A Fuzzy Decision Support System with Semantic Knowledge Graph for Personalized Asthma Monitoring: A Conceptual Modeling

Ayan Chatterjee[a]

Dept. of Digital Technology, STIFTELSEN NILU, 2007 Kjeller, Norway

Keywords: Fuzzy Ontology, Decision Support System, Asthma Monitoring, Knowledge Representation.

Abstract: Asthma, a complex chronic respiratory condition, poses significant management challenges, necessitating personalized monitoring for optimal treatment outcomes and individual well-being. This study introduces a Fuzzy Decision Support System (FDSS) for personalized asthma monitoring, leveraging semantic reasoning techniques and SPARQL querying to enhance decision-making accuracy and provide individualized assessments of asthma control and exacerbation risk. By utilizing semantic reasoning, the FDSS captures intricate relationships among asthma parameters, health data, triggers, and treatment outcomes, enabling precise management decisions. Development involves creating an ontology to encapsulate asthma domain knowledge, representing fuzzy logic, integrating crisp and fuzzy clinical variables, and executing SPARQL queries for fuzzy inference. The proposed FDSS demonstrates the feasibility of integrating these techniques for personalized asthma management, offering flexibility and adaptability to improve treatment outcomes and quality of life. Further research is needed to validate its efficacy in real-world healthcare settings.

1 INTRODUCTION

Asthma is a significant global health issue, prevalent across all ages, particularly affecting children (WHO, 2019). This chronic lung disease causes airway inflammation and hyper-responsiveness, leading to wheezing, breathlessness, chest tightness, and coughing (Gibson, 2000). Effective asthma management requires regular symptom tracking, lung function assessment, trigger identification, and therapeutic adjustments (Kang, 2024). In 2019, asthma affected 262 million people worldwide, resulting in 455,000 deaths (WHO, 2019). In the U.S., over 25 million individuals have asthma, including more than 5 million children (Cleveland Clinic, 2023). Proper monitoring can control symptoms and allow individuals to lead active lives, while avoiding triggers is crucial for symptom relief (WHO, 2019). The high asthma mortality in lower-income nations underscores the need for better diagnostic and treatment strategies. The World Health Organization aims to reduce the burden of asthma and progress towards universal health coverage. Asthma is classified into allergic and non-allergic types, triggered by factors such as allergens, air pollution, weather conditions, tobacco smoke, and food allergens (Ajami, 2022). Symptoms vary widely in frequency and severity, with each individual reacting differently. Traditional asthma monitoring methods often use simplistic decision systems and static protocols, failing to account for the disease's complexity. These methods typically categorize patients as controlled or uncontrolled based on fixed criteria for symptom severity, lung function, or medication use, which can lead to suboptimal management (Pinnock, 2015). There is a pressing need for advanced decision support systems that integrate variability among patients, environmental factors, and treatment nuances. A promising approach is combining logic, semantics, reasoning, rules, and querying to create a robust framework for personalized asthma care. Semantic reasoning can capture and interpret complex relationships between asthma types, symptoms, triggers, and treatment outcomes, enhancing decision-making and management effectiveness.

The integration of Clinical Decision Support Systems (CDSS) in digital health is crucial for remote monitoring and decision-making, particularly for asthma management, leading to improved outcomes (Dramburg et al., 2020). Key CDSS components include monitoring, digital technology, decision-making, and remote communication. Successful CDSS requires context awareness and personaliza-

[a] https://orcid.org/0000-0002-1051-2814

Chatterjee, A.
A Fuzzy Decision Support System with Semantic Knowledge Graph for Personalized Asthma Monitoring: A Conceptual Modeling.
DOI: 10.5220/0012910500003838
Paper published under CC license (CC BY-NC-ND 4.0)
In *Proceedings of the 16th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2024) - Volume 2: KEOD*, pages 143-150
ISBN: 978-989-758-716-0; ISSN: 2184-3228
Proceedings Copyright © 2024 by SCITEPRESS – Science and Technology Publications, Lda.

