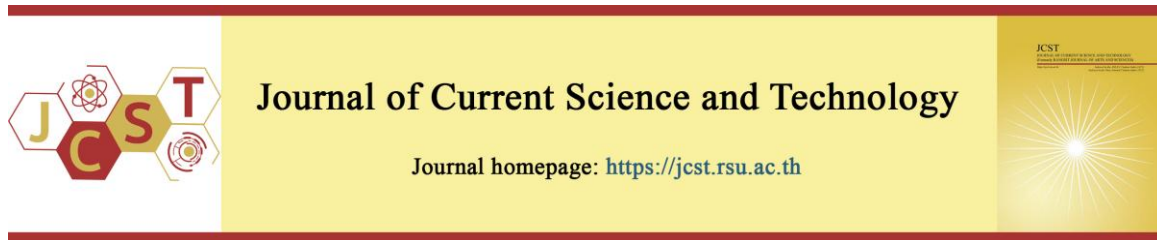


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An Ontology-Driven Ambient Assisted Living Framework for Personalized Elderly Care with Health-Risk Inference

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Abstract

As the global elderly population increases, there is a growing need for structured long-term care systems that support independent living and explainable health monitoring. This study presents AALHealthIoT, a Web Ontology Language (OWL) 2 DL-based ontology framework for Ambient Assisted Living (AAL) that integrates physiological measurements, environmental conditions, and personal profile attributes within a unified semantic architecture. Unlike existing Internet of Things (IoT) ontologies such as SSN/SOSA, SAREF, SAREF4EHAW, and OntoDomus, which primarily emphasize interoperability, AALHealthIoT operationalizes cross-domain health-risk inference using Semantic Web Rule Language (SWRL) rules grounded in publicly available clinical guidelines. The ontology comprises 188 classes, 159 object properties, 30 data properties, and 2,077 axioms and was developed using the NeOn methodology. Validation included structural verification, pitfall detection, logical consistency checking, competency-question testing, and quantitative performance evaluation. Under controlled synthetic scenarios ranging from 50 to 1,000 seniors (up to 8,000 ontology individuals), SWRL reasoning remained under 2 seconds, while SPARQL Protocol and RDF Query Language (SPARQL) query latency remained below 1 second, even for the most complex cross-domain queries. These results demonstrate that ontology-driven semantic reasoning can provide an explainable and computationally feasible foundation for decision support in community-based AAL environments.

Keywords: *ambient assisted living, ontology, SWRL, SPARQL, semantic web, semantic reasoning, knowledge graph*

1. Introduction

Population aging is increasing the demand for structured long-term care and continuous health monitoring in community settings. As longevity increases and family sizes decline, healthcare systems face growing pressure to manage chronic conditions and environmental risks among the elderly. According to recent demographic projections and regional policy analyses, the elderly population is expected to continue to grow over the coming decades, intensifying demands on healthcare infrastructure and long-term care services (Sakamoto, 2025; Vo & Fong, 2025).

In Thailand, the national aging policy and the National Long-term Plan for Older Persons have established long-term care (LTC) strategies integrated with the Universal Health Coverage framework to support older adults with varying levels of dependency (Chanprasert, 2021). Community-based long-term care in Thailand involves coordination among family caregivers, trained community volunteers, and healthcare professionals who monitor health status, assess activities of daily living (ADL), and classify older adults according to dependency levels, such as homebound or bedridden conditions (Ministry of Public Health, 2024). However, these workflows rely

on heterogeneous data collected from wearable devices, home sensors, manual assessments, and caregiver observations. The lack of semantic interoperability across these data sources leads to fragmented information, inconsistent interpretation, and limited explainability in risk assessment and care planning.

Ambient Assisted Living (AAL) technologies have emerged as promising solutions for supporting the independence of the elderly through Internet of Things (IoT)-based monitoring and intelligent services (Choi et al., 2024; Jovanovic et al., 2022). Nonetheless, existing AAL systems frequently exhibit three critical limitations: (i) fragmented and semantically inconsistent data representations, (ii) limited support for cross-domain reasoning that combines physiological and environmental factors, and (iii) opaque decision-making mechanisms that reduce explainability (Zieni et al., 2025). While threshold-based alerts and machine-learning models can detect anomalies, they often lack formal semantic integration and transparent rule-based linkage between inferred risk conditions and actionable recommendations.

Recent advances in semantic technologies have led to the development of ontology-driven frameworks and domain standards for healthcare and AAL. Prior studies have applied ontologies to smart-home and healthcare monitoring, while recent work has integrated IoT environments with rule-based reasoning for context-aware health monitoring (Bampi et al., 2025; Ngankam et al., 2022; Zeshan et al., 2023). Furthermore, domain standards such as SAREF4EHAW provide a semantic foundation for eHealth and aging-well applications, supporting interoperability and the formal representation of healthcare-related entities, devices, and services (European Telecommunications Standards Institute, 2024). These developments indicate that semantic modeling in healthcare and AAL is already well established. However, existing approaches primarily emphasize interoperability, monitoring, and device integration, with comparatively less attention to explicitly operationalizing clinically grounded cross-domain health-risk inference that combines physiological, environmental, and personal profile information within a unified reasoning framework. This limitation is particularly evident in the lack of integrated support for recommendation-oriented knowledge and systematic ontology-level evaluation.

To address these challenges, this study proposes AALHealthIoT, a Web Ontology Language (OWL) 2 DL-based ontology that integrates physiological observations, environmental conditions, and personal profile attributes within a modular semantic

architecture. Beyond structural modeling, AALHealthIoT operationalizes explicit cross-domain reasoning using Semantic Web Rule Language (SWRL) rules to infer health risk categories from combined physiological and environmental factors and to associate inferred states with structured recommendation entities. In addition, the study introduces a structured validation protocol that extends beyond conventional ontology evaluation by incorporating competency-question verification, logical consistency testing, pitfall detection, quantitative performance measurement of reasoning and SPARQL Protocol and RDF Query Language (SPARQL) query execution, and comparative capability analysis against established ontologies.

To clarify the scope of the problem, this research focuses on two representative domains commonly observed in community-based elderly care: blood pressure assessment and heat-related illness risk. These domains were selected because of their high prevalence among aging populations and the availability of clinically defined risk thresholds. Rather than attempting to model the full complexity of all AAL scenarios, AALHealthIoT establishes a modular semantic core that supports selected cross-domain reasoning patterns while remaining extensible for future domain expansion.

This work makes the following three main contributions:

- 1) It develops AALHealthIoT, a unified OWL 2 DL ontology that explicitly integrates physiological observations, environmental exposure, and personal profile attributes to enable structured semantic interoperability in AAL environments.
- 2) It formalizes SWRL-based reasoning patterns that infer health-risk categories from combined physiological and environmental conditions and automatically associate inferred states with structured recommendation entities.
- 3) It proposes a multi-stage validation framework comprising pitfall detection (OOPS!), logical consistency verification, competency-question testing, quantitative performance measurement, and comparative capability analysis against state-of-the-art ontologies.

This paper is organized as follows. Section 1.1 reviews related work, Section 2 presents the research objectives, Section 3 describes the methodology, Sections 4 and 5 introduce the ontology-driven AAL framework and its implementation, Section 6 reports the validation and evaluation results, Section 7 discusses the findings, and Section 8 concludes the paper with future directions.

1.1 Related Work

As the global population ages, there is a growing need for AAL systems that help older adults maintain their independence and enhance their quality of life (Mir et al., 2025). AAL addresses this need by integrating IoT devices, smart-home technologies, and intelligent services to deliver personalized support. AAL research can be broadly grouped into three approaches: (i) sensing and monitoring systems, (ii) artificial intelligence- and machine learning-based risk detection, and (iii) semantic and knowledge-based frameworks.

1.1.1 Sensing and Monitoring Systems

Recent research has focused on wearable sensors, home monitoring, and digital tools that track health and environmental conditions to identify risks and provide timely assistance (Jovanovic et al., 2022). For example, Wang et al. (2025) demonstrated how contactless environmental sensors can recognize the daily activities of older adults in smart-home environments. These approaches offer practical and non-intrusive solutions for continuous monitoring. However, several sensing-oriented AAL systems remain fragmented, addressing specific problems without integrating heterogeneous data sources into a unified interpretative framework (Valero et al., 2021). As a result, physiological signals, environmental readings, and contextual information are often processed independently, limiting cross-domain reasoning and consistent risk assessment.

1.1.2 Artificial Intelligence and Machine Learning-Based Systems

Artificial intelligence (AI) and machine learning (ML) techniques are widely applied in AAL systems for activity recognition, anomaly detection, and predictive risk assessment (Kim et al., 2025; Mihoub, 2021). These approaches frequently achieve high predictive accuracy and support automated monitoring in elderly-care settings. However, many ML models operate as black-box systems, providing limited transparency into their internal decision-making processes. In healthcare-related applications, the lack of interpretability has been identified as a major obstacle to trust, accountability, and the wider adoption of AI systems (Ennab & Mcheick, 2022). Additionally, ML models often rely on context-specific training datasets and may require retraining when deployed in new environments, reducing their portability across heterogeneous community-care settings.

These limitations indicate that purely data-driven approaches may be insufficient when

transparent cross-domain integration and structured semantic reasoning are required, thereby motivating the development of complementary semantic frameworks that emphasize structured knowledge representation and rule-based reasoning.

1.1.3 Semantic and Knowledge-Based Approaches

Ontology-driven frameworks aim to address interoperability and reasoning challenges in AAL systems through formal semantic modeling. Existing approaches can be analyzed across three dimensions: (i) domain coverage, (ii) reasoning and recommendation support, and (iii) validation and scalability.

