Data Analytics For Health and Connected Care: Ontology, Knowledge Graph and Applications

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Abstract. Connected care applications are increasingly used to achieve a more continuous and pervasive healthcare follow-up of chronic diseases. Within these applications, objective insights are collected by using Artificial Intelligence (AI) models on Internet of Things (IoT) devices in patient's homes and by using wearable devices to capture biomedical parameters. However, to enable easy re-use of AI applications trained and designed on top of sensor data, it is important to uniformly describe the collected data and how this links to the health condition of the patient. In this paper, we propose the DAHCC (Data Analytics For Health and Connected Care) ontology, dataset and Knowledge Graph (KG). The ontology allows capturing the metadata about the sensors, the different designed AI algorithms and the health insights and their correlation to the medical condition of the patients. To showcase the use of the ontology, a large dataset of 42 participants performing daily life activities in a smart home was collected and annotated with the DAHCC ontology into a KG. Three applications using this KG are provided as inspiration on how other connected care applications can utilize DAHCC. The ontology, KG and the applications are made publicly available at `https://dahcc.idlab.ugent.be`. DAHCC's goal is to integrate care systems such that their outcomes can be visualised, interpreted and acted upon without increasing the burden of healthcare professionals who rely on such systems.

Keywords: Connected Care · Open health data · Ontology

1 Introduction

From the perspective of healthcare professionals, our current healthcare system brings many challenges as well as opportunities for digital healthcare [4]. Each healthcare professional already takes care of multiple people as more and more in-person visits have to be reduced to an absolute minimum. Connected care solutions, including remote patient monitoring and secure communications between clinicians or caregivers and their patients, may rapidly become the first choice to provide care in a public health system [21].

First steps have already been taken to provide such connected care solutions. Smart cities are designed using smart sensors to track the well-being of their citizens [10], ambient intelligent homes where sensors track and derive information from their residents in a privacy-friendly manner are being deployed [5] and patients with specific healthcare-related problems are equipped with smart sensors, such as wearables, to track biometric properties [7].

Those care applications deliver insightful information for caregivers and health professionals and should eventually help them to work more effectively [25]. Artificial Intelligence (AI) applications, such as Human Activity Recognition (HAR), can be used to monitor the physical abilities of elderly [9]. The HAR outcome or prediction can be seen as new knowledge, which can be of interest to a healthcare professional [1].

However, monitoring and analysing all the data produced by intelligent sensors and care applications should not increase the burden and stress of those who rely on them [3]. Therefore, a uniform method is needed to both describe the connected care applications and associated data. By doing this, the derived knowledge from those care applications can be easily integrated into new smart applications and can be automatically reported using insightful dashboards. They can also be used in autonomous alerting tools to inform health care professionals when unwanted behaviour or situations of high risk occur.

In this paper, we present the Data Analytics for Health and Connected Care (DAHCC) Ontology, a method to semantically describe sensor data, human activities, smart applications, health actors, faulty or unwanted behaviour and link them all together. To facilitate the idea behind DAHCC and the creation of new connected care applications, an ambient intelligent dataset was created and semantically enriched into a Knowledge Graph (KG) with over 40 participants performing daily and nightly activities. Example applications show how new connected care applications can be developed based on this dataset. Both the used method (ontology), datasets, KG, as well as the used applications are made available online under an MIT license.

The remainder of this paper defines in Section 2 the different existing techniques to describe healthcare resources and applications uniformly. The creation of the DAHCC ontology based on the multiple reused industry standards and well-adopted ontologies is provided in Section 3. Section 4 describes the creation of the dataset and Section 5 details how it was transformed into a KG. The applications built upon this KG are described in Section 6.

2 Related Work

Monitoring of patients in either an ambient life setting or for general healthcare purposes covers a large research domain. The usage of IoT devices and wearables was crucial in the development of these applications [13]. In the last decade, healthcare ontologies became popular to incorporate and combine domain knowledge with these sensory devices. Table 1 summarises the field of connected care ontologies. Most of these ontologies are not publicly available to be reused in other applications or were designed for a specific use case within a connected care setting.

