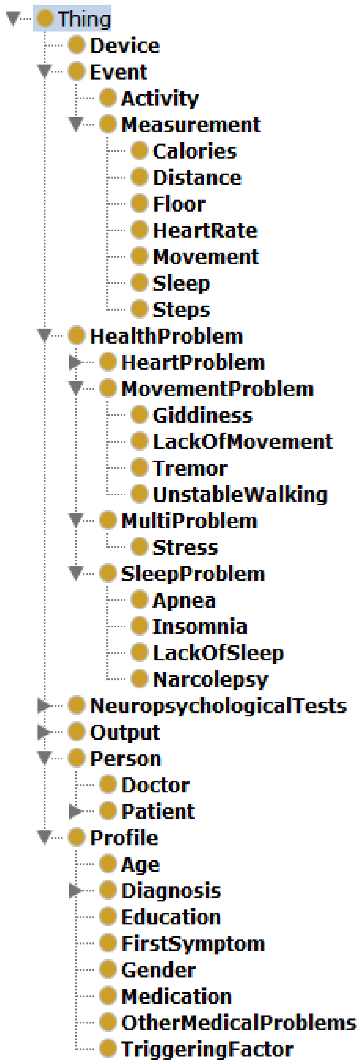

Figure 3 - Classes of the proposed ontology

D. *Analysis & Interpretation with SPIN*

We used the TopBraid composer [16], a tool for modeling and developing semantic data applications, to present the SPIN rules. TopBraid allows us to easily develop SPIN rules in the form of SPARQL queries, which is more readable than regular SPIN syntax. In practice, the following three code blocks act as examples in order to present in SPIN language three simple semantic rules that were applied to the system ontology.

The following code block shows the implementation of SPIN rule for Sleep problem “Lack of Sleep”. Applying this rule produces the addition of a new property that represents the type of sleep problem “Lack of Sleep” in the objects of the ontology (users of a support system). If the patient's sleep duration is less than 300 minutes, then it is considered that there is a sleep problem (lack of sleep).

SPIN rule for sleep problem “Lack of Sleep”.

```
CONSTRUCT {
?p owl:hasSleepProblem "Lack of Sleep "}
WHERE {
   ?p a :Person .
            ?p :duration ?d.
            FILTER (?d <300 )}
```

The following rule in SPARQL and SPIN adds new knowledge to the system Ontology. If the sleep duration of the patient with dementia is greater than 480 minutes then we conclude that there is a sleep problem (too much sleep).

SPIN rule for sleep problem “Too much Sleep”.

```
CONSTRUCT {
?p owl:hasSleepProblem "Too much sleep "}
WHERE {
   ?p a :Person .
            ?p :duration ?d.
            FILTER (?d >480 )}
```

The following code block shows the implementation of the simple semantic rule “Lack of Exercise”. If the steps of the participant with dementia are less than 80 and we conclude that there is a lack of exercise.

SPIN rule for problem “Lack of Exercise”.

```
CONSTRUCT {
?p owl:hasProblem "Lack Of Exercise" }
WHERE {
?p a :Person .
            ?p :steps ?st1.
            FILTER (?st1<80)}
```

E. *Visualization on Clinician Dashboard*

The final step and ultimate purpose of our developed Semantics system, is to provide to the clinician experts the appropriate tools in order to monitor the patients and allow them, through the information that our framework provides, to make the proper decision regarding the treatment course of each patient. In order to give the clinicians the ability to have an overview of the activities or their derived problems, we created a visualization dashboard, where all the necessary analytical metrics are provided in a coherent, robust and user-friendly manner. As shown in Figure 4, the information about the patient’s activities are depicted through eye-friendly tables and charts. Our implementation tried to evade complex and tiresome tables with numbers, and translated all the raw information into visualizations that are easy to understand.