1) Domain Coverage

Domain coverage refers to the range of concepts represented in an ontology, including sensing, environmental context, physiological information, and personal profile characteristics. The W3C SSN/SOSA ontology (Haller et al., 2018) provides standardized modeling for sensors and observations, thereby enabling IoT interoperability. However, it is domain-agnostic and does not explicitly model elderly-specific health risks or care recommendations. SAREF (Reda et al., 2022) emphasizes device interoperability, while OntoDomus focuses on smart-home environments and contextual representation (Ngankam et al., 2022). Furthermore, domain standards such as SAREF4EHAW provide a formal semantic framework for eHealth and aging-well applications by representing health actors, body area networks, health devices, observations, and related services (European Telecommunications Standards Institute, 2024). As a domain-specific standard, SAREF4EHAW represents a closer semantic reference point for this study than generic interoperability ontologies such as SSN/SOSA or core SAREF. However, it is not primarily designed to operationalize explicit rule-based health-risk inference or recommendation-oriented semantic reasoning. These studies show that semantic support for sensing, smart-home environments, and healthcare-related concepts is increasingly well developed. Nevertheless, they do not primarily focus on clinically grounded cross-domain health-risk inference that jointly integrates physiological, environmental, and personal profile information within a unified, recommendation-oriented framework for elderly care.

2) Reasoning and Recommendation Support

Effective AAL systems require semantic mechanisms to infer health risks and provide actionable guidance. Although SSN/SOSA and SAREF support

structured observation modeling, they do not incorporate clinical risk semantics or recommendation constructs. OntoDomus supports contextual automation, but it is not intended for clinically interpretable health-risk reasoning. More recent ontology-driven studies have extended semantic reasoning in healthcare settings. For example, Bampi et al. (2025) proposed an ontology-driven AAL monitoring system that combines SSN/SOSA, DogOnt, and SNOMED CT with SWRL-based reasoning to derive context-sensitive findings in smart-home healthcare environments. Zeshan et al. (2023) presented an IoT-enabled ontology-based remote patient monitoring framework that uses a patient-centric ontology and SWRL rules to support abnormal-condition detection, context-aware reasoning, and Quality-of-Service (QoS)-aware alert management. These studies show the practical value of ontology-based reasoning in healthcare monitoring. However, their main focus remains on monitoring, alerting, and interoperability rather than explicit recommendation-oriented semantic modeling and clinically grounded cross-domain health-risk inference within a unified ontology. More generally, recommendation logic in ontology-driven healthcare monitoring systems is often limited or implemented outside the core ontology, which may reduce semantic transparency and explainability in healthcare decision support.

3) Validation and Scalability

Validation and scalability concern whether an ontology has been systematically evaluated for logical consistency, competency coverage, and computational performance as data volumes increase. Although several ontology-driven AAL and healthcare systems demonstrate conceptual feasibility and practical monitoring potential, structured competency-question validation, ontology pitfall analysis, and quantitative reasoning and query-performance evaluation are not consistently reported. Consequently, the robustness and practical deployment readiness of many existing semantic frameworks remain difficult to assess, particularly in heterogeneous community-based long-term care environments.

In community-based long-term care settings, caregivers must interpret heterogeneous physiological and environmental data to identify actionable risk states. Existing ontology-driven approaches provide important foundations for interoperability, smart-home representation, healthcare monitoring, and semantic reasoning. However, they tend to place greater emphasis on device abstraction, semantic integration, alert-oriented monitoring, and system-

level performance evaluation than on explicitly operationalizing clinically grounded cross-domain risk reasoning, structured recommendation modeling, and systematic ontology-level evaluation within a unified semantic framework. This gap motivates the development of AALHealthIoT, which integrates physiological observations, environmental conditions, and personal profile information through SWRL-based inference and systematic ontology-level validation within an OWL-based architecture.

2. Objectives

The main objective of this study is to develop and evaluate AALHealthIoT, an OWL 2 DL-based ontology framework that operationalizes clinically grounded, cross-domain health-risk inference for community-based elderly care by integrating physiological, environmental, and personal profile information within a unified semantic model. To this end, the study validates the resulting framework through structural and logical consistency checking, competency-question testing, and quantitative assessment of reasoning and SPARQL query performance under controlled, scalable scenarios.

3. Research Methodology

This study adopts the Design Science Research Methodology (DSRM) proposed by Peffers et al. (2007) as a guiding framework to systematically develop, demonstrate, and evaluate a semantic AAL system. The methodology consists of six stages as follows.

3.1 Problem Identification and Motivation

The requirement identification was further informed by Thailand's official caregiver training guidelines (Ministry of Public Health, 2024), which specify practical monitoring procedures for blood pressure assessment, environmental risk awareness, and elderly self-care support within community-based LTC programs. These documented workflows provide structured operational expectations for caregivers and highlight the need for integrated interpretation of physiological and environmental data. The proposed ontology, therefore, formalizes these practice-oriented requirements into a unified semantic framework to support explainable cross-domain reasoning.

3.2 Define Objectives for a Solution

The objectives of this study were defined as follows in response to the problems identified above:

- O1 (Modeling): To develop an OWL ontology as a unified semantic framework integrating

three domains (physiological, environmental, and personal profile data), with at least 180 core classes, and to align it with SSN/SOSA standard vocabularies for interoperability.

- O2 (Reasoning): To implement a rule-based reasoning layer using SWRL rules to infer blood-pressure-related and heat-related risk conditions, incorporate age as a relevant contextual factor, and generate personalized self-care recommendations, including behavioral, dietary, and herbal interventions.

- O3 (Evaluation): To validate the framework through (i) structural and logical consistency checks using OOPS! and the Pellet reasoner, (ii) functional verification through 7 competency questions (CQs); and (iii) performance assessments measuring reasoning and SPARQL query times on datasets ranging from 400 to 8,000 individuals.

3.3 Design and Development

This stage produced the core design artifacts of the study. The primary artifact is an OWL ontology developed in Protégé (v5.6.5), comprising both the T-Box (classes, object properties, data properties, and axioms) and the A-Box (instance-level representations of physiological and environmental observations). The ontology includes more than 180 core classes and aligns selected constructs with the W3C SSN/SOSA vocabulary to ensure interoperability. A SWRL rule base comprising 18 rules (12 blood pressure rules and 6 heat-related rules) was implemented to encode clinically grounded thresholds and rule-based risk inference. A set of SPARQL queries was constructed to operationalize the seven competency questions (CQ1–CQ7) and verify reasoning outcomes. Additionally, a synthetic dataset generator was implemented in Python to automatically produce Resource Description Framework (RDF) instance data for controlled scalability testing.

3.4 Demonstration

A functional prototype was developed to integrate the ontology, the SWRL rule base, and SPARQL queries within a reasoning environment. Synthetic physiological values (e.g., systolic/diastolic blood pressure, body temperature) and environmental temperature readings were generated within clinically meaningful ranges derived from national health guidelines. Values were sampled across predefined clinical thresholds to ensure balanced representation of normal and risk categories and to activate classification rules. Generated data were transformed into RDF triples and processed using the Pellet reasoner. The demonstration verified that heterogeneous sensor inputs could be semantically integrated, classified, and

linked to personalized recommendations through rule-based inference.

3.5 Evaluation

Evaluation was conducted under controlled experimental conditions. Structural validation ensured RDF/OWL compliance, and the quality of the ontology design was assessed using OOPS! (Ontology Pitfall Scanner). Logical consistency and SWRL rule execution were verified using the Pellet reasoner. Competency questions were operationalized via SPARQL queries, and reasoning and query-execution times were measured across datasets ranging from 400 to 8,000 individuals. Each experiment was repeated five times, and the results are reported as mean $\pm$ standard deviation. Experiments were conducted on a workstation equipped with an Intel® Core™ Ultra5 226V (2.10 GHz) processor and 16 GB of RAM, running Windows 11 (64-bit), ensuring reproducibility. Reported performance measurements reflect reasoning and query execution time and exclude ontology loading overhead. Detailed quantitative results are presented in Section 6.

3.6 Communication

The findings of this research are disseminated through academic publications to facilitate knowledge transfer within the research community.

4. Ontology-Driven AAL Framework

This study introduces AALHealthIoT, an ontology-driven AAL framework that integrates simulated sensor data, semantic modeling, rule-based reasoning, and validation processes to support elderly-care applications, as shown in Figure 1.

In Figure 1, the perception layer provides the raw inputs used in this study. These include simulated physiological signals, such as body temperature, blood pressure, and heart rate, as well as environmental sensor values for ambient temperature and related conditions. All signals were obtained from predefined datasets to emulate data from wearable or IoT devices, allowing the ontology to be evaluated safely across both normal and abnormal scenarios without accessing personal health information.

The proxy layer standardizes these heterogeneous inputs into a unified JavaScript Object Notation (JSON) schema, ensuring consistent formatting before semantic processing. In the data storage layer, standardized data are mapped to RDF triples aligned with the AALHealthIoT ontology, creating structured, machine-interpretable representations. The reasoning layer hosts the semantic

rule engine, which applies SWRL rules to the enriched knowledge base. These rules operationalize expert knowledge to infer higher-level contextual conditions, such as heat-risk categories or health-related abnormalities, from combined sensor observations. The reasoning process generates new inferences that extend the ontology's A-Box and support personalized, explainable decision logic. The ontology schema (T-Box), including classes, properties, and SWRL rules, is defined at design time and remains structurally stable. Reasoning operates over instance-level data (A-Box), which are designed to evolve dynamically as new observations are ingested and semantically annotated. In this prototype, data ingestion was simulated for controlled evaluation rather than implemented as real-time streaming. Nevertheless, the architecture supports the incremental addition of new instances, allowing reasoning results to be updated as new data become available.