Table 1. Overview of existing Healthcare-related ontologies

Ontology	Available	Reused Ontologies	Semantically describe
ACCIO [17]	Yes	SSN	Ambient patient rooms
Telehealth [12]	No	ICD, ICF, SNOMED-CT	Patient profile
HealthIoT [20]	No	NaN	Medical devices
SAREF4EHAW [14]	Yes	SAREF	Monitoring health actors
e-Health [11]	No	SSN	Device communication
IFO [19]	No	NaN	IoT health and fitness data
LHR [18]	No	SNOMED-CT, SSN	Health care data exchange
SHCO [24]	Yes	SAREF	Patient-doctor interactions
Do-Care [8]	No	FOAF, SOSA, ICNP	Nurse interactions
DAHCC	**Yes**	**SAREF, EEP, OWL Time**	**Connected care**

The ACCIO ontology [17] exploits and integrates the heterogeneous data by utilising a continuous care ontology for patient rooms of the future in a hospital setting. It was one of the first ontologies co-created with nurses, caregivers, patients, doctors and professionals working in the healthcare industry. The ontology is used to exploit and integrate heterogeneous data. The Patient-Centric for Telehealth ontology [12] was designed with an explicit focus on the personality traits of the patients to describe diseases, functioning and physiological measurement. It does, however, not integrate sensor-related information. The HealthIoT ontology [20] aims to represent the semantic interoperability of the medical connected objects and their data. The ontology focuses only on the medical aspects of the devices and provides rules to analyse the detected vital signs. Those analyses can be delivered to a healthcare professional. SAREF4Health ontology [14] is an extension of SAREF, a framework for smart appliances references. The SAREF ontology describes how sensors and sensor data can be described and linked to each other. The SAREF4Health extension specifies eHealth/Ageing-well (EHAW) domain-related resources and defines how the sensor data relates to health actors. Care-specific needs or how new systems can provide additional information towards a connected care system are not provided in this SAREF4Health extension. The e-Health ontology [11] tries to reduce programmatically implementing the interpretation of the data sender and data receiver for each new healthcare device added into a system. This ontology lowers the efforts needed to extend a current healthcare setup in an ambient living context. The IoT fitness ontology (IFO) [19] presents a semantic data model useful to consistently represent health and fitness data from heterogeneous IoT sources and integrate them into semantic platforms to enable automatic reasoning by inference engines. This ontology does not take into account standards such as SSN or SAREF to describe the sensor and data. Linked Health Resource (LHR) ontology [18] integrates health data from different services as linked resources. The healthcare-IoT ontology [22] provides semantic interoperability among heterogeneous devices and users in the healthcare domain. The ontology models the exchange of health care data and home environment data. The smart healthcare ontology (SHCO) [24] define concepts for monitoring doctors and patients anytime, anywhere. SHCO is presented as a semantic model by extracting healthcare knowledge such as doctor-patient records, recommended diagnoses and treatment policies. This ontology only uses rather static non-sensory information. The Do-Care ontology [8] is modular and incorporates the International Classification for Nursing Practice (ICNP) ontology together with inference rules. The methodology is dynamic and adjustable to meet possible changes in the medication market, medical discoveries, and personal users' profiles. Nurse interactions are the main focus of this ontology.

Each of these ontologies describes a clear subpart within the connected care domain. Almost all ontologies already reused existing ontologies such as SSN or SAREF. Some of them are also made open-source and are available online for further reuse. However, an ontology which describes all concepts related to connected care, ambient living, patient care and their interaction with healthcare professionals is currently not available. Moreover, there doesn't exist to our knowledge an ontology which links AI models, with their predictions and model configuration, to the monitored context or situation of a healthcare actor. Such an ontology is of high need as more and more AI models are being used within healthcare. Those models generate new insights that, when semantically described, can deliver even more advanced input to healthcare professionals. In this paper, the DAHCC ontology is created to resolve this need.

3 DAHCC Ontology Creation

The DAHCC ontology describes real-world connected care entities (person, sensor, activities, etc.) and their interrelationships. It also models domain knowledge, e.g., performing human activities & profile data or location information where those sensors are installed. The design of DAHCC ontology was based on three types of information sources:

- Structured documents, e.g. the descriptions of the used sensors and monitoring systems in technical specifications & APIs, in-take documents used by caregivers, etc.
- An assessment of existing ontologies that could be reused.

– Some knowledge is only available from the stakeholders, who perform day-to-day assessment & handling of deviating situations. To derive this information, decision tree workshops were organised with nurses and caregivers as described in [16].

The structured documents contained mostly resident-specific, privacy-sensitive information. We kept those fields that are interesting for healthcare-related cases. SAREF Core[5], SAREF4BLDG[6], SAREF4EHAW[7], SAREF4WEAR[8], Execution-Executor-Procedure (EEP)[9] and the OWL Time ontology[10] were reused within DAHCC. The decision tree workshops resulted in a long list of care intervention reasons, and an indication of which data/information the caregivers used to assess alarming situations and how they handle them. The information inside these decision trees was used to define new concepts regarding patient monitoring within the DAHCC ontology.

