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

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Abstract: Traditional health insurance models are often static, reactive, and poorly aligned with the dynamic and personalized nature of patient health data. These limitations are increasingly evident in modern healthcare ecosystems that demand real-time, context-aware services. Addressing this gap, this study proposes a novel semantic, ontology-driven architecture for personalized health insurance assignment, designed to adapt dynamically to electronic health records (EHR), clinical diagnoses, and real-time physiological data. Unlike prior systems that lack semantic reasoning or integration with heterogeneous data sources, the proposed framework integrates OWL-based ontologies, Semantic Web Rule Language (SWRL), and SPARQL querying into a multi-layered architecture involving IoT devices, fog computing, and cloud services. A key innovation lies in its ability to infer and assign composite insurance policies based on patient-specific conditions, supporting personalized, adaptive, and explainable decision-making. A prototype system was implemented using Protégé, Apache Jena, and the Pellet reasoner, and tested on five representative patient scenarios. Evaluation results demonstrate sub-second reasoning latency, high semantic accuracy, and robust policy alignment with clinical profiles. This framework advances value-based health insurance by enabling real-time policy automation, enhanced transparency, and scalable integration across smart healthcare domains. These results suggest that the system can support scalable integration into national health insurance platforms and improve patient-centered policy delivery.

Keywords: SEMANTIC INSURANCE ARCHITECTURE; ONTOLOGY-DRIVEN REASONING; PERSONALIZED POLICY ASSIGNMENT; SMART HEALTHCARE SYSTEMS; EHR INTEGRATION

1. Introduction

The increasing demand for equitable, accessible, and cost-effective healthcare services has placed unprecedented pressure on global healthcare systems. According to the World Health Organization (WHO), an effective healthcare system must deliver quality care at any time and location while safeguarding patients from financial risks (WHO, 2022). However, most existing health insurance models remain rigid, reactive, and ill-equipped to accommodate the personalized and dynamic nature of modern patient care.

In recent years, health informatics has shifted from passive data storage to intelligent, context-aware systems capable of driving autonomous decisions. The rise of digital health technologies such as the Internet of Things (IoT), mobile health platforms, and cloud computing has transformed how healthcare is delivered and consumed. These innovations enable continuous patient monitoring, improved clinical decision-making, and enhanced coordination between stakeholders (Mojeed et al., 2024). As healthcare data becomes increasingly rich and real-time, insurance systems must evolve from claim-centric models to proactive, patient-specific approaches that adapt to individual needs in real time.

Several prior studies have proposed smart healthcare architectures leveraging cloud, fog computing, and sensor technologies (Chia Chuan et al., 2025; Sharmila & Jaisankar, 2021). However, many of these frameworks fall short in integrating the broader healthcare ecosystem, particularly the insurance sector, into an intelligent, unified infrastructure. Moreover, while semantic technologies have been applied to medical knowledge representation and clinical decision support (Croce et al., 2024; Valentini et al., 2023), their application in dynamic health insurance modeling remains largely underexplored. Additionally, few studies have examined how these technologies can support the operational needs of insurance providers, such as fraud detection, policy customization, and patient-centric reimbursement systems.

This study addresses this gap by proposing a semantic, ontology-driven framework for personalized health insurance policy assignment. Unlike previous approaches that rely on static rules or limited personalization, the proposed system dynamically matches patient-specific attributes such as age, health status, and clinical diagnoses with customized policy components using formal ontologies and semantic reasoning.

This research also aspires to inform future implementations of adaptive insurance systems that go beyond static risk classification, enabling fairer, data-driven policy generation in emerging economies. The main objectives of this study are:

- To design a multi-layered smart healthcare architecture that connects EHRs, IoT devices, and insurance logic;
- To develop a domain-specific OWL ontology enriched with SWRL rules and SPARQL queries for automated policy assignment;
- To implement and evaluate the proposed system using representative patient profiles and performance metrics.

The key scientific contributions of this work include:

- A novel integration of semantic web technologies with real-time healthcare data for intelligent insurance decision-making;
- A reusable and scalable ontology-based framework for dynamic insurance policy generation;
- An end-to-end architecture enabling transparency, explainability, and personalization in smart insurance ecosystems.

The remainder of this paper is organized as follows: Section 2 describes the proposed system architecture, Section 3 outlines the ontology design and reasoning mechanism, Section 4 presents the implementation and evaluation results, and Section 5 discusses key findings, limitations, and directions for future research.

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.

