Uncovering the semantics of PD patients' movement data collected via off-the-shelf wearables

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***Abstract*—Wearable sensors are used in monitoring patients with neurodegenerative diseases (ND), such as Parkinson Disease (PD), to collect movement data for the analysis and the assessment of patients' symptoms. To become interoperable and interlinked with other related personal health data, collected data through sensors embedded in wearable devices need to be semantically described in a commonly agreed, explicit, and formal way. Personal health records (PHRs) including patients' Magnetic Resonance Imaging (MRIs), medical prescriptions, and medical advice, can provide a unified view of personal health to health specialists, decreasing their efforts to constantly assess patients' condition via traditional methods. This study aims to present our work for collecting movement data of PD patients through wearables, analyzing them to uncover their inherent semantics, and employing these semantic insights to annotate data in a formal and explicit way to facilitate interlinking with other related heterogeneous data. The movement data was collected via unobstructive wearable technology for health monitoring, and existing formal semantic models were examined for their suitability to be reused and extended for the semantic annotation of the collected movement data. Furthermore, this paper reports early work towards representing such knowledge in the form of a Knowledge Graph (KG) to support rule-based high-level event recognition, such as a missing dose event, for monitoring PD patients and alerting their doctors.**

Keywords—Sensors, Wearables, Parkinson Disease, Ontology, Data Integration, PHKG

I. Introduction

The current investigation emphasizes the necessity of utilizing smart and edge-devices, with related applications, to gather, combine, and evaluate personal health data in real-time with the aim to recognize high-level events such as "missing dose" or "fall" of patients with PD, enhancing their care through wearable technology and semantic data analysis techniques. Specifically, the study addresses the challenge of semantically linking sensor data (e.g., measuring movement) with PD-related personal health data, such as MRI scans and medical prescriptions, to obtain a more comprehensive understanding of the disease and its effects on patients' daily living and behavior. Several studies have previously investigated sensor-based monitoring of PD, which necessitates comprehensive sensor-based monitoring in both clinical and everyday settings. To achieve interoperability and data interlinking, movement and kinesis-related data of PD patients, including tremor and bradykinesia, must be appropriately structured and semantically described according to specific standards and paradigms, such as W3C [1] standards for the Semantic Web (SW) and Linked Data (LD).

Therefore, the aim of this study is to collect movement data of PD patients through wearable sensors, analyze them in a way that enables the understanding (uncover) of their semantics, and use these semantics to semantically annotate the data for interoperability and interlinkage with other related data. Moreover, the primary focus of this study is on utilizing unobtrusive wearable technology for health monitoring. To this end, an off-the-shelf wearable, specifically a Samsung Galaxy Watch (46mm SM- R800), was utilized along with a custom application we have developed on Tizen 4.0 OS and deployed on the watch for the experimental data collection.

The contribution of our work, as presented in this paper, is as follows. Initially, a custom smart app for off-the-shelf wearable device has been developed and deployed, utilizing its sensors (accelerometer, gyroscope, pedometer, heart rate monitor). Experimental data were collected from PD patients during specific tasks related to Activities of Daily Living (ADLs). Experimental data collected are analyzed using a data analytics tool, uncovering their semantics (data semantics' understanding). Furthermore, existing formal models (ontologies) are examined in terms of their suitability for semantically annotating the related data and the data to be integrated with towards a unified model for PD patient personal health monitoring and alerting. Significantly, suitable semantics for the semantic annotation of PD movement data collected from off-the-shelf wearables are proposed and specified. In addition, suitable semantics are evaluated (in a high-level event-related scenario) for reasoning with integrated personal health data towards recognizing high-level events for alerting, such as a 'missing dose' event.

The paper is structured as follows: background knowledge and related work are presented in Section II. The proposed approach and its early results are presented in Section III. Moreover, Section III presents Wear4PDmove ontology developed for early experimentation. Section IV concludes the paper with a discussion on current outcomes as well as the next steps planned on this research line.

II. BACKGROUND AND RELATED WORK

A. Background

Achieving interoperability of diverse data is a crucial challenge in the realm of Internet of Things or by the acronym IoT-based environments. IoT denotes the network of interconnected entities and the technology that facilitates communication within and between them, and between the entities and the cloud. With the advent of low-cost computer chips and high-bandwidth communication channels, billions of entities are now connected to the Internet. However, the data generated by these IoT-enabled entities, particularly sensor data, often have proprietary formats and lack common terms and vocabularies. In addition, IoT-enabled entities are extremely heterogeneous in terms of communication protocols, data formats, and technologies. Although sensor data can be manually retrieved from smart health/fitness devices, such as bands and smartwatches, through data export functionalities, the data are often stored in formats such as Comma Separated Value (CSV), eXtensible Markup Language (XML), or JavaScript Object Annotation (JSON). This heterogeneity creates a challenge for developers of IoT systems/apps in achieving interoperability at the syntax and semantic levels [2]. To overcome this challenge, it is crucial to adopt common syntax and semantics that are understandable to both humans and machines [3]. However, achieving syntactic and semantic interoperability is particularly difficult in the face of the heterogeneous nature of the data generated by diverse IoT-enabled entities and the multitude of different metadata vocabularies proposed for semantic annotation and description [4].

The utilization of Semantic Web of Things (SWoT) technology can address issues related to data and information heterogeneity. Semantics, which deal with the study of meaning and truth, constitute an empirical field based on intuition, enabling communication in a particular formal language, and generating meanings of expressions and relationships. To represent semantically annotated linked data, the Resource Description Framework (RDF) is the most widely adopted data modeling technology, capable of unifying and linking heterogeneous data obtained from diverse sources [5], [6].