3.1 DAHCC Ontology

The DAHCC ontology exists out of five sub ontologies which have links to each other. Each of these ontologies reuses one or more of the mentioned, already existing ontologies, combined with new concepts derived from the provided workshops [16]. These workshops brought together ontologists, healthcare providers and people who monitor patient calls. The results of these workshops are identified use cases by the participants, a long list of call reasons and resulting decision trees of how care is provided or how a person monitors patient calls. These decision trees were consolidated by the ontologist into two decision trees: one for the nurses and one for the caregivers. The information inside these decision trees was used to define new concepts regarding patient monitoring and handling of call operations within the DAHCC ontology. For the extensive documentation of the ontological concepts, we refer the interested reader to the ontology section at `https://dahcc.idlab.ugent.be`. The remainder of this section describes the 5 different sub ontologies in the DAHCC dataset.

Activity Recognition The Activity Recognition sub ontology defines how the concepts of activities, performed by a saref:HealthActor, can be predicted using an activity recognition model. The ontology also describes how such a model can be defined, together with its configuration and input and output data. The ontology describes more in general lifestyles, routines and anomaly classes for, e.g., unwanted daily or nightly activities. The Activity Recognition ontology will be used to describe all the concepts related to both performed and predicted

[5] https://saref.etsi.org/core/v3.1.1/
[6] https://saref.etsi.org/saref4bldg/v1.1.2/
[7] https://saref.etsi.org/saref4ehaw/v1.1.1/
[8] https://saref.etsi.org/saref4wear/v1.1.1/
[9] https://iesnaola.github.io/EEP/index-en.html
[10] https://www.w3.org/TR/owl-time/

activities, together with their link to the models/techniques used to detect them, the performed routines and the lifestyle of the health actor. An overview of this ontology is provided in Figure 1.

Monitored Person The Monitored Person sub ontology, as shown in Figure 2, describes the person itself who is monitored by all sensors and who performs the human activities and routines. It also describes the possible diseases, addictions, mental illnesses or allergies this monitored person can have. Medication and the current mental state of the monitored person are also defined as concepts within this ontology. This Monitored Person ontology has a strong link to the Activity Recognition ontology to link human activities.

Sensors and Actuators This Sensors and Actuators sub ontology describes a numerous amount of sensors and actuators that produce data and can be equipped inside a household. Besides the sensors and the measurement properties, this ontology also defines where those sensors are placed and which appliance or rooms they analyse. This subontology is shown in Figure 3 and mainly extends the SAREF Core and SAREF4BLD ontologies with ambient life-specific concepts.

Sensors And Wearables Similar to the Sensors and Actuators ontology, the Sensors and Wearables ontology (Figure 4) describes the wearables and sensors that can be attached to or near a monitored person. This sub ontology extends the SAREF4WEAR ontology and adds specific connected care concepts to it. Wearables range from medical devices using simple near-field communication or Bluetooth connections to send medical parameters to a cloud environment, as well to more sophisticated smartwatches to track residents inside a building 24/7.

Caregiver The Caregiver sub ontology defines the link between caregivers and monitored persons. It uses the SAREF4EHAW concepts to assume the possible relation between health actors. Additionally, it also describes how the required care can propagate to the responsible entity or caregiver. It also defines the Care Provisioning activity. An overview of this ontology is provided in Figure 5.

4 DAHCC Dataset

To show how the DAHCC Ontology can be used to annotate healthcare data and how this is beneficial for the creation of connected care applications and extracting knowledge, a large ambient intelligent data collection campaign at the HomeLab of the IDLab research group of Ghent University was performed. The HomeLab is an actual standalone house offering a unique residential test environment for IoT services and smart living. A wide range of IoT technologies