The application and validation layer verifies and interacts with the ontology through competency questions, structural and logical checks, and pitfall detection. SPARQL queries retrieve inferred conditions and personalized recommendations, while

performance tests assess reasoning time and computational overhead. A systematic comparison with existing ontologies further confirms the expanded reasoning capability and broader coverage of AALHealthIoT. Together, these mechanisms ensure that the ontology remains reliable, interpretable, and efficient for elderly-care scenarios.

5. Ontology Engineering and Implementation

Knowledge representation and ontology engineering provide the basis for structuring heterogeneous data into meaningful, machine-interpretable knowledge. The AALHealthIoT ontology development follows the NeOn methodology (Suárez-Figueroa et al., 2015) by combining Scenario 1 (development from specification) with Scenario 4 (reuse and re-engineering of ontological resources). While core domain concepts such as health risk and personalized recommendation were newly developed, selected constructs from the W3C SSN/SOSA ontology were reused and extended to ensure interoperability. This hybrid approach preserves standardized sensor semantics while enabling domain-specific cross-domain health reasoning.

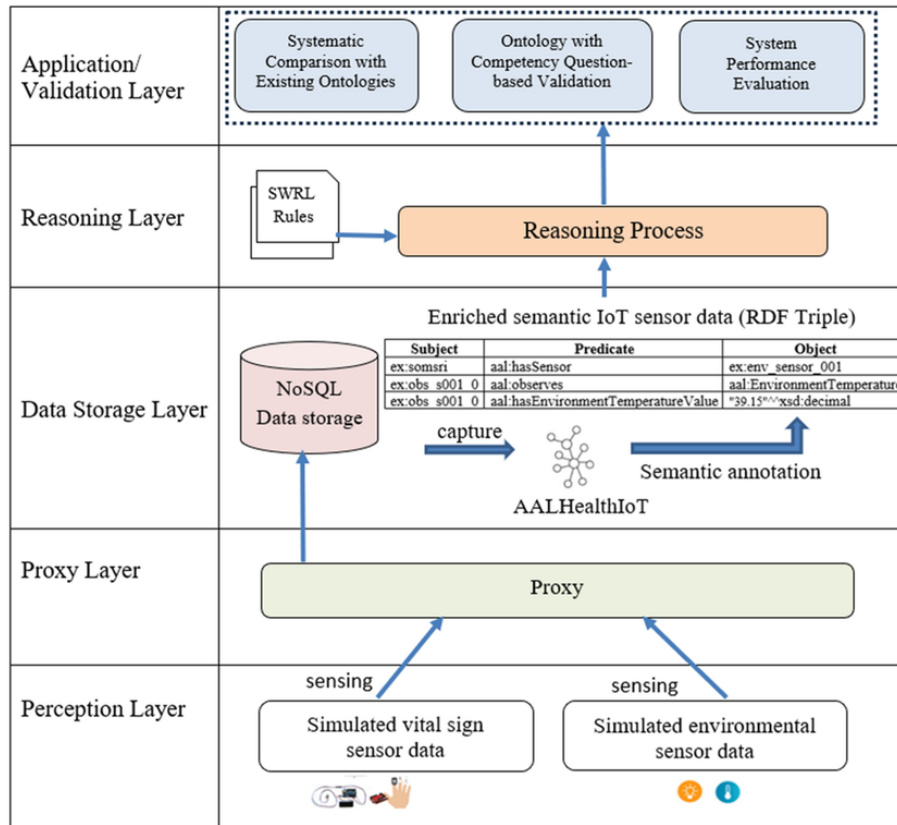


Figure 1 Proposed Ontology-Driven AAL Framework

Table 1 Example of T-Box Components of the AALHealthIoT Ontology

Type	Description	Examples
Classes	Key concepts representing the elderly and caregivers, sensors, and observed phenomena.	Senior, Caregiver, Sensor, MeasurementUnit, VitalSignSensor, HomeEnvironmentSensor, HealthCondition, BodyTemperatureObservation
Object Properties	Semantic links between classes.	hasCarer, hasSensor, hasCondition, hasPractice, hasObservation, hasStatus, hasMeasurementUnit, isSuggestedTo, hasPotentialRiskToBe
Data Properties	Quantitative attributes describing measurements and events.	hasAge, hasGender, hasName, hasDescription, hasContactInformation, hasExerciseRegularly, hasValue, hasValueTimeStamp,
Axioms	Logical restrictions to ensure semantic consistency and reasoning capability.	BloodPressureSensor $\sqsubseteq$ VitalSignSensor BloodPressure $\sqsubseteq$ VitalSignMeasurement hasPotentialRiskToBe $\sqsubseteq$ hasCondition EnvironmentTemperatureSensor $\sqsubseteq$ HomeEnvironmentSensor hasCarer $\equiv$ isCarerOf

5.1 Ontology-Based Knowledge Representation

In this research, ontology-based modeling is based on Description Logic (DL), which provides a formal approach to knowledge representation. The proposed system maintains the classical distinction between the Terminological Box (T-Box) and the Assertional Box (A-Box), which distinguishes domain-level schema definitions from instance-level data. The T-Box captures the conceptual schema of the domain, including classes, object properties, data properties, and logical axioms. Table 1 presents selected examples of T-Box components in the AALHealthIoT ontology.

The axioms in Table 1 define major structural relationships in the ontology. Subclass axioms ($\sqsubseteq$), such as $\text{BloodPressureSensor} \sqsubseteq \text{VitalSignSensor}$ and $\text{BloodPressure} \sqsubseteq \text{VitalSignMeasurement}$, establish hierarchical specialization and enable inheritance-based reasoning. The subproperty axiom $\text{hasPotentialRiskToBe} \sqsubseteq \text{hasCondition}$ refines a general condition relation into a more specific risk relation. The inverse property definition $\text{hasCarer} \equiv \text{inverseOf isCarerOf}$ ensures bidirectional consistency between caregiver and senior relationships, which enables automatic inference of reciprocal links.

According to Table 1, the T-Box represents a stable conceptual schema that remains unchanged during reasoning. In contrast, the A-Box contains assertions about specific individuals—such as seniors, caregivers, sensors, and their observations. For example, a 39.15°C reading is modeled as an instance of $\text{BodyTemperatureObservation}$ with its related properties. While the T-Box defines the static conceptual schema, the A-Box grows dynamically as sensor data arrive, forming an evolving knowledge base. Heterogeneous IoT inputs are semantically

annotated and converted into RDF triples by mapping JSON attributes to ontology properties and validating them against the T-Box. These A-Box instances ensure semantic consistency and support reasoning within the AALHealthIoT ontology.

5.2 Ontology Conceptualization and Modeling

Ontology conceptualization was guided by predefined Competency Questions (CQs), formulated prior to ontology implementation, to define the domain scope, entity hierarchies, and reasoning requirements. The CQs were derived from publicly available clinical guidelines (Ministry of Public Health, 2024) and representative AAL use cases reported in the related literature. These questions served as design constraints that informed class identification, property modeling, and SWRL rule construction, thereby ensuring traceability between domain requirements and the ontology's structure. Table 2 presents the competency questions that shaped the conceptual design.

To address these CQs, a clear distinction was maintained between T-Box and A-Box modeling. Stable domain abstractions (e.g., RiskCategory , HealthCondition , and Observation) are represented as classes, whereas dynamic measurement data and individual elderly profiles are modeled as instances. This separation ensures logical consistency and supports scalable reasoning over evolving IoT data.

The Person (modeled as Senior) concept is introduced to enable individual-level reasoning and contextual personalization. Since risk inference and recommendation rules operate at the individual level, modeling the elderly individual as a first-class entity allows the ontology to associate measurements,

inferred risks, and recommended actions within a coherent semantic structure.

Measurement events are modeled as instances of `sosa:Observation`, while risk categories remain conceptual classes to support SWRL-based classification. To prevent ambiguity in numeric values, body temperature and environmental temperature are represented as distinct subclasses of `sosa:Observation`, aligned with `sosa:ObservableProperty`, ensuring context-aware interpretation.

Table 3 illustrates the semantic transformation of raw IoT data into RDF triples. Vital-sign and environmental measurements are modeled using domain-specific data properties (e.g., `aal:hasEnvironmentTemperatureValue`), which are defined as subproperties of `sosa:hasSimpleResult` to preserve interoperability with SSN/SOSA.

In the Proxy Layer, incoming sensor readings are first standardized into a unified JSON schema (`sensor_id`, `sensor_type`, `value`, `unit`, `timestamp`). A rule-based Python module (OWLReady2 and RDFLib) automatically transforms each JSON record

into RDF individuals and triples aligned with AALHealthIoT and SSN/SOSA. In this implementation, `aal:madeBySensor` is defined as a subproperty of `sosa:madeBySensor` to maintain semantic alignment while avoiding the overhead of external dependencies during controlled benchmarking. The `sensor_type` field determines the observation class and associated observed property, while value, timestamp, and unit are represented as typed literals or linked unit individuals. The resulting triples are inserted into the RDF graph prior to SWRL reasoning and SPARQL evaluation.

While Table 3 illustrates a simplified observation instance for clarity, the ontology remains fully compatible with the W3C SSN/SOSA framework and supports richer semantic annotations, including deployment context, observed feature, and device metadata. The current prototype adopts a lightweight modeling approach to maintain reasoning efficiency, while preserving extensibility for future semantic enrichment.