In order to address the challenge of semantically bridging the heterogeneity of sensor data and information , several semantic models/standards have been proposed/developed. The Semantic Sensor Network [7] (SSN) ontology and the Sensor, Observation, Sample, and Actuator (SOSA) [8] ontology are commonly used to represent knowledge related to sensors and observations. The Smart Applications Reference Ontology (SAREF) [9] is designed to promote interoperability between IoT solutions. Its extension, SAREF4WEAR, is specifically developed for the representation of knowledge related to wearables. Another ontology, the Data Analytics for Health and Connected Care (DAHCC) ontology [10], has been proposed to describe the required semantics for linking wearables and sensors to sensing abilities, building upon the SAREF and SAREF4WEAR ontologies. Additionally, the Parkinson Movement Disease Ontology (PMDO) [11] is an application ontology developed to support PD and movement disorder focused informatics tools for patient care and clinical research. PMDO focuses on parkinsonian disorders and is organized into three main categories: neurological findings, treatment plans, and instruments used to evaluate various traits of PD.

The use of SW technologies can enable the integration of different datasets and the sharing of information and knowledge on the Web [5]. The framework utilized RDF data modeling as a key approach for achieving semantic interoperability in IoT-enabled health devices.

Ontologies can be used for the semantic modeling of data and information, as well as to explain the behavior of objects, entities, and systems. The semantic annotation and enrichment of raw sensor data using ontologies enables the explicit representation of the data that supports knowledge creation. While significant progress has been made in developing semantic models for healthcare interpretation, there is still a great interest and potential for developing models around sensor data related to PD and wearable devices. A health-related ontology is a conceptual model that provides meaning and structure to health data and information exchanged across related applications, services, and systems. Health ontologies can be used to represent, integrate, share, and infer health-related knowledge in a common and agreed format among the involved humans (patients, doctors) and/or software agents.

B. Related Work

Broad research has been made in the direction of exploiting sensor data in order to monitor and predict different symptoms of NDs. Data from accelerometer and gyroscope sensors are mostly used for movement identification. In [12] authors used movement data collected from a custom-developed wearable device, mounted on the wrist like a smartwatch, and equipped with an accelerometer and gyroscope, to create an assessment system to differentiate the severity of symptoms in PD patients. Accelerometer data were also modeled and analyzed [13] to predict Freezing of Gait (FoG) in PD patients. Several studies address the problem of PD monitoring highlighting the need for health monitoring during ADLs [14], taking into consideration that clinical experiments only consider the severity of motor symptoms during the length of the recording, failing to capture the continuously changing patient's motor state during the day. To enhance the interoperability of health data collected from patients, previous work [2] proposed a semantic interoperability framework for personal health analytics. Moreover, in [15] authors present a rule-based approach that utilizes wearable lifestyle sensor data and OWL 2 ontologies to detect health-related problems and improve the efficiency and effectiveness of care through remote and intelligent assessment, while promoting the creation of interoperable KGs and infusing expert knowledge in the form of Shapes Constraint Language (SHACL) constraints and rules. In another related work [16], researchers collected movement data using wearable sensors during preplanned common tasks of ADLs from individuals with PD and other disorders to examine misdiagnosis of PD. They modeled accelerometer and gyroscope data to train Machine Learning (ML) models for analysis and classification of the individuals and examined the specificity of wearable technologies regarding the detection of PD, concluding that wearable technologies can guarantee heterogeneous data collection as well as their real-time data processing. In [17], data from wearable sensors, worn in the lower back, have been analyzed for comparison of bradykinesia, tremor and FoG between PD patients in laboratory conditions and patients during ADLs. These related works demonstrate the importance of PD patients monitoring under unsupervised ADLs.

Only a few related works have developed systems with the aim to achieve remote monitoring in real-time. In [18], patients were monitored using commercial wrist sensors paired with a smartphone, to automatically estimate the severity of most of the PD motor symptoms. As a result, a decision support system (DSS) that notifies clinicians for the detection of new symptoms or the worsening of existing ones was introduced. Other researchers [19] acquired a dataset of 8,661 minutes of Inertial Measurement Unit (IMU) data from 30 patients, with annotations related to the motor state (OFF, ON, DYSKINETIC) and created a smart application that can detect OFF, ON, or DYSKINETIC motor state of PD patients. Another study [20] was conducted with the purpose to create a device for assessing the tremor and bradykinesia of PD patients with higher accuracy. Physical movements were recorded by a bracelet mounted with a triaxial accelerometer and a gyroscope. Based on this related work, there is a lack of expert systems that can monitor patients in real time, during ADLs, with the use of commercial, off-the-shelf wearable devices.

In the field of health data modeling and annotation various studies have been conducted, proposing solutions and patterns for data interoperability and integration, however, to the best of our knowledge, there is no solution related to PD monitoring and alerting that incorporates integrated movement data collected from wearable sensors and other health-related personal data e.g., prescriptions, MRIs. In [21] authors developed an ontology for patients having cardiovascular diseases (CVDs) aiming to overcome the issue of semantic interoperability in the healthcare domain showing that RDF is efficient in terms of facilitating semantic interoperability. Malik et al. (2016) [22] explained the mechanism and processes followed in Big Data for the transformation of heterogeneous data to semantically enriched simplified data using RDF, and Iglesias et al. [23] proposed an RDF Mapping Language (RML) interpreter that converts raw data in various formats into an RDF information graph. His mapping approach transformed raw data into RDF for the development of a knowledge base (KB) used for the realization of an IoT-based health-care system. In [24] authors developed an ontology-based platform named Active Healthy Aging (AHA) platform whose objective was to integrate existing tools, hardware, and software that assist individuals in improving and/or maintaining a healthy lifestyle. Furthermore, in [25] authors proposed an ontology-driven interactive healthcare application with wearable sensors aiming to achieve customized healthcare service.

