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# A Semantic Ontology-Driven Architecture for Personalized Health Insurance Assignment in Smart Healthcare Ecosystems

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**Abstract:** The growing complexity of healthcare systems and the surge in demand for personalized patient care have exposed the limitations of traditional insurance models, which remain largely static, reactive, and disconnected from real-time clinical data. This study presents a novel, ontology-driven health insurance framework that leverages semantic reasoning to deliver dynamically adaptive, context-aware insurance policy recommendations based on Electronic Health Records (EHR), health status, and clinical diagnoses. The proposed architecture integrates Internet of Things (IoT) devices, fog computing infrastructure, and cloud-based data repositories within a modular, multi-layered system design. Central to the framework is an OWL-based ontology that formalizes the relationships between patient attributes and policy components, enhanced with Semantic Web Rule Language (SWRL) for inferencing and SPARQL for semantic querying. A prototype implementation was developed using Protégé, Apache Jena, and the Pellet reasoner, and evaluated on five representative patient scenarios. Results demonstrate sub-second policy inference time, high semantic accuracy, and the ability to construct composite insurance packages aligned with individual clinical profiles. This approach not only improves interoperability and policy automation but also supports regulatory traceability and patient-centric service delivery. The findings underscore the potential of semantic technologies to revolutionize value-based insurance systems through intelligent decision-making, real-time policy customization, and scalable integration across heterogeneous healthcare domains.

**Keywords:** SEMANTIC HEALTH INSURANCE; ONTOLOGY-BASED POLICY ASSIGNMENT; CONTEXT-AWARE REASONING; SMART HEALTHCARE SYSTEMS



## 1. Introduction

The increasing demand for equitable, accessible, and cost-effective healthcare has placed immense pressure on global healthcare systems. According to the World Health Organization (WHO), a well-functioning healthcare system must deliver quality services to all individuals, whenever and wherever needed, while protecting them from financial hardship (Organization, 2022). However, despite this imperative, current healthcare insurance models often operate within rigid financial frameworks that overlook the dynamic nature of patient health and personalized needs.

Emerging technologies such as the Internet of Things (IoT), cloud computing, and mobile health are revolutionizing how healthcare services are delivered and consumed. These innovations enable continuous patient monitoring, data-driven insights, and improved communication between stakeholders (Mojeed Dayo Ajegbile et al., 2024). In this evolving context, healthcare insurance must shift from reactive, claim-centric models to proactive, patient-centric systems that support real-time policy adaptation.

Several researchers have proposed smart healthcare architectures that leverage IoT and cloud computing. For instance, Sharmila and Jaisankar (2021) introduced a three-layer architecture involving body area networks (BAN), cloud storage, and user interfaces for real-time health monitoring. Similarly, Chia Chuan et al. (2025) emphasized the role of fog computing as an intermediary layer to reduce latency and improve processing efficiency. Despite these advances, many existing architectures fail to incorporate the broader healthcare ecosystem, including insurance providers, regulatory bodies, and support services, into a unified framework.

Ontology-based approaches have also gained attention for their potential to represent and manage healthcare knowledge semantically. Ontologies enable interoperability and facilitate reasoning over heterogeneous data sources (Croce et al., 2024; Valentini et al., 2023). Standardized medical ontologies such as SNOMED-CT, ICD-10, and FMA provide structured vocabularies for clinical terms, diagnoses, and anatomical data (Ayams et al., 2025). Furthermore, ontologies have been used in personalized decision-support systems to improve chronic disease management (Román-Villarán et al., 2022; Spoladore et al., 2024).

In the context of healthcare insurance, semantic modeling remains underexplored. While Al-Thawadi et al. (2022) proposed a cloud-based recommendation system for insurance plan selection using XML retrieval techniques, it lacked integration with real-time health data and dynamic policy adjustment. More recent works have demonstrated the feasibility of combining semantic rules with wearable data to infer health status and generate personalized interventions (Chatterjee et al., 2023), yet few have extended this to insurance policy management.

This paper bridges this gap by proposing a smart healthcare insurance model grounded in ontology-driven reasoning. The model dynamically assigns customized insurance packages based on patients' electronic health records (EHR), wearable sensor data, and clinical diagnoses. By integrating semantic web technologies—such as SWRL rules and SPARQL queries—with a multi-layer smart healthcare architecture, the system supports adaptive insurance policy generation and reduces administrative burdens.

The main contributions of this study are as follows:

- A holistic smart healthcare architecture integrating technology and healthcare ecosystem partners;
- A novel business model for healthcare insurance that adapts to real-time health data;
- An ontology-driven policy assignment system utilizing SWRL rules and SPARQL queries to automate insurance package recommendations.

The remainder of this paper is organized as follows: Section 2 details the proposed system architecture. Section 3 discusses the ontology design and rule-based reasoning. Section 4 describes the implementation and evaluation, and Section 5 concludes with future research directions.

## 2. System Architecture

Fig. 1 illustrates the system architecture of the proposed Smart Healthcare Insurance Platform. The platform employs a multilayer design to enable dynamic assignment of personalized insurance policies, leveraging three key data inputs: (1) Electronic Health Records (EHRs), (2) real-time physiological monitoring data, and (3) semantically enriched health information. This modular architecture ensures interoperability, scalability, and adaptive policy customization.