tion, adapting to individual circumstances and specific needs. Al-Dowaihi et al. (Al-Dowaihi, 2013) developed a prototype for asthma self-management in high pollution environments, which also alerts healthcare providers. Anantharam et al. (Anantharam, 2015) created kHealth, which uses sensor data to help physicians determine asthma severity and improve patient quality of life. Ra et al. (Ra, 2016) introduced AsthmaGuide, a cloud-based system that uses smartphones for real-time data collection and patient empowerment. Dieffenderfer et al. (Dieffenderfer, 2016) developed a wearable sensor system to study the impact of environmental factors on asthma. Quinde et al. (Quinde, 2018) proposed context-aware systems to enhance personalized asthma management, while Gyrard et al. (Gyrard, 2018) combined multiple knowledge sources to personalize chronic disease management. Galante et al. (Galante, 2022) developed a context-based asthma control method and demonstrated a self-monitoring approach, though lacking dynamism. Ajami et al. (Ajami, 2022) created an ontology-driven model for personalized asthma risk detection and exacerbation prediction. Vatsal et al. (Vatsal, 2024) developed an AI ensemble model for asthma exacerbation forecasting, showing potential for enhanced prediction accuracy and individualized treatment. Molfino et al. (Molfino, 2024) reviewed AI advancements in asthma management, while Wieczorek et al. (Wieczorek, 2024) evaluated automated acoustic analysis for asthma diagnosis and monitoring. These studies address heterogeneity in system modeling, rule-based, or AI-driven decision-making, but often neglect comprehensive context representation and unified knowledge models.

To enhance decision-making accuracy and adaptability, this study introduces a Fuzzy Decision Support System (FDSS) for personalized asthma monitoring, incorporating semantic reasoning techniques. Fuzzy logic (Wikström, 2014) offers a flexible approach for handling uncertain and imprecise data, enabling more precise and context-sensitive decisions. Semantic reasoning, including OWL-based knowledge representation (Chatterjee, 2021) and SPARQL querying (Chatterjee, 2022b), further refines decision-making by capturing intricate data patterns. By integrating fuzzy logic with semantic reasoning, this FDSS addresses conventional asthma monitoring limitations and provides clinicians with personalized, actionable insights for improved asthma management. The identified research questions for this study are − **a.** How does a semantic knowledge graph enhance the development of a FDSS for personalized asthma monitoring? **b.** What are the challenges and considerations in representing fuzzy knowledge in FDSS? and **c.** How does knowledge base, crisp values and their fuzzy representations, facilitate personalized assessments and rule-based decision-making in asthma management using the FDSS?

This is strictly a technical proof-of-concept study; rather than a clinical study, and focuses on the conceptual modeling and its theoretical verification. The future study will focus more on technical validation using robust datasets. The paper is structured as follows. Section 2 elaborates the proposed FDSS and associated approaches for system modeling. Section 3 describes the implementation, answers the research questions, and elaborates study limitations and future scope. Moreover, the paper is concluded in Section 4.

2 PROPOSED WORK

The design and development of the proposed FDSS involve following key aspects.

2.1 System Architecture

The proposed FDSS architecture (see Fig. 1) includes the following layers − *Data Acquisition Layer:* Collects patient data from sources such as electronic health records (EHRs), clinical assessments, wearable devices, and patient-reported data, including context like asthma attack triggers and factors. *Data Preprocessing Layer:* Ensures data quality, consistency, and compatibility through cleaning, normalization, feature extraction, and transformation. *Ontology Construction Layer*: Constructs an OWL ontology representing asthma monitoring knowledge with classes, properties, relationships, individuals, logical operators (AND, OR, NOT), inference rules (TBox and ABox), and axioms. It integrates relevant ontologies (Ajami, 2022), such as Asthma from BioPortal, weather from COPDology, food allergens from FoodOn, and symptoms from SNOMED-CT. *Fuzzy Knowledge Representation Layer:* Encodes fuzzy knowledge in the ontology using linguistic variables, membership functions, and fuzzy rules, storing both crisp values and fuzzy representations of clinical variables. *Fuzzy Inference Engine Layer:* Uses SPARQL queries to perform fuzzy inference on patient data for personalized asthma control and exacerbation risk assessments. *Decision Support Layer:* Combines fuzzy inference results with clinical guidelines to provide actionable recommendations for asthma management. *User Interface Layer:* Offers a user-friendly interface with dashboards and visualization tools for clinicians to input data, view recommendations, and track patient progress. *Integration Layer:* Ensures FDSS

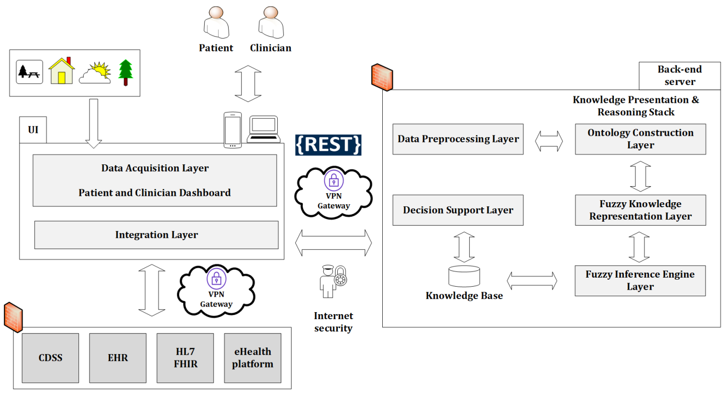

Figure 1: The architecture of the proposed Fuzzy Decision Support System (FDSS).

integration with EHR systems, CDSS, telemedicine platforms, and Fast Healthcare Interoperability Resources (FHIR), adhering to HL7 standards (Chatterjee, 2022a) for interoperability and data exchange.

