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ONTOLOGY-BASED ELDERLY CARE PLATFORM: A BIG DATA AND IOT SYSTEM USING FIWARE ARCHITECTURE

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A B S T R A C T

As the global population ages, the need for effective elderly care solutions becomes increasingly critical. The complex needs and diverse characteristics of the aging population need to be addressed and appropriate tools provided to help support them. This paper presents a novel elderly care platform and its key components. A specific elderly-related ontology is designed to structure the vast array of relevant data, from medical histories to personal preferences. Thus we ensure that all aspects of care are harmonized and centered on the individual's needs. We discuss the design of the ontology, which not only supports the integration and analysis of diverse data types, but also enhances decision-making processes through semantic reasoning. The core of the platform is a dynamic elderly care system that leverages Big Data and IoT technologies to monitor health indicators, manage care schedules, and facilitate communication between caregivers and the elderly. The paper is also focused on data storage and security built on proven technology of FIWARE which allows for scalability and adaptability across different care settings.

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1. BIG DATA FOR ELDERLY CARE AND SERVICES

Big Data for elderly care and services is not just a technological advancement but a necessity for managing the challenges of an aging population, improving their quality of life, healthcare, and overall well-being. By enabling predictive healthcare, smarter homes, personalized treatments, and social integration, this data ensures elderly individuals can lead healthier, safer, and more fulfilling lives. Governments, healthcare providers, and tech companies must collaborate to harness the potential of Big Data for elderly care. Some key reasons why Big Data is essential for elderly care, are as follows:

Healthcare Monitoring and Predictive Analysis – Healthcare Monitoring and Predictive Analysis refers to the continuous collection, integration, analysis, and interpretation of health-related data to monitor patient conditions, identify health risks, predict future outcomes, and support clinical decision-making.

The approach is based on three primary categories of data:

- Physiological data (e.g., heart rate, blood pressure, body temperature, glucose levels, and other vital signs).

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- Behavioral data (e.g., physical activity, dietary habits, sleep patterns, medication adherence, and lifestyle factors).
- Environmental data (e.g., air quality, temperature, humidity, noise levels, and other environmental exposures).

Data may be collected from a variety of sources, including medical devices, wearable sensors, mobile applications, self-assessment questionnaires, interviews, clinical examinations, and electronic health records. The integration of these diverse data sources enables comprehensive health monitoring and supports the development of predictive models for personalized and preventive healthcare (Hong at al., 2019; Saxena et al., 2017; Garcia & Rodriguez, 2017).

Personalized Medicine and Treatment Plans – Healthcare professionals can develop personalized treatment and care plans tailored to the individual needs of each patient by analyzing physiological, behavioral, lifestyle, and environmental data. Such data-driven approaches enable a more comprehensive understanding of a patient's health status, risk factors, and daily habits, supporting more accurate diagnoses and targeted interventions.

For elderly patients, continuous monitoring and predictive analytics can significantly improve treatment adherence and health outcomes. By analyzing medication schedules, health indicators, and behavioral patterns, healthcare systems can generate personalized reminders, alerts, and recommendations to ensure that medications are taken correctly and on time. In addition, caregivers and healthcare providers can be notified of missed doses or unusual health events, enabling timely intervention when necessary.

Personalized treatment plans can also be dynamically adjusted based on changes in a patient's condition, activity levels, environmental exposures, or response to treatment. This proactive and adaptive approach supports preventive healthcare, reduces the risk of complications and hospitalizations, and contributes to improved quality of life, particularly for older adults and individuals living with chronic diseases (Almirall et al., 2012; Snyderman et al., 2016; Schleidgen et al., 2013).

Smart Home and Assisted Living Technologies – Smart healthcare technologies play a crucial role in supporting independent living and improving the quality of care for older adults. Smart pillboxes can provide timely medication reminders, monitor medication adherence, and automatically notify caregivers or healthcare professionals when doses are missed. In addition, wearable devices can continuously track vital health parameters, including heart rate, blood pressure, blood oxygen saturation, physical activity levels, and glucose concentrations (Bekiaris et al., 2009; Eisa & Moreira, 2012; Lauterbach et al., 2012).

Social and Mental Well-being - connecting elderly individuals with community programs and social events. Communication is an important aspect of human well-being, particularly in the context of elderly care, where maintaining social connections and ensuring timely access to support services are essential. In this domain, technological devices and digital tools that facilitate communication play a pivotal role in enhancing the quality of life, safety, and overall well-being of older adults. Key technologies include video communication systems, video cameras, and remote medical sensing devices. These tools enable continuous interaction with family members, caregivers, and healthcare professionals while also supporting remote monitoring and health management. By providing real-time communication and health-related information, such technologies contribute to early intervention, improved care coordination, reduced social isolation, and greater independence for older adults (Bellet & Frijters, 2019; Hunter et al., 2018; Reevy & Deason, 2014; Zeidner & Matthews, 2016).

Resource Allocation and Policy Planning – Caregiver organizations and governments are facilitated to allocate caregiver resources efficiently (Moran et al., 2013; Priestley et al., 2006).