In addition, there are recent related studies [26], [27] that exploit the benefits of KGs, and especially Personal Health Knowledge Graphs (PHKGs), in the development of smart health applications. In [28] authors developed a system named IoT Semantic Annotations System (IoTSAS) for processing and interpreting sensor stream data in real time by integrating different semantic annotations. The system developed provides information in real-time to citizens about the health implications from air pollution and weather conditions. In [29] authors used data collected from several IoT fitness vendors to form a standard context-aware resource graph, linking other health-related ontologies. They developed a web portal for integrating, sharing, and analyzing heterogeneous IoT health and fitness data through a customizable dashboard. In [30] authors developed SensorStream, a log extension that enables the connection of IoT data to process events, as well as a set of semantic annotations to describe the scenario and environment during data collection, preserving the full context required for data-analysis, so that logs can be analyzed even when scenarios or hardware are rapidly changing. Authors in [31] proposed an OWL-based integration using an ontology that model health data and Web of Things (WoT) services together with home environment data from formal ontology-described WoT services. Their prototype implementation showed that their method successfully integrates the health data and home environment data into a resource graph. The integrated data are machine-understandable and cross-system reusable, thanks to the semantics and ontology links represented in RDF. Related work includes a variety of approaches to semantically annotate IoT data for interlinking them with other related heterogeneous data sources, however, to the best of our knowledge, there are no studies that develop PHKGs by integrating streaming sensor (movement) data collected via commercial wearables, and other PHR data, for PD patients' monitoring and alerting of their doctors.

III. Understanding PD Movement Data

A. *Data Collection*

In our early experimentation with PD patients and off-the-shelf wearables, we aimed to collect sample sensor data during specific custom-designed and controlled activities (drawing on lines, walking on lines, hand lifting of small artifacts). We conjecture that a small sample dataset can be used for discovering patterns and uncovering data semantics through their analysis. For this reason, we have monitored two PD patients (evaluation subject), one female and one male, of approximately the same age (70s), and one healthy person of the same age (control subject), during the pre-planned activities. We choose to monitor the participants in their most familiar environment, their home, with the use of a smartwatch. A TIZEN-based JavaScript application was developed and deployed on a Samsung smartwatch, exploiting the data recording of four sensors (accelerometer, gyroscope, pedometer, and heart rate). The app collects movement data every 300 milliseconds i.e., three times per second, and stores them in comma separated files (.csv).

Data collection was performed though specific ADLs and exercises. The first activity is the drawing on a specific line pattern (Activity_1a) and a drawing game of connecting dots (Activity_1b). Both activities are relating with drawing, and are executed in sequence. The participants were sitting on a chair during this activity. The second activity is a balance exercise (Activity_2). The patient is standing up holding an artifact (e.g., a stone) that weighs ~1kg. The hand holding the stone is stretched forward to shoulder height with the forearm remaining still and in parallel with the ground. The patient must hold the artifact at this position for 90 seconds and must repeat this activity 3 times, with 4 minutes rest in-between. By the Activity_1 (1a, 1b), we aim to collect data through an artistic task like drawing because, as related research presents [32], the artistic and writing behavior of patients is affected by the PD (and vice-versa). Activity 2 is related to PD symptoms like tremor and instability, characterized as a hand balance activity. Although it seems simple, this activity is relatively demanding for the participants. Experimenting with Activity_3 (walking on a straight line), we aim to collect movement data recorded from the pedometer sensor.

An important factor that drove our early experimentation is the medical treatment of these patients. Both PD patients were getting their daily dosage of Levodopa every 4 hours

(Daily Dosage Interval (DDI) = 4 hours) starting from 8:00 a.m. to 8:00 p.m. For that reason, we decided to repeat the activities twice, 30 minutes before getting the pill and thirty minutes after getting the pill. The time of the monitored activities was 11:30 a.m. (30 minutes before the dosage of 12:00 p.m.) and 12:30 p.m. (30 minutes after the dosage of 12:00 p.m.). The healthy participant also performed the same activities at 11:30 a.m. and 12:30 p.m. even though he is not receiving any treatment. We choose 11:30 a.m. because it is 3,5h later than the first dosage of the day and 12:30 p.m. because 20min is the minimum time for the Levodopa treatment to take effect. Our main objective is to identify any patterns in the movement data related to the medical treatment and the effectiveness of the cure. Another long-term objective is to discover relations between PD patients and artistic behavior. Both objectives will be realized via discovering and analyzing data semantics.

B. *Data Analyis*

Raw data are collected in .csv files, one file per sensor (e.g., accelerometer.csv), and every record contains the name of the sensor and the measurements of each sensor tagged with the timestamp of the measurement. For example, a line from accelerometer.csv contains name of sensor, timestamp, x-axis acceleration (α_x), y-axis acceleration (α_y), and z-axis acceleration (α_z):

<Acc,2022-07-23T06:45:59.082Z, -2.043470621109009, -1.478764414787292,9.205188751220703>

Initially, all the records were merged based on the type of sensor, creating one fact table per sensor. Eventually, four fact tables were loaded into MS PowerBi data analytics and visualization tool. The loaded tables were processed, and new columns were manually added, annotating the measurements per participant (1,2,3), per activity (Activity_1a, Activity_1b, Activity_2, Activity_3), per medicine DDI, and per medicine state (before or after the pill). In this section a description of the analysis of accelerometer data is presented. In the related figures provided, apart from α_x, α_y, and α_z calibrated, the total acceleration is also presented. Equation (1) calculates total acceleration using acceleration on all axis (x, y, z) and equation (2) calculates acceleration on z axis calibrated using gravitational acceleration (3). For the analysis, dimensional tables were created, and the overall schema of the experimental data have emerged.