2.2 Nature of Data

Asthma monitoring involves collecting diverse data from sensors, questionnaires, and medical surveillance (Merchant, 2018). Personal data includes demographics (age, gender, location, occupation, smoking status), asthma severity (severe, mild, moderate), and physiological metrics (BMI, SpO2, heart rate, body temperature). Age distinctions are crucial, differentiating between Adult-onset (age < 18) and Pediatric (age < 5) asthma. Asthma types include Exercise-induced, Occupational, and Asthma-COPD overlap syndrome, with causes such as allergies, chemicals, genetics, and infections. Symptoms range from intermittent to persistent, including chest tightness, coughing, shortness of breath, and wheezing, with severe attacks showing anxiety, pain, nasal congestion, and cyanosis. Sensors detect air pollutants like temperature, humidity, and particulate matter, aiding in trigger identification. Sensor data, often continuous, falls into physiological or environmental categories. Effective asthma management requires frequent monitoring and personalized decision-making (Chakraborty, 2023), which an FDSS can support, potentially reducing hospitalizations and costs. Analyzing both general and sensor data enables informed treatment adjustments and preventive measures.

2.3 Ontology and Reasoning

Designing and developing an ontology and reasoning involves defining formal representations of concepts, relationships, and inference rules within the ontology. Proposed ontology can be mathematically represented as:

$$O = \{C, P, I, \phi, R\}$$

where: C = set of classes representing key concepts in asthma monitoring (e.g., Patient, Symptom, Personal Information, Medication, TreatmentPlan), P = set of properties representing relationships between classes (e.g., hasSymptom, hasMedication, hasTreatmentPlan), I = set of individuals or instances of classes, ϕ = Set of logical formulas representing axioms and constraints (e.g., a patient can have multiple symptoms, but only one treatment plan at a time), and R = set of inference rules for deriving new knowledge from existing data and ontology axioms (e.g., If a patient has a specific combination of symptoms, recommend a personalized treatment plan based on historical data, if a patient's environmental exposure data indicates high levels of allergens, suggest adjustments to the treatment plan to account for potential exacerbation). The same can be represented mathematically as follows – $C = \{C_1, C_2, \ldots, C_n\}$, $P = \{(C_i, C_j)\}$, where (C_i, C_j) denotes a property between classes C_i and C_j, and

$$I = \{i_1, i_2, ..., i_m\},$$

where i_j is an instance of class C_k.

$$\Phi = \{\forall x (C(x) \to P(x)), \exists x (C(x) \land Q(x))\}$$

where $C(x)$ and $P(x)$ are predicates representing class membership and property relationships, respectively. A simplified example using first-order logic is as follows, –

$P(x)$ represent the predicate "x is a patient".

$O(x,y)$ represent the predicate "x has observation y".

$S(x,y)$ represent the predicate "x has symptom y".

$T(x,y)$ represent the predicate "x has treatment plan y".

Axioms:

$\exists p \in P$: There exists at least one patient in the ontology
$\forall x \exists y : P(x) \rightarrow O(x,y)$: Patient has observation plans
$\forall x \exists y : P(x) \rightarrow T(x,y)$: Patient has a treatment plan
$\forall x \forall y : T(x,y) \rightarrow R(x,y)$: Every treatment plan is recommended for the patient

Inference Rules:

$\forall x \forall y : P(x) \wedge S(x,y_1) \wedge S(x,y_2) \wedge \ldots$
$\rightarrow T(x,z)$: If a patient exhibits specific symptoms, recommend a personalized treatment plan