Table 2 Competency Questions

CQ ID	Competency Question	Addressed by Implementation
CQ1	Can the ontology infer health risks from vital sign measurements?	Yes
CQ2	Can it recommend self-care practices for specific risk conditions?	Yes
CQ3	Can it retrieve the risk conditions of a particular elderly individual?	Yes
CQ4	Can it provide specific behavioral recommendations for identified health risks?	Yes
CQ5	Can it suggest dietary or herbal remedies for minor health abnormalities?	Yes
CQ6	Can it infer and advise on risks arising from environmental factors (e.g., extreme heat)?	Yes
CQ7	Can it perform reasoning and querying across heterogeneous, cross-domain datasets (e.g., IoT and healthcare)?	Yes

Table 3 Example of JSON-to-RDF transformation for semantic annotation

JSON data	RDF triple
<pre>{ "sensor_id": "EnvSensor_001", "sensor_type": "EnvironmentTemperature", "value": 39.15, "unit": "Celsius", "timestamp": "2025-07-28T14:54:27" }</pre>	<pre>ex:obs_s001_0 rdf:type aal:EnvironmentTemperatureObservation ; aal:madeBySensor ex:env_sensor_001 ; sosa:observedProperty aal:EnvironmentTemperature ; aal:hasEnvironmentTemperatureValue "39.15"^^xsd:decimal ; aal:hasTimestamp "2025-07-28T14:54:27"^^xsd:dateTime ; aal:hasUnit aal:DegreeCelsius .</pre>

5.3 Ontology Implementation

The next step is the actual development of the ontology, using Protégé, a widely adopted open-source ontology editor that offers a graphical user interface to facilitate the creation of the ontology components (Musen, 2015). The AALHealthIoT ontology was implemented in OWL 2 and aligned with selected elements of the W3C SSN/SOSA ontology to ensure interoperability with established IoT semantic standards. Rather than redefining sensing semantics, AALHealthIoT directly reuses core SSN/SOSA constructs and extends them with domain-specific subclasses for elderly health monitoring and risk inference.

The ontology explicitly reuses the following SSN/SOSA elements:

- 1) Reused Classes: `sosa:Sensor`, `sosa:Observation`, and `sosa:ObservableProperty`.
- 2) Reused properties: `sosa:madeBySensor`, `sosa:observedProperty`, and `sosa:hasSimpleResult`.

Domain-specific subclasses extend these foundational concepts. For example, `VitalSignSensor` and `HomeEnvironmentSensor` are modeled as subclasses of `sosa:Sensor`, while specialized observation classes such as `EnvironmentTemperatureObservation` extend `sosa:Observation`. Measurement properties (e.g., `hasEnvironmentTemperatureValue`, `hasBPSystolicValue`) are defined as subproperties of `sosa:hasSimpleResult` to maintain semantic compatibility while enabling domain-specific modeling.

For clarity, the ontology structure can be summarized as a simplified four-layer conceptual architecture comprising ten core classes. The user includes Senior and Caregiver. The sensing layer includes `Sensor`, `VitalSignSensor`, `HomeEnvironmentSensor`, and `Observation`. The health inference layer includes `HealthCondition`, which covers blood pressure stages, elevated, and hypotension categories, and `HeatRiskLevel`. The action layer includes `Practice` and `Recommendation`. This layered abstraction separates sensing, risk inference, and intervention, thereby providing a clear reasoning pathway while maintaining alignment with SSN/SOSA standards.

5.4 Semantic Rule-Based Ontology Reasoning

The proposed AAL architecture integrates semantic rule-based ontology reasoning as a core component of knowledge processing. Building on the semantic structure of the T-Box and A-Box, reasoning enables anomaly detection and knowledge derivation. In this study, rule-based reasoning was implemented using SWRL rules, which can enhance knowledge

representation and support intelligent decision-making within Semantic Web applications (Zhang & Lobov, 2024). These rules encode domain knowledge by linking observed data to health conditions and recommended practices. They classify blood pressure into clinical categories and infer heat-related risks from temperature data and individual profiles. Example blood pressure rules are shown in Table 4. All health-related inference conditions were formulated in accordance with publicly available healthcare guidelines issued by the Thai Hypertension Society (2024).

Table 4 presents selected SWRL rules for inferring blood pressure conditions in elderly individuals from systolic and diastolic measurements. These rules categorize readings into clinical states, such as Hypertension Stages 1–3, Elevated, Normal, or Hypotension, based on ontology-defined thresholds. For example, Rule S01 identifies Hypertension Stage 3 when both values exceed critical limits, and Rule S02 links this condition to appropriate health advice. These rules, expressed in SWRL and grounded in description logic semantics, demonstrate how logical reasoning supports automated health assessment in AALHealthIoT. Additional rules following the same structure enable broader monitoring, including heat-related risk inference, as shown in Table 5. All heat-related inference rules were derived from publicly accessible clinical guidelines issued by the Ministry of Public Health (2022).

The SWRL rules implemented in this study were derived from publicly available clinical guidelines and standardized threshold definitions issued by recognized health authorities, including the Thai Hypertension Society (2024) for blood pressure classification and the Ministry of Public Health (2022) for heat-related risk conditions. The threshold values (e.g., systolic and diastolic ranges) follow established clinical categorization criteria to ensure medical relevance. In total, the ontology comprises 12 blood pressure rules (six classification–recommendation pairs) and 6 heat-related rules. Mutually exclusive numeric ranges were defined to prevent overlapping classifications and rule conflicts. The rule logic is intended to support a semantic decision-support demonstration rather than function as a standalone diagnostic system.

The robustness of this reasoning layer depends on its behavior under imperfect data conditions. Because AALHealthIoT is based on Description Logic, it follows the Open World Assumption (OWA). Therefore, when required sensor data are missing or incomplete, such as an absent diastolic blood pressure value, the relevant SWRL rules are not activated, and no inference is generated for that condition. This helps prevent

potentially unsafe false-positive health inferences based on partial evidence. To reduce the possibility of conflicting rules, the framework defines mutually exclusive numeric ranges for clinical thresholds, including blood pressure stages and heat-risk levels, thereby avoiding overlapping classifications. In addition,

any logical inconsistencies that arise are identified during consistency checking with the Pellet reasoner, ensuring that only logically valid inferences are retained in the knowledge base. More systematic handling of incomplete and conflicting data is left for future work.

Table 4 SWRL Rules for Blood Pressure Inference

Rule ID	Rule (in SWRL syntax)
S01	<code>aal:Senior(?s) ^ aal:hasSensor(?s, ?ss) ^ aal:hasBPSystolicValue(?ss, ?bpsv) ^ swrlb:greaterThanOrEqual(?bpsv, 180) ^ aal:hasBPDdiastolicValue(?ss, ?bpdv) ^ swrlb:greaterThanOrEqual(?bpdv, 110) -> aal:hasPotentialRiskToBe(?s, aal:blood_pressure_hypertension_stage_3)</code>
S02	<code>aal:Senior(?s) ^ aal:hasPotentialRiskToBe(?s, aal:blood_pressure_hypertension_stage_3) ^ aal:hasSuggestionOfPractice(aal:blood_pressure_hypertension_stage_3, ?p) ^ aal:hasPractice(?p, ?a) -> aal:isSuggestedTo(?s, ?a)</code>
S03	<code>aal:Senior(?s) ^ aal:hasSensor(?s, ?ss) ^ aal:hasBPSystolicValue(?ss, ?bpsv) ^ swrlb:greaterThanOrEqual(?bpsv, 160) ^ swrlb:lessThanOrEqual(?bpsv, 179) ^ aal:hasBPDdiastolicValue(?ss, ?bpdv) ^ swrlb:greaterThanOrEqual(?bpdv, 100) ^ swrlb:lessThanOrEqual(?bpdv, 109) -> aal:hasPotentialRiskToBe(?s, aal:blood_pressure_hypertension_stage_2)</code>
S04	<code>aal:Senior(?s) ^ aal:hasPotentialRiskToBe(?s, aal:blood_pressure_hypertension_stage_2) ^ aal:hasSuggestionOfPractice(aal:blood_pressure_hypertension_stage_2, ?p) ^ aal:hasPractice(?p, ?a) -> aal:isSuggestedTo(?s, ?a)</code>
S05	<code>aal:Senior(?s) ^ aal:hasSensor(?s, ?ss) ^ aal:hasBPSystolicValue(?ss, ?bpsv) ^ swrlb:greaterThanOrEqual(?bpsv, 140) ^ swrlb:lessThanOrEqual(?bpsv, 159) ^ aal:hasBPDdiastolicValue(?ss, ?bpdv) ^ swrlb:greaterThanOrEqual(?bpdv, 90) ^ swrlb:lessThanOrEqual(?bpdv, 99) -> aal:hasPotentialRiskToBe(?s, aal:blood_pressure_hypertension_stage_1)</code>
S06	<code>aal:Senior(?s) ^ aal:hasPotentialRiskToBe(?s, aal:blood_pressure_hypertension_stage_1) ^ aal:hasSuggestionOfPractice(aal:blood_pressure_hypertension_stage_1, ?p) ^ aal:hasPractice(?p, ?a) -> aal:isSuggestedTo(?s, ?a)</code>
S07	<code>aal:Senior(?s) ^ aal:hasSensor(?s, ?ss) ^ aal:hasBPSystolicValue(?ss, ?bpsv) ^ swrlb:greaterThanOrEqual(?bpsv, 130) ^ swrlb:lessThanOrEqual(?bpsv, 139) ^ aal:hasBPDdiastolicValue(?ss, ?bpdv) ^ swrlb:greaterThanOrEqual(?bpdv, 85) ^ swrlb:lessThanOrEqual(?bpdv, 89) -> aal:hasPotentialRiskToBe(?s, aal:blood_pressure_elevated)</code>
S08	<code>aal:Senior(?s) ^ aal:hasPotentialRiskToBe(?s, aal:blood_pressure_elevated) ^ aal:hasSuggestionOfPractice(aal:blood_pressure_elevated, ?p) ^ aal:hasPractice(?p, ?a) -> aal:isSuggestedTo(?s, ?a)</code>
S09	<code>aal:Senior(?s) ^ aal:hasSensor(?s, ?ss) ^ aal:hasBPSystolicValue(?ss, ?bpsv) ^ swrlb:greaterThanOrEqual(?bpsv, 90) ^ swrlb:lessThanOrEqual(?bpsv, 129) ^ aal:hasBPDdiastolicValue(?ss, ?bpdv) ^ swrlb:greaterThanOrEqual(?bpdv, 60) ^ swrlb:lessThanOrEqual(?bpdv, 84) -> aal:hasPotentialRiskToBe(?s, aal:blood_pressure_normal)</code>
S10	<code>aal:Senior(?s) ^ aal:hasPotentialRiskToBe(?s, aal:blood_pressure_normal) ^ aal:hasSuggestionOfPractice(aal:blood_pressure_normal, ?p) ^ aal:hasPractice(?p, ?a) -> aal:isSuggestedTo(?s, ?a)</code>
S11	<code>aal:Senior(?s) ^ aal:hasSensor(?s, ?ss) ^ aal:hasBPSystolicValue(?ss, ?bpsv) ^ swrlb:lessThan(?bpsv, 90) ^ aal:hasBPDdiastolicValue(?ss, ?bpdv) ^ swrlb:lessThan(?bpdv, 60) -> aal:hasPotentialRiskToBe(?s, aal:blood_pressure_hypotension)</code>
S12	<code>aal:Senior(?s) ^ aal:hasPotentialRiskToBe(?s, aal:blood_pressure_hypotension) ^ aal:hasSuggestionOfPractice(aal:blood_pressure_hypotension, ?p) ^ aal:hasPractice(?p, ?a) -> aal:isSuggestedTo(?s, ?a)</code>

