

Hybrid Multi-logic Reasoning Framework Over Ontologies for Decision Support in Neurodevelopmental Disorders

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Abstract. Neurodevelopmental disorders pose significant challenges for clinical decision support because their assessment involves heterogeneous data, evolving developmental trajectories, uncertainty, and, at times, conflicting evidence. In this paper, we present the Hybrid Multi-Logic Autism Ontology framework (HML-AutismOnt), a modular, layered architecture developed to extend the Autism Ontology. We designed this extension to address the limitations of traditional decision support systems in Neurodevelopmental Disorders (NDDs) management, particularly the difficulty of representing temporal evolution, conflicting clinical evidence, and normative constraints within care pathways. The framework integrates temporal, fuzzy, modal, deontic, and paraconsistent logics to model evolving states, uncertain observations, guideline-driven obligations, and potentially inconsistent evidence. We describe the system architecture, the hybrid reasoning workflow, and the organizational strategy that combine ontology-based knowledge representation with modular reasoning services. The resulting framework promotes semantic interoperability, enables structured multi-logic inference, and supports consistent reasoning over complex domain knowledge. More broadly, this work contributes to the design of semantic information systems capable of handling heterogeneous, uncertain, and temporally evolving data in real-world neurodevelopmental care.

Keywords: Ontology Engineering · ontology enrichment · Hybrid Reasoning · Knowledge Representation · Decision Support Systems · Semantic Information Systems · Neurodevelopmental Disorders · Non-classical Logics

1 Introduction

Neurodevelopmental Disorder (NDDs) constitute a heterogeneous group of conditions arising from atypical brain development and significantly affect personal,

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social, academic, and occupational functioning [8] and [25]. Among them, Autism Spectrum Disorder (ASD) stands out for its high prevalence, complex clinical presentation, and substantial impact on individuals, families, and healthcare systems [8,22].

Specifically, according to American Psychiatric Association (APA) and World Health Organization (WHO), ASD is a neurodevelopmental condition characterized by persistent early-onset deficits in social communication and restricted or repetitive behaviors. As a spectrum disorder, it involves graded difficulties in these domains, which can result in functional limitations in everyday life. Its severity is classified into three levels of support (1 to 3), indicating the degree of assistance required [8,31].

The increasing prevalence of autism, compared with other NDDs, has not only widened the discrepancy in the number of cases, but also amplified educational, clinical, and computational challenges. This mounting pressure highlights the urgent need for semantic models that can: *i*) integrate diverse clinical and contextual data; *ii*) capture variability, uncertainty, and potentially conflicting evidence in diagnosis; and *iii*) support individualized adjustments as described in the Diagnostic and Statistical Manual of Mental Disorders, 5th Ed., Text Revision (DSM-5-TR) [8,9,29].

Real-world challenges, for instance, pose greater computational challenges. NDDs pose significant challenges from a computational perspective, particularly due to their intrinsic heterogeneity, temporal evolution, and the frequent coexistence of uncertain or even conflicting clinical evidence. These characteristics make it difficult for traditional ontology-based decision support systems, especially those grounded in classical Description Logic (DL), to adequately represent and reason in such domains. Within this broader context, ASD emerges as a particularly demanding case, given its high prevalence, complex clinical presentation, and substantial impact on individuals, families, and healthcare systems [22].

We are long ago convinced that overcoming such limitations requires robust semantic technologies. Ontologies have long been a powerful computational framework for the biomedical field. The Unified Medical Language System (UMLS), in 1993, laid the groundwork for semantic integration across heterogeneous biomedical sources [21], while in 1996 the GALEN ontology was among the first to apply formal ontological principles specifically to the representation of clinical and biomedical knowledge [28]. In 2015 and 2016, the first two works that formally use ontologies, in the computational/logical sense, using OWL or similar, specifically for neurodevelopmental disorders, appear [16,23]. Although formal ontologies have been developed for other NDDs, such as Attention-Deficit/Hyperactivity Disorder (ADHD) [6], specific learning disorders, including dyslexia [27], and intellectual disability [19], their application to the autism domain remains particularly challenging.

However, ontologies based on DL, thus classical logic, face significant limitations when applied to ASD. Symptom severity is inherently graded rather than binary [3,24]; developmental trajectories require explicit temporal model-

ing [15,20]; clinical decisions often involve normative and ethical considerations [26,30]; differential diagnoses rely on notions of possibility and necessity [12,34]; and multi-source assessments frequently contain genuine contradictions [10,17]. These characteristics exceed the expressive capacity of standard Web Ontology Language (OWL) 2 DL and Semantic Web Rule Language (SWRL), thus limiting the precision, adaptability, and clinical utility of existing ontologies. However, although new frontiers in representation can be reached by integrating non-classical logic into ontologies, compatibility with OWL 2 DL must be preserved for decidability [7].