In description logics (DL), a TBox ($\mathcal{T}$) represents the terminology or schema of the ontology, an ABox represents the assertion or instance data, and an RBox ($\mathcal{R}$) represents the relationship between classes and properties; the same has been incorporated into the mathematical model for ontology and reasoning in the context of personalized asthma monitoring. As an example, the concepts can be represented as:

$$\mathbf{T} : \{\forall x(\mathrm{AP}(x) \rightarrow \mathrm{P}(x)), x(\mathrm{HS}(x,y) \rightarrow \mathrm{S}(x) \wedge \mathrm{P}(y))\},$$
$$\mathbf{A} = \{\mathrm{AP}(a), \mathrm{S}(s), \mathrm{HS}(a,s)\},$$

where a is an instance of AsthmaPatient class, s is an instance of Symptom class, and (a,s) asserts the relationship HasSymptom between AsthmaPatient and Symptom, and

$$\mathbf{R} = \{\mathrm{F}(HS), \mathrm{I}(HS,SO)\},$$

where $\mathrm{F}(HS)$ specifies that the property HasSymptom is functional, and $\mathrm{I}(HS,SO)$ indicates the inverse relationship between HasSymptom and SymptomOf. Inference rules have been applied to the TBox and ABox to derive new knowledge from existing assertions and schema definitions.

Let n be the number of classes, m be the number of properties, and k be the knowledge base size. The time complexity for building the ontology model is $O(n+m+k)$. Consistency checks and completeness verification involve traversing the ontology structure and logical evaluations. Overall complexity is influenced by the ontology size, inference rules complexity, ontology refinement extent, and test data size.

2.4 Fuzzy Knowledge Representation

Integrating fuzzy knowledge into the personalized asthma monitoring ontology enhances adaptability and depth by accommodating uncertainty and vagueness in healthcare data. Fuzzy ontology improves modeling of imprecise concepts, relationships, and membership degrees, addressing challenges in subjective symptom categorization. Unlike conventional ontologies that struggle with subjective evaluations like ”mild,” ”moderate,” or ”severe,” fuzzy ontology captures these assessments accurately, enabling precise reasoning and decision-making in asthma care. Fuzzy sets and membership functions represent linguistic variables and their degrees of membership.

Let’s consider, X: Universe of discourse (set of all possible values), $\mu_A(x)$: Membership function representing the degree of membership of an element x in the fuzzy set A, and A: Fuzzy set defined over universe X. Each patient p is associated with fuzzy sets representing observational variables:

$$\text{Observations}(p) = \{(A_1,\mu_{A1}),(A_2,\mu_{A2}),\ldots,(A_n,\mu_{An})\}$$

where A_i represents a linguistic variable and μ_{Ai} represents its corresponding membership function. Therefore, fuzzy logic system (FLS) can be mathematically represented as:

$$\text{FLS} = (X, \{A_1,A_2,\ldots,A_n\}, \{\mu_{A_1},\mu_{A_2},\ldots,\mu_{A_n}\}, \text{Rules})$$

$\mu_{A_i}(x)$ represents the degree of membership of of crisp value x in linguistic variable A_i.

The fuzzy sets in the ontology modifies the TBox (a set of logical formulas defining fuzzy classes, properties, and relationships), ABox (a set of assertions or instance data with fuzzy degrees of membership), and RBox (a set of logical formulas defining fuzzy properties and their characteristics).

$$TBox = \{\forall x(A(x) \rightarrow \mu A(x)), \forall x(B(x) \rightarrow \mu B(x)), R(A,B), \ldots\}$$

Here, $\forall x(A(x) \rightarrow \mu A(x))$ represents the first part of $TBox$, $\forall x(B(x) \rightarrow \mu B(x))$ represents the second part, $R(A,B)$ represents the relation between A and B.

$$ABox = \{(a,\mu_A(a)),(b,\mu_B(b)),(c,\mu_C(c)),\ldots\}$$

where $\mu_A(a)$, $\mu_B(b)$, $\mu_C(c)$, etc., represent membership functions.

$$RBox = \{\forall x(A(x) \wedge B(x) \rightarrow R_1(x)), \text{Functional}(R_1), \text{InverseOf}(R_1,R_2), \ldots\}$$

Fuzzy inference rules apply fuzzy logic operations to fuzzy sets to derive new fuzzy knowledge. If A is true with degree $\mu_A(x)$ and B is true with degree $\mu_B(x)$, then C is true with degree $\min(\mu_A(x),\mu_B(x))$. As an example, let, *Crisp value Set − Symptom Severity:* {Low, Medium, High} $\in$ {1, 10}, Medication Adherence: {Low, Medium, High} $\in$ {1, 10}, and Environmental Sensitivity: {Low, Medium, High} $\in$ {1, 10}, *Predicate* *logic statements* − HighSymptomSeverity(x): Patient x or $P(x)$ has high symptom severity level, LowMedicationAdherence(x): $P(x)$ has low medication adherence, HighEnvironmentalSensitivity(x): $P(x)$ has high environmental sensitivity, UncontrolledAsthma(x): $P(x)$ has uncontrolled asthma, and HighExacerbationRisk(x): $P(x)$ has high exacerbation risk, and *Fuzzy rules* − Rule − 1: UncontrolledAsthma ← HighSymptomSeverity ∨ LowMedicationAdherence, and Rule − 2: HighExacerbationRisk ← HighEnvironmentalSensitivity.