Table 5 SWRL Rules for Heat-Related Illness Inference

Rule ID	Rule (in SWRL syntax)
H01	aal:Senior(?s) ^ aal:hasAge(?s, ?a) ^ swrlb:greaterThanOrEqual(?a, 60) -> aal:SeniorAgeRiskToHeatRelatedIllness(?s)
H02	aal:SeniorAgeRiskToHeatRelatedIllness(?s) ^ aal:hasSensor(?s, ?es) ^ aal:hasEnvironmentTemperatureValue(?es, ?ev) ^ swrlb:greaterThanOrEqual(?ev, 35.0) ^ swrlb:lessThanOrEqual(?ev, 38.0) -> aal:hasHeatRiskLevel(?s, aal:Heat caution)
H03	aal:SeniorAgeRiskToHeatRelatedIllness(?s) ^ aal:hasSensor(?s, ?es) ^ aal:hasEnvironmentTemperatureValue(?es, ?ev) ^ swrlb:greaterThanOrEqual(?ev, 38.1) ^ swrlb:lessThanOrEqual(?ev, 40.0) -> aal:hasHeatRiskLevel(?s, aal:Heat extreme caution)
H04	aal:SeniorAgeRiskToHeatRelatedIllness(?s) ^ aal:hasSensor(?s, ?es) ^ aal:hasEnvironmentTemperatureValue(?es, ?ev) ^ swrlb:greaterThanOrEqual(?ev, 40.1) ^ swrlb:lessThanOrEqual(?ev, 43.0) -> aal:hasHeatRiskLevel(?s, aal:Heat danger)
H05	aal:SeniorAgeRiskToHeatRelatedIllness(?s) ^ aal:hasSensor(?s, ?es) ^ aal:hasEnvironmentTemperatureValue(?es, ?ev) ^ swrlb:greaterThanOrEqual(?ev, 43.1) -> aal:hasHeatRiskLevel(?s, aal:Heat Extreme Danger)
H06	aal:Senior(?s) ^ aal:hasSensor(?s, ?es) ^ aal:hasEnvironmentTemperatureValue(?es, ?ev) ^ swrlb:greaterThanOrEqual(?ev, 35.0) ^ swrlb:lessThanOrEqual(?ev, 38.0) ^ aal:hasPotentialRiskToBe(?s, aal:blood pressure elevated) -> aal:hasHeatRiskLevel(?s, aal:Heat caution)

Table 6 Ontology Validation Summary

Tool used	Version	Purpose	Criteria	Outcome
W3C RDF Validator	Online service	RDF syntax validation	RDF/XML structural correctness	No syntax errors detected
Ontology Pitfall Scanner! (OOPS!)	Online service	Ontology design quality assessment	Pitfall detection	Critical structural pitfalls were eliminated, reducing the total number from 47 to 0 after refinement.
Pellet Reasoner	2.2.0	Logical consistency and SWRL execution	Unsatisfiable classes, rule inference correctness	No inconsistencies; rules executed as expected

6. Ontology Validation and Evaluation Framework

This section validates and evaluates the AALHealthIoT ontology with respect to structural soundness, logical consistency, functional expressiveness, and performance. The assessment examines whether the ontology can reliably support cross-domain reasoning, SWRL-based inference, and SPARQL retrieval for elderly-care scenarios.

6.1 Foundational Ontology Validation

The validation of the proposed ontology was conducted through a structured four-stage framework. This framework integrates standard ontology validation procedures and automated tools to ensure robustness and reliability. Table 6 shows the ontology validation summary.

Details of each stage of ontology validation are shown as follows.

Stage 1: Structural and Syntactic Validation

The first stage ensured that the ontology complied with W3C standards for syntactic correctness and structural integrity, using the W3C RDF Validator to confirm RDF/OWL compliance. This guarantees that the ontology can be reliably parsed and reused across platforms. AALHealthIoT contains 2,077 axioms, including 776 logical axioms that define semantic relationships and constraints. It also includes 188 classes, 159 object properties, and 30 data properties. This ontology size is appropriate for modeling cross-domain AAL knowledge, providing sufficient semantic detail for practical reasoning while remaining lightweight, as evidenced by efficient processing during reasoning. Figure 2 shows the AALHealthIoT ontology metrics.

Ontology metrics:	
Metrics	
Axiom	2,077
Logical axiom count	776
Declaration axioms count	390
Class count	188
Object property count	159
Data property count	30
Individual count	0
Annotation Property count	16
Class axioms	
SubClassOf	357
EquivalentClasses	11
DisjointClasses	27
GCI count	0
Hidden GCI Count	11
Object property axioms	
SubObjectPropertyOf	80
EquivalentObjectProperties	0
InverseObjectProperties	66

Figure 2 AALHealthIoT Ontology Metrics

Stage 2: Common Ontology Design Pitfalls Detection

The second evaluation stage used the Ontology Pitfall Scanner! (OOPS!) to identify common modeling issues. The initial scan revealed problems such as disconnected elements, missing annotations, properties without domains or ranges, undeclared inverse relations, untyped classes, and missing equivalent-class declarations, along with ontology-level issues such as absent disjointness constraints, inconsistent naming, and missing license information. These findings indicated weaknesses in documentation and semantic specification. After iterative refinements, including adding annotations, defining domains and ranges, standardizing naming, and adding licensing metadata, a follow-up OOPS! check showed that critical structural pitfalls were eliminated, reducing the total number from 47 to 0. This result highlights the value of automated pitfall detection in supporting high-quality ontology engineering.

Stage 3: Logical Consistency Checking

Logical consistency and rule execution were verified using the Pellet reasoner (v2.2.0) within Protégé under default classification settings. Pellet was chosen over other OWL 2 DL reasoners (e.g., HermiT) because of its native support for SWRL rule processing within Protégé, which was required for health-risk inference. The reasoning process confirmed that the ontology contained no unsatisfiable classes or logical inconsistencies and that all defined rules generated valid inferences. For example, when the environmental temperature reached 39.2°C, the individual wipa, previously

classified as SeniorAgeRiskToHeatRelatedIllness, was automatically assigned the heat-risk level Heat_extreme_caution according to Rule H03. This inference was triggered by the rule specifying that if an individual vulnerable to heat-related illness experiences an environmental temperature between 38.1°C and 40.0°C, the corresponding heat-risk level is set to Heat_extreme_caution. This example demonstrates that the ontology and rule set support accurate and explainable reasoning outcomes, reinforcing confidence in the ontology's logical soundness and suitability for deployment in reasoning-based health applications.

Stage 4: Functional Validation

Functional validation was performed using the Competency Questions (CQs) listed in Table 2, each representing a realistic elderly-care scenario. These questions cover key tasks such as detecting abnormal vital signs (CQ1), providing personalized self-care guidance (CQ2, CQ4), retrieving an individual's risk profile (CQ3), suggesting dietary or herbal remedies (CQ5), and addressing environmental and IoT-based scenarios, such as heat-risk assessment (CQ6) and cross-domain data integration (CQ7). All CQs were successfully answered using SWRL rules and SPARQL queries, confirming that the ontology supports the reasoning and decision-making processes required in practical AAL applications.

Figure 3 provides a representative example of how selected CQs are operationalized within the ontology, demonstrating the process from data acquisition and semantic annotation to reasoning and SPARQL-based retrieval.