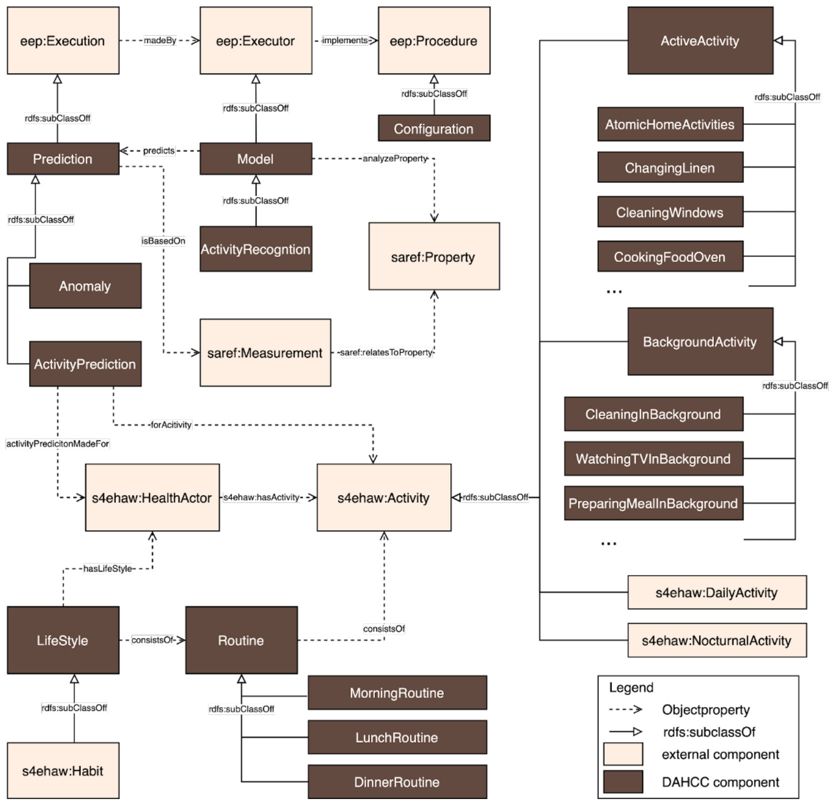

Fig. 1. Overview of the DAHCC Activity Recognition sub ontology

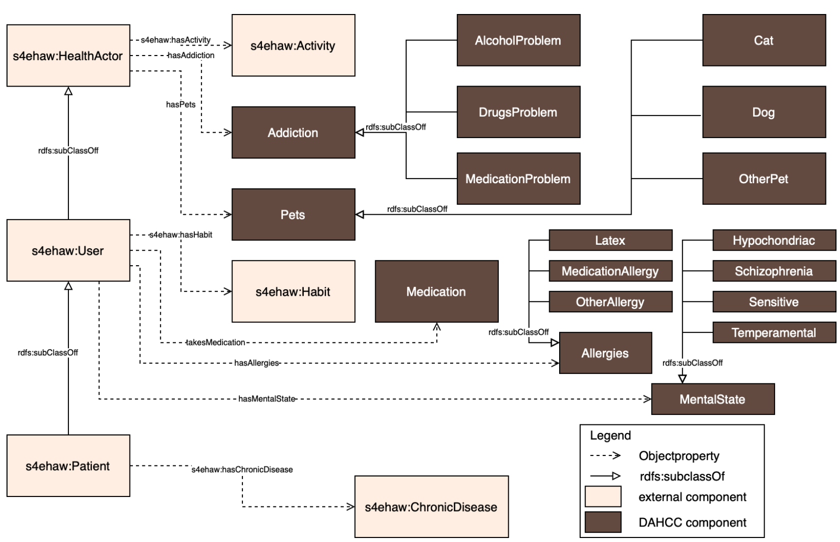

Fig. 2. Overview of the DAHCC Monitored Person sub ontology

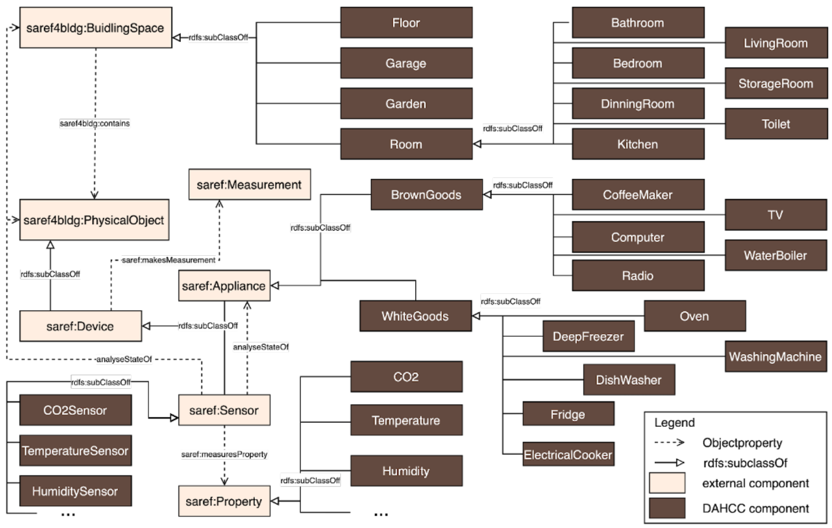

Fig. 3. Overview of the DAHCC Sensors and Actuators sub ontology

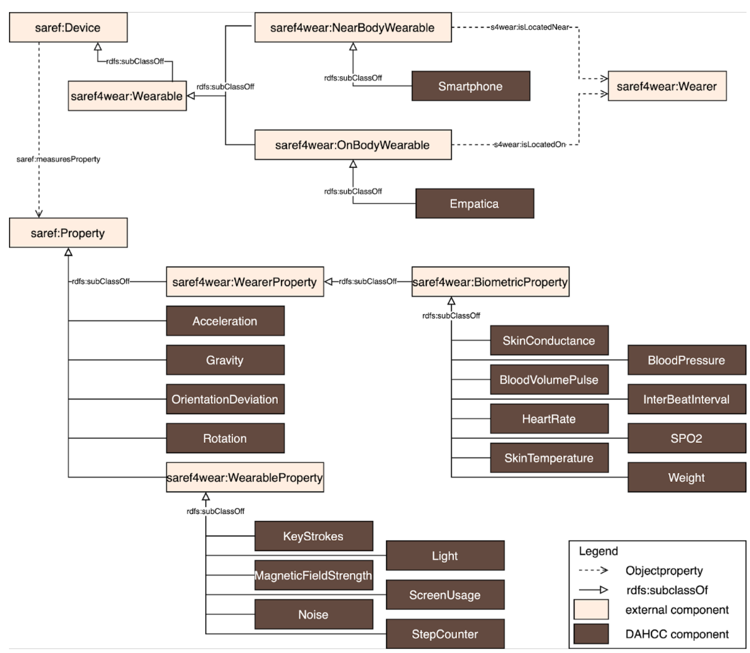

Fig. 4. Overview of the DAHCC Sensors and Wearables sub ontology

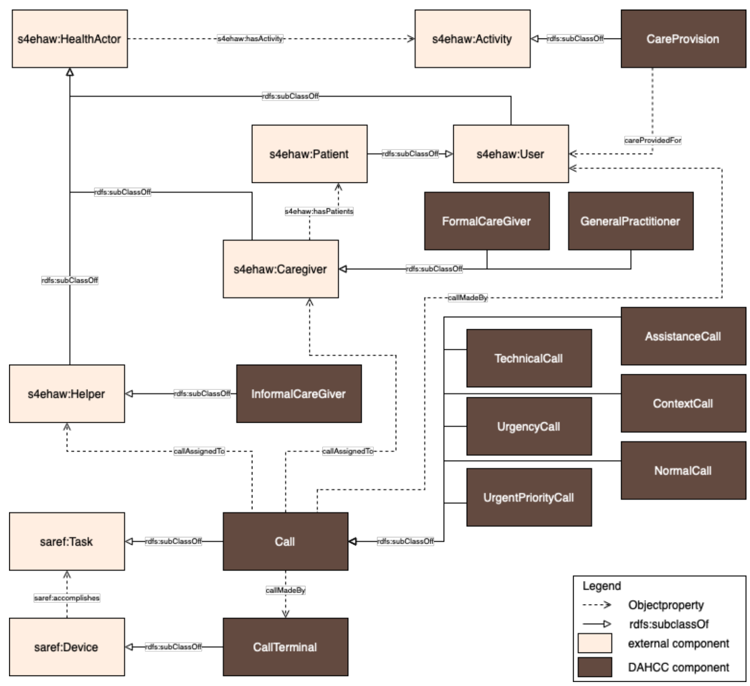

Fig. 5. Overview of the DAHCC Caregivers sub ontology

are deployed, and the set-up allows to add new devices using technical corridors, hollow floors and ceilings[11].

In total, 42 participants were invited to the Homelab and were asked to either perform their daily or nightly routines. Both the Homelab and the participants were equipped with a large number of sensors which try to capture the participant's activities. The data collected for each participant, as well as the daily life annotated activities, are made available at `https://dahcc.idlab.ugent.be/dataset.html`.