Improved Emergency Response – Data from smart devices ensures immediate response in case of emergencies like falls, heart attacks, or accidents. The collected data can be transmitted in real time to healthcare providers, caregivers, or family members, enabling continuous health monitoring, early detection of potential health issues, and timely medical intervention when necessary (Fountain et al., 2019; Roush & Tyson 2012; Wu et al., 2022).

Enhanced Caregiver Support – Smart systems using Big Data identify stress patterns in caregivers, suggesting breaks or additional support (Graham et al., 2006; Toseland et al., 2004).

Enhanced Quality of Life – Technology driven by Big Data allows seniors to live independently for longer periods. Anticipating needs through data reduces hospitalizations and increases overall health outcomes (Hussain et al., 2019; Krumholz, 2014).

This paper introduces an innovative elderly care platform and its essential components: semantic data solutions, data space, and data security. A specialized elderly-focused descriptive model (ontology) has been developed to systematically organize a broad spectrum of relevant data, ranging from medical histories to personal preferences. This model ensures that all aspects of care are seamlessly integrated and tailored to individual needs.

The ontology's design not only facilitates the integration and analysis of diverse data sources but also strengthens decision-making processes through semantic reasoning.

At the core of the platform is a dynamic elderly care system, harnessing Big Data and IoT technologies to track health metrics, manage care schedules, and enhance communication between caregivers and elderly individuals (Langensiepen et al., 2016; Long & Zhu, 2019).

Additionally, the paper emphasizes data storage and security, utilizing the proven **FIWARE** technology to ensure scalability and adaptability across various care environments.

2. DESCRIPTIVE STRUCTURE CAPTURING THE KNOWLEDGE FOR AGING PEOPLE

The development of the elderly care platform highlighted the need for efficient classification, indexing, and retrieval of data related to aging individuals. This necessity served as the primary motivation for designing and developing a systematic ontological structure for representing knowledge about aging, referred to as the elderly-related descriptive model or ontology.

The ontology development process was inherently iterative, beginning with the definition of its scope. This phase was driven by multiple brainstorming sessions with domain experts, including healthcare providers, doctors, and semantic web specialists. These discussions facilitated the identification of potentially relevant terms, though, at this stage, the terms alone represented concepts without well-defined relationships, leading to ambiguities and differing perspectives. One key challenge that emerged was the difficulty in determining a fixed set of concepts and their interrelations.

To address this, the concepts identified during brainstorming were organized into thematic areas, forming natural sub-groups that provide structure to the ontology. The next step involved developing precise definitions for these concepts. As the ontology underwent experimental application, additional facts and logical rules relevant to the domain were discovered and incorporated to refine the model. These enhancements were implemented within the platform to enable reasoning functionality, further improving the data integration and decision-making capabilities of the system.

In our ontological model the knowledge for aging people is described (Figure 1) by three “thematic entities” (also called levels of knowledge). Each of these entities is enriched with a set of sub-levels, covering a wide range of characteristics.

The first entity focuses on human relations. Within the broad set of **Human**-related classes**,** the authors have identified **Communication, Attitude, Care,** and **Health** as the most essential for representing the relationships between CareTakers and other Humans. In the association between **Human** and **Attitude**, **Human** exhibit **Attitude** toward others. Similarly, in the association with the **Communication** class, a **Human** engages in communication with another **Human**. The association between **CareTaker** and **CareGiver**, which are sub classes of **Health**, represents the most significant outcome of their relationship, emphasizing the caregiving and well-being dynamics between these two roles.

The primary focus of the presented ontology is the **CareTaker** class. Within the ontology hierarchy, the **Human** class serves as its super class, representing a more general concept that shares common attributes and relationships with its sub classes. The **CareTaker** class is specifically designed to establish a relationship with the **CareGiver** class, which is also defined as a subclass of **Human**. In this relationship, the **CareTaker** assumes the role of receiving care, while the **CareGiver** provides care and support. This relationship represents one of the most important concepts in the proposed ontology—the need for specialized care and assistance for older adults and individuals who require support in their daily activities. The relationship is modeled as an association between the CareTaker and CareGiver classes, where the role of the classes CareTaker is defined as receiving care, (*receive*) while the role of the CareGiver is defined as providing care *(provide)*. This association captures the fundamental caregiving interaction and serves as a core element of the ontology's representation of care and support networks. The relationship between the CareGiver and Care classes models the fact that a CareGiver fulfills their responsibilities by providing care services. This relationship is represented through an association between the two classes, where the CareGiver assumes the role of *provide*, while the Care class is associated with the role *providedBy*. This association captures the essential interaction through which care activities are delivered to individuals requiring support and assistance.

The class Attitude models psychological tendencies that are expressed through the evaluation of a particular entity, object, individual, or concept with varying degrees of favor or disfavor. They are multidimensional constructs influenced by a range of cognitive, emotional, and behavioral factors, which shape their formation, expression, and impact on human behavior and decision-making. The concept of Attitude is strongly associated with Human behavior and social relationships. It is modeled through an association between the Human and Attitude classes, where Human assumes the role *exhibit* and Attitude assumes the role *exhibitedBy*. This association represents the expression of attitudes by individuals and enables the modeling of psychological dispositions that influence perceptions, interactions, and decision-making processes. Class Context models a purposeful process through which individuals, groups, or systems exchange information, ideas, emotions, and knowledge in order to achieve specific objectives. It is

inherently contextual which influences how messages are created, transmitted, received, and understood by the participants involved. Each communication between humans has also purposefulness. The relation between classes Human and Communication is modeled by association where Human has role *engagedIn* and Communication - *initiatedBy*.