To address these limitations, we focused specifically on ASD and introduced Hybrid Multi-Logic AutismOnt (HML-AutismOnt), a hybrid multi-logic framework that systematically extends the AutismOnt ontology through a modular layered architecture [14]. AutismOnt is a comprehensive ontology for ASD that supports automated inference via SWRL rules and has been applied to clinical decision support, text annotation, and interdisciplinary research [5,14,32]. By integrating non-classical logics, including fuzzy, paraconsistent, temporal, modal, and deontic reasoning, the proposed architecture significantly enhances the semantic expressivity of the ASD characteristics. The resulting models are more nuanced and clinically actionable, overcoming the inherent limitations of traditional first-order ontological approaches while preserving full interoperability with the original AutismOnt.

This paper makes the following contributions: *i*) the extension of AutismOnt with a hybrid multi-logic representation framework that captures heterogeneous and evolving domain knowledge; *ii*) the integration of five complementary non-classical logics—modal, temporal, fuzzy, deontic, and paraconsistent—within a unified reasoning model; *iii*) the definition of a hybrid rule-based mechanism Hybrid Semantic Web Rule Language (H-SWRL) that enables cross-logic inference over annotated ontology assertions; *iv*) the design of a modular semantic architecture that supports the coordinated execution of heterogeneous reasoning services; and *v*) Demonstration of the framework's applicability through a longitudinal decision-support scenario involving complex, evolving data.

The remainder of this article is structured as follows. Section 2 synthesizes the relevant previous work. In Sect. 3, we present the proposed framework. Section 4 presents a detailed illustrative hypothetical example through a longitudinal case study of a ninth-year-old boy's assessment. Section 5 examines the implications of the findings and delineates the limitations of the study. Finally, Sect. 6 offers concluding remarks.

2 Related Work

In this section, we examine ontology-based methodologies that have become pivotal for the systematic organization and semantic integration of knowledge in the field of ASD and other NDDs. In recent years, several influential ontology-driven frameworks and models have been proposed. We highlight their principal achievements and clarify how the architecture we developed both builds

upon and advances this body of work by concurrently incorporating five non-classical logical formalisms. To situate our proposal within the existing research landscape, we begin by discussing foundational approaches that are primarily formulated within the classical logic paradigm.

A seminal contribution in this area is the Autism DSM-ADI-R Ontology (ADAR) developed by [23], which was among the first systems to employ OWL and SWRL rules to infer ASD phenotypes directly from Autism Diagnostic Interview-Revised (ADI-R) assessment data. This ontology demonstrated high precision in aligning patient responses with the diagnostic criteria of DSM-5-TR. The study provided compelling evidence for the practical utility of formal ontologies in phenotype extraction. However, the approach was limited to the logic of classical DL, which offers only limited capabilities for representing the severity of symptom classification and for handling inconsistent or conflicting clinical information.

AutismOnt was introduced by [14] and remains the most comprehensive ontology exclusively dedicated to ASD. Developed in Protégé using the OWL 2 DL formalism, it comprises 676 classes and more than 124 properties, covering diagnostic criteria, phenotypic manifestations, risk factors, interventions, comorbid conditions, and aspects of life. The ontology supports automated reasoning through SWRL rules and has been successfully applied to clinical decision support systems and text annotation tasks. Although it provides a comprehensive, structured foundation, its dependence on crisp bivalent logic limits its ability to model the inherent vagueness, temporal dynamics, and contradictory information frequently encountered in ASD assessments. We therefore adopted AutismOnt as the foundational ontology of our framework and extended it while preserving full backward compatibility.

In our survey of recent partial hybrid methodologies, we observed that the work of [4] introduced a composite framework that integrates ontological representations with machine learning algorithms and multi-criteria decision-making techniques to enhance the diagnostic precision of ASD, explicitly incorporating sociodemographic variables into the analysis. Their approach exhibited promising results in integrating heterogeneous data sources, but the hybridization remains partial and does not incorporate non-classical logics to handle graded severity or ethical constraints. Another notable work on partial hybrid approaches is Autism Spectrum Disorder Knowledge Base (AsdKB) created by [33], a Chinese knowledge base that focuses on screening for ASD and providing expert recommendations. The system integrates ontological knowledge with factual data in Resource Description Framework (RDF) format, providing valuable multilingual support. However, it also operates primarily within classical logic, leaving room for extensions that address temporal evolution and contradictory evidence.