The proposed architecture consists of four primary layers:

- Healthcare Cloud Layer
- Network Communication Layer
- Context Management Layer
- Application Layer

Each layer plays a distinct role in enabling real-time policy adaptation, data integration, and personalized insurance services. Figure 1 provides a high-level view of the architecture.

### 2.1 Healthcare cloud layer

This layer serves as the central repository for patient Electronic Health Records (EHRs) and health data streams collected from distributed sources. It leverages secure cloud infrastructure to store, process, and share structured and unstructured data. The cloud layer enables interoperability between healthcare providers, insurance companies, and smart devices by using standardized data exchange protocols and APIs.

The EHR includes the patient's demographic data, medical history, current diagnoses, treatment plans, prescribed devices, and doctor's claims. This data serves as the semantic context for reasoning about insurance coverage.

### 2.2 Network communication layer

This layer handles secure and reliable data transmission between smart healthcare devices, fog nodes, cloud storage, and insurance applications.

It includes: (1) Device-to-Fog: Wearable and implantable devices (e.g., continuous glucose monitors, heart rate sensors) transmit data via WBAN and ambient sensor networks to nearby fog nodes for preprocessing. (2) Fog-to-Cloud: Processed data is uploaded to the healthcare cloud through encrypted and low-latency channels. (3) Cloud-to-Application: Insurance agents and policy systems access data via secure interfaces for real-time decision making.

Standard communication protocols such as HTTPS, MQTT, and RESTful APIs are used to ensure compatibility and security.

### 2.3 Context management layer

This is the core intelligence layer of the architecture and includes four main modules:

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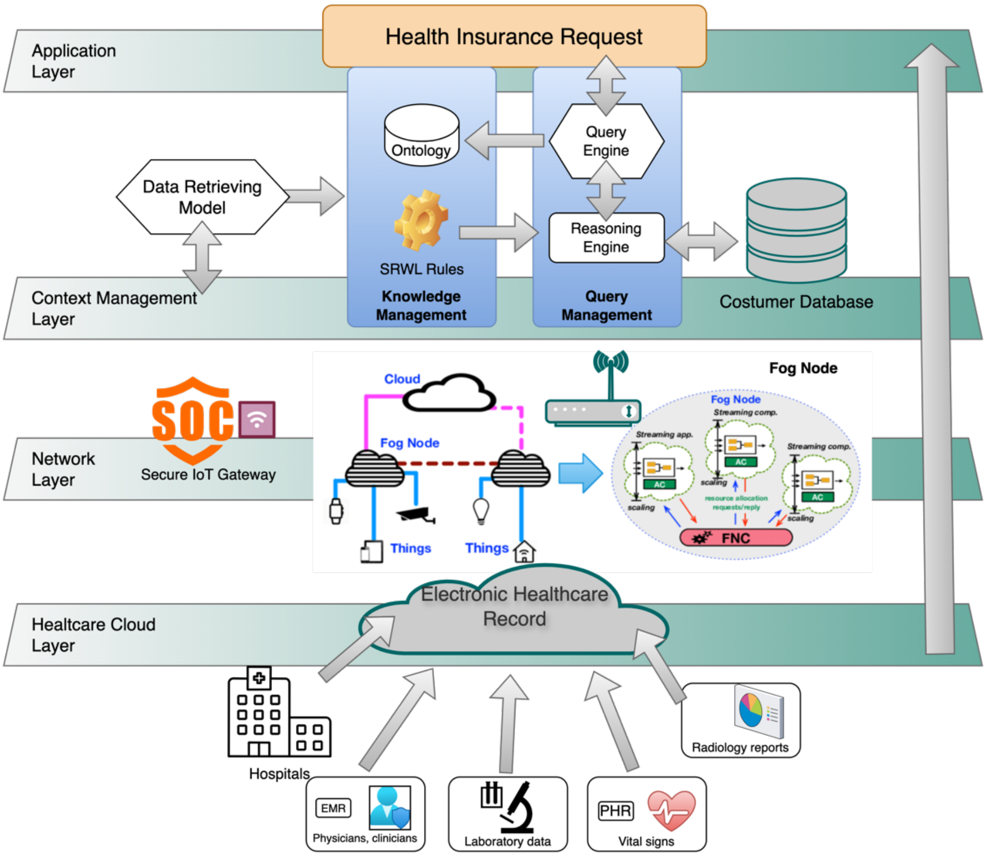


Fig 1. System architecture diagram of the proposed Smart Healthcare Insurance Platform. The multi-layer design integrates Electronic Health Records (EHRs), real-time physiological monitoring, and semantic health data processing to enable dynamic, personalized insurance policy generation. Key components include data acquisition, AI-driven decision-making, and compliance-aware policy delivery.

*a. Query management engine*

Acts as the interface between the application layer and backend services. It receives the patient ID input and initiates data retrieval and reasoning processes.

*b. Data retrieval engine*

Responsible for fetching the relevant EHR attributes and diagnostic indicators from the cloud repository based on the incoming request.