Let's fuzzify the predicate logic statements for Participant $P(x)$ using linguistic variables and membership functions − Symptom Severity: High or HighSymptomSeverity($P(x)$) (Membership: 0.8), Medication Adherence: Low or LowMedicationAdherence($P(x)$) (Membership: 0.5), and Environmental Sensitivity: High or HighEnvironmentalSensitivity($P(x)$) (Membership: 0.7). The centroid method (Chakraverty, 2019) which has been used for defuzzification, calculates the center of gravity of the aggregated fuzzy output to determine the crisp output value for further decision-making with SPARQL in fuzzy ontology. According to the fuzzy Rule − 1, the membership degree of UncontrolledAsthma for $P(x)$: $\mu_{\text{UncontrolledAsthma}}(P(x)) = \max(0.8, 0.5) = 0.8$, and According to the fuzzy Rule − 2, the membership degree of HighExacerbationRisk for $P(x)$: $\mu_{\text{HighExacerbationRisk}}(P(x)) = 0.7$. Based on centroid defuzzification method, the crisp output for UncontrolledAsthma is 1 and for HighExacerbationRisk is 0.7.

Below are sample queries to retrieve the a. fuzzy sets for different degrees of symptoms, asthma severity, and tiredness with their defuzzified membership values, and b. the current degree of asthma severity and frequency of symptoms for patients :

Query:1 - Retrieve Fuzzy Sets for Degree of asthma severity, tiredness, and frequency of symptoms

```
SELECT ?severity ?tiredness ?frequency ?memvalue
 WHERE {
        ?severity a :DegreeOfAsthmaSeverity ;
        ?tiredness a :Tiredness ;
        ?frequency a :FrequencyOfSymptoms ;
            :hasMembershipValue ?memvalue .
    }
```

Query:2 - Retrieve Asthma Severity and Symptom Frequency for Patients

```
SELECT ?patient ?severity ?symptom ?frequency
 WHERE
    {
       ?patient a :Patient ;
        :hasAsthmaSeverity ?severity .
       ?patient :hasSymptom ?symptom .
       ?symptom :hasFrequency ?frequency .
    }
```

2.5 Proposed Algorithm

Algorithm 1 integrates asthma patient data and fuzzy ontology for personalized care recommendations. It evaluates fuzzy rules based on symptoms and demographics, optimizing care by considering their interaction and enhancing recommendation efficacy.

Algorithm 1: Personalized Asthma Monitoring and Rule-based Decision-Making.

Require:
- Patient data including symptoms and demographic factors
- Fuzzy ontology with properties, linguistic terms, membership functions, fuzzy rules, and SPARQL queries.

Ensure: Personalized care recommendations based on the patient's symptom profile and demographic characteristics

1: Retrieve patient observable and measurable data from Ontology
2: Execute SPARQL Queries to obtain fuzzy outcomes for each symptom and demographic factor
3: Evaluate fuzzy rules using the fuzzy outcomes
4: Aggregate the fuzzy rule activations
5: Generate personalized care recommendations based on the aggregated rule activations
6: **return** Personalized care recommendations

Goal: The algorithm aims to trigger logical rules of the form (A IMPLIES B) or its equivalent (NOT(A) OR B) for generating tailored recommendations after decision-making. If certain variables are inferred as true, recommendations are provided based on the originating semantic data. **Time Complexity:** Retrieving patient data has a complexity of $O(1)$ or $O(n)$ if iterating over 'n' patients. Executing SPARQL queries has a complexity of $O(m)$, where 'm' is the number of queries. Evaluating fuzzy rules has a complexity of $O(r)$, where 'r' is the number of rules. Aggregating fuzzy rule activations and generating recommendations both have a complexity of $O(1)$. Therefore, the overall time complexity is $O(m+r)$.