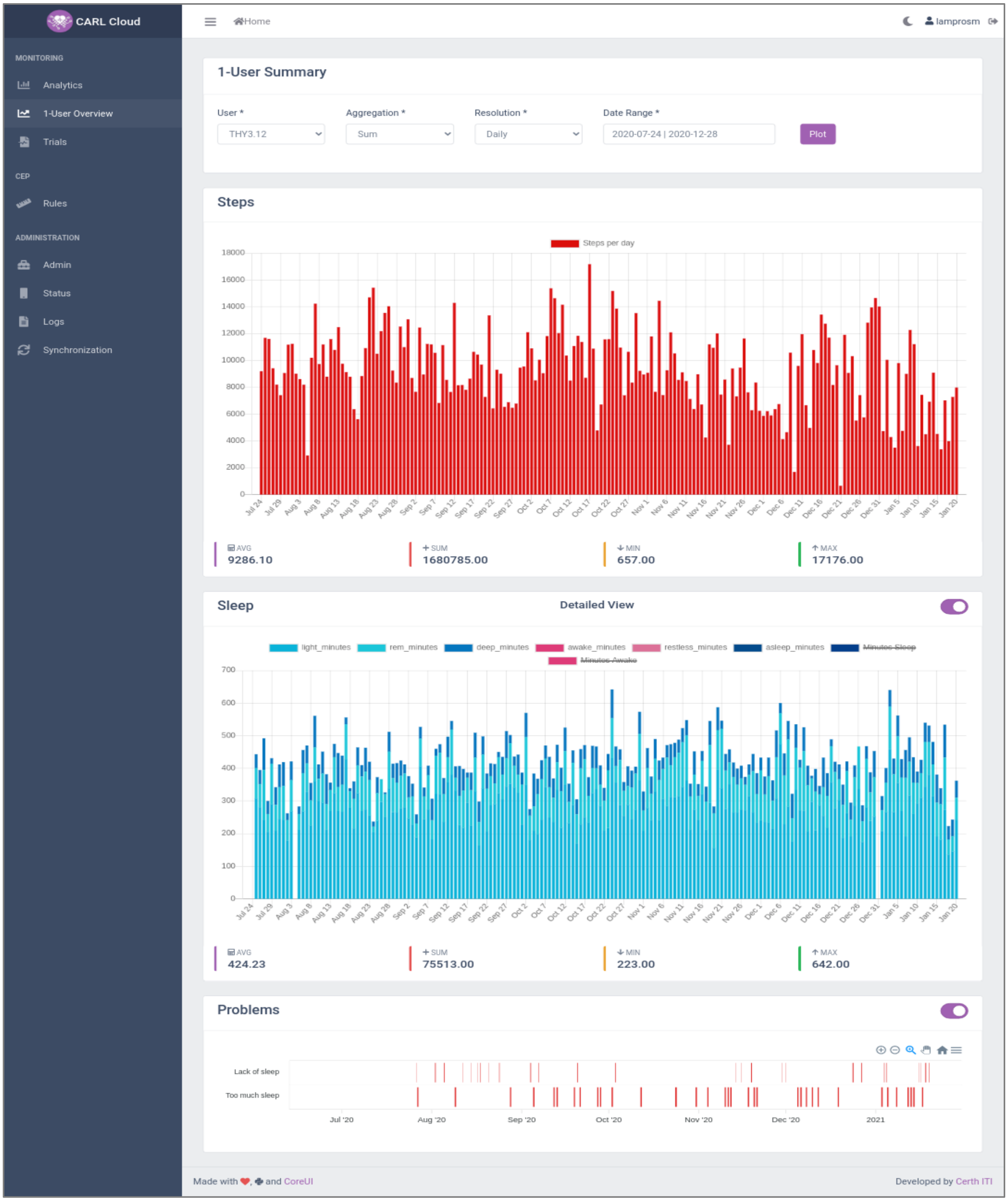

Figure 4 - Dashboard of Steps, Sleep and Problems generated

IV. USE CASE

For the evaluation of the proposed architecture we consider the following use case scenario performed on real-world data from participants recruited in the framework of the support2LIVE project. There were two patients with Dementia that were measured and evaluated. The duration of the first participant is for the full length of October 2020, while the measurements for the second participant is January 2021. The initial sensor data was modeled by using the system ontology and stored in the Knowledge Base. Then, the proposed semantic techniques were applied and in particular the semantic rules of the system were checked.

Figure 5 shows the measurement of sleep minutes of Patient 1. Likewise, Figure 6 shows the measurement of sleep minutes of Patient 2, while Figure 7 presents their measurements of steps per day. All data are processed, and results are shown, in the form of health-related problems that the patient experiences during this time.

Specifically, as shown in Figure 5 the first patient with dementia slept below the limit of 300 minutes (Table 5, Rule 4) on October 26. The results of these measurements are shown in Figure 8 with the creation and visualization of the "Lack of Sleep" problem. In addition, the patient slept above the limit set by Rule 3 (Table 5, 480 minutes) on October 3, and this resulted in the creation of the problem “Too Much Sleep”. This shows on example of how highlighting health-related problems from a dataseries would help the clinicians to efficiently and effectively detect issues that would otherwise take more time and examination.