$$\alpha_{total} = \sqrt{\alpha_x{}^2 + \alpha_y{}^2 + \alpha_z{}^2} \tag{1}$$

$$\alpha_{z_{calibrated}} = \alpha_z - \alpha_g \tag{2}$$

$$\alpha_g = 9{,}8\, m/s^2 \tag{3}$$

The early analysis has yielded significant insights that inform the semantic annotation of the collected data. The visualizations show the start time of activities and the sets, in addition to the computation of the execution time. The gray vertical strips in Fig. 1 identify the sets that were performed by Participant 1 during the hand balance activity (Activity_2). The fluctuation of the measures occurs at the same time, in

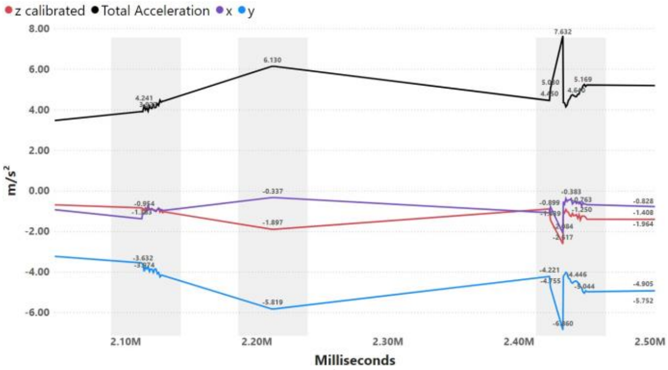

Fig. 1. Participant 1, hand balance, before medication

milliseconds, passed from the beginning of the activity. Z calibrated ($\alpha_{z\ calibrated}$) in Fig. 1 indicates the effort of the participant to hold his hand stable during the hand balance activity (Activity_2). During Activity_2, the screen of the smartwatch points to the sky and Z measures the acceleration on the axis from the earth to the sky. Consequently, the Z calibrated is more stable than X and Y on the related Fig. 1. The lack of measurements is presented in the figures as a straight line, indicating the time between the sets.

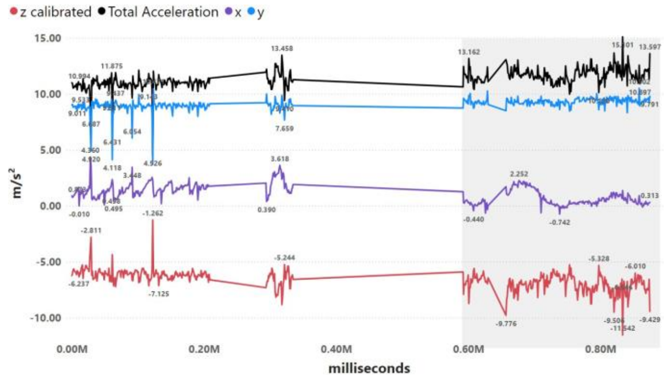

Fig. 2. Participant 2, sketching, after medication

Participant 2's measurements in Fig. 2 exhibit tremor symptoms, as shown by the constant changes in all three axes. The grey vertical stripe in Fig. 2 identifies Activity_1b which seems more demanding and results in more acceleration changes than activity_1a. Conversely, Participant 1 seems able to keep his hand stable, as demonstrated by small peaks in Fig. 1. These observations may signify differences in symptoms between the two participants.

In Fig. 3, a comparison between the two participants is presented. Data depicted on the figure are collected during sketching activities (Activity_1a, Activity_1b), after the participants’ dosing of Levodopa. Measures from Participant 1 (on the left of Fig. 3) have less fluctuations than measures of Participant 2 (on the right). During sketching activities, the participant's hand is moving until finishing the draw. Acceleration is generally defined as the change in speed during a period. Analyzing Fig. 3 in accordance with this definition we can conclude that Participant 1 is drawing at a more stable pace, whereas Participant 2 is drawing with variations in the speed of the moves. On the right chart we can clearly distinguish the sketching subcategories of Activity_1a and Activity 1b. Activity_1b concerns drawing the connection of dots, a more demanding and time-consuming activity than Activity_1a. In the right chart of Fig. 3 we can observe Activity_1b after 600000 milliseconds on the grey background. The fluctuations of acceleration on Participant 2 cannot be translated to quicker moves because, as it is derived by the millisecond axis, Participant 2 completed the activities in 874000 milliseconds, whereas Participant 1 completed the activities in 37000 milliseconds. Consequently, constant changes in the acceleration of Participant 2 could potentially be a sign of tremor. On the other hand, lack of changes on Participant's 1 movement acceleration could possibly depict movement stability while drawing.

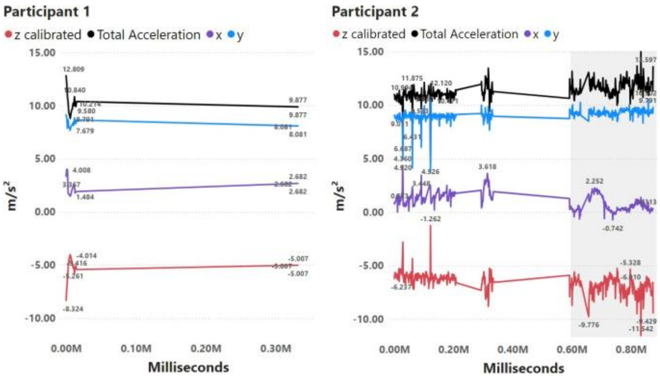

Fig. 3. Participant 1 and Participant 2, sketching, after medication

Based on the initial analysis of the accelerometer data, it has been observed that the constant fluctuations in the measures (x, y, z) could be indicative of the motor symptoms experienced by patients. However, the relationship between the fluctuations and the symptoms seems to depend on the specific activity being performed, as each activity requires different movements from the participants. Higher levels of fluctuations suggest greater instability in movement, while lower fluctuations may indicate slower movement (bradykinesia). It is also important to consider the dosing time, i.e., the time when the participant took their medication prior to the activity, as it can provide insight into the patient's condition and help distinguish between different activities.