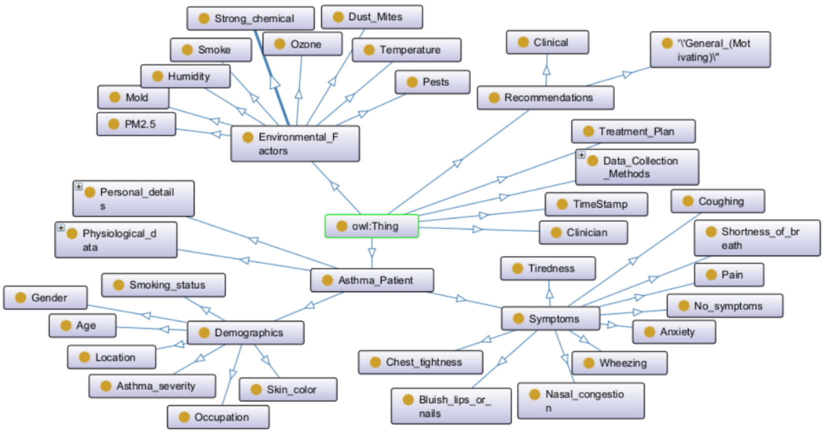

Figure 2: Key classes of the proposed ontology using OWLViz in Protégé.

Space Complexity: Storing patient data requires $O(n)$ space. The space required for the fuzzy ontology is $O(k+r)$, accounting for linguistic terms and fuzzy rules. Thus, the overall space complexity is $O(k+r)$. The time and space complexities primarily depend on the number of SPARQL queries executed (m) and the number of fuzzy rules (r). **Evaluation:** The concept is evaluated using the "Asthma Disease Prediction Dataset" (Dataset, 2024), which includes patient data, environmental factors, and medical history to predict asthma onset, severity, and treatment outcomes.

2.6 Experimental Setup

Fuzzy OWL 2 in Protégé was used to design the ontology model, including classes, properties, relationships, and individuals, while the Fuzzy DL reasoner verified its consistency.

3 IMPLEMENTATION AND DISCUSSION

The important classes of fuzzy ontology are depicted in Fig. 2 (Axiom: 150, Logical axiom: 90, Declaration axiom: 102, Class: 75, object property: 45, data property: 63, and class axioms: 95). In Protégé, using the Fuzzy DL reasoner, it achieved a reasoning time of under 40.0 seconds without reporting any inconsistencies. When loaded into the Jena workspace with the "OWL_MEM_MICRO_RULE_INF" ontology specification in TTL format (OWL full), the reading time was approximately 4.0-4.5 seconds. Queries for ontology classes, ontologies, and statement elements (predicate, subject, object) using Jena were executed in under 3.0 seconds, 1.0 seconds, and 4.0 seconds respectively. Each ontology model, representing a complete RDF graph, is associated with a document manager (default global document manager: "OntDocumentManager") to facilitate ontology document processing. In the ontology API, all classes representing ontology values inherit from "OntResource" with common attributes (versionInfo, comment, label, seeAlso, isDefinedBy, sameAs, differentFrom) and methods (add, set, list, get, has, remove). This paper presents a mathematical model for personalized recommendation generation based on SPARQL queries on top of a fuzzy ontology. The model utilizes set theory to define patient attributes, filter functions, and recommendation functions. It dynamically generates tailored recommendations for asthma management based on patient characteristics and severity of their asthma condition. The used dataset helps in this regard for the proposed theoretical concept evaluation. Let, P represent the set of patients in the fuzzy ontology. Each patient $p \in P$ has attributes such as tiredness $T(p)$, difficulty in breathing $D(p)$, severity $S(p)$, and age $A(p)$. Defined filter function F to select patients, based on specific criteria:

$$F(p) = \begin{cases} 1 & \text{if } T(p) \geq t_{\min} \text{ and } D(p) \geq d_{\min} \text{ and } A(p) \geq a_{\min} \\ 0 & \text{otherwise} \end{cases}$$

Where:

$t_{\min}$ is the minimum threshold for tiredness,
$d_{\min}$ is the minimum threshold for difficulty in breathing,
$a_{\min}$ is the minimum age threshold.

Next, let R denote the set of recommendations. For each patient p selected by F, the generated personalized recommendations r are based on their severity $S(p)$ using fuzzy logic rules. The recommendation function G is defined as:

$$G(p) = \begin{cases} \text{"Administer emergency treatment"} & \text{if } S(p) = \text{"Severe"} \\ \text{"Increase medication dosage"} & \text{otherwise} \end{cases}$$

Finally, a SPARQL query has been executed on the fuzzy ontology to filter patients based on F, and for each selected patient, generate personalized recommendations using G. The result is a set of patient-recommendation pairs $\{(p_1,r_1),(p_2,r_2),\ldots\}$, providing tailored asthma management recommendations for each patient.