Regarding the second patient, as shown in Figure 6, the user slept below the limit of 300 minutes (Table 5, Rule 4) on January 3 and 7. The problems generated by the system for these measurements are shown in Figure 9 with the creation and visualization of the "Lack of Sleep" problem. In addition, the patient slept above the limit set by Rule 3 (Table 5, 480 minutes) on January 2, and this resulted in the creation of the problem “Too Much Sleep”. Similarly to the previous case, our framework efficiently detects the underlying health-related problems in both activity and sleep.

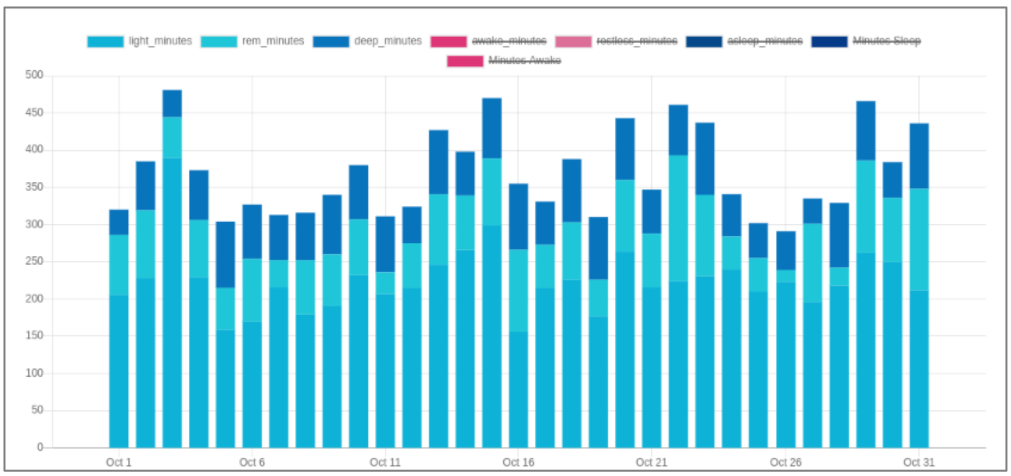

Figure 5 - Patient 1 Sleep

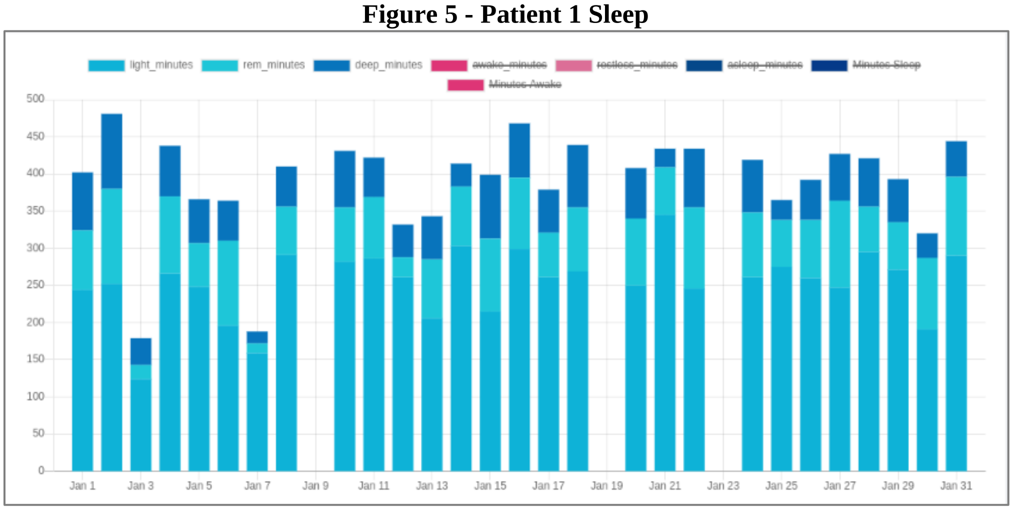

Figure 6 - Patient 2 Sleep

Finally, in Figure 7, it is observed that on January 8 and 20 the patient took a low number of steps. As a result, this measurement generates the problem (Rule 11) “Lack of Movement”, is shown in Figure 9.

This example showcases the ability of the system to highlight problems of relatively high importance to the users. Specifically, this user’s steps are generally low everyday, but detected problem occurs and emphasizes only on the days of exceptionally low activity (as shown in Figure 7 and Figure 9), something that the human eye would not that easily and efficiently detect.