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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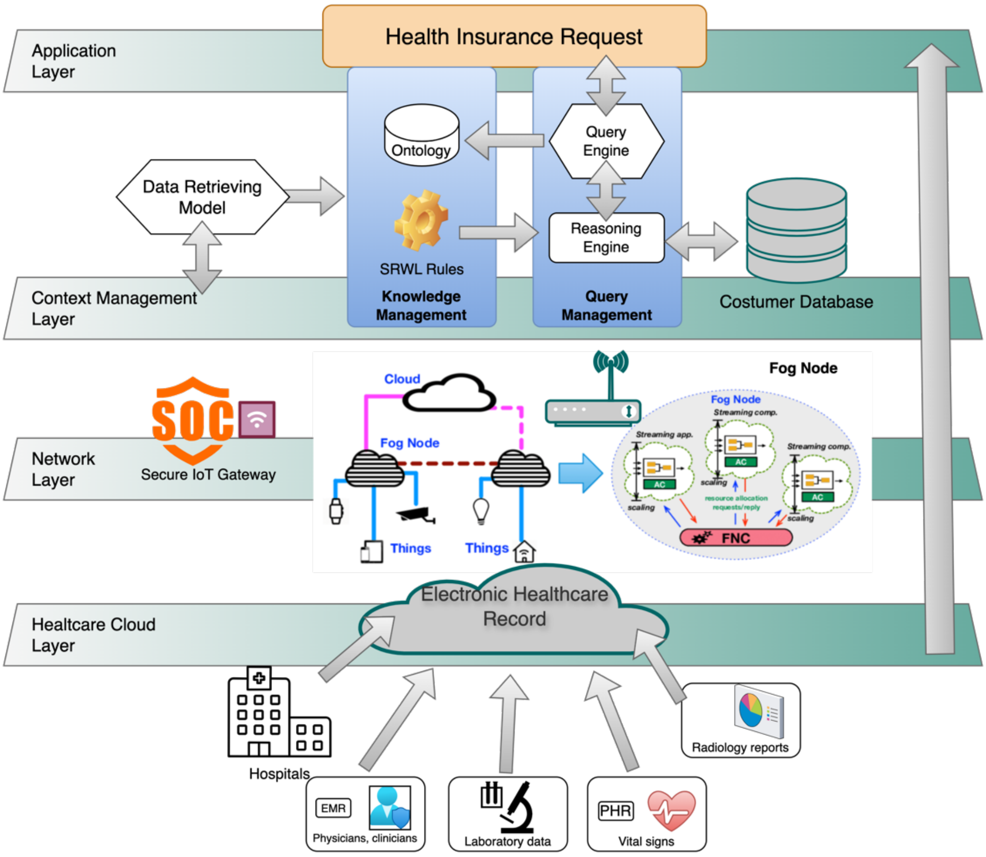


Fig 1. System architecture diagram of the proposed Smart Healthcare Insurance Platform. The multi-layer design integrates Electronic Health Records (EHRs), real-time physiological monitoring, and semantic health data processing to enable dynamic, personalized insurance policy generation. Key components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