*c. Knowledge management engine*

This module includes an OWL-based ontology, SWRL rules, and an inference engine (Pellet). The ontology models:

- Customer profiles (age, health status, diagnosis)
- Insurance policy classes (basic, lifestyle, chronic condition support)
- Associated treatments and device requirements

SWRL rules encode medical and insurance logic to infer the most appropriate policy packages, and SPARQL queries extract actionable insights.

*d. Customer database*

A local warehouse that stores policy history, configurations, and the mapping between EHR inputs and generated insurance outputs. This layer ensures synchronization between the inferred results and actual policy updates.

### 2.4 Application layer

The topmost layer provides an interface for insurance agents and healthcare providers. It enables:

- Real-time policy assignment: Based on newly uploaded EHRs or doctor claims.
- Policy updating: Automatically adapts insurance coverage as the patient's health status changes.
- Device configuration management: Coordinates the logistics of IoT-based healthcare devices to support treatment.

This layer supports user-friendly web and mobile applications to interact with the backend system, retrieve results, and view the insurance decision rationale.

### 2.5 Workflow summary

The workflow of the proposed smart healthcare insurance system is designed to enable dynamic and automated policy assignment based on patient-specific clinical contexts. The system actively processes health data, applies semantic reasoning, and reconfigures insurance policies to match evolving health profiles. The steps below describe the operational workflow in detail:

*a. Customer initiation*

The process begins when a customer submits a request for health insurance coverage. This request may originate from a new enrollee or an existing policyholder undergoing health status changes.

*b. Agent input and patient identification*

The insurance agent actively inputs the customer's unique identifier into the system interface. This identifier serves as the primary key to retrieve the patient's Electronic Health Record (EHR).

*c. Health data retrieval*

Upon receiving the input, the system initiates a secure query to the healthcare cloud infrastructure. It retrieves structured EHR data, which includes demographic attributes, current diagnoses, prescribed treatments, and relevant technological requirements.

*d. Semantic reasoning and policy inference*

The context management engine activates a semantic inference pipeline. It utilizes an OWL-based ontology, embedded SWRL (Semantic Web Rule Language) rules, and a DL (Description Logic)-compliant reasoner to evaluate the patient's health status. The reasoning engine identifies the most appropriate insurance policy class—such as basic, lifestyle management, or chronic disease support—and selects relevant service packages tailored to the individual's needs.

*e. Policy assignment and synchronization*

Once inferred, the system automatically updates the customer's insurance profile in the internal policy database. Simultaneously, it synchronizes this update with the central healthcare repository to ensure data consistency across organizational boundaries.

*f. Device configuration and service orchestration*

If the assigned policy includes health monitoring devices (e.g., wearable glucose sensors or motion detectors), the system coordinates with the device provisioning unit. It schedules delivery, installation, and remote configuration, ensuring timely deployment of patient-specific support services.

By integrating real-time health data with semantic knowledge representation and automated reasoning, the proposed system empowers insurers to deliver precise, adaptive, and cost-effective policy solutions. This end-to-end automation reduces administrative burden, minimizes claim disputes, and promotes proactive health management through continuous policy alignment with clinical needs as can be seen in Fig. 2.