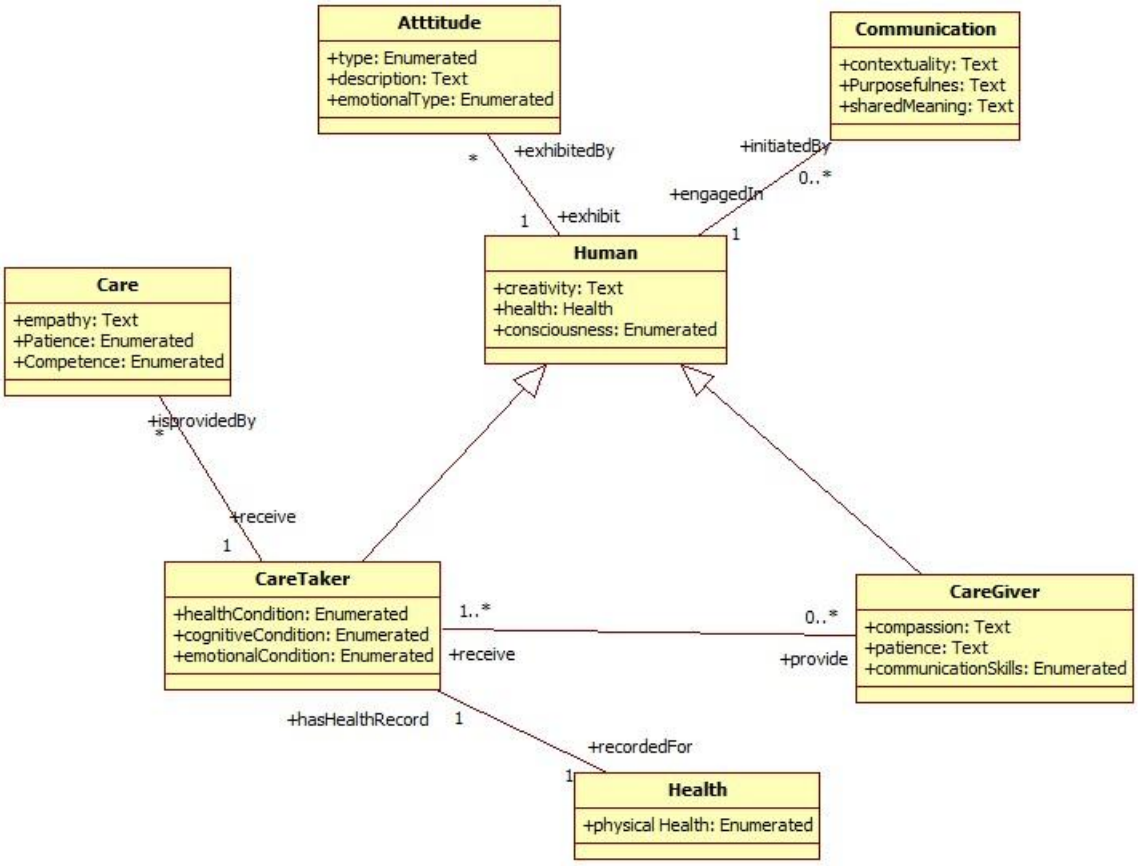


Figure 1. Human relations

The second entity (Figure 2) focuses on descriptive details of the living environment, providing a better understanding of the living conditions of older adults. The core concept involves categorizing living environments into two primary group**s** - **Physical Environment** and **Ideal Environment.**

The most significant classes in the **Physical Environment** include:

- **Place** – Represents the location where the **CareTaker** resides, modeled using the **Place** class.
- **Facility** – Specifies the exact residence of the elderly individual.

The Physical Place represents a geographically identifiable location in the real world where activities, interactions, or events may occur. In the proposed model, a Physical Place is modeled by class **Place** which is characterized by several key attributes, including the place name, longitude, latitude, and place description.
The **placeName** provides a human-readable identifier that allows the location to be easily recognized and referenced by users and systems. The **latitude** and **longitude** attributes define the precise geographical coordinates of the location, enabling accurate positioning, mapping, navigation, and spatial analysis. These coordinates facilitate the integration of spatial services and support location-aware applications.

The **placeDescription** provides additional contextual information about the location, such as its purpose, characteristics, accessibility, facilities, environment, or relevance within a specific domain. This descriptive information enhances the semantic representation of the place and supports a more comprehensive understanding of its role in the modeled environment.

Together, these attributes enable the representation of both the physical and contextual aspects of a location, allowing systems to capture, analyze, and utilize spatial information for activity monitoring, service delivery, resource management, and personalized support. In the context of elderly care, physical places may include homes, healthcare facilities, community centers, recreational areas, pharmacies, or other locations relevant to the daily activities, health, and well-being of older adults. In the presented model, the **Place** class contains a

collection of **Facility** classes that represent the physical resources, services, and infrastructure available within a specific location. This relationship enables a detailed description of the environment and the amenities that can support the activities and well-being of individuals.