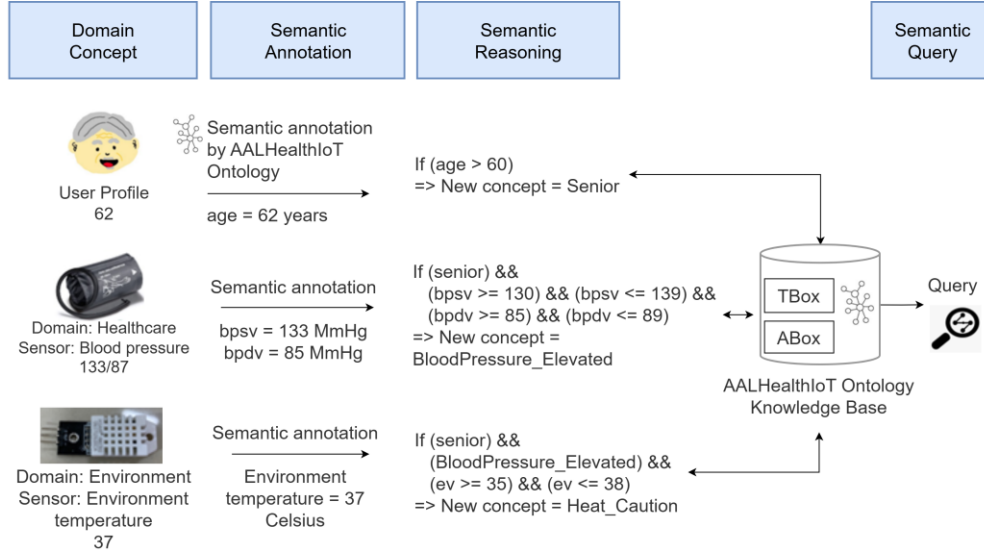


Figure 3 Example of SWRL rule-based inference in Protégé

Figure 3 illustrates the AALHealthIoT reasoning pipeline, showing how the ontology processes heterogeneous data for senior-care decision support. The workflow begins with domain inputs from user profiles, health sensors, and environmental measurements, for example, a temperature of 37°C, a blood pressure reading of 133/87 mmHg, and the age of a 62-year-old user. These raw values lack contextual meaning on their own. Through semantic annotation, they are transformed into machine-interpretable concepts defined by standardized classes and properties, enabling semantic interoperability and consistent interpretation across healthcare platforms, IoT systems, and decision support applications. When these data are semantically annotated, they are subjected to reasoning through SWRL-based rules. For example, the system infers the term "Senior" when the user's age is 60 years or older. It also assesses healthcare data to determine whether the condition `blood_pressure_elevated` is assigned to a senior based on systolic and diastolic blood pressure readings within predetermined thresholds. This illustrates the ontology's capacity to infer health-risk conditions from vital-sign measurements, thereby addressing CQ1. The inferred conditions are not only descriptive; they are linked to contextual self-care guidelines recorded in the ontology's knowledge base. This allows the system to suggest specific behavioral practices for managing identified risks (CQ2 and CQ4). Through SPARQL queries over the ontology's A-Box, the system can retrieve the particular risk profile of an elderly individual, such as identifying that they are experiencing `Heat_caution` due to both elevated blood pressure and high environmental temperature (CQ3). In addition, the ontology can associate minor abnormalities

with dietary or herbal interventions, such as recommending potassium-rich foods (Chan et al., 2024) or herbal infusions to mitigate moderate blood pressure elevation (Li et al., 2019) (CQ5).

The reasoning process also incorporates environmental factors into its assessment. For example, when a senior with `blood_pressure_elevated` is exposed to ambient temperatures between 35–38°C, the ontology infers a risk condition, `Heat_caution`, thereby satisfying the requirement to infer and advise on risks arising from environmental factors (CQ6). The integration of IoT-based environmental sensing data with healthcare measurements demonstrates the system's ability to perform reasoning and querying across heterogeneous, cross-domain datasets, ensuring semantic interoperability between domains (CQ7).

The SPARQL query in Listing 1 exemplifies how the AALHealthIoT ontology retrieves an elderly user's heat-related risk condition and corresponding self-care recommendations.

Listing 1. SPARQL query for retrieving a senior's heat-related risk condition, recommended self-care practices, and additional resources (addresses CQ3, CQ4, and CQ6).

The SPARQL query in Listing 1 retrieves the senior individual inferred to be at Heat Caution risk, along with related self-care suggestions and additional resources. The reasoning layer integrates user profile, health, and environmental data, such as age 62, blood pressure 133/87 mmHg, and temperature 37°C, to infer the Heat Caution condition. The retrieved results include suggested practices, such as hydration and limited outdoor activity, as well as a self-care video associated with the Heat Caution level.

```

SELECT ?Senior ?HeatCondition ?SuggestionOfPracticesDescription ?AdditionalResource
WHERE {
  ?Senior aal:hasHeatRiskLevel ?HeatCondition.
  ?HeatCondition aal:hasDescription ?HeatConditionDescription.
  ?HeatCondition aal:hasSuggestionOfPractice ?SuggestionOfPractices.
  ?SuggestionOfPractices aal:hasDescription ?SuggestionOfPracticesDescription.
  OPTIONAL {
    ?SuggestionOfPractices aal:hasAdditionalResourceForSuggestion ?AdditionalResource
  }
}

```

Table 7 Ontology Reasoning Time

Dataset Size (Number of Seniors)	Total Individuals	Mean (ms) ± SD (ms)
50	400	1,009.30 ± 17.6
100	800	1,046.51 ± 22.4
500	4,000	1,474.21 ± 40.3
1000	8,000	1,797.20 ± 52.8

Table 8 Ontology Querying Time (Mean ± SD ms)

Dataset Size (Number of Seniors)	CQ1	CQ2	CQ3	CQ4	CQ5	CQ6	CQ7
50	0.30 ± 0.04	0.20 ± 0.04	0.59 ± 0.09	0.93 ± 0.04	0.05 ± 0.00	19.23 ± 0.84	33.88 ± 1.75
100	0.38 ± 0.07	0.21 ± 0.05	0.60 ± 0.09	1.87 ± 0.21	0.05 ± 0.00	37.61 ± 0.35	63.20 ± 0.91
500	0.94 ± 0.08	0.40 ± 0.01	0.80 ± 0.10	8.46 ± 0.72	0.05 ± 0.01	193.64 ± 2.94	320.25 ± 3.87
1000	1.36 ± 0.07	0.73 ± 0.07	1.11 ± 0.12	17.55 ± 1.27	0.06 ± 0.01	384.17 ± 7.85	635.63 ± 6.39

6.2 Ontology Reasoning Time and Scalability Evaluation

To evaluate the computational feasibility of AALHealthIoT in Ambient Assisted Living (AAL) scenarios, a controlled reasoning-time experiment was conducted, focusing on SWRL rule execution. Experiments were performed on a workstation equipped with an Intel® Core™ Ultra5 226V (2.10 GHz) processor and 16 GB of RAM, running Windows 11 (64-bit), with Python 3.10.8 and OWLReady2 (v0.45). Reasoning was executed using OWLReady2 with Pellet-based classification enabled to ensure consistency between SWRL rule processing and the logical validation stage.

Synthetic datasets were generated to approximate realistic AAL monitoring conditions, simulating 50, 100, 500, and 1,000 elderly individuals. Each senior was associated with physiological measurements (e.g., systolic and diastolic blood pressure and body temperature) and environmental readings structured according to clinically defined thresholds for hypertension and heat-related risks. Measurement values were generated using uniform random sampling within clinically defined threshold ranges, with proportional allocation across normal and high-risk categories to ensure balanced rule activation and comprehensive

scenario coverage. Each senior was linked to multiple observation instances, resulting in 400, 800, 4,000, and 8,000 total ontology individuals, respectively. The term “total individuals” refers to the combined number of senior profiles, sensors, and observation instances. For each senior, two sensor instances (vital-sign and environmental) and their corresponding observation records were instantiated, resulting in a proportional increase in the number of ontology individuals across dataset sizes. Each configuration was executed five times, excluding an initial warm-up run. Reported reasoning times represent the mean of repeated executions and include SWRL rule execution and ontology classification but exclude ontology loading time. The results are presented in Table 7.

The results demonstrate that SWRL rule execution remains computationally feasible across all tested dataset sizes. Reasoning time increases moderately with ontology size, reflecting the expected computational cost of SWRL evaluation and OWL DL classification. Even at the largest scale (1,000 seniors; 8,000 individuals), total reasoning time remained under 2 seconds (1,797.20 ms). To assess overall system usability, SPARQL querying performance on the inferred ontology graph is evaluated next.

6.3 Ontology Querying Time Evaluation

SPARQL query performance was evaluated on the inferred ontology graph, following Pellet classification, using synthetic datasets of 50, 100, 500, and 1000 seniors. The experimental environment and evaluation protocol were identical to those described in Section 6.2. Each senior was associated with a vital-sign sensor, an environmental sensor, and multiple environmental temperature observations. To ensure controlled and reproducible benchmarking, remote ontology imports were disabled, and a local property (aal:madeBySensor) was used in place of sosa:madeBySensor. This avoided the overhead of external SSN/SOSA dependencies and ensured that performance measurements reflected only the internal ontology structure.

All competency-question queries (CQ1–CQ7) were pre-compiled using prepareQuery() to eliminate parsing overhead and isolate graph-matching cost. For each dataset size, queries were executed six times, with the first run discarded as a warm-up. Mean execution time and standard deviation (ms) were computed from the remaining runs. The results are shown in Table 8.