The current analysis of sensor data is in its early stages, and further examination of the available dataset is necessary. More in-depth analysis of the sensor data is needed to ascertain how different activities affect the medical status of the patients and to identify which activities are more impacted by specific medical conditions. The early accelerometer analysis suggests that Activity_2 (hand balance) may not be influenced by the medical status of the patient. In addition, it is recommended to incorporate additional physics equations in the analysis and explore the relationships between activities, dosing, and other measures within a semantic model.

C. *Data Semantics*

Our early analysis has yielded important semantic insights that have informed the development of an ontology to represent knowledge pertaining to dynamic movement data collected from off-the-shelf wearables worn by PD patients. The primary objective of this ontology (Wear4PDmove ontology) is to facilitate the integration of this data with static or historical PHR data or other data related to the patient, and eventually, to reason with this integrated data. The resulting semantically annotated and integrated personal health data, structured in the form of a personal health knowledge graph (PHKG), can be utilized in various applications related to monitoring and alerting of PD patients, as well as athletes and the general public. For example, a fall prevention alert can be generated by an application (health or other) based on a set of rules that consider both the person's health record (i.e., athletes, PD patients, healthy persons) and real-time assessments of their movement obtained by analyzing data from wearable sensors. PHKGs that represent integrated and unified knowledge of personal health data obtained from wearables and PHRs can help mitigate the risk of false positive or negative alerts. Our decision to focus on PHKGs is also consistent with recent work on the topic [26], [27], which has identified several challenges in this area.

The Wear4PDmove ontology has been developed to enable the integration of, and the reasoning with, different types of health data, including dynamic data collected from wearables and static data obtained from PHRs. Its primary purpose is to provide a unified schema for personal health knowledge that can be used to semantically annotate the integrated data in the form of a KG, which can then be queried and analyzed to identify high-level events such as missed doses or patient falls. This enables improved monitoring and alerting capabilities for patients with PD. The Wear4PDmove ontology facilitates the representation, integration, sharing, and inference of personal health-related knowledge, thereby supporting personalized medicine and enhancing the quality of patient care.

Starting with the sensor-wearables semantics that are proposed for the representation of sensor-related and wearable-related knowledge, we propose the reuse of the SSN/SOSA, PMDO, and DAHCC ontologies directly imported, and the indirect (imported from DAHCC) use of SAREF and its extensions (SAREF4EHAW, SAREF4WEAR). SAREF4WEAR is the SAREF extension for the Wearables domain, and the SAREF4EHAW is the SAREF extension for the eHealth/Ageing-well domain. A list of the proposed main/key terms of the Wear4PDmoveOnto ontology for the sensor-wearables module are presented in TABLE I. The table describes the terms and their corresponding descriptions for the observation of a patient's movement as a feature of interest. It also includes the use of *sosa:Observation* and *sosa:hasFeatureOfInterest* to observe the patient's movement monitored by the sensors of the smartwatch and its properties, such as *BradykinisiaUpperLimpForPDpatient* and *TremorForPDPatient*. Additionally, the table includes the use of the *dahcc:Accelerometer* and *sosa:observes* to specify the specific accelerometer sensor that observes the wearable acceleration. Regarding the PD module, the PMDO ontology is reused for representing knowledge related to the Parkinson domain. The classes and object properties of PD module were expanded in order to fit into our research scope. A list of the proposed main/key terms of the Wear4PDmoveOnto vocabulary for the PD module are presented in TABLE II.

TABLE I. TERMS FOR THE SENSOR-WEARABLE MODULE

Terms	Description
sosa:Observation, sosa:hasFeatureOfInterest, w4pd:PatientMovement	The observation of a patient and its movement as a feature of interest. E.g., <PD-patient-Observation-001> rdf:type sosa:Observation; <PD-patient-Observation-001> sosa:hasFeatureOfInterest w4pd:PDpatient-001; <PD-patient-Observation-001> sosa:hasFeatureOfInterest w4pd:PatientMovement;

sosa:ObservedProperty, pmdo: BradykinisiaUpperLimpForPDpatient mdo: TremorForPDPatient dahcc:WearableAcceleration	The observed property of the wearable acceleration. E.g., <PD-patient-Observation-001> sosa:observedProperty pmdo: BradykinisiaUpperLimpForPDpatient; <PD-patient-Observation-001> sosa:observedProperty mdo: TremorForPDPatient; <PD-patient-Observation-001> sosa:observedProperty dahcc: Wearable_Acceleration_for_PD_movement;
dahcc:Accelerometer, sosa:observes,	The specific accelerometer sensor that observes the wearable acceleration. E.g., <Acc22-sensor> rdf:type dahcc:Accelerometer; <Acc22-sensor> rdfs:label "Samsung Sensor Accelerometer 22";
dahcc:Wearable Acceleration	<Acc22-sensor> sosa:observes dahcc:WearableAcceleration;
sosa:resultTime	The specific result time. E.g., <Observation-0041> sosa:resultTime "2022-07-06T12:36:12.150Z"^^ xsd:dateTime;

Although broad enough, combining existing ontologies cannot totally support our intended schema, even in this early ontology engineering phase. The first identified requirement that cannot be satisfied by existing ontologies are datatype properties related to the results occurred from the analysis of raw data from the sensors. Concepts that are directly derived/inferred from our data analysis, such as Fluctuation, Instability, Bradykinesia, will be represented in the proposed ontology Calculations of x, y, z value and time intervals (such as total acceleration) add value to the analysis and their results can be linked with activities and PD symptoms. Therefore, the results from these calculations will be annotated by data properties with Boolean data types like *hasTremor* and *hasBradykinisiaOfUpperLimp*. The *ActivitiesofDailyLiving* class (PMDO) must be enriched with semantics (subclasses) such as *SketchingActivity*, *WalkingActivity* and every other activity that will be used for data collection (e.g., eat, dance, listen to music, drawing, watch TV). The activities will be measured by off-the-self wearables, therefore SAREF's *isMeasuredByDevice* object property and *OnBodyWearable* class were initially used with the intention to be expanded. A class that will represent the DDI schedule of participants and their medical status is of high significance for the proposed model, since the aim is to relate activities, treatment, and other entities with the dosing intervals of Levodopa (or other medication). *Diagnosis* and *DailyDosagePlan*, that contains the DDI schedule, were defined as subclasses of *MedicalPrescription* which is one of the classes that define the *PersonalHealthRecord.*