Each **Facility** is characterized by a ***facilityName*** and a *type.* The facility name provides a unique and human-readable identifier, while the facility type categorizes the facility according to its function and purpose. Examples of facility types include homes, healthcare facilities, pharmacies, rehabilitation centers, recreational areas, transportation services, educational centers, shopping facilities, and emergency services. The relationship between the **Human** and **Facility** classes models the facilities in which a person resides, receives services, or participates in activities. This association captures the connection between individuals and the physical facilities that support their daily living, healthcare, social engagement, and well-being. The roles of **Human** and **Facility** in the associations are resides and shelters.

Advancements in the **Internet of Things (IoT)** have enabled the deployment of various sensors that measure environmental and physiological parameters, significantly improving the quality of life for facility residents. The **Device** class models the integration and utilization of Internet of Things (IoT) technologies within the proposed ontology. Devices represent physical smart objects capable of sensing, monitoring, processing, or transmitting information, thereby enabling the collection of real-time data and supporting intelligent decision-making processes. The devices are positioned in facilities modeled with aggregation relation.

Each **Device** is characterized by several key attributes, including the ***deviceName, deviceType***, and ***manufacturer***. The device name provides a unique and human-readable identifier, while the device type specifies the functional category of the device, such as wearable sensors, smart watches, medical monitoring devices, smart pill dispensers, environmental sensors, emergency alert systems, or communication devices. The manufacturer attribute identifies the organization responsible for producing the device and provides information relevant to device management, interoperability, maintenance, and technical support.

In this context, the relationship between **Human** and **Device** models the engagement between individuals and technological devices. The relationship is presented as association between the both classes where the role of **Human** is *uses* and the role of **Device** is *maintained*.

The **Ideal Environment** consists of conceptual elements such as **Policy** and **Science**, both of which directly impact human life:

- **Policy** – Regulates legal frameworks and behavioral guidelines for humans.
- **Science** – Plays a crucial role in enhancing the quality of life for **CareTakers** by introducing scientific advancements in areas covered human life.

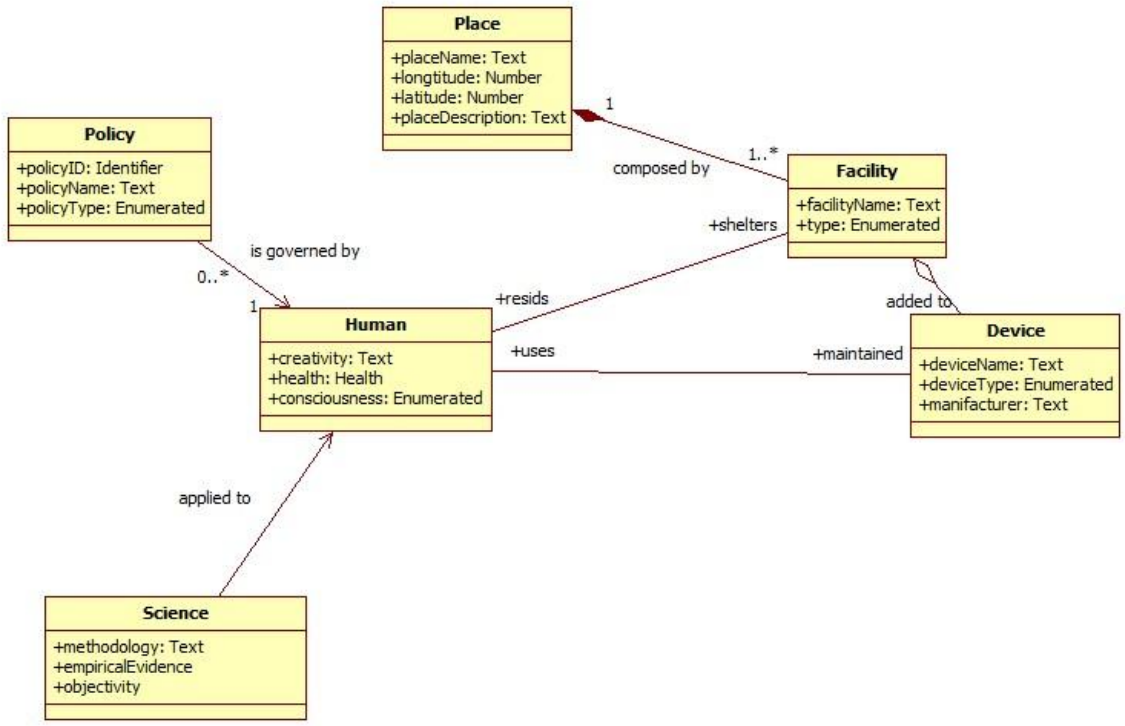


Figure 2. Living environment

In the proposed ontology, the **Policy** class represents the set of rules, guidelines, procedures, and regulations that govern decision-making, service provision, access control, and care management within the elderly people care ecosystem. The **Policy** class is characterized by several key attributes, including *policy**ID,** policyName,* and ***policyType***. The ***policyID*** provides a unique identifier for each policy, enabling efficient management, referencing, and traceability. The *policyName* offers a human-readable description that facilitates understanding and administration of the policy. The *policyType* categorizes policies according to their purpose and domain of application, such as healthcare policies, privacy policies, security policies, medication management policies, emergency response policies, access control policies, and care coordination policies.