As shown in Table 8, CQ1–CQ5 exhibited consistently low execution times across all dataset sizes, reflecting shallow graph patterns and limited join complexity. CQ4 showed a moderate increase at larger dataset sizes due to additional type constraints on risk-condition instances. In contrast, CQ6 and CQ7 involved multi-hop joins across heterogeneous entities (seniors, sensors, observations, and inferred risk states) and therefore incurred higher latency. Nevertheless, both queries demonstrated stable growth trends as the dataset size increased. Even at 1,000 seniors, the most complex cross-domain query (CQ7) remained below one second, confirming practical scalability for AAL deployments.

6.4 Analysis of Computational Overhead

To further examine scalability characteristics, memory consumption and incremental CPU overhead were evaluated during SWRL rule execution and OWL DL classification. Experiments were conducted

across progressively larger datasets (50–1000 seniors), and the results are presented in Table 9.

Memory usage was measured using the psutil library by monitoring the peak resident set size (RSS) of the Python process before and after reasoning. CPU overhead was recorded using time.perf_counter() and reflects incremental processing time within the Python runtime. These measurements excluded ontology loading time and Java Virtual Machine (JVM) heap allocation associated with the Pellet reasoner.

As shown in Table 9, baseline memory consumption increases proportionally with dataset size due to the growth in ontology individuals. However, the additional memory required during reasoning remains nearly constant (0.13–0.14 MB). Similarly, incremental CPU overhead remains stable at approximately 0.02 seconds across all configurations, indicating negligible additional processing burden within the Python environment. When interpreted alongside the reasoning time results in Section 6.2, these findings indicate that AALHealthIoT maintains stable measured resource utilization as the ontology scales and introduces minimal additional computational overhead within the evaluated environment.

6.5 Comparative Evaluation

To position AALHealthIoT within the broader landscape of IoT and sensor-enabled environment ontologies, a structured comparative evaluation was conducted against representative baseline ontologies and recent ontology-driven AAL and healthcare frameworks, including SSN/SOSA, SAREF, SAREF4EHAW, OntoDomus, Bampi et al. (2025), and Zeshan et al. (2023). The comparison was organized along two dimensions: (1) functional coverage with respect to the defined competency questions (CQ1–CQ7), and (2) ontology design characteristics, as documented in their respective specifications.

Table 9 Computational overhead across different dataset sizes

Dataset Size (Number of Seniors)	Total individuals	Pre-Reasoning Memory (MB)	Post-Reasoning Memory (MB)	Memory usage (MB)	CPU usage time (s)
50	400	38.16	38.29	0.13	0.02
100	800	38.63	38.77	0.14	0.02
500	4000	40.92	41.06	0.14	0.02
1000	8000	44.97	45.11	0.14	0.02

6.5.1 Functional Coverage Analysis

A comparative analysis of ontology-based AAL and healthcare frameworks in relation to the competency-question-driven semantic requirements of this study is presented in Table 10. The comparison focuses on domain coverage and key functional capabilities, based on constructs explicitly described in the original ontology specifications and associated publications.

In Table 10, the terms Full, Partial, and None indicate the degree of support identified in the published ontology specifications and reviewed sources for each competency-question requirement defined in this study. Full indicates that the compared ontology or framework provides explicit constructs and, where relevant, operational reasoning support closely aligned with the corresponding competency. Partial indicates that relevant concepts, relations, or limited reasoning support are present, but the competency is not addressed in the same explicit or fully operationalized manner. None indicates that no clear evidence of support for the specific competency was identified in the reviewed specification or publication. These labels should therefore be interpreted as comparative analytical judgments

within the scope of the reviewed materials rather than as absolute claims about all possible extensions or implementations.

The comparison in Table 10 indicates that generic ontologies such as SSN/SOSA and SAREF mainly provide support for sensor and device interoperability, while explicit support for clinically grounded health-risk semantics and recommendation-oriented knowledge is less evident in the reviewed sources. OntoDomus contributes contextual smart-home modeling, and SAREF4EHAW provides a closer domain-specific semantic foundation for eHealth and aging-well applications. In addition, more recent ontology-driven systems, such as Bampi et al. (2025) and Zeshan et al. (2023) show that patient-level condition detection can be supported through ontology-based reasoning. Nevertheless, from the perspective of the competency questions defined in this study, these works appear to focus more strongly on monitoring, alerting, and interoperability than on the combination of explicit health-risk semantics, cross-domain reasoning, and structured recommendation modeling emphasized in AALHealthIoT.

Table 10 Comparative Analysis of Ontology-Based AAL and Healthcare Frameworks

Competency Question	This work	SSN/SOSA	SAREF	SAREF4EHAW	Onto-Domus	Bampi et al. (2025)	Zeshan et al. (2023)	Rationale
CQ1	Full	Partial	Partial	Partial	None	Partial	Partial	SSN/SOSA and SAREF model observations, but their core specifications focus primarily on observation modeling rather than explicit clinical risk semantics. SAREF4EHAW models health actors, devices, and observations. Bampi et al. (2025) and Zeshan et al. (2023) support monitoring-oriented reasoning, whereas this study specifically targets the operationalization of clinically grounded risk semantics.
CQ2	Full	None	None	Partial	None	None	Partial	Self-care recommendation modeling is outside the primary scope of SSN/SOSA, SAREF, and OntoDomus. SAREF4EHAW includes health-related domain constructs, and Zeshan supports alert-oriented decision logic, but explicit recommendation-oriented semantic modeling was not identified in their core specifications.

Table 10 Cont.

Competency Question	This work	SSN/SOSA	SAREF	SAREF4EHAW	Onto-Domus	Bampi et al. (2025)	Zeshan et al. (2023)	Rationale
CQ3	Full	Partial	Partial	Partial	Partial	Full	Full	Existing baseline ontologies focus on observation and contextual access rather than explicit health-risk inference. Bampi et al. (2025) and Zeshan et al. (2023) enable patient-level condition detection through ontology-based reasoning. However, their approaches are primarily optimized for monitoring and alert generation, whereas AALHealthIoT provides a more explicit and queryable representation of clinically grounded health-risk semantics.
CQ4	Full	None	None	Partial	None	Partial	Partial	Existing approaches primarily focus on monitoring and alerting. SAREF4EHAW includes health-related semantics, and Bampi et al. (2025) and Zeshan et al. (2023) support alerting, but behavioral recommendations were not explicitly identified as core constructs in the reviewed specifications.
CQ5	Full	None	None	None	None	None	None	Explicit modeling of dietary or herbal recommendations was not identified in the documented scope of the compared approaches, representing a targeted domain extension provided by AALHealthIoT.
CQ6	Full	Partial	Partial	Partial	Partial	Full	Partial	Environmental modeling is supported in SSN/SOSA, SAREF, OntoDomus, and partly in SAREF4EHAW. Bampi et al. (2025) more explicitly integrate patient, environmental, and device contexts, whereas Zeshan et al. (2023) focus more on patient monitoring. However, clinically grounded, integrated health-risk reasoning with explicit recommendation support was not identified as a core feature in the reviewed specifications.
CQ7	Full	Partial	Partial	Partial	Partial	Full	Partial	Existing ontologies provide partial support for heterogeneous semantic integration, while Bampi et al. (2025) more explicitly connect patient, environmental, and device domains. However, the explicit operationalization of unified cross-domain health-risk inference combined with recommendation-oriented reasoning was not identified among the reviewed approaches, which is a core focus of AALHealthIoT.

6.5.2 Ontology Design Characteristics

In addition to functional coverage, structural and design characteristics further distinguish AALHealthIoT from the selected baselines. Table 11 summarizes the key architectural and modeling differences.

The comparison in Table 11 shows that generic and baseline ontologies primarily emphasize interoperability, device abstraction, and generic observation modeling without explicit support for domain-specific health-risk semantics or integrated recommendation mechanisms. Domain-specific and recent ontology-driven systems, including SAREF4EHAW, Bampi et al. (2025), and Zeshan et al. (2023), provide stronger support for health-related

modeling and patient-level condition detection, but tend to place greater emphasis on interoperability, monitoring, and alert-oriented reasoning than on explicit recommendation-oriented semantic modeling and systematic ontology-level evaluation. Overall, AALHealthIoT further develops foundational IoT modeling approaches by incorporating elderly-specific health-risk constructs, clinically grounded thresholds, and structured recommendation semantics while maintaining compatibility with established standards. Its novelty lies not in expanding sensor taxonomies but in operationalizing clinically grounded cross-domain health-risk inference and recommendation-oriented reasoning within a unified OWL 2 DL-based semantic framework.

Table 11 Structural and Design Characteristics Comparison

Properties	SSN/ SOSA	SAREF	SAREF4E-HAW	OntoDomus	Bampi et al. (2025)	Zeshan et al. (2023)	AALHealthIoT (this work)
Primary Design Objective	Generic IoT sensor and observation modeling	Device interoperability and measurement abstraction	Domain-specific semantic foundation for eHealth and aging-well interoperability	Smart-home activity and assistance modeling	Ontology-driven AAL monitoring with context-sensitive clinical findings	Ontology-based remote patient monitoring and alert management	Elderly health monitoring with integrated risk reasoning
Domain Scope	Domain-independent	Domain-independent	eHealth and aging-well	AAL-oriented (activity-focused)	Smart home, healthcare, and patient context	Patient-centric healthcare monitoring	Health-oriented AAL
Health Risk Semantics	Not explicitly formalized	Not explicitly formalized	Partial	Not explicitly formalized	Partial	Partial	Explicit modeling of health-risk conditions
Recommendation Modeling	Outside primary scope	Outside primary scope	Not explicitly modeled	Outside primary scope	Not explicitly modeled	Alert-oriented (rule-based)	Personalized self-care recommendations
Cross-Domain Integration	Partial	Partial	Partial	Partial	Explicit integration of patient, environment, and device domains	Partial	Explicit integration of physiological, environmental and personal profile domains
Rule-Based Reasoning	No health-specific rules	No health-specific rules	No explicit rule-based health-risk reasoning layer	Activity/context-oriented logic	Jena-based rule inference for context-sensitive clinical findings	SWRL-based abnormal-condition detection and alert logic	SWRL-based health, environmental and personal profile inference
Individual-Level Condition Detection	No	No	Partial	No	Yes	Yes	Yes

Table 11 Cont.