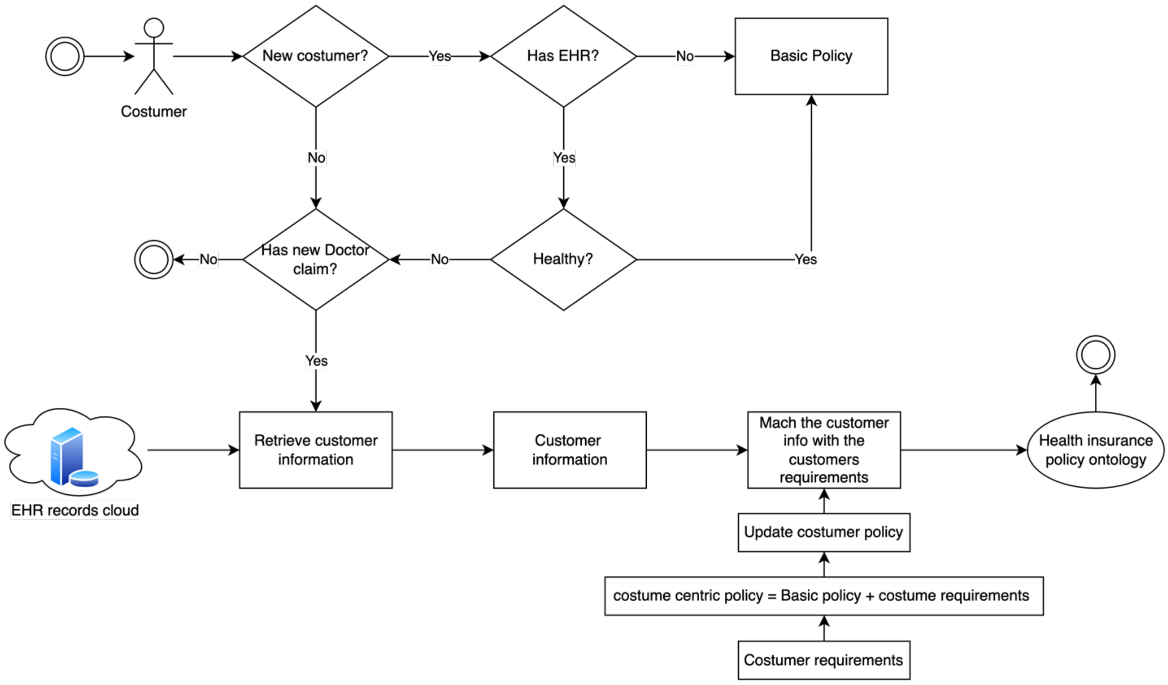


Fig 2. Workflow diagram of smart insurance assignment

## 3. Ontology-Based Insurance Modeling

The core innovation of the proposed smart healthcare insurance system lies in its ontology-driven decision framework, which enables semantic representation and automated reasoning over complex patient profiles and insurance requirements. By leveraging ontological models, the system achieves interoperability, reusability, and context-awareness—critical features for dynamic healthcare environments.

### 3.1 Ontology design

We developed a domain-specific ontology that formalizes the relationship between patient attributes, health status, age groups, diagnosed conditions, and corresponding insurance policy packages. The ontology is constructed using OWL (Web Ontology Language) and implemented in the Protégé environment. It comprises two primary high-level classes: `Customer` and `InsurancePolicy`, along with supporting subclasses that define policy types and treatment packages.

*a. Key Ontology Classes*

The core structure of the proposed ontology comprises several key classes designed to capture the semantic relationships between patient characteristics and insurance policies. The `customer` class represents the insurance applicant and includes essential attributes such as age, health status, and diagnosed condition. The `InsurancePolicy` class serves as a parent category for three specialized subclasses: `BasicPolicy`, which is designated for healthy individuals and further categorized into `ChildBasicPolicy`, `AdultBasicPolicy`, and `ElderlyBasicPolicy`;`LifestyleManagement Policy`, which addresses individuals at risk or in a pre-disease state requiring preventive interventions and monitoring; and `SelfManagementPolicy`, which supports patients with chronic conditions needing long-term care and technological assistance. Complementing these, the `SupportPackage` class encapsulates IoT-based and non-pharmacological treatment options, such as glucose monitors, activity trackers, and dietary coaching, while the `DeviceRequirement` class specifies the technical parameters of devices necessary for implementing patient-specific interventions. These classes are interconnected to form a semantic framework that enables context-aware reasoning, as depicted in Fig. 3.

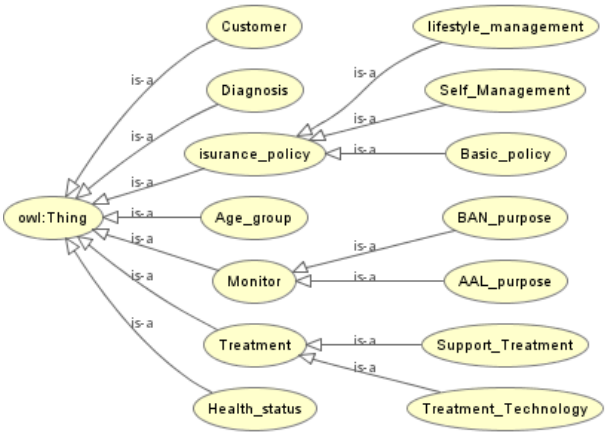


Fig 3. Ontology class hierarchy diagram

### 3.2 Rule-based policy assignment

To infer appropriate insurance policies based on attributes derived from electronic health records (EHR), the system utilizes domain-specific rules written in Semantic Web Rule Language (SWRL), executed through the Pellet reasoner for consistency checking and rule evaluation. For instance, if a customer is 18 years old or younger and in a healthy condition, the system assigns a ChildBasicPolicy. Similarly, individuals between the ages of 19 and 45 who are also healthy are matched with an AdultBasicPolicy. In cases where the customer is aged between 30 and 60, has a health status indicating the need for follow-up, and is diagnosed with borderline diabetes, the system assigns an AdultActivityMonitorPackage along with a DietManagementAppPackage to support preventive care. For customers over 70 years old diagnosed with Type 1 Diabetes, the system recommends both an ElderlyInsulinPumpPackage and an ElderlyMotionMonitoringPackage to ensure continuous disease management. These rules allow the system to generate personalized insurance policy configurations tailored to individual health profiles and clinical needs.

### 3.3 SPARQL query engine

Once the SWRL rules are applied and new class assertions are inferred within the ontology, the system utilizes SPARQL queries to dynamically retrieve the updated insurance policy details associated with a specific customer. This querying process allows for efficient access to inferred knowledge by extracting relevant policy classes and support packages based on the customer's profile and health conditions. For instance, a typical SPARQL query such as `DESCRIBE Customer:patient_001` retrieves all relevant semantic information for the identified customer. This mechanism enables seamless integration with external systems, including policy management platforms, mobile applications, and healthcare provider interfaces, thus ensuring real-time, personalized insurance service delivery.