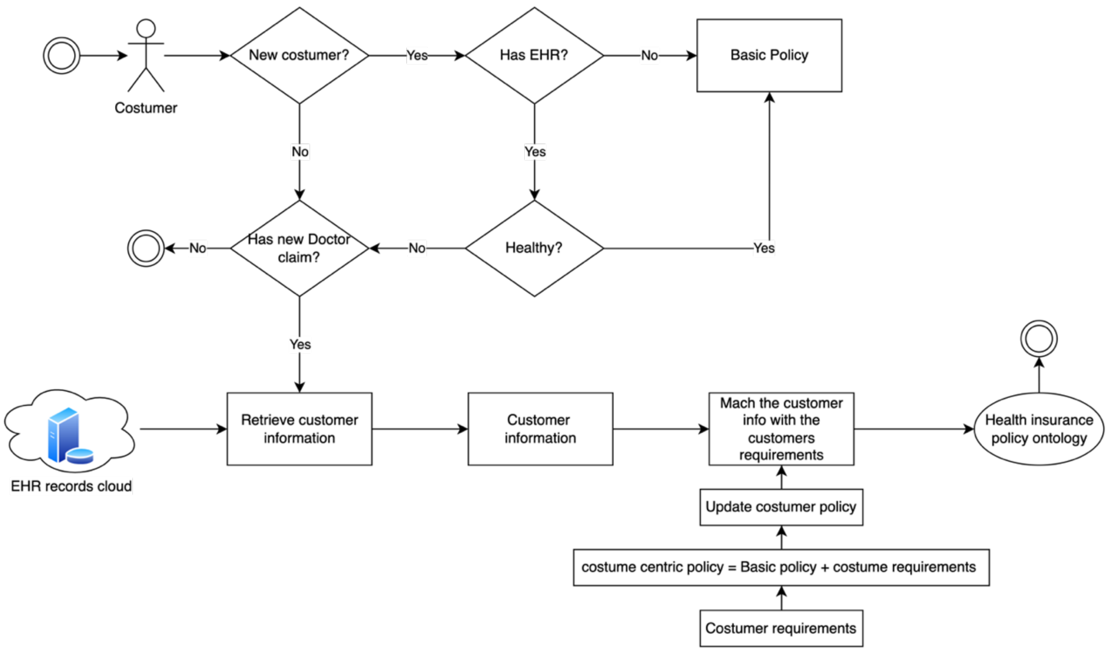


Fig 2. Workflow diagram of smart insurance assignment.

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.

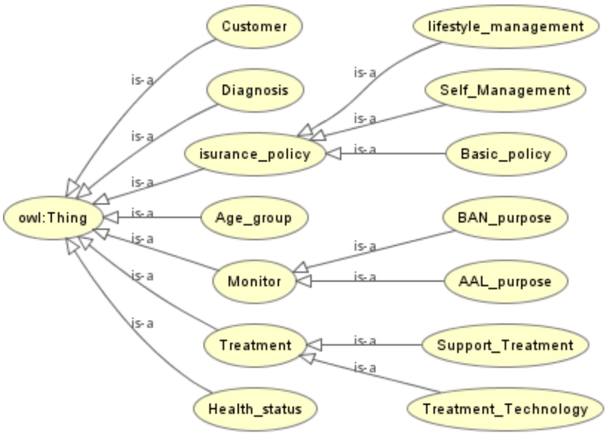


Fig 3. Ontology class hierarchy diagram.

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 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

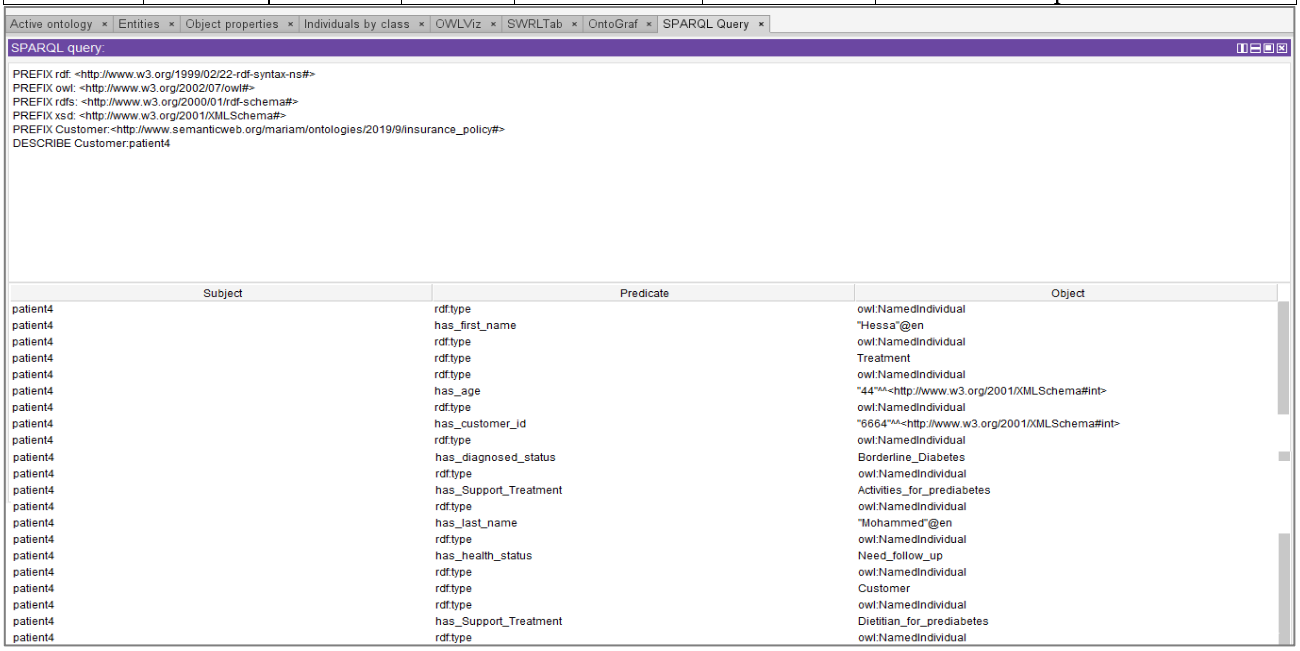
4.3 Reasoning and rule execution

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.