4.1 Data collection setup

To derive the daily and nightly activities, a data platform was designed to capture and store the sensor readings and participant annotations. An overview of this platform is provided in Figure 6. The rooms within the Homelab were also equipped with many contextual sensors. People Counters and the AQURA Indoor localization system of Televic Healthcare[12] were used to derive the indoor

[11] `https://www.ugent.be/ea/idlab/en/research/research-infrastructure/homelab.htm`

[12] `https://www.televic-healthcare.com/en/solutions/wireless-nurse-call-systems/wireless-localisation-tags`

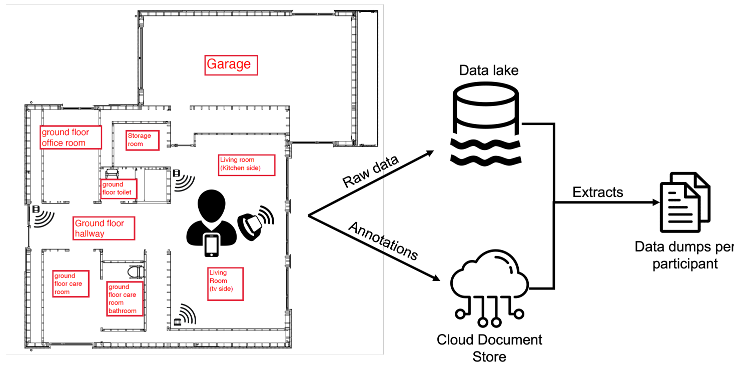

Fig. 6. Overview of the DAHCC Homelab data collection campaign. Data captured from different sensors and wearables was sent to the data lake. Data dumps for each participant with sensor data and annotating labels are generated and made available.

location of the participants. Door contact sensors were installed on every door, window and cabinets in the kitchen the grab their open and close states. Velbus sensors[13] were used to control and monitor the lights, indoor temperature, opening or closing of the blinds and the energy consumption of all appliances. A specifically designed water running sensor was used to detect when water was being used from the faucets in the bathroom and kitchen. At last, several rooms were equipped with a CO2, Humidity and Loudness sensor. All these Homelab sensors were integrated using the DYAMAND platform [15]. DYAMAND collects the data from these sensors and provides it in a JSON format to the data lake.

A web application was designed that allows participants to (a) enter the activities they perform as part of a routine, and (b) indicate when they start/stop a specific activity. The app was used during the whole data collection to allow participants to annotate the actions they are performing. Every time a participant interacted with the application (when a start, end or cancel button was pressed), a timestamp together with the performed action was sent to a log file on a cloud document store. This log file was later on analysed to derive the annotations.

Together with this annotation app, each participant was asked to install two additional smartphone applications: (a) the streaming application to collect data from a wearable (Empatica E4[14]) and smartphone sensors and send them to the data lake, and (b) the Sleep as Android application[15] (to track sleep during the night protocol). Besides the wearable device, the blood pressure, body weight, body temperature and spO2 biomedical parameters were measured at the start of the day if the participant gave their approval inside the informed consent.

[13] `https://www.velbus.eu`
[14] `https://www.empatica.com`
[15] `https://sleep.urbandroid.org`

4.2 Collected data

In total, 31 “day in life” participants and 12 “night” participants enrolled in this data collection campaign and annotated, on average, 70.7 activities using the mobile annotation app. On average, more than 1 gigabyte of data was collected for every participant. Before making the gathered data publicly available, the data samples were anonymized by erasing the date information within the timestamps of the sensor values (the original times were kept). Also, the participant numbers were randomised, such that participant 1 isn’t the first participant who gathered data within this data collection campaign.

5 DAHCC KG

The described dataset in Section 4 was transformed based on the DAHCC ontology into a KG linking all information together. To create this KG, we performed to following steps:

- In a first step, we mapped the Homelab floor plan and location of all sensors and actuators based on the DAHCC Sensor and Actuators sub ontology. We also semantically defined all the major appliances and provided the link to those sensors that measure their energy consumption. The semantic representation of the Homelab is made available as an additional resource[16].
- Secondly, we also mapped the used Empatica E4 wearable and other biomedical devices using the Sensors and Wearables sub ontology. Again, we made this resource available for future reference.
- In a third step, all the data from the data collection participants were transformed into a semantic representation using a Python script. This script maps each sample to a participant-specific URI identifier and links it to the concept described in the Sensors and Actuators and Sensors and Wearables sub ontologies.
- A similar Python script was created to map the participants’ annotations onto the concepts of the Activity Recognition sub ontology.