### 3.4 Ontology validation and consistency

To rigorously validate the ontology model, we employed the Pellet reasoner to systematically verify logical consistency across all defined classes, object properties, and SWRL-based inference rules. This consistency checking ensures the structural soundness and semantic correctness of the ontology. Furthermore, we conducted extensive scenario-based testing, wherein representative patient profiles were simulated to evaluate the accuracy and reliability of the automated policy assignment mechanism. The observed outcomes demonstrated a high degree of alignment with established clinical guidelines and domain-specific insurance practices. Importantly, the ontology is designed with modular extensibility, enabling seamless integration of additional healthcare dimensions such as genetic risk factors, social determinants of health, and actuarial models for cost optimization—thereby ensuring scalability and adaptability to evolving healthcare informatics requirements.

## 4. System Implementation and Evaluation

To validate the proposed ontology-based smart healthcare insurance framework, a prototype system was implemented and tested using representative patient scenarios. The primary objective was to demonstrate the feasibility of automated, rule-based insurance policy assignment that is responsive to patient health profiles and clinical needs.

### 4.1 System architecture and development tools

The system prototype was implemented using a multi-layered architecture, as described in Section 3. The key components and tools used are summarized below:

- Ontology Editor: Protégé 5.5 was employed for ontology design and management, including the

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definition of classes, properties, individuals, and rule sets.

- Reasoning Engine: Pellet (Incremental Mode) was integrated as the OWL reasoner to perform consistency checking and infer new class memberships based on SWRL rules.
- Rule Language: SWRL (Semantic Web Rule Language) was used to express decision logic linking patient conditions to insurance policies.
- Query Engine: Apache Jena's SPARQL engine was used to extract inferred policy results from the ontology.
- User Interface: A minimal user interface was developed to simulate the role of an insurance agent submitting a customer ID and receiving an assigned policy.

### 4.2 Implementation scenario and datasets

To assess the functionality of the system, five anonymized patient scenarios were constructed. Each scenario simulates a customer submitting an insurance request. The system processes the patient's Electronic Health Record (EHR) and applies semantic reasoning to assign a suitable policy. Table 1 summarizes the test scenarios.

Each record includes structured attributes such as `age`, `healthStatus`, and `diagnosedCondition`, all of which are modeled as object and data properties in the ontology.

Table 1. Test scenarios for system evaluation.

| CASE | AGE | HEALTH STATUS | DIAGNOSIS | EXPECTED POLICY ASSIGNMENT |
|---|---|---|---|---|
| (1) | 6 | Healthy | None | Child Basic Policy |
| (2) | 30 | Healthy | None | Adult Basic Policy |
| (3) | 66 | Healthy | None | Elderly Basic Policy |
| (4) | 44 | Need Follow-up | Borderline Diabetes | Adult Lifestyle Management |
| (5) | 70 | Unhealthy | Diabetes Type 1 | Elderly Self-Management |