The relation between **Policy** and **Human** is represented through the association *isgovernedBy* which is the most common in such type of relations.

The The Science class is characterized by several key attributes, including ***methodology***, ***empirical evidence***, *and* ***objectivity***.

methodology refers to the structured processes, techniques, and procedures used to conduct scientific investigations. It encompasses research designs, data collection methods, experimental protocols, and analytical approaches that ensure the reliability and validity of scientific findings.

empiricalEvidence represents knowledge derived from observation, measurement, experimentation, and real-world data. Evidence-based findings provide the scientific foundation for healthcare recommendations, treatment plans, preventive measures, and care management strategies. In elderly care, empirical evidence is essential for identifying effective interventions, understanding age-related conditions, and evaluating the impact of healthcare services on quality of life.

objectivity refers to the impartial and unbiased evaluation of information based on observable facts and verifiable data rather than personal opinions or assumptions. Objectivity ensures that scientific conclusions are based on evidence and can be independently validated. This attribute is particularly important in healthcare, where accurate and unbiased information is critical for safe and effective decision-making.

The relationship between **Human** and **Science** is modeled through the association, which captures the impact of scientific achievements on caregiving practices and overall well-being. The relationship between **Human** and **Science** is modeled through the association, which captures the impact of scientific achievements on caregiving practices and overall well-being. The name of association is *applied to*.

The third entity (Figure 3) includes classes **Human, Activity, Ability, Process, Crisis** and **Status**, revealing behavioral and state aspects of caretaker's life. A key element of human life is **Activity.** The Attributes of Activity typically refer to the characteristics or qualities that define specific actions or tasks within a system or process. These can vary widely depending on the context (e.g., physical activity, business activity, software activity), but generally, the attributes might include:

Duration is the length of time the activity takes to complete.

Frequency refers to *h*ow often the activity occurs within a given time frame.

Intensity is the level of effort or resources required to perform the activity.

Complexity represents the degree of difficulty or the number of steps involved in the activity.

Cost means the resources (e.g., time, money, labor) required to complete the activity.

Outcome is the result or output generated from performing the activity.

The relation between **Activity** and **Human** is modeled through the association between **Human** and **Activity** classes, and is named *perform*. It indicates that **Humans** engage in various activities. Humans also possess abilities, which they acquire over time through experience and learning.

Through participation in various activities, a human develops and acquires a range of abilities. In presented ontology the **Ability** class represents the capabilities and capacities that enable an individual to perform specific tasks, adapt to situations, and interact effectively with others. It is characterized by attributes such as ***endurance***, ***memory***, and ***empathy***.

Endurance refers to the capacity to sustain physical or mental effort over time.

Memory represents the ability to retain, store, and recall information, which is essential for learning, decision-making, and daily activities.

Empathy describes the ability to understand and share the feelings, perspectives, and experiences of others, facilitating effective communication and social interaction.

The class **Status** models status of seniors. The **status of an elderly person, in proposed ontology is** assessed through three key attributes: ***physicalCondition***, ***emotionalCondition***, and ***mentalCondition***. Together, these attributes provide a comprehensive understanding

of an individual's overall well-being, quality of life, and need for support. The status of an elderly person can be viewed as the combined evaluation of these three dimensions:

- ***physicalCondition*** determines functional independence and health.
- ***emotional Condition*** reflects psychological well-being and social integration.
- ***mentalCondition*** measures cognitive performance and decision-making capacity.

These attributes enable caregivers, healthcare professionals, and support systems to identify risks, design personalized care plans, and improve the quality of life of older adults.

A c**risis of aged adults** represents a situation that poses a significant threat to the health, safety, well-being, or independence of an older person and requires immediate assessment and intervention. The crisis in proposed ontology is characterized by attributes *crisisType*, ***severityLevel***, and ***urgency***.

crisisType **i**dentifies the nature of the crisis affecting the elderly individual.

The Process **class for older adults** represents a sequence of activities, behaviors, or events that occur during the daily life, care, health management, or social participation of an elderly individual. The process is characterized by its ***triggerEvent***, ***expectedDuration***, and *F**requency***.

- ***triggerEvent*** **d**efines the condition or occurrence that initiates the process.
- ***expectedDuration*** **s**pecifies the estimated time required for the process to be completed. Duration may range from minutes or hours (e.g., taking medication) to days or weeks (e.g., rehabilitation or recovery programs).
- ***Frequency*** **i**ndicates how often the process occurs.

The association, named *performs*, between **Human** and **Ability** highlights both **i**nherent abilities and those gained through engagement in **Activities**. An essential relational chain includes the associations between **Human** and **Crisis** and between **Human** and **Process**. These relationships are modeled as - u*ndergoes* – Representing how a **Human** experience a **Crisis** and *initiates* – Indicating that a **Human** can trigger or start a **Process**. Together, these associations provide a structured representation of the interactions between humans, their abilities, activities, and life events.