These partial hybrid approaches have led to recent works that incorporate specific non-classical elements. For example, [18] presented a hybrid reasoning model for the care of ASD that integrates rule-based, case-based, and process-mining reasoning within an ontological framework. Their system is particularly

useful for predicting behavioral trajectories and supporting intervention planning. Nevertheless, it does not incorporate fuzzy, modal, or deontic logics, which limits its capacity to model the severity, possibility, and normative aspects of symptoms simultaneously. Recently, [4] developed an intelligent fuzzy-neural framework specifically for sensory assessment in autism, using hierarchical linguistic modeling and risk-based temporal decision-making. [4] takes an important step toward tackling vagueness in sensory processing, but its scope is restricted to fuzzy and temporal aspects, leaving paraconsistent, modal, and deontic reasoning entirely unexplored.

Within the broader framework of hybrid logics applied to biomedical domains, composite systems integrating multiple non-classical logics have been investigated across various medical specialties, producing promising and empirically encouraging outcomes. Fuzzy-temporal approaches have been used to model disease progression in cardiology [11], while paraconsistent logics have helped to manage contradictory laboratory findings in oncology [1]. Modal and deontic logics have been combined to support the compliance of ethical guidelines in intensive care units [13]. Despite these advances in adjacent domains, no existing work in the investigation of NDDs or ASD has achieved the full concomitant integration of modal, temporal, fuzzy, deontic, and paraconsistent logics within a single ontology. The HML-AutismOnt framework fills this gap, occupying a prominent position at the cutting edge of both scientific interest and computational innovation, standing at the forefront of advanced research in the field. Table 1 summarizes the main related studies.

We have structured Table 1 so that each column corresponds to a parameter of interest related to the analyzed work. Regarding the table, we will use the terms *parameter* and *column* interchangeably. Thus, the scope of the column *scope* specifies which aspect – diagnosis, care, sensory – of ASD was investigated by the respective authors. *Logic support* corresponds both to the non-classical logics that are supported and to specific technologies used alongside them; for example, classical + Machine Learning (ML)/Multi-Criteria Decision Making (MCDM) denotes that the model exclusively supports formal ontologies grounded in first-order logic, combined with machine learning ML and multi-criteria decision making MCDM, but does not include any non-classical logical component. The *hybrid integration* shows, when applicable, the integrations with which the model is compatible. *Clinical applicability* specifies the practical use cases that benefit the most from the model. The *implementation maturity* parameter highlights the research's key technical achievements. The *Year* corresponds to the publication or presentation of the results of the work. Finally, the *key contributions* highlight the main advances in knowledge within the respective research domain. Finally, the *key contributions* describe the main contribution of the work to the advancement of knowledge within the respective research domain.

Our comparative analysis reveals that, although previous work has made valuable contributions, none have realized the full, simultaneous integration of the five non-classical logic architectures proposed in this article. Our approach,

Table 1. Related works with ontologies and hybrid systems for ASD/NDD.

Work	Scope	Logic support	Hybrid integration	Clinical applicability	Implementation maturity	Year	Key contribution
[23] (ADAR)	ASD-specific	Classical DL + SWRL	None	Phenotype inference from ADI-R	Protégé; high accuracy	2015	First OWL-based DSM inference
[14] (AutismOnt)	ASD-specific	Classical DL + SWRL	None	Diagnosis and treatment support	Protégé; 676 classes; BioPortal	2022	Comprehensive classical ASD ontology
[4]	ASD diagnosis	Classical + ML/MCDM	Partial (ML)	Hybrid diagnosis with sociodemographic data	ML + ontology	2022	Machine-learning hybridization
[33] (AsdKB)	ASD (Chinese)	Classical + factual KB	None	Screening and recommendation	RDF/Linked Data	2023	Multilingual knowledge base
[18]	ASD care	Classical + RBR + CBR + process mining	Partial (reasoning)	Hybrid reasoning for care planning	Ontology + CBR	2025	Hybrid ASD care model
[2]	ASD sensory	Fuzzy + temporal	Partial (fuzzy-temporal)	Sensory assessment	Fuzzy-neural framework	2025	Fuzzy sensory framework
HML-AutismOnt	ASD/NDD	Fuzzy + paraconsistent (Eτ) + temporal + modal + deontic	Full	Longitudinal decision support; explainable and ethically grounded	Protégé + custom hybrid reasoner	2026	First five-logic hybrid framework

therefore, marks a decisive advance in meeting the complex demands of modeling real-world scenarios of ASD.