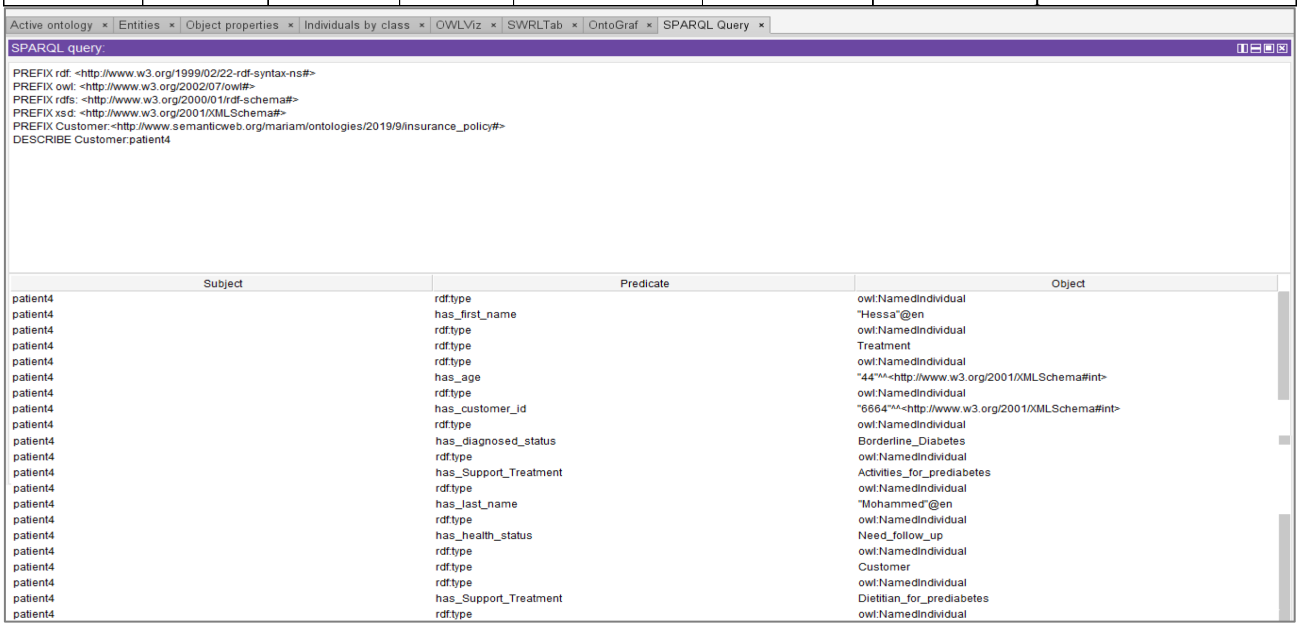
### 4.3 Reasoning and rule execution

Upon receiving the patient ID input, the system initiates a semantic reasoning process by retrieving the patient's Electronic Health Record (EHR) from the integrated healthcare cloud repository. The structured data—comprising attributes such as age, health status, and diagnosed condition—is then evaluated against a predefined set of Semantic Web Rule Language (SWRL) rules within the ontology-based framework described in Section 3.2.

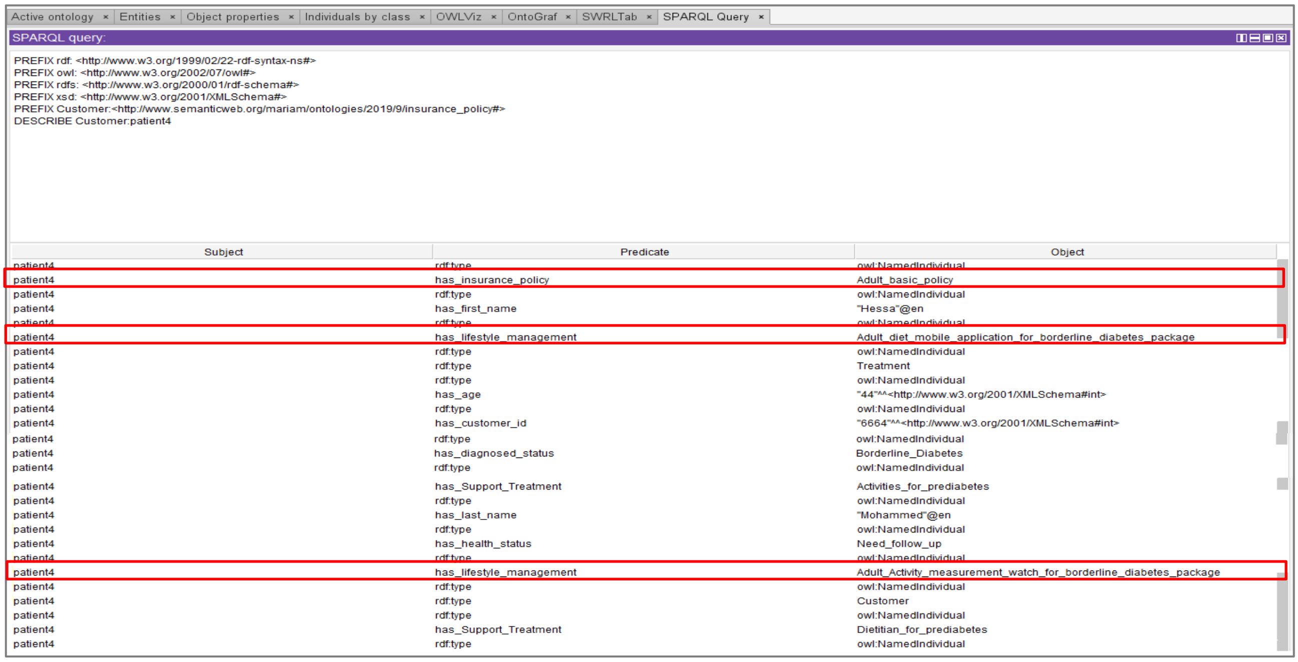
The Pellet reasoner, integrated with the OWL ontology, performs description logic-based inference to classify the patient into the `appropriate InsurancePolicy` subclass. This process results in the dynamic generation of individualized insurance coverage recommendations based on both demographic and clinical determinants.

Fig. 4 illustrates the inference mechanism in which SWRL rules are activated to derive a tailored insurance policy. The reasoning engine not only matches patient profiles to predefined policy packages but also supports composite policy creation through rule chaining and object property inference.

| PATIENT ID | FIRST NAME | LAST NAME | AGE | HEALTH STATUS | DIAGNOSIS | EXPECTED POLICY ASSIGNMENT |
|---|---|---|---|---|---|---|
| 6577 | Jamre | Husain | 44 | Need Follow-up | Borderline Diabetes | - Activities for prediabetes<br>- Dietitian for prediabetes |




(a)




(b)

Fig 4. Case 4 record (a) before and (b) after applying the SWRL rules

As you can see in for example, in Case 4, involving a 44-year-old adult diagnosed with borderline diabetes and categorized under the "Need Follow-up" health status, the reasoning system inferred a composite policy package consisting of:

- Adult Basic Policy
- Activity Monitor Package for Prediabetes
- Diet Management Application for Prediabetes

This inference is based on conditional logic encoded in SWRL, which matches the combination of age range, diagnosed condition, and health risk indicators to relevant insurance components. The inclusion of both monitoring and lifestyle intervention packages reflects a preventive and proactive insurance strategy aligned with personalized healthcare objectives.