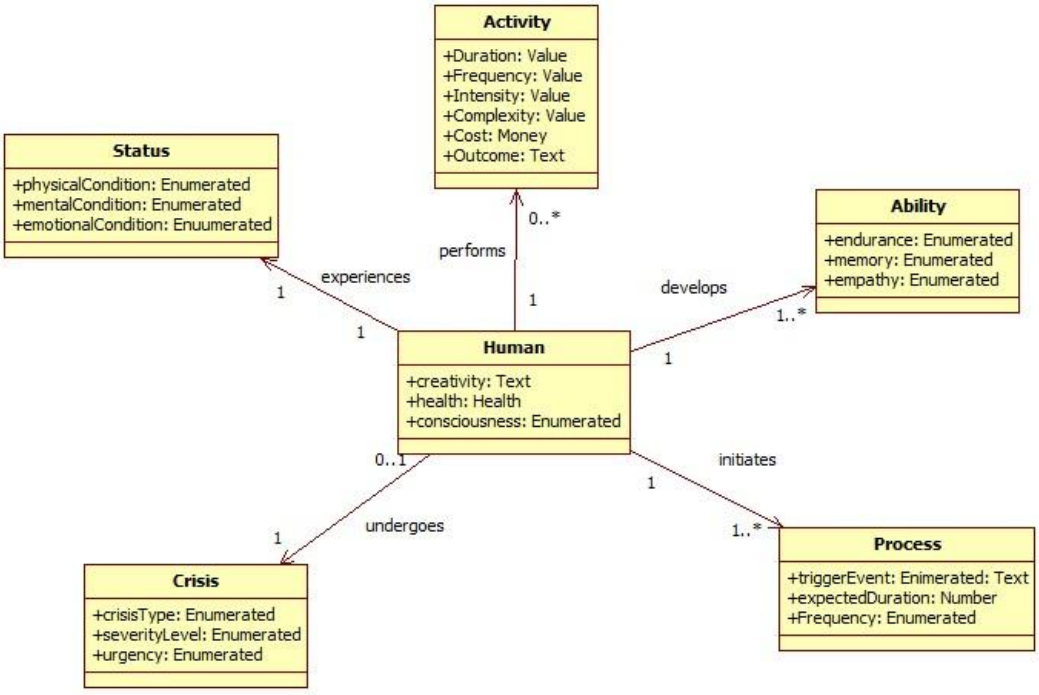


Figure 3. Behavior and state

For example, the following statement determines the dependence between the Activities of Human and the value of her/his Ability. Next, changing some values of the Status class may lead to Crisis.

The elderly-related ontology can be used in a wide area of research and analysis in the domain, such as: analysis of the aged adult state and generating alerts with different levels of severity. Tracing and monitoring the physical and mental state of seniors. Establishing possibilities for social relations etc.

3. PROTOTYPE PLATFORM FOR AGED ADULTS CARE

The upper described ontology was used as a data model of an elderly care prototype platform (Chikalanov et al., 2024) based on Big Data. The most important functionality of that platform are:

1) *Medical and health monitoring.*
2) 2.*Appointment and medication reminders, and personalized care plans*.
3) *Emergency alerting.*
4) *Communication tools in elderly care*. Tools in this domain include video cameras and remote medical sensing devices.
5) *Activity tracking*

Figure 4 presents its high-level architecture of the developed platform. The architecture is mashed on multi-layer architectural principle. Is built for distinguished layers of high internal cohesion and minimal cohesion out of them. The communication between layers is based on a well-defined API. The highest layer is web based UX/UI running in the user's browser. The next one is Business logic composed by microservices plus the database. The third layer consists of services wrapping respective FIWARE generic enablers. The last layer is the device layer. The multitude of possible devices communicate with service through different IoT agents which are sub classes of a generic Iot agent supplied by FIWARE.

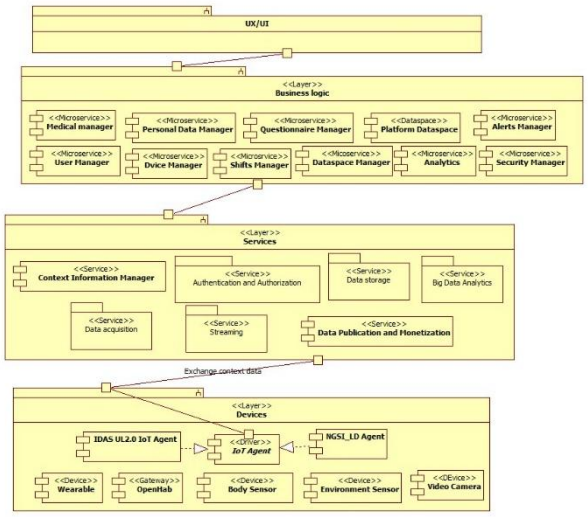


Figure 4. High level architecture elderly care platform

4. DATA SPACE AND DATA SECURITY

The data space subsystem is based on FIWARE Generic Enablers. The architecture is built on the following key principles:

The data space subsystem is based on FIWARE Generic Enablers. The architecture is built on the following key principles:

1. *Interoperability*

Data exchange with storage is based on the **NGSI-LD protocol**, an open, standardized protocol developed by **ETSI (European Telecommunications Standards Institute)** for managing and sharing context information in dynamic, distributed environments.

The key features include context management and a semantic data model.

In the proposed architecture, the **NGSI-LD** protocol is supported by the **Orion-LD Context Broker**.