3 Proposed Hybrid Multi-logic AutismOnt Framework

This section introduces the main technical contribution of this work: HML-AutismOnt, a hybrid multi-logic framework that extends the established AutismOnt ontology through a modular, layered architecture. This architecture preserves full backward compatibility with existing OWL 2 DL–based applications, while supporting the seamless integration of five complementary non-classical logics—modal, temporal, fuzzy, deontic, and paraconsistent — facilitating meaningful reasoning in ASD.

3.1 Architectural Overview

The framework is implemented using a modular, layered architecture with four layers, as shown in Fig. 1.

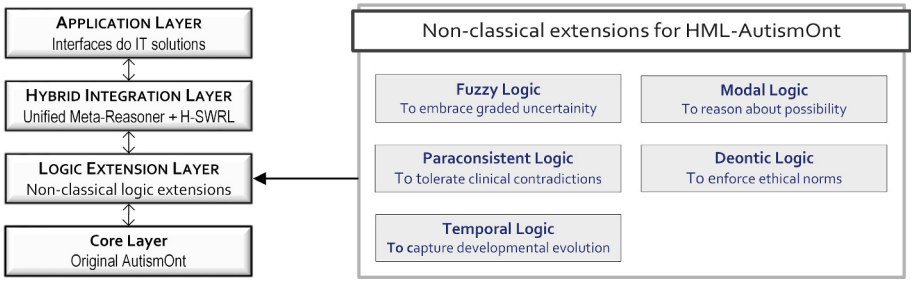

Fig. 1. HML-AutismOnt: Four-Layer Hybrid Multi-Logic Framework Architecture.

This layered design ensures that legacy applications that depend on the original AutismOnt continue to function without modification, while new hybrid capabilities become immediately available. In the following, we describe each layer and the meta-reasoner algorithm responsible for delegating and synthesizing H-SWRL[1] rules or hybrid queries.

The HML-AutismOnt framework comprises four layers. The ***Core Layer*** hosts the original AutismOnt ontology [14], preserving all 676 classes, 124 properties, and the existing SWRLs rules. The ***Logic Extension Layer*** implements five independent non-classical logic extensions—one for each logic—through annotation properties and custom reasoners: fuzzy, paraconsistent, temporal, modal, and deontic. The ***Hybrid Integration Layer*** consists of a unified meta-reasoner and the extended rule language H-SWRL, which allows atoms from different logics to be combined within a single rule. Finally, the ***Application Layer*** provides interfaces for clinical decision support, longitudinal prediction, explainability, and integration with electronic health records.

In fact, as clinical questions or patient assertions enter the ***Application Layer*** and are formalized as RDFs triples with hybrid reasoning goals, the request is forwarded by standardized Application Programming Interface (APIs) to the Hybrid Integration Layer. The Meta-Reasoner parses the incoming H-SWRL rule or query, decomposes it into classical OWL 2 DL and non-classical atoms, constructs an enriched ontology snapshot, and dispatches sub-tasks to the ***Logic Extension Layer***. The five extensions operate concurrently and return partial results as annotated triples, certainty values, temporal intervals, modal

[1] H-SWRL: A syntactic extension of standard SWRL that supports mixed atoms – classical, fuzzy-graded, paraconsistent-evidential, temporal, modal, and deontic – in the same body/head of rule. Parsing and translation to executable form are performed at runtime via a parser.

labels, and normative assessments to the Meta-Reasoner, which integrates these results into a unified hybrid inference with full provenance and returns them to the ***Application Layer*** for clinical output generation.

3.2 Core Layer

The ***Core Layer*** constitutes the immutable foundation of the HML-AutismOnt framework. It hosts the original AutismOnt ontology [14], encoded natively in OWL 2 DL, preserving all 676 classes, 124 object and data properties, and the complete set of pre-existing SWRL rules. The layer supports classical reasoning exclusively through standard OWL 2 DL reasoners such as HermiT, Pellet, and FaCT++. The diagram in Fig. 2 illustrates the internal structure and interfaces of the Core Layer.

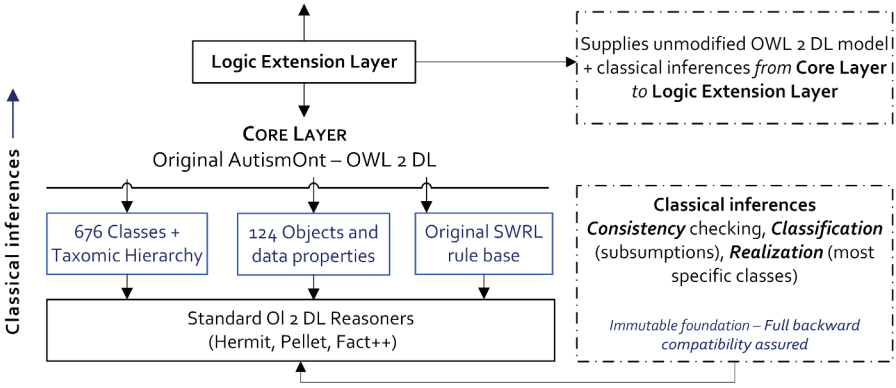

Fig. 2. ***Core Layer*** of the HML-AutismOnt.