The ability to generate such multi-component policies showcases the expressive power of ontology-driven systems and highlights their applicability in modeling complex, context-sensitive relationships within the domain of smart health insurance. Moreover, this semantic reasoning approach enhances transparency and traceability in decision-making, which are critical for regulatory compliance, auditability, and clinical trust.

### 4.4 SPARQL-based retrieval

After reasoning is completed, SPARQL queries are used to extract the final policy for each individual. The query engine retrieves relevant has_insurance_policy and has_lifestyle_management relationships for the customer node.

A sample SPARQL query to retrieve the assigned policies is shown below:

```
PREFIX rdf:
<http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX ins:
<http://www.example.org/insurance#>
DESCRIBE ins:Customer_6664
```

The query returns a structured RDF graph containing the assigned policy classes and associated devices.

### 4.5 Evaluation results and observations

To assess the operational validity and functional performance of the proposed ontology-driven smart insurance policy system, we conducted a series of controlled test scenarios. Each test case was designed around a synthetic patient profile that varied across key attributes including age, health status, and diagnosed medical conditions. The primary evaluation criteria encompassed: (i) accuracy of insurance policy assignment, (ii) execution latency of the semantic reasoning engine, and (iii) semantic consistency and clinical plausibility of the inferred insurance packages.

The system demonstrated robust performance across all five scenarios, with each case resulting in a correctly inferred insurance policy configuration aligned with clinical expectations and business logic. Policy assignment was driven by SWRL-based reasoning over the ontology, utilizing the Pellet reasoner. Average inference time per case was consistently below one second, suggesting that the system is suitable for real-time applications in operational healthcare insurance workflows.

Table 1 summarizes the test cases, detailing the demographic and clinical characteristics of each patient, the resulting policy components assigned, and the reasoning performance metrics.

Table 2. Test scenarios for system evaluation.

| CASE | AGE | HEALTH STATUS | DIAGNOSIS | ASSIGNED POLICY COMPONENTS | REASONING TIME |
|---|---|---|---|---|---|
| (1) | 6 | Healthy | None | Child Basic Policy | < 1s |
| (2) | 30 | Healthy | None | Adult Basic Policy | < 1s |
| (3) | 66 | Healthy | None | Elderly Basic Policy | < 1s |
| (4) | 44 | Need Follow-up | Borderline Diabetes | Adult Basic + Activity Monitor + Diet Management Package | < 1s |
| (5) | 70 | Unhealthy | Diabetes Type 1 | Elderly Basic + Insulin Pump + Motion Sensor Package | < 1s |

These empirical findings offer several key insights:

*a. Semantic modularity and flexibility*

The ontology supports a compositional approach to insurance policy construction. Depending on the patient's EHR data and diagnosed conditions, the system can dynamically assemble compound policy packages without manual intervention, thereby reducing the risk of under- or over-coverage.

*b. Transparency and explainability*

The use of SWRL rules ensures that policy inference is not a "black box" operation. Each decision pathway is fully traceable, and the provenance of each inferred policy component can be audited, satisfying explainability requirements for clinical and regulatory contexts.

*c. Data dependency and quality constraints*

Evaluation confirms that accurate policy inference hinges upon the semantic completeness and consistency of EHR data. Standardized coding practices and interoperability across healthcare information systems are vital to realize the full potential of the proposed framework.

*d. Interoperability and standard alignment*

By leveraging existing ontologies such as SNOMED CT, ICNP, and FOAF, the system ensures semantic interoperability with broader healthcare and insurance ecosystems. This design facilitates future integration with clinical decision support systems and federated data sources.

*e. Scalability outlook*

Although the present prototype is limited in scope, the underlying architecture is designed to be extensible. With proper optimization, the system can support a larger knowledge base covering a wider spectrum of diseases, treatment modalities, and insurance variants.

In summary, the evaluation validates the capability of the system to deliver automated, personalized, and adaptive healthcare insurance recommendations in a manner that is both semantically rigorous and clinically grounded.

## 5. Discussion and Future Work

This study introduced a semantic, ontology-driven framework for dynamic healthcare insurance policy assignment, leveraging context-aware reasoning based on electronic health records and real-time health data. The evaluation results from the prototype implementation demonstrate the technical feasibility, semantic robustness, and practical relevance of such an approach in modern healthcare informatics.

### 5.1 Theoretical implications

From a theoretical standpoint, this work contributes to the growing body of literature on semantic healthcare modeling, expanding it into the relatively underexplored domain of insurance informatics. Unlike traditional business rule engines or static classification schemes, the use of Web Ontology Language (OWL) and SWRL enables not only high-level abstraction but also machine-interpretable logic that can adapt to the continuous evolution of patient profiles.

Moreover, the layered system architecture bridges the data-driven intelligence of healthcare IoT with the policy-based governance of insurance administration. This convergence reflects a paradigm shift from actuarial models based solely on population risk pools toward individualized, value-based insurance planning. It lays a conceptual foundation for future work on self-learning insurance systems that co-evolve with patient wellness trajectories.