2. Standardized Data Contracts

Standardized data contracts are achieved through the **NGSI-LD protocol**, which provides a common semantic framework for describing, exchanging, and managing data across interoperable systems. NGSI-LD enables machine-readable contracts that define data structures, usage rights, licensing terms, access permissions, and compliance requirements. By leveraging linked data principles and standardized context models, NGSI-LD ensures consistent interpretation of data, facilitates secure and trustworthy data sharing, and supports regulatory compliance across organizational and technological boundaries.

3. Data Discoverability

Metadata and semantic descriptions facilitate the **discovery of relevant datasets**.
Implemented using **Orion-LD** and **CKAN**.

4. Scalability and Decentralization

Large-scale data sharing is supported by **MySQL**, which can be horizontally scaled and geographically distributed.

Additionally, **HDFS (Hadoop Distributed File System)** is used as a highly scalable and fault-tolerant distributed storage system, designed to manage large data volumes across multiple machines.
This architectural solution enables the development of large-scale data spaces related to aged care, providing a foundation for **Machine Learning (ML) and Deep Learning (DL)** applications.

5. Data Marketplace & Monetization

The architecture supports various monetization models, including subscriptions, pay-per-use, and revenue-sharing mechanisms.

The **FIWARE CKAN** Generic Enabler is responsible for managing these functionalities.

6. Security & Trust

The implemented trust model is based on FIWARE Generic Enablers, specifically **KeyRock Identity Management**, **AuthZForce**, and **Wilma PEP Proxy**, which together provide a comprehensive framework for identity management, authentication, authorization, and access control. **KeyRock Identity Management** serves as the central component for managing digital identities within the platform. **Wilma PEP Proxy** acts as a Policy Enforcement Point (PEP) that intercepts incoming requests and validates the authentication credentials provided by users or services. **AuthZForce** functions as the authorization engine and Policy Decision Point (PDP). It evaluates access control policies and determines whether a particular user, application, or service is authorized to perform a requested action on a specific resource.

7. Semantic Interoperability

A specialized Descriptive Structure Capturing the Knowledge for Aging People is applied to ensure semantic interoperability.

The **Orion-LD Context Broker** is a key of the data space**.** It is responsible for managing and facilitating context-aware data exchange using the **NGSI-LD** protocol. It acts as a central hu**b** that enables systems, applications, and services to share, access, and update context information in real-time. Using **Orion-LD** helps in carrying out the following critically important functions. - Context Data Management, NGSI-LD Standard Compliance, Real-time Context Updates & Subscriptions, Interoperability & Data Exchange, Scalability & Federation, Integration with Other FIWARE Components – described further in the current publication, Provides **s**tructured, real-time data for AI, ML, and analytics applications.

MongoDB is used as temporary storage of last versions of data acquired by Orion-LD. It is designed to efficiently handle and store large volumes of data using a combination of scalability, flexibility, and distributed architecture.

In presented architecture **FIWARE Cygnus** is a data persistence enabler that plays a crucial role in **data spaces** by ensuring reliable and scalable data storage, transformation, and integration. It acts as a bridge between **Orion-LD** and various storage back ends, enabling data to be persisted for historical analysis, machine learning and predictive intelligence.

The role of presented Data Space is to allow storing of petabytes aged people data, which will can be used later as base for Machine Learning (Figure 5).

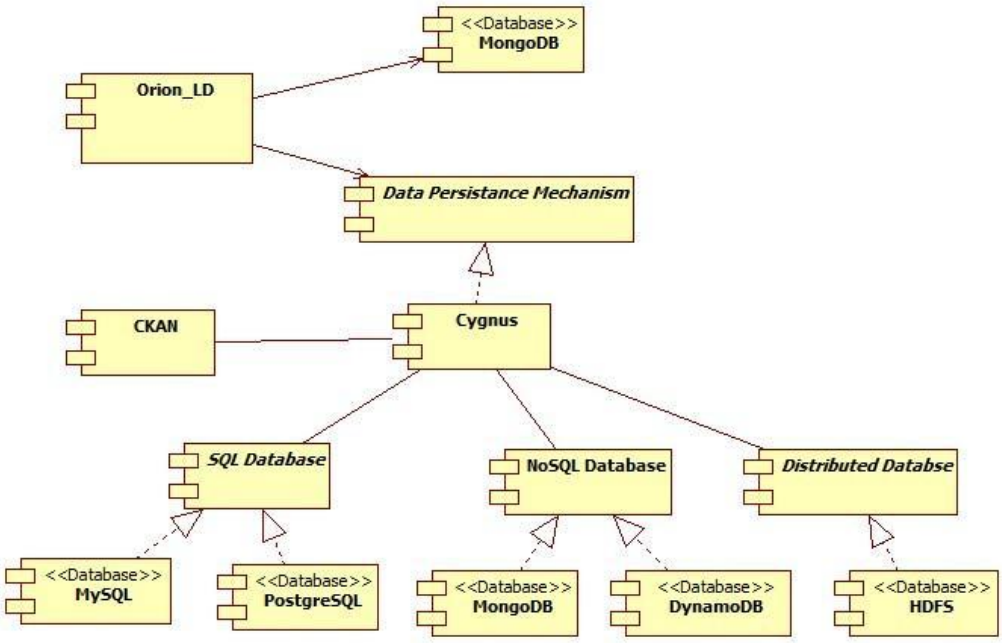


Figure 5. High level architecture of data space designed for elderly care platform

CKAN is a **Generic Enabler (GE)** for open data management that enables the storage, discovery, sharing, and monetization of data within data spaces related to senior people care. It is based on **CKAN**, a widely used open-source data management system, and is intended to support context-aware data from the **Orion-LD** Context Broker.