The Core Layer supplies the entire unmodified base ontology, together with the results of the classical inferences above, to the logic extension layer via standard loading of the OWL API model.

The main classical inference services provided by the ***Core Layer*** are *consistency checking*, *classification*, and *realization*.

Consistency Checking: Verifies whether the ontology (TBox + RBox + ABox + CBox) is satisfiable and contains no logical contradictions. Real-world example: If an individual patient is asserted to belong simultaneously to the disjoint classes `SevereAutism` and `NoSymptoms`, the reasoner immediately detects an inconsistency and prevents any further inference.

Classification computes the complete inferred class hierarchy by deriving all subsumption relations ($\sqsubseteq$). Real-world example: The reasoner automatically infers that `SocialCommunicationDeficit` $\sqsubseteq$ `CoreASDPhenotype` and that `HighFunctioningAutism` $\sqsubseteq$ `AutismSpectrumDisorder`, even when these relations are not explicitly asserted.

Realization determines, for each individual, the most specific (most restrictive) classes to which it belongs. Real-world example: Given the patient instance `Alex` with observed properties, the reasoner realizes that `Alex` is an instance of `ModerateASD`, rather than merely the more general `AutismSpectrumDisorder`.

In runtime, the ***Logic Extension Layer*** receives the unmodified OWL 2 DL model from the ***Core Layer*** as input and applies non-classical extensions only as annotation overlays and external reasoners. This strict compartmentalization ensures that legacy applications can continue to issue queries directly to the ***Core Layer*** and receive exclusively classical inferences, without any requirement to recognize or interact with the hybrid extensions implemented in the layers above it.

3.3 Logic Extension Layer

The ***Logic Extension Layer*** implements five independent, pluggable extensions—one for each non-classical logic. To optimize implementation straightforwardness and full backward compatibility, every extension is realized exclusively through OWL annotation properties, added at runtime via the OWL API, and lightweight custom reasoners or SWRLs built-ins. We made no alterations to the axioms of the ***Core Layer***; the extensions operate as optional superimposed modules. This design preserves full modularity, allowing each extension to be activated or deactivated independently at deployment time. We incorporated the logic as follows:

- **Fuzzy Logic** through the FuzzyOWL 2 plugin, annotating graded properties such as `hasSocialCommunicationDeficitSeverity` and `hasSensoryHypersensitivityLevel` aligned with ASD severity levels.
- **Paraconsistent** Annotated Evidential Logic Eτ by annotating assertions with pairs of favorable and contrary evidence (μ, λ), supported by a custom lightweight reasoner that computes net certainty without trivialization.
- **Temporal Logic** through Linear Temporal Logic (LTL) operators expressed via annotation properties and custom SWRL built-ins.
- **Modal Logic** using Kripke-style possible-world annotations (`modalPossible` and `modalNecessary`).
- **Deontic Logic** through annotation properties that express obligation (O), permission (P), and prohibition (F).

The *interface point* directed downward toward the ***Core Layer*** receives unmodified AutismOnt classes, properties, and SWRL rules through standard OWL model loading mechanisms. Conversely, the *interface point* directed upward toward the ***Hybrid Integration Layer*** returns an enriched, annotated ontology snapshot, accompanied by partial inference results, such as graded membership values, certainty measures, temporal intervals, modal labels, and normative verdicts.

3.4 Hybrid Integration Layer

The ***Hybrid Integration Layer*** acts as the central orchestration engine of HML-AutismOnt. This layer is stateless and fully modular, allowing any subset of extensions to be activated without changes to the code. It unifies classical OWL 2 DL reasoning with the five non-classical extensions provided by the ***Logic Extension Layer***, enabling atoms from different logics to be combined within a single rule while preserving full backward compatibility. For maximum ease of implementation, the layer can be implemented entirely on top of the OWL API (Java). It consists of the two tightly coupled, self-contained components: *i*) *Unified Meta-Reasoner* that is a lightweight orchestrator that *i*) parses incoming H-SWRL rules/queries, *ii*) decomposes each atom by logic type, *iii*) dispatches sub-tasks in parallel to the appropriate extensions in the ***Logic Extension Layer***, *iv*) collects partial results, and *v*) performs result synthesis, consistency checking, and provenance tracking. The Unified Meta-Reasoner pseudo-code algorithm is provided in Algorithm 1.