Finally, several object properties that are not defined in related ontologies, but they are emerged from our early analysis, must be specified. A first representative set is the following:

- *isPerformedBy* (inverse of *performs*), to relate an activity with the patient that performs it,
- *hasPersonalHealthRecord*, to link patients with their PHR details,
- *hasDosageTime*, to connect the patient with the timestamp of receiving the dosage.

TABLE II. TERMS FOR THE PD MODULE

Terminology	Description
w4pd:DailyDosagePlan, (**subClassOf**) w4pd: MedicalPrescription	<MedicalPrescription> rdfs:label "Medical Prescription"; <DailyDosagePlan> w4pd:hasDosageTime w4pd: TimeOfFirstDosage;
w4pd: Diagnosis, (**subClassOf**) w4pd: PersonalHealthRecord	<PersonalHealthRecord> rdfs:label "Personal Health Record"; <Diagnosis> rdfs:label "Diagnosis";
w4pd: DosageTime, (**subClassOf**) saref: Time	<Time> <DosageTime> w4pd:hasDosageTime w4pd: TimeOfFirstDosage;
w4pd: MedicalPrescription, (**subClassOf**) w4pd: PersonalHealthRecord	<PersonalHealthRecord> rdfs:label "Personal Health Record"; <MedicalPrescription> rdfs:label "Medical Prescription";
w4pd: NotifyDoctor, (**subClassOf**) w4pd: AlertingNotification	<AlertingNotification> rdfs:label "Alerting Notification Function"'; <NotifyDoctor> rdfs:label "Notify Doctor";
w4pd: PD_Patient, (**subClassOf**) w4pd: Patient	<Patient> rdfs:label "Patient"; <PD_Patient> w4pd:hasPersonalHealthRecord w4pd: PersonalHealthRecord;
w4pd: PDpatientFalllingEvent Observation, (**subClassOf**) w4pd: RecognizedEvent	<RecognizedEvent> rdfs:label "PD patient recognized event observation"; <PDpatientFalllingEventObservation> rdfs:label "PDpatient Fallling Event Observation"
w4pd:Patient, (**subClassOf**) :Person	<Person> rdfs:label "One individual"; <Patient> rdfs:label "Patient";
w4pd: PersonalHealthRecord	<PersonalHealthRecord> rdfs:label "Personal Health Record";
mdo:ActivitiesofDailyLiving	<ActivitiesofDailyLiving>
mdo:Tremor	<Tremor>
pmdo: BradykinesiaofUpperLimb	<BradykinesiaofUpperLimb>
pmdo:Treatment	Patients related with treatments and linked with the re- sult of activity observation.
pmdo:ClinicalState	Diagnosis among a number of diseases that can mimic Parkinson's disease.

The Wear4PDmove ontology has been designed a) to represent knowledge related to i) patients' movement, ii) patients' daily activities, and iii) details of patients' personal health record, b) to semantically integrate data from various sources, including i) wearables and ii) personal health records, to provide a unified view of personal health in real-time for monitoring and alerting purposes, c) to facilitate reasoning with unified personal health data that is represented in the form of a KG, and d) to support the recognition of high-level events in the personal health domain for PD, such as a 'missing dose' or 'patient fall' event.

In essence, the goal of the Wear4PDmove ontology is to offer an inclusive and fused model for personal health information of patients with PD, to support customized monitoring and alerting, as well as advanced data analytics and decision-making. The developed ontology incorporates/reuses related ontologies, and introduces novel classes and properties to fulfill the specified requirements. In Fig. 1, an example set of triples describing an inferred PD patient observation is presented. The example includes information about the accelerometer sensor used to observe wearable acceleration in PD patients, the patient and patient movement features of interest, the PD patient observation, and the properties observed during the observation (bradykinesia of upper limp, tremor, and wearable acceleration). It also includes additional information such as the result time of the observation.

```
@Prefixes:
      rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
      rdfs: <http://www.w3.org/2000/01/rdf-schema#>
      sosa: <http://www.w3.org/ns/sosa/>
      w4pd: <http://i-lab.aegean.gr/ontologies/Wear4PDmoveOnto#>
Triples:
1. <Acc22-sensor>                                   a     dahcc: Accelerometer;
2.      sosa: observes          <Wearable_Acceleration_for_PD_movement>.
3. <Wearable_Acceleration_for_PD_movement>    a     dahcc: WearableAcceleration.
4. <PDpatient-002>         a          sosa: FeatureOfInterest.
5. <PatientMovement>       a          sosa: FeatureOfInterest.
6. <PD-patient-Observation-002>   a  sosa: Observation;
7.      sosa:hasFeatureOfInterest          <PDpatient-002>;
8.      sosa:hasFeatureOfInterest          <PatientMovement>;
9.      sosa:madeBySensor                  <Acc22-sensor>;
10.     sosa: observedProperty             <BradykinisiaUpperLimpForPDpatient>;
11.     sosa: observedProperty             <TremorForPDPatient>;
12.     sosa: observedProperty             <Wearable_Acceleration_for_PD_movement>;
13.     w4pd:hasBradykinisiaOfUpperLimp     true
14.     w4pd:hasTremor                      false
15.     w4pd:obsAfterDosing                 true
16.     sosa: resultTime                   "2022-08-04T12:42:12.150Z"^^xsd:dateTime.
17.     rdfs:label                         "PDpatient Observation-002"
```