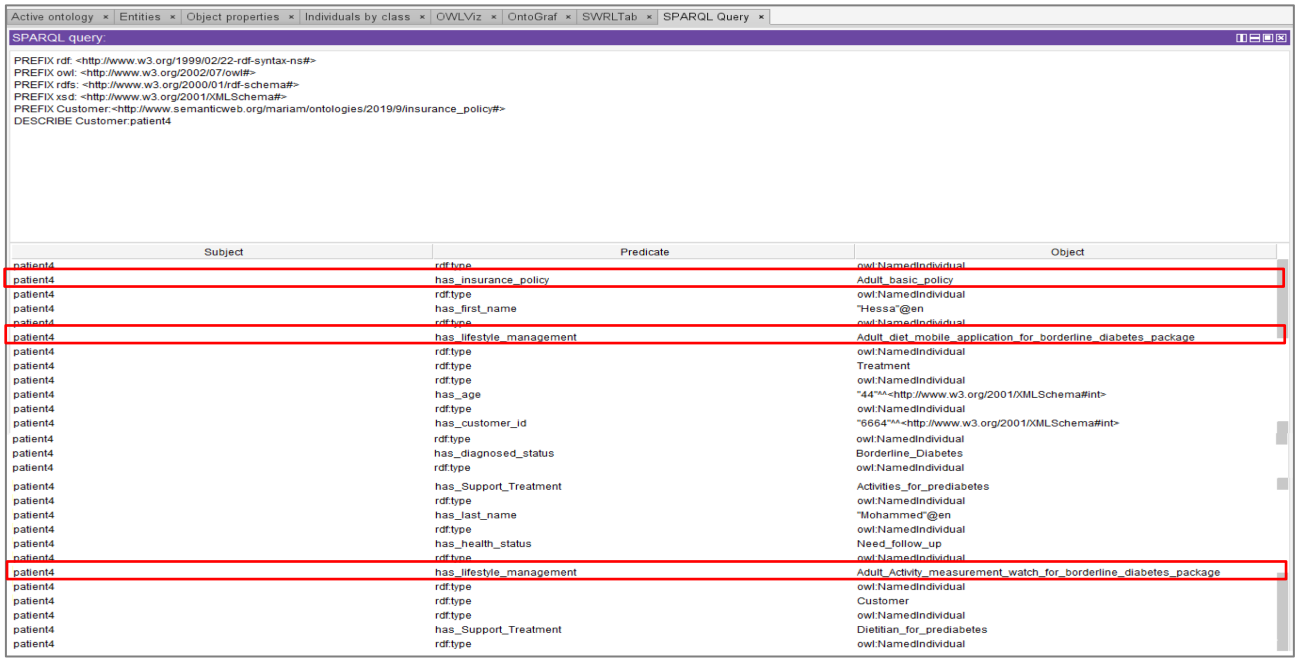
The Pellet reasoner, integrated with the OWL ontology, performs description logic-based inference to classify the patient into the `appropriate InsurancePolicy` subclass. This process results in the dynamic generation of individualized insurance coverage recommendations based on both demographic and 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 • 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 2 summarizes the test cases, detailing the demographic and clinical characteristics of each patient, the resulting policy components assigned, and the reasoning performance metrics.

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.

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

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:

- 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.
- Operational Efficiency: Rule-based automation reduces manual claims processing, administrative overhead, and policy dispute resolution, improving system throughput and consistency.
- 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 study proposed a semantic, ontology-driven framework for personalized health insurance assignment in smart healthcare ecosystems. By integrating OWL-based ontologies, SWRL reasoning, and SPARQL querying within a multi-layered system architecture, the framework enables dynamic policy generation based on electronic health records, real-time monitoring data, and clinical conditions.

Prototype implementation and scenario-based evaluations demonstrated that the system can deliver accurate, explainable, and timely insurance policy recommendations. The reasoning engine achieved sub-second inference times while maintaining semantic consistency and alignment with patient-specific needs. These findings confirm the feasibility and practical utility of semantic technologies to automate insurance decision-making in complex healthcare environments.

The key contributions of this research include: (i) a modular and extensible architecture that supports adaptive policy generation; (ii) a domain-specific ontology that captures insurance logic in a reusable format; and (iii) a transparent reasoning mechanism that enhances explainability and trust.

Future work will focus on expanding the ontology to cover broader insurance categories, incorporating machine learning for adaptive rule generation, and deploying the system in real-world healthcare insurance settings. Additional research is also needed to address data heterogeneity, ensure privacy compliance, and evaluate scalability in large-scale deployments.

Author 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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