The proposed fuzzy ontology includes properties, such as "Age Group", "Degree of Asthma Severity", "Frequency of Symptoms", "Effectiveness of Medication", and "Recommendation". Fuzzy rules recommend treatment adjustments based on these properties. Moreover, specific symptoms and demographic factors are incorporated into the ontology to personalize asthma monitoring and care. The logical structure of the ontology is supported by the features of the adopted dataset. The extended structure of the fuzzy ontology includes properties such as "Tiredness" (Tiredness(x), where x represents the degree of tiredness experienced by the patient, and membership functions: $\mu_{\text{Low}}(x)$, $\mu_{\text{Medium}}(x)$, and $\mu_{\text{High}}(x)$), "Dry-Cough" (Dry-Cough, where Dry-Cough(x) is true if the patient experiences a dry cough and false otherwise), "Difficulty-in-Breathing" (Difficulty-in-Breathing(x), where x represents the severity of difficulty in breathing, and membership functions: $\mu_{\text{Low}}(x)$, $\mu_{\text{Medium}}(x)$, $\mu_{\text{High}}(x)$), "Sore-Throat" (Sore-Throat, where Sore-Throat(x) is true if the patient experiences a sore throat and false otherwise), "Severity" (Severity(x), where x represents the severity levels, and membership function: $\mu_{\text{Mild}}(x)$, $\mu_{\text{Moderate}}(x)$, $\mu_{\text{Severe}}(x)$), and Age with corresponding linguistic terms and membership functions. Age has been found as an important property in asthma monitoring and care. Thus, let, A_1, A_2, A_3, and A_4 represent the fuzzy sets for the following age categories: $A_1(x)$: Less than 5 years, $A_2(x)$: 5-18 years, $A_3(x)$: 18-65, and $A_4(x)$: Greater than 65 years.

For evaluation on the adopted dataset, two fuzzy rules have been considered from the rule-base or knowledge base (KB) for personalized recommendation generation: *Rule − 3:* IF Tiredness is high AND DifficultyInBreathing is moderate THEN Increase Medication Dosage (IMD), and *Rule − 4:* IF Severity is severe THEN Administer Emergency Treatment (AET). The defuzzified decision is obtained through the centroid method after applying fuzzy rules and obtaining fuzzy outputs.

An example SPARQL query for generating personalized asthma recommendations based on specific criteria and fuzzy properties is:

```
SELECT ?recommendation
WHERE {
  ?patient :hasSymptom ?symptom .
  ?symptom :Tiredness ?tiredness .
  ?symptom :Difficulty-in-Breathing ?breathing .
  ?symptom :Severity ?severity .
  ?patient :hasDemograph ?demo .
  ?demo :hasAge ?age .
  FILTER (?tiredness ≥ 0.7 && ?breathing ≥ 0.5
          && ?age ≥ 18)
  BIND (IF(?severity = :Severe, “AET”,
          “IMD”) AS ?recommendation)
}
```

Patient data, including tiredness, breathing difficulty, and severity, is filtered to identify adults with high tiredness and moderate breathing difficulty. Recommendations for increasing medication or administering emergency treatment are made based on fuzzy rules and severity. The aggregated fuzzy output is defuzzified using the centroid method to provide a clear recommendation. For example, if a patient has tiredness = High (0.8), DifficultyInBreathing = Moderate (0.6), and Severity = Moderate (0.4), the system generates a recommendation to "Increase Medication Dosage" based on *Rule 3*. If the centroid value exceeds a threshold (e.g., 0.5), the recommendation is confirmed. The implementation addresses the research questions as follows: First, the semantic knowledge graph, shown in Fig. 2, underpins the FDSS for personalized asthma monitoring, efficiently handling reasoning tasks with quick processing in Protégé and Jena environments. Second, although representing fuzzy knowledge in the FDSS is complex, the ontology integrates fuzzy rules effectively, enabling tailored recommendations based on properties like tiredness and breathing difficulty. Third, the synergy between the knowledge base, crisp values, and their fuzzy representations supports personalized monitoring and decision-making. SPARQL queries use criteria such as tiredness and breathing difficulty to generate tailored recommendations, with defuzzification providing clear insights for asthma management. Overall, the algorithm integrates patient data, rule-based logic, and fuzzy ontology via SPARQL queries to deliver customized asthma monitoring recommendations. In this context, fuzzy ontology surpasses general ontology by effectively capturing and representing uncertainty and imprecision in patient data, thus enhancing decision-making accuracy. It improves personalized asthma monitoring by handling uncertainty, offering flexibility, and integrating with semantic web technologies. Fuzzy ontology-based SPARQL enhances interpretability and adaptability, though scalability issues may arise with growing data volumes. Future research could integrate machine learning models to address these scalability concerns and improve predictive power and automatic feature learning in the FDSS for asthma management.