### 5.2 Practical contributions

The proposed system provides a blueprint for integrating real-time health monitoring, policy automation, and personalized service delivery into a unified framework. Key benefits include:

1. Proactive Care Enablement: By automatically aligning insurance coverage with current health status, the system enables insurers to incentivize preventive interventions and reduce long-term healthcare costs.
2. Operational Efficiency: Rule-based automation reduces manual claims processing, administrative overhead, and policy dispute resolution, improving system throughput and consistency.
3. Patient-Centered Design: Individuals receive tailored policy packages, which may include device subscriptions, lifestyle management tools, and chronic disease support based on actual needs rather than generic tiers.

These capabilities align well with global movements toward value-based healthcare and digital transformation in insurance services, including initiatives under the WHO's Universal Health Coverage (UHC) agenda.

### 5.3 Limitations

Despite promising results, this study has several limitations that warrant consideration:

- Prototype Scope: The current implementation includes a limited ontology size, rule set, and patient cases. Real-world deployment would require significant expansion and integration with national/international medical standards and policy libraries.
- Static Rulebase: Although SWRL supports expressive reasoning, it is inherently static. Adapting to emerging diseases, evolving policy guidelines, or rare edge cases may require dynamic rule learning or integration with AI/ML-based inference mechanisms.
- Data Quality Dependency: The effectiveness of policy assignment heavily depends on the quality, granularity, and semantic richness of input EHR data. Data heterogeneity and interoperability challenges in multi-institutional settings remain non-trivial.

Security and Privacy Concerns: The system deals with highly sensitive patient and insurance data. Ensuring compliance with data protection regulations (e.g., HIPAA, GDPR) and implementing fine-grained access controls will be critical for real-world deployment.

### 5.4 Future work

To address these limitations and further enhance the system's capabilities, several avenues for future research are identified:

- Integration with Machine Learning: Future versions can incorporate ML algorithms to learn policy optimization patterns from historical insurance claims and adjust SWRL rules dynamically based on predictive modeling.
- Expanding Ontology Coverage: Broader incorporation of external ontologies such as HL7 FHIR, UMLS, and ICD-11 will enhance interoperability and improve reasoning scope for diverse clinical domains.
- Explainable AI and Rule Transparency: Combining semantic reasoning with explainable AI models will improve user trust and facilitate clearer communication of policy decisions to end-users and regulators.
- Federated Deployment Architecture: Developing a distributed, federated version of the system could support cross-institutional deployments without centralizing sensitive patient data—aligning with privacy-preserving computation trends.
- Smart Contract Integration: Future iterations may incorporate blockchain-based smart contracts for automated policy enforcement, fraud detection, and decentralized claims management.

By aligning emerging health technologies with semantic computing, this work provides a scalable and intelligent pathway toward next-generation health insurance systems—ones that are not only responsive to patient needs but also adaptable to the broader dynamics of healthcare delivery in the digital age.

## 5. Conclusion

This paper presented an ontology-driven framework for smart healthcare insurance policy assignment, addressing the growing need for personalized, context-aware, and dynamically adaptive insurance models in the era of digital health. By integrating semantic web technologies—including OWL ontologies, SWRL rules, and SPARQL queries—with a multi-layered smart healthcare architecture, the system demonstrates how policy decisions can be automated, explainable, and responsive to real-time patient data.

The key contributions of this research include: (i) a modular system architecture that connects EHRs, IoT-enabled health monitoring, and insurance policy logic; (ii) an extensible ontology that models patient profiles and insurance policy types; and (iii) a rule-based reasoning engine capable of inferring tailored insurance packages based on clinical and demographic parameters.

Prototype implementation and scenario-based evaluations confirm the system's ability to deliver accurate, explainable, and efficient insurance recommendations aligned with individual health profiles. The reasoning engine performed with sub-second latency, enabling real-time decision support, while maintaining semantic consistency across diverse patient contexts.

Ultimately, this study advances the state of the art in healthcare insurance informatics by shifting from static, reactive policy models toward intelligent, proactive systems. The framework sets a foundation for future developments in AI-assisted health insurance, semantic interoperability, and value-based care delivery.

Further research will explore the integration of machine learning for adaptive rule generation, expansion of the ontology to cover a broader spectrum of medical and policy concepts, and deployment in real-world insurance ecosystems at scale.

## Authors' Contributions

The authors collaboratively contributed to the conception, design, and execution of this research. Adiyah Mahiruna led the theoretical formulation of the ontology-driven insurance framework, designed the semantic architecture, and was responsible for developing the core ontology model using OWL and SWRL. Devin L. Revilla implemented the reasoning engine, integrated SPARQL-based querying, and conducted the evaluation scenarios, ensuring technical robustness and system validation. Nenita I. Prado conducted a comprehensive review of existing literature, contributed to the development of the use-case model and policy scenarios, and contextualized the system within current healthcare insurance practices. All authors jointly contributed to the manuscript's writing, critically revised its content for scientific accuracy and coherence, and approved the final version for submission.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## Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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