The associated interface points originate downward from the ***Logic Extension Layer***, which obtains enriched annotations and intermediate inference outputs (including graded memberships, certainty levels, temporal intervals, modal labels, and normative verdicts). They also originate indirectly from the ***Core Layer***, which is accessed via the Logic Extension Layer to reach the unaltered AutismOnt base model. On the upward side, the interface points connect to the ***Application Layer***, which delivers consolidated hybrid inference results along with complete provenance information and explanation traces.

3.5 Application Layer

The Application Layer constitutes the outermost tier of HML-AutismOnt. The layer is deliberately thin and stateless, performing no reasoning itself and ensuring complete separation of concerns while preserving full usability and interoperability. Consume consolidated hybrid inferences produced by the Hybrid Integration Layer and expose them through user-facing standardized interfaces for clinical decision support, longitudinal prediction, explainability, and integration of Electronic Health Record (EHR). For maximum ease of implementation, the layer can be realized as a set of lightweight standards-compliant components built on common web technologies, such as Spring Boot, React, and FHIR. The main components accommodated in this layer include the following:

- *Clinical Decision Support Module*: REpresentational State Transfer (REST)-full API endpoints that deliver real-time assessment of the ASD profile, severity evaluations, and intervention recommendations.
- *Longitudinal Prediction Module*: Web service that generates developmental trajectories and future-state forecasts using temporal and fuzzy inferences.
- *Explainability & Provenance Module*: Generates human-readable reports and visualizations that include graded certainty, temporal context, modal possibilities, normative justifications, and full inference provenance.

– *Legacy Integration Service*: Bidirectional endpoints to import patient data and export hybrid reasoning results to appropriate information systems.

The *interface point* directed downward toward the ***Hybrid Integration Layer*** receives consolidated hybrid inferences, including graded memberships, certainty values, temporal intervals, modal labels, normative verdicts, and complete provenance traces. In contrast, the *interface point* directed outward toward *external actors and systems* exposes REST API, web dashboards, Fast Healthcare Interoperability Resources (FHIR) resources, and export formats to end users, investigators, and interoperable platforms.

3.6 Hybrid Rule Language and Inference

The central innovation is the hybrid extension H-SWRL, which allows atoms from all five logics to appear in a single rule. Three representative rules illustrate the approach.

Rule 1: Social Communication and Intervention Recommendation

$$\frac{\begin{array}{l}\mathsf{Patient}(p)\\ \mathsf{Fuzzy}(p, \mathit{SocCommDef}, \mathit{Moderate}, \delta \geq 0.65)\\ \mathsf{Para}(p, \mathit{RRB}, \mu \geq 0.60, \lambda \leq 0.35)\\ \mathsf{Temp}(p, \mathbf{F}_{\leq 12\mathrm{m}}(\mathit{ABA} \rightarrow \mathit{SocImp} \geq 0.30))\\ \mathsf{Modal}(p, \Diamond\, \mathit{ComorbidAnxiety})\\ \mathsf{Deon}(\mathit{Recommend}(p, \mathit{HighIntensityABA}))\end{array}}{\mathsf{Infer}(p, \mathit{HighPriorityABA_Monitoring}) \wedge \mathsf{Cert}(0.82)} \quad (1)$$

Rule 1 means that if a patient exhibits a moderate deficit in social communication with a fuzzy confidence level of at least 0.65, presents restricted and repetitive behaviors parameterized by $\mu \geq 0.60$ and $\lambda \leq 0.35$, has demonstrated a social improvement of at least 0.30 following Applied Behavior Analysis (ABA) intervention within the past 12 months, may have comorbid anxiety, and high-intensity ABA is clinically recommended, then it is inferred that the patient requires high-priority ABA monitoring, with a certainty of 0.82.