4 CONCLUSION

The FDSS for personalized asthma monitoring leverages semantic reasoning and fuzzy logic to enhance asthma care. By using ontological representation, fuzzy reasoning, and SPARQL queries, the FDSS offers a flexible framework for personalized decision-making, potentially improving treatment effectiveness and patient quality of life. Future work should focus on validating the FDSS's effectiveness and practicality in real-world healthcare settings.

REFERENCES

Ajami, H. (2022). First steps of asthma management with a personalized ontology model. *Future Internet*, 14(7):190.

Al-Dowaihi, D. (2013). Mbreath: Asthma monitoring system on the go. In *2013 International Conference on Computer Medical Applications (ICCMA)*, pages 1–4. IEEE.

Anantharam, P. (2015). Knowledge-driven personalized contextual mhealth service for asthma management in children. In *2015 IEEE international conference on mobile services*, pages 284–291. IEEE.

Chakraborty, A. (2023). Development of an iot-enabled cost-effective asthma patient monitoring system: Integrating health and indoor environment data with statistical analysis and data visualization. *Internet of Things*, 24:100942.

Chakraverty, S. (2019). Defuzzification. *Concepts of Soft Computing: Fuzzy and ANN with Programming*, pages 117–127.

Chatterjee, A. (2021). An automatic ontology-based approach to support logical representation of observable and measurable data for healthy lifestyle management: Proof-of-concept study. *Journal of Medical Internet Research*, 23(4):e24656.

Chatterjee, A. (2022a). Hl7 fhir with snomed-ct to achieve semantic and structural interoperability in personal health data: a proof-of-concept study. *Sensors*, 22(10):3756.

Chatterjee, A. (2022b). Personalized recommendations for physical activity e-coaching (ontorecomodel): ontological modeling. *JMIR Medical Informatics*, 10(6):e33847.

Cleveland Clinic (2023). https://my.clevelandclinic.org/health/diseases/6424-asthma.

Dataset (2024). https://www.kaggle.com/datasets/deepayanthakur/asthma-disease-prediction.

Dieffenderfer, J. (2016). Low-power wearable systems for continuous monitoring of environment and health for chronic respiratory disease. *IEEE journal of biomedical and health informatics*, 20(5):1251–1264.

Dramburg, S., Marchante Fernández, M., Potapova, E., and Matricardi, P. M. (2020). The potential of clinical decision support systems for prevention, diagnosis, and monitoring of allergic diseases. *Frontiers in Immunology*, 11:575892.

Galante, C. M. (2022). Asthma management updates. *Nursing2023*, 52(2):25–34.

Gibson, P. G. (2000). Monitoring the patient with asthma: an evidence-based approach. *Journal of Allergy and Clinical Immunology*, 106(1):17–26.

Gyrard, A. (2018). Personalized health knowledge graph. In *CEUR workshop proceedings*, volume 2317. NIH Public Access.

Kang, H.-q. (2024). The experience of shared decision-making for people with asthma: A systematic review and metasynthesis of qualitative studies. *Health Expectations*, 27(2):e14039.

Merchant, R. (2018). Digital health intervention for asthma: patient-reported value and usability. *JMIR mHealth and uHealth*, 6(6):e7362.

Molfino, N. A. (2024). Machine learning approaches to predict asthma exacerbations: A narrative review. *Advances in Therapy*, 41(2):534–552.

Pinnock, H. (2015). Supported self-management for asthma. *Breathe*, 11(2):98–109.

Quinde, M. (2018). Personalisation of context-aware solutions supporting asthma management. In *Computers Helping People with Special Needs: 16th International Conference, ICCHP 2018, Linz, Austria, July 11-13, 2018, Proceedings, Part II 16*, pages 510–519. Springer.

Ra, H.-K. (2016). Asthmaguide: an asthma monitoring and advice ecosystem. In *2016 IEEE Wireless Health (WH)*, pages 1–8. IEEE.

Vatsal, S. K. (2024). Advanced ensemble learning approach for asthma prediction: Optimization and evaluation. In *2024 International Conference on Automation and Computation (AUTOCOM)*, pages 283–288. IEEE.

WHO (2019). https://www.who.int/news-room/fact-sheets/detail/asthma.

Wieczorek, K. (2024). Acoustic biomarkers in asthma: a systematic review. *Journal of Asthma*, (just-accepted):1–18.

Wikström, R. (2014). *Fuzzy ontology for knowledge mobilisation and decision support*. PhD thesis, Åbo Akademi-Åbo Akademi University.