For each participant, the output of these scripts generated NTRIPLE files, which were combined and gzipped to reduce the KG file size. Those individual KG files, per participant, were also made available at `https://dahcc.idlab.ugent.be/dataset.html`.

6 DAHCC Semantic Applications

Inspired by the available DAHCC KG, we created three applications which can be used to derive new knowledge from or infer useful results for healthcare professionals. A first application defines how the available domain knowledge within

[16] `https://github.com/predict-idlab/DAHCC-Sources`

the DAHCC ontology can be used to generate more advanced events using reasoning. A second application describes how semantic rule mining based on the inferred knowledge can be performed. A third application shows how such a rule can be incorporated into a semantic stream reasoning engine. Implementations and examples on how to use each of these applications are provided in a GitHub repository[17].

6.1 Semantic higher-order events generation

The DAHCC KG defines the sensor data and corresponding metric information. Due to all the available knowledge, we can reduce this KG by transforming groups of sensor observations into more relevant events happening inside the Homelab. Most sensors measured the state of an appliance or object within a certain room, e.g. the Velbus energy sensors measure the energy consumption of the cooking top in the kitchen. Instead of storing only the data observations in a semantic format, the usages of appliances and objects were also inferred based on the sensor values inside the KG.

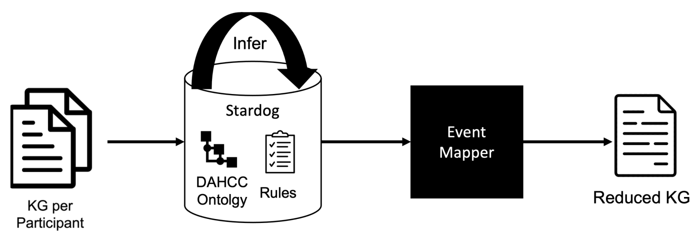

Fig. 7. Overview of the Inferred Knowledge generation. This generator was adapted from `https://www.stardog.com/labs/blog/stream-reasoning-with-stardog/`

In this approach, the semantic observation samples are loaded within a Stardog[18] database together with the DAHCC ontology and some generic, predefined rules. Reasoning-on-query is then executed on these observation samples within the Stardog database to get the inferred and derived events. For each defined rule, a specific event is created when inferred (e.g. the Start command rule creates an on state event for a specific appliance).

Next to the action and corresponding appliance or physical object related to the occurring action, both the time when this event happens and the participant who executes the action are stored. The annotated activities, the inferred events and sensor observations were all combined within a new KG which now only contains events instead of a large number of observations.

[17] `https://github.com/predict-idlab/DAHCC-Sources/tree/main/Applications`
[18] `https://www.stardog.com`

Within this application, the DAHCC ontology is used to deliver additional context information to enrich the raw data. Since the specific Homelab appliances, rooms and sensors are described by such DAHCC components, rules could be designed to combine the data and metadata to generate new insights. Those defined rules are due to the use of the DAHCC ontology generically and are easy to interpret.

The creation of higher-order events is needed in a healthcare setting to reduce the number of raw data samples that have to be monitored by a healthcare professional. Due to the available ontology and the metadata described by this ontology, simplifications of the data can be provided to create more interpretable information about what is going on in a smart home.

6.2 Deriving rules for shower events

The previous application generates more advanced events to monitor the behaviour of a person in an ambient house setting. Additionally, it would also be beneficial to detect the lifestyle activities performed by these people as those activities define the current behaviour and state of the person. Based on the available data and metadata, and to ensure the detection method is interpretable, a semantic rule mining application was designed to derive lifestyle rules based on the semantic events generated by the previous application. The INK rule miner [23] was used to derive task-specific rules for one group of activities (e.g. shower events) compared to all other events. This rule miner is based on the INK representation to embed the KG but performs a task-specific rule mining operation based on Bayesian rule set [26]. The task here is to find semantic rules which discriminate against one type of activity as best as possible regarding precision (defining how many predicted rule outcomes were relevant) and recall (defining how many relevant triggered rule outcomes were retrieved). Table 2 shows examples of relevant rules found for the Shower, Toilet and Washing Hands activities. For all tasks, a highly imbalanced set of labels has been provided and the INK rule mining parameters were set to mine the most precise rules. Therefore, the recall scores are significantly lower than the precision scores for the obtained rules.