Rule 2: Sensory Sensitivity and Early Intervention Window

$$\frac{\begin{array}{l}\mathsf{Patient}(p)\\ \mathsf{Fuzzy}(p, \mathit{SensoryHypersensitivity}, \mathit{High}, \delta \geq 0.75)\\ \mathsf{Para}(p, \mathit{SleepDisturbance}, \mu \geq 0.70, \lambda \leq 0.25)\\ \mathsf{Temp}(p, \mathbf{G}_{0\text{–}36\mathrm{m}}(\mathit{EarlySensoryIntegrationTherapy} \rightarrow \mathit{ReducedMeltdowns}))\\ \mathsf{Modal}(p, \Box\, \neg \mathit{SevereLanguageDelay})\\ \mathsf{Deon}(\mathit{Recommend}(p, \mathit{SensoryIntegrationTherapy}))\end{array}}{\mathsf{Infer}(p, \mathit{UrgentSensoryIntegrationProtocol}) \wedge \mathsf{Cert}(0.79)} \quad (2)$$

The rule 2 means that if a patient exhibits high sensory hypersensitivity with a fuzzy confidence level of at least 0.75, presents a sleep disturbance parameterized by $\mu \geq 0.70$ and $\lambda \leq 0.25$, has shown reduced meltdowns after early sensory integration therapy in the window of 0 to 36-months, does not have severe language delay, and sensory integration therapy is clinically recommended, then it is inferred that the patient requires an urgent sensory integration protocol, with a certainty of 0.79.

Rule 3: Comorbidity Risk and Ethical Shared Decision-Making

$$\frac{\begin{array}{l}\mathsf{Patient}(p)\\ \mathsf{Fuzzy}(p, \mathit{IntellectualDisabilityRisk}, \mathit{Moderate}, \delta \geq 0.55)\\ \mathsf{Para}(p, \mathit{EpilepsyComorbidity}, \mu \geq 0.65, \lambda \leq 0.30)\\ \mathsf{Temp}(p, \mathbf{U}_{\leq 8\mathrm{y}}(\mathit{RegularEEGMonitoring} \rightarrow \mathit{EarlyEpilepsyDetection}))\\ \mathsf{Modal}(p, \Diamond\, \mathit{IntellectualDisability})\\ \mathsf{Deon}(\mathit{Permit}(\mathit{SharedDecisionMakingWithParents}(p, \mathit{GeneticTesting})))\end{array}}{\mathsf{Infer}(p, \mathit{ConditionalGeneticTestingProtocol}) \wedge \mathsf{Cert}(0.76)} \quad (3)$$

Finally, rule 3 means that if a patient exhibits a moderate risk of intellectual disability with a fuzzy confidence level of at least 0.55, presents an epilepsy comorbidity parameterized by $\mu \geq 0.65$ and $\lambda \leq 0.30$, has demonstrated early detection of epilepsy resulting from regular EEG monitoring up to 8 years of age, may have intellectual disability, and shared decision-making with parents regarding genetic testing is ethically permitted, then it is inferred that the patient requires a conditional genetic testing protocol, with a certainty of 0.76.

3.7 The Meta-Reasoner Delegation Algorithm

To provide a concrete example of the orchestration mechanism, Algorithm 1 fully specifies the delegation and synthesis process executed by the Unified Meta-Reasoner.

The algorithm guarantees complete traceability by linking each inference step to its origin logic extension and maintains a strict separation of concerns between orchestration and specialized reasoning.

Algorithm 1. Unified Meta-Reasoner Delegation and Synthesis Algorithm

Input: H-SWRL rule R or hybrid query Q
Output: Consolidated hybrid inference result I_{hybrid} with provenance trace P
$A \leftarrow ParseR, Q$
$A = \{a_1, a_2, \ldots, a_n\}$
    $a_i \in A$
$T(a_i) \leftarrow IdentifyLogicTypea_i$
$T(a_i) \in \{\text{Classical}, \text{Fuzzy}, \text{Paraconsistent}, \text{Temporal}, \text{Modal}, \text{Deontic}\}$
$A_{\text{classical}} \leftarrow \{a_i \in A \mid T(a_i) = \text{Classical}\}$
$A_{\text{nonclassical}} \leftarrow A \setminus A_{\text{classical}}$
Delegation phase
$\mathcal{R}_{\text{nc}} \leftarrow \emptyset$
    $a_i \in A_{\text{nonclassical}}$
$E_i \leftarrow E_{T(a_i)}$
$r_i \leftarrow ReasonE_i, a_i$
$\mathcal{R}_{\text{nc}} \leftarrow \mathcal{R}_{\text{nc}} \cup \{r_i\}$
Classical reasoning phase
$\mathcal{R}_{\text{cl}} \leftarrow OWLReasoningA_{\text{classical}}$
$\mathcal{R}_{\text{partial}} \leftarrow \mathcal{R}_{\text{cl}} \cup \mathcal{R}_{\text{nc}}$
Synthesis phase
$\Delta_{\text{fuzzy}} \leftarrow AggregateFuzzyDegrees\mathcal{R}_{\text{partial}}$
$\Theta_{\text{temporal}} \leftarrow PropagateTemporalRelations\mathcal{R}_{\text{partial}}$
$\Phi_{\text{modal}} \leftarrow ApplyModalFilters\mathcal{R}_{\text{partial}}$
$\Omega_{\text{deontic}} \leftarrow ApplyDeonticConstraints\mathcal{R}_{\text{partial}}$
$C_{\text{para}} \leftarrow ComputeParaconsistentCertainty\mathcal{R}_{\text{partial}}$
$C_{\text{para}} = \mu - \lambda$
$\mathcal{F} \leftarrow DetectCrossLogicConflicts\mathcal{R}_{\text{partial}}$
$I_{\text{hybrid}} \leftarrow IntegrateResults\Delta_{\text{fuzzy}}, \Theta_{\text{temporal}}, \Phi_{\text{modal}}, \Omega_{\text{deontic}}, C_{\text{para}}, \mathcal{F}$
$P \leftarrow BuildProvenanceTraceA, \mathcal{R}_{\text{partial}}, I_{\text{hybrid}}$
return (I_{hybrid}, P)