Fig. 1. Example of RDF triples representing related knowledge

In order to evaluate the initial versions of the Wear4PDmove ontology, a scenario related to "missing dose" was implemented and evaluated in Protégé 5.5. A SWRL rule was defined to detect a missing dose (high-level) event and notify the doctor if tremor or bradykinesia (low-level events) were detected ("*IF tremor or bradykinesia is detected, THEN a missing dose event is recognized and a notification to the doctor is sent*"). Competency questions were evaluated using Pellet reasoner and Snap SPARQL plugin, and the inferred knowledge was queried using SPARQL. The source files related to the ontology, example SPARQL queries, SWRL rules, and screenshots from the Protégé tool, can be accessed on our GitHub repository[1].

IV. Conclusion and Future Work

In the field of PD, wearable sensors are employed to collect movement data to evaluate and analyze patients' symptoms. Assessing patients' symptoms during ADLs is crucial. One of the key contributions of our work is the utilization of an off-the-shelf wearable device for gathering movement data from PD patients as they engage in ADLs within their personal environment, providing valuable insights for monitoring and managing PD. The semantics of the collected data were revealed through data analysis conducted using MS PowerBi. Based on related semantic models, a set of semantics identified from the early analysis were transformed into requirements for developing an ontology in the PD movement data analysis domain. By further analysis and understanding of PD movement data semantics, it is expected that the community will get much closer to a holistic understanding of the disease, as well as to a better understanding of human movement in general [33].

Another significant contribution of our work lies in the development of the Wear4PDmove ontology. This ontology represents another novelty as it aims to semantically integrate various sources of personal health data for PD patients, facilitate reasoning with unified personal health data, and support the recognition of high-level events. The ontology reuses related ontologies and introduces novel classes and properties to support customized monitoring and decision-making.

Our research is limited in the following manner. Firstly, the study was conducted with a relatively small sample size of patients. As such, the generalizability of the findings may be somewhat restricted. Additionally, it is worth noting that the conclusions drawn in this study predominantly stem from the analysis of data collected specifically from the accelerometer sensor. While accelerometer data can provide valuable insights, it is crucial to recognize the potential benefits of incorporating other data sources and corroborating the findings using additional methods or sensors.

To establish broader applicability, our future plans include the extension of this work through additional data collections, via other off-the-self wearables (smart gloves, socks, shoes), on a larger and more diverse sample. Furthermore, additional physics equations will be implemented in the related analysis, and be examined in context of the proposed ontology, to uncover and eventually represent relationships between activities, dosing, and other measures. Future work also includes the constant refinement of the engineered Wear4PDmove ontology which is now on version 1.0 (was version 0.5 at the time of paper submission)and its use for the development of PHKGs. In the future, one potential direction is to create extensive PHKGs and evaluate them in a proof-of-concept edge-side application designed for monitoring PD patients and alerting their doctors. The application would be used to assess the severity of symptoms, detect when a dose is missed, and predict/prevent falls.

References

[1] World Wide Web Concortium. Available Online: https://www.w3.org/

[2] Ullah, F., Habib, M. A., Farhan, M. ,Khalid, S., Durrani, M. Y., and Jabbar, M. Y.: Semantic interoperability for big-data in heterogeneous IoT infrastructure for healthcare. In: Sustainable Cities and Society, vol. 34, pp. 90–96 (2017) doi: 10.1016/j.scs.2017.06.010.

[3] Jabbar, S., Ullah, F. , Khalid, S., Khan, M., and Han, K.:Semantic Interoperability in Heterogeneous IoT Infrastructure for Healthcare. In: Wireless Communications and Mobile Computing, vol. 2017, pp. 1–10 (2017) doi: 10.1155/2017/9731806.

[4] Venceslau, A., Andrade, R., Vidal, V., Nogueira, T. and Pequeno, V.: IoT Semantic Interoperability: A Systematic Mapping Study. In: Proceedings of the 21st International Conference on Enterprise Information Systems, (2019) doi: 10.5220/0007732605350544.

[5] Reda, R., Piccinini, F. and Carbonaro, A. Towards Consistent Data Representation in the IoT Healthcare Landscape. In: Proceedings of the

[1] https://github.com/KotisK/Wear4PDmove

2018 International Conference on Digital Health (2018) doi: 10.1145/3194658.3194668.

[6] Vandana, C.P. and Chikkamannur, A. A.: Semantic Ontology Based IoT-Resource Description. In: International Journal of Advanced Networking and Applications, vol. 11, no. 01, pp. 4184–4189 (2019) doi: 10.35444/ijana.2019.11018.

[7] Semantic Sensor Network Ontology. Available Online: https://www.w3.org/TR/vocab-ssn/

[8] Sensor-Observation-Sampling-Actuator ontology. Available Online: https://www.w3.org/2015/spatial/wiki/SOSA_Ontology

[9] Smart Applications REFerence Ontology, and extensions. Available Online: https://saref.etsi.org/

[10] Data Analytics for Health and Connected Care. Available Online: https://dahcc.idlab.ugent.be/

[11] Parkinson and Movement Disorder Ontology. Available Online: https://bioportal.bioontology.org/ontologies/PMDO

[12] Kim, H. B. et al.: Wrist sensor-based tremor severity quantification in Parkinson's disease using convolutional neural network. In: Computers in Biology and Medicine, vol. 95, pp. 140–146(2018) doi: 10.1016/j.compbiomed.2018.02.007.

[13] Kleanthous, N., Hussain, A. J., Khan, W. and Liatsis, P.: A new machine learning based approach to predict Freezing of Gait. In: Pattern Recognition Letters, vol. 140, pp. 119–126 (2020) doi: 10.1016/j.patrec.2020.09.011.