Properties	SSN/ SOSA	SAREF	SAREF4E-HAW	OntoDomus	Bampi et al. (2025)	Zeshan et al. (2023)	AALHealthIoT (this work)
Validation approaches	W3C standardization and cross-domain semantic interoperability use cases	Standards-based interoperability design and application-oriented use cases	Standards-based specification, use-case instantiation, and domain modeling	Scenario-based smart-home context validation	Smart-home deployment, latency, and resource usage	Monitoring accuracy and alert-oriented decision support	Competency questions, SWRL reasoning tests, SPARQL query evaluation, scalability, and overhead analysis
Number of classes	23	33	Modular ontology; exact total not emphasized in the specification	6 sub-ontologies, but the number of classes was not explicitly reported	Not explicitly reported	Not explicitly reported	188
Number of object properties	36	64	Modular ontology; exact total not emphasized in the specification	Not explicitly reported	Not explicitly reported	Not explicitly reported	159
Number of data properties	2	8	Modular ontology; exact total not emphasized in the specification	Not explicitly reported	Not explicitly reported	Not explicitly reported	30

7. Discussion

The evaluation results demonstrate that AALHealthIoT provides a coherent semantic framework for integrating physiological, environmental, and personal profile information in Ambient Assisted Living (AAL) scenarios. The ontology combines OWL-based reasoning and SPARQL querying to infer hypertension-related and heat-related risks using clinically grounded thresholds encoded as SWRL rules. Structural validation and reasoning checks confirm logical consistency and modeling soundness.

Performance results indicate that reasoning remains computationally feasible (under 1.8 seconds for 1,000 individuals), and even the most complex cross-domain queries execute in less than 1 second. These findings suggest that the framework is suitable for periodic decision support workflows in non-real-time AAL environments.

Beyond technical validation, ontology enables transparent and explainable inference. Health-risk classifications are derived from explicit rule logic rather than opaque predictive models, allowing caregivers to trace how specific measurements lead to risk identification and recommended actions. This

interpretability is particularly important in elderly-care contexts and supports extensibility when new sensors or conditions are introduced.

The comparative evaluation also clarifies AALHealthIoT's contribution relative to existing ontology-based AAL and healthcare frameworks. Generic ontologies such as SSN/SOSA and SAREF provide strong support for interoperability, sensor abstraction, and observation modeling, while OntoDomus contributes a contextual smart-home representation for assisted-living environments. More recent domain-specific systems, including SAREF4EHAW, Bampi et al. (2025), and Zeshan et al. (2023), provide stronger support for health-related modeling and patient-level condition detection through health-oriented semantic structures and rule-based monitoring logic. However, these approaches tend to emphasize monitoring, semantic integration, and system-level performance evaluation more strongly than explicit recommendation-oriented semantic modeling and systematic ontology-level evaluation. In particular, they place less emphasis on explicitly operationalizing clinically grounded cross-domain risk reasoning that jointly integrates physiological, environmental, and personal profile

information within a unified semantic framework. In contrast, AALHealthIoT explicitly formalizes clinically grounded health-risk semantics, integrates these heterogeneous dimensions within a unified reasoning framework, and links inferred risk states to structured recommendation entities. In addition, the proposed ontology is supported by a systematic evaluation framework that combines competency-question validation, logical consistency checking, ontology pitfall detection, and quantitative reasoning and query-performance analysis. These aspects help distinguish the proposed ontology from existing approaches by moving beyond individual-level condition detection toward more explicit health-risk semantics and recommendation-oriented reasoning.

At this stage, synthetic data were used to provide a controlled, reproducible, and ethically appropriate basis for evaluating ontology behavior, SWRL rule execution, query performance, and scalability under predefined conditions. This approach is suitable for an initial ontology-engineering study because it allows the assessment of the semantic structure, reasoning logic, and competency-question coverage independently of noise, missing values, and deployment-specific variability in real-world sensing environments. By generating values that systematically span clinically relevant thresholds, the evaluation also verified that the rule base behaved as intended across scenarios ranging from normal conditions to elevated blood-pressure states and heat-related risks. In addition, synthetic data enabled performance benchmarking without the immediate privacy or ethical constraints associated with accessing real-time elderly health records during the design and development phase. However, the resulting inference and performance outcomes should be interpreted as evidence of methodological and technical feasibility rather than clinical validity or field readiness. Real-world sensor data may introduce variability, incompleteness, and contextual complexity that are not represented in the present evaluation. Accordingly, further validation with real-world datasets and user-centered deployment remains necessary.

Several limitations remain. Although the present evaluation demonstrates methodological and technical feasibility, it was conducted in controlled experimental settings using synthetic datasets rather than real-world sensor data. In addition, the implementation concentrates on representative blood-pressure-related and heat-related scenarios rather than covering the full spectrum of elderly health conditions. Future work will involve real-world deployment, user-centered validation, direct

requirement elicitation from elderly users and caregivers during field implementation and usability evaluation, and extension of the ontology to additional health domains.

8. Conclusion

This study introduced AALHealthIoT, an ontology-driven semantic framework designed to support clinically grounded cross-domain health-risk inference in Ambient Assisted Living (AAL) environments. The ontology integrates physiological measurements, environmental observations, and personal profile attributes within a unified OWL 2 DL-based model aligned with IoT and semantic interoperability principles. Beyond structural integration, AALHealthIoT explicitly formalizes health-risk semantics and links inferred risk states to structured recommendation entities, thereby supporting recommendation-oriented reasoning in elderly-care contexts.

The proposed ontology comprises 188 classes, 159 object properties, and 30 data properties, providing a structured semantic foundation for representing heterogeneous AAL knowledge. Under controlled synthetic scenarios ranging from 50 to 1,000 seniors (up to 8,000 ontology individuals), the evaluation confirmed that all seven predefined competency questions were successfully addressed through SWRL inference and SPARQL querying, while logical consistency was verified with no unsatisfiable classes. SWRL reasoning remained computationally feasible, with execution times between 1.0 and 1.8 seconds, and SPARQL query latency remained below 1 second. Lightweight structural queries were executed in milliseconds, whereas observation-intensive cross-domain queries demonstrated predictable scaling behavior without combinatorial growth. Memory overhead during reasoning remained nearly constant (0.13–0.14 MB), indicating stable resource utilization as the ontology scaled. These results show that AALHealthIoT supports explainable cross-domain semantic reasoning across heterogeneous AAL data while maintaining practical performance for periodic decision-support workflows in non-real-time environments.

The comparative evaluation further showed that, although existing ontologies and ontology-driven systems provide valuable support for interoperability, monitoring, and patient- or individual-level condition detection, they place less emphasis on explicitly operationalizing clinically grounded health-risk semantics, recommendation-oriented semantic modeling, and systematic ontology-level evaluation within a unified framework. In this respect,

AALHealthIoT contributes not only cross-domain inference capability but also a more explicit semantic representation of health-risk knowledge and recommendations for elderly care.

Despite these findings, the present evaluation was conducted using synthetic datasets under controlled laboratory conditions. Future work will therefore focus on (1) validating the ontology using real-world sensor data collected from smart-home or assisted-living settings, (2) conducting user-centered studies involving elderly participants and caregivers to evaluate explainability and usability, and (3) integrating the ontology into a scalable deployment architecture to assess performance under realistic streaming workloads.

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10. Abbreviations

Abbreviation	Full Term
AAL	Ambient Assisted Living
ADL	Activities of Daily Living
AI	Artificial Intelligence
A-Box	Assertional Box
CQs	Competency Questions
DL	Description Logic
DSRM	Design Science Research Methodology
IoT	Internet of Things
JSON	JavaScript Object Notation
LTC	Long-Term Care
ML	Machine Learning
OOPS!	Ontology Pitfall Scanner!
OWA	Open World Assumption
OWL	Web Ontology Language
QoS	Quality of Service
RDF	Resource Description Framework
SAREF	Smart Applications REFerence
SOSA	Sensor, Observation, Sample, and Actuator
SPARQL	SPARQL Protocol and RDF Query Language
SSN	Semantic Sensor Network
SWRL	Semantic Web Rule Language
T-Box	Terminological Box

11. CRediT Statement

Suksawat Saelim: Conceptualization, Methodology, Software, Investigation, Formal Analysis, Validation, Data Curation, Resources, Writing – Original Draft, Writing – Review & Editing.

Udsanee Pakdeetrakulwong: Conceptualization, Methodology, Software, Investigation, Project Administration, Validation, Writing – Original Draft, Writing – Review & Editing.

Naruapon Suwanwijit: Conceptualization, Investigation, Visualization, Validation, Writing – Original Draft, Writing – Review & Editing.

12. Declaration of Conflict of Interest

The authors declare no conflicts of interest.

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