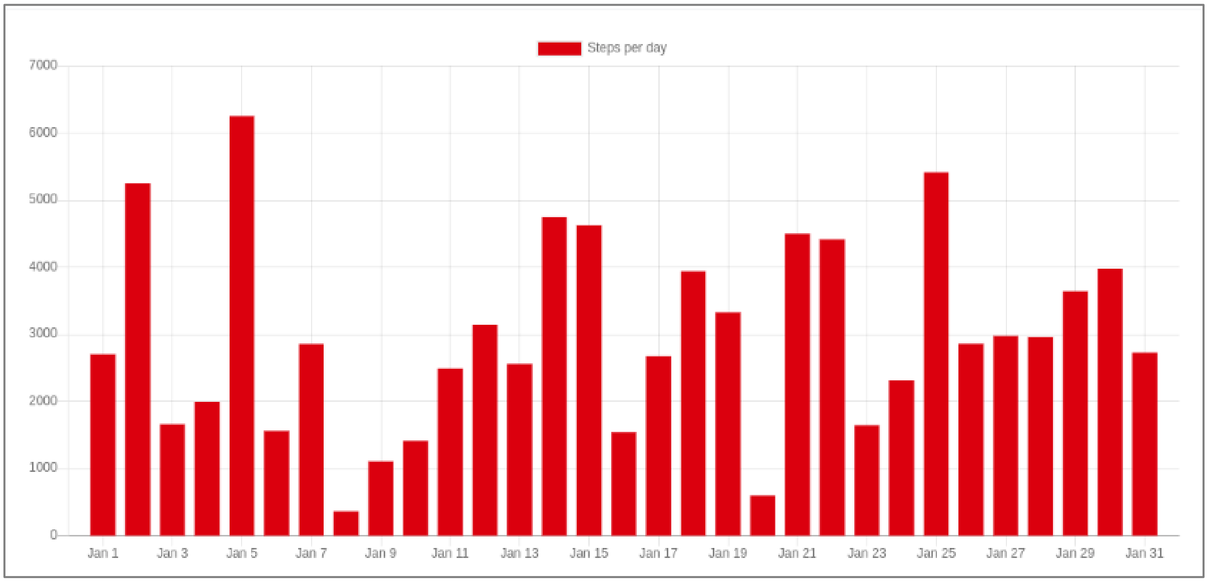

Figure 7 - Patient 2 Steps

Figure 8 - Patient 1, Problems Generated by the System

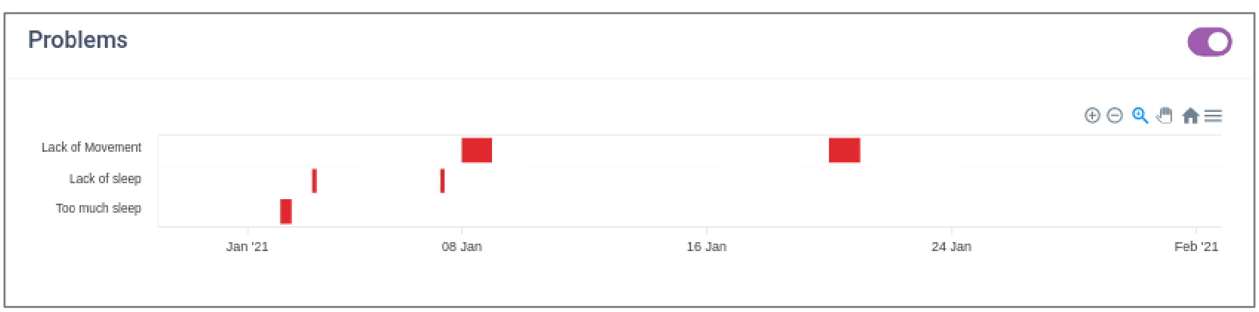

Figure 9 - Patient 2, Problems Generated by the System

V. CONCLUSION AND FUTURE WORK

In this paper, we presented our approach towards the definition of a semantic system for Health-related Problem detection that combines ontologies and SPIN Rules. Architectures related to the proposed framework are listed, and the advantages of using the SPIN language to create semantic rules are presented. The main purpose of the proposed architecture is to generate new knowledge from the original raw data, especially recognition of healthcare problems for people with dementia. The system is validated through a proof-of-concept use case scenario where a wearable sensor gathers data from a real participant, and the framework extracts the expected Health-related Problems.

As future work, we plan to evaluate the framework in a formal clinical trial with real participants. Participants will be recruited in the spectrum of dementia, as well as healthy controls, and use the wearables for several months. The framework will be used to extract problems and clinical experts will evaluate its accuracy, usability and usefulness for the disease. In the long run, the system will be able to support decision making of the clinicians and facilitate them in adjusting non-pharmaceutical interventions.

ACKNOWLEDGMENT

This work was co-financed by the European Union and Greek national funds through the Operational Program Competitiveness, Entrepreneurship and Innovation, under the call RESEARCH-CREATE-INNOVATE, project code: T1EDK-02668.

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