Table 2. Results of the performed rule mining operation on the dataset

Event	Rule	Precision	Recall
Shower	hasEvent.kitchen.Temperature >21.75 and hasEvent.bathroom.Loudness_mean >46.83 and NOT hasEvent.personIn§kitchen	0.9411	0.6153
Toilet	hasEvent.LightSwitchOnIn§toilet1 and NOT hasEvent.personIn§kitchen	0.8175	0.5734
WashingHands	hasEvent.LightSwitchOnIn§toilet1 and hasEvent.using§waterpump	0.8600	0.3385

The DAHCC ontology delivers in this application the additional knowledge to mine more insightful rules. Without the DAHCC ontology, rules will be less generic and it will be harder to mine rules based on related data observations (e.g. observations from similar sensors or observations made within the same room). Mining rules automatically is also needed to create an interpretable, but adaptive healthcare monitoring system where a human only has to verify but not create the rules.

6.3 Semantic stream reasoning

Mining rules based on semantic events deliver useful insights into the daily life pattern of a person. Rule-based systems are frequently used as connected care applications as they are both reliable and interpretable. We created a semantic stream reasoning application to show how DAHCC can be used for such a technique.

An overview of this semantic stream Reasoning unit is provided in Figure 8. First, the raw data samples are mapped in a semantic format one by one. Next, those semantic observations are fed to a C-SPARQL [2] engine. C-SPARQL is used here in combination with an RSP-Service[19]. This combination of RSP and C-SPARQL makes it possible to dynamically load query rules to detect the lifestyle activities of a person. In the last step, the query is performed on a window of obtained semantic events and when a result can be inferred, this semantic result is sent to a monitoring application.

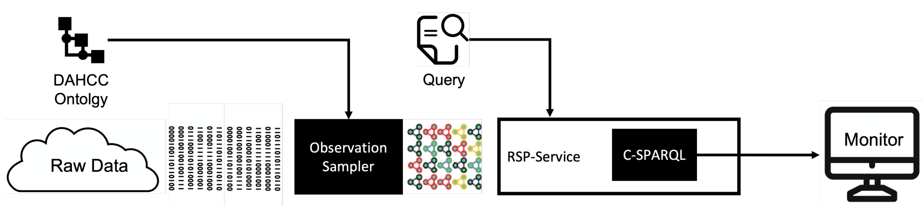

Fig. 8. Overview of the semantic stream reasoning setup

An instantiated application where we try to find shower activities within a semantic data stream is made available. Again the DAHCC components described the semantic observations, on which the shower query rule is defined. Multiple sensor values to determine the location of the person and the humidity sensor values within the bathroom are combined in order to generate a rule-based prediction. The whole setup and the defined rule-based predictions are also semantically described using the DAHCC ontology.

In the healthcare sector, semantic stream reasoning can be used to monitor a patient with specific care needs. Cases exist where based a smart room adapts

[19] https://github.com/streamreasoning/rsp-services

to the needs of a patient suffering a concussion [6]. Using the DAHCC ontology different alert levels and priorities can be automatically defined and monitored based on the patient's care needs and the available sensors and actuators inside a smart home.

7 Discussion & Conclusion

In this work, we presented DAHCC, a combined resource which provides healthcare knowledge in numerous settings using a maintained ontology and a large dataset to build and create semantic connected care applications. All the resources, the resource creation files and example semantic connected care applications files are made open source.

The applicability of the ontology is evaluated by transforming the dataset into a semantic format, resulting in a KG. The construction of these KG files was created using a script because all the original raw dataset files had a similar structure. Techniques exist to provide a more user-friendly and standardized way to transform such data files into a semantic representation. The applicability and overview of these existing techniques, their benefits and drawbacks, were left out of scope in this research.

The open-sourced KG is based on all raw sensor input from a smart lab environment. Therefore, the KG shows only one part of the available DAHCC ontology. The goal of the DAHCC ontology is that additional instances such as designed artificial intelligence models or patient-specific information are also made available in such a KG. The design of such an artificial intelligence model is kept to a minimum and is part of future work. Patient-specific information was not incorporated in the dataset as anonymization of the participants was required to make it publicly available.

At last, the ontology itself was built by taking into account the input from different people within the healthcare domain. While the current setting was mainly focused on how ambient living and connected care systems can be combined, the ontology itself is defined and constructed to be further extended or adapted when new information or new use cases become available. Making the ontology open-source makes it possible for other researchers to further extend it.

Resource Availability Statement: The DAHCC ontology, datasets and KG are available online from `https://dahcc.idlab.ugent.be`. The source code for the applications is available on Github at `https://github.com/predict-idlab/DAHCC-Sources`.

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