[14] Battista, L. and Romaniello, A.: A novel device for continuous monitoring of tremor and other motor symptoms. In: Neurological Sciences, vol. 39, no. 8, pp. 1333–1343 (2018) doi: 10.1007/s10072-018-3414-2.

[15] Stavropoulos, T. G., Meditskos, G., Lazarou, I., Mpaltadoros, L., Papagiannopoulos, S., Tsolaki, M., & Kompatsiaris, I. (2021). Detection of Health-Related Events and Behaviours from Wearable Sensor Lifestyle Data Using Symbolic Intelligence: A Proof-of-Concept Application in the Care of Multiple Sclerosis. *Sensors*, *21*(18), 6230. https://doi.org/10.3390/s21186230

[16] Talitckii A. et al.: Avoiding Misdiagnosis of Parkinson's Disease with the Use of Wearable Sensors and Artificial Intelligence. In: IEEE Sensors Journal, pp. 1–1, 2020, doi: 10.1109/jsen.2020.3027564.

[17] Galperin, I. et al.: Associations between daily-living physical activity and laboratory-based assessments of motor severity in patients with falls and Parkinson's disease. In: Parkinsonism & Related Disorders, vol. 62, pp. 85–90 (2019) doi: 10.1016/j.parkreldis.2019.01.022.

[18] Tsiouris, K. M., Gatsios, D., Rigas, G., Miljkovic, D., Koroušić Seljak, B., Bohanec, M., Arredondo, M. T., Antonini, A., Konitsiotis, S., Koutsouris, D. D., & Fotiadis, D. I. PD_Manager: an mHealth platform for Parkinson's disease patient management. *Healthcare technology letters*, *4*(3), 102–108 (2017). https://doi.org/10.1049/htl.2017.0007.

[19] Pfister, F. M. J. et al.: High-Resolution Motor State Detection in Parkinson's Disease Using Convolutional Neural Networks. In: Scientific Reports, vol. 10, no. 1.(2020) doi: 10.1038/s41598-020-61789-3.

[20] Channa, A., Ifrim, R.-C., Popescu, D. and Popescu, N.: A-WEAR Bracelet for Detection of Hand Tremor and Bradykinesia in Parkinson's Patients. In: Sensors, vol. 21, no. 3, p. 981 (2021) doi: 10.3390/s21030981.

[21] Ahamed, J. , Mir, R. N. and Chishti, M. A.: RML based ontology development approach in internet of things for healthcare domain. In: International Journal of Pervasive Computing and Communications, vol. 17, no. 4, pp. 377–389 (2021) doi: 10.1108/ijpcc-01-2021-0026.

[22] Malik K. R. et al.: Big-data: transformation from heterogeneous data to semantically-enriched simplified data. In: Multimedia Tools and Applications, vol. 75, no. 20, pp. 12727– 12747 (2015) doi: 10.1007/s11042-015-2918-5.

[23] Iglesias, E., Jozashoori, S., Chaves-Fraga, D., Collarana, D. and Vidal, M.-E.: SDM- RDFizer. In: Proceedings of the 29th ACM International Conference on Information & Knowledge Management. (2020) doi: 10.1145/3340531.3412881.

[24] Díaz-Rodríguez, N. et al.: An Ontology for Wearables Data Interoperability and Ambient Assisted Living Application Development. In: Recent Developments and the New Direction in Soft-Computing Foundations and Applications, pp. 559–568 (2018) doi: 10.1007/978-3-319-75408-6_43.

[25] Kim, J., Kim, J., Lee, D. and Chung, K.: Ontology driven interactive healthcare with wearable sensors. In: Multimedia Tools and Applications, vol. 71, no. 2, pp. 827–841 (2012) doi: 10.1007/s11042-012-1195-9.

[26] Shirai, S., Seneviratne, O. and McGuinness, D. L.: Applying Personal Knowledge Graphs to Health. (2021) doi: 10.48550/arXiv.2104.07587.

[27] Gyrard, A., Gaur, M, Shekarpour, S., Thirunarayan, K. and Sheth, A.: Personalized Health Knowledge Graph. In: CEUR workshop proceedings, vol. 2317, p. 5 (2018) Accessed: Oct. 07, 2022. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8532078/

[28] Sejdiu, B., Ismaili, F. and Ahmedi, L.: IoTSAS: An Integrated System for Real-Time Semantic Annotation and Interpretation of IoT Sensor Stream Data. In: Computers, vol. 10, no. 10, p. 127 (2021) doi: 10.3390/computers10100127.

[29] Reda, R., Piccinini, F., Martinelli, G. and Carbonaro, A.: Heterogeneous self-tracked health and fitness data integration and sharing according to a linked open data approach. In: Computing, vol. 104, no. 4, pp. 835–857 (2021) doi: 10.1007/s00607-021-00988-w.

[30] Malburg, L., Gruger, J. and Bergmann, R.: An IoT-Enriched Event Log for Process Mining in Smart Factories. In: ArXiv, (2022) doi: 10.48550/arXiv.2209.02702.

[31] Peng, C. and Goswami, P.: Meaningful Integration of Data from Heterogeneous Health Services and Home Environment Based on Ontology. In: Sensors, vol. 19, no. 8, p. 1747 (2019) doi: 10.3390/s19081747.

[32] Koletis, A., Markopoulos, A. and Kotis. K.: Discovering Semantic Relations between Neurodegenerative Diseases and Artistic Behaviors. In: Challenges, vol. 13, no. 2, p. 36 (2022) doi: 10.3390/challe13020036.

[33] Stergiou, N, Decker, L. M.: Human movement variability, nonlinear dynamics, and pathology: is there a connection? In: Hum Mov Sci, 30(5), pp. 869-88 (2011) doi: 10.1016/j.humov.2011.06.002.