Further on we will present a security mechanism implemented. It is based on FIWARE security related generic enablers (Figure 6).

As Identity management we use KeyRock generic enabler. It covers various aspects, including user access to secure data such as users personal data, living environment data, user activities, health, relations, self-assessment, as well as secure and personal authentication. It is also used as authorization and trust management, user profile management, privacy protection, Single Sign-On (SSO) for services supplied by platform.

In the presented security service, we use FIWARE Wilma as Policy enforcement point. Wilma acts as a security gateway, verifying user identities and enforcing access control policies in coordination with the **FIWARE** Identity Manager **(Keyrock)** and Policy Decision Point **(AuthZForce)**. The security flow is as follows;

When a client or user sends a request to access a protected resource:

- Wilma intercepts the request and extracts the OAuth2 token from it.
- Wilma forwards the token to Keyrock (Identity Manager) for validation.
- If additional policy evaluation is needed, Wilma sends a request to AuthZForce (Policy Decision Point).
- Based on the access policies and user roles, **AuthZForce** returns an access decision (allow or deny).

If access is granted, **Wilma** forwards the request to the protected resource. If denied, it blocks the request and sends an appropriate error message.

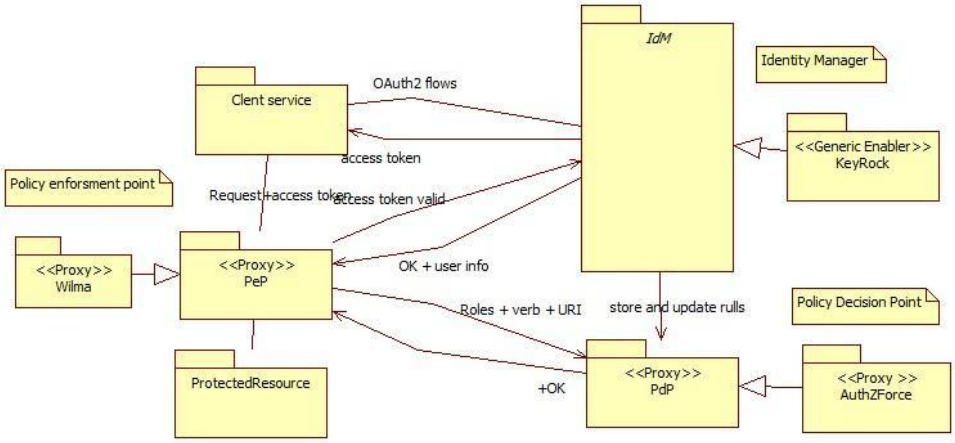


Figure 6. Security model architecture

5. CONCLUSION AND FUTURE WORK

Elderly care platforms are essential due to the growing aging population and increasing demand for personalized care solutions. They enhance quality of life for seniors by providing remote monitoring, timely assistance, and improved healthcare accessibility. Such platforms ensure seniors' safety, independence, and well-being, reduce caregiver burden, and facilitate efficient resource management within healthcare systems. The development of an elderly-related ontology, data space architecture, and security mechanisms provides a structured, scalable, and secure approach to managing data and knowledge in elderly care systems. By integrating semantic data models, the ontology ensures standardized representation of key concepts such as **CareTakers, CareGivers, Health, Activities, Abilities,** and **Processes**, enabling efficient data classification, indexing, and retrieval. The ontology-driven approach also facilitates , allowing seamless integration with **IoT** systems, healthcare applications, and decision-making tools.

The presented ontology played a critical role in building presented data spaces by providing a standardized, shared semantic framework. The data space architecture is designed to support large-scale, decentralized, and privacy-aware data interoperability as sharing, ensuring secure data storage, discoverability, and controlled access. The use of NGSI-LD-based standardized data contracts further enhances semantic interoperability, enabling cross-domain integration and AI-driven reasoning capabilities.

To address security and privacy concerns, the system implements robust authentication, authorization, and data protection mechanisms. FIWARE's **KeyRock, Wilma,** and **AuthZForce** enablers are used to enforce strict access control policies, ensuring that sensitive data related to elderly individuals remains protected. Additionally, encryption, randomization, and compliance with regulatory standards **(**such as **GDPR** and **HIPAA)** further strengthen the security framework.

Overall, the proposed elderly care platform integrates ontology-based data modeling, a flexible data space architecture, and advanced security mechanisms, creating a comprehensive, privacy-preserving, and intelligent system that enhances the quality of life, safety, and well-being of elderly individuals. Future work will focus on extending the ontology, optimizing real-time data processing, and enhancing AI-driven analytics to further improve elderly care services.

Future work on the elderly-care domain semantic description will include the extension of its current formal specification with conceptualization of complex data concerning aged population care and well being. Thus, the target domain will be completely presented and formalized and will provide tools for profound observations and interdisciplinary research.

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