4 Illustrative Example: Longitudinal Decision-Support Scenario

To demonstrate the practical utility of the HML-AutismOnt framework, we present a longitudinal decision-support scenario involving a representative pediatric case. The example spans an 18-month period and integrates heterogeneous data sources that capture uncertainty, temporal evolution, and potentially conflicting observations. Figure 3 illustrates the workflow associated with this scenario.

4.1 Input Scenario

We consider the case of Alex (age 6y2m) with heterogeneous input data derived from multiple sources, including developmental history, behavioral observations, and standardized evaluation results. The input indicates delayed language development, difficulties in social interaction, sensory hypersensitivity, and variable

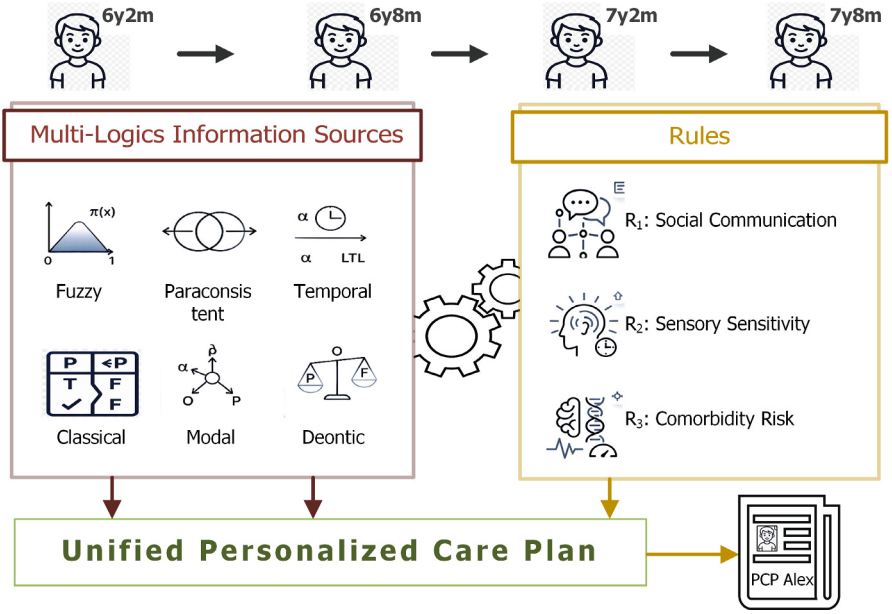

Fig. 3. Workflow of a hypothetical evaluation performed in an environment that implements our architecture.

reports in different contexts. We map this information into structured ontology instances and annotate it across multiple logical dimensions, including graded severity (fuzzy), potentially conflicting observations (paraconsistent), temporal evolution, and contextual constraints.

4.2 Initial Assessment Data (Age 6y2m)

Standard assessment instruments (e.g. Autism Diagnostic Observation Schedule, 2nd Ed. (ADOS-2), ADI-R, acSRS-2) were used to derive structured input observations. Key findings include moderate-to-high social-communication difficulties, evidence of repetitive behaviors, and variability between measures reported by parents and teachers. The key findings of the initial assessment were as follows:

- Moderate impairment in social-communication and repetitive behaviors;
- High severity reported by parents and moderate scores reported by teachers;
- Significant sensory hypersensitivity and sleep disturbances.

Figure 4 illustrates Alex's decision-support scenario milestones through the 18-month time frame.

4.3 Application of Hybrid Rules

The HML-AutismOnt framework processed the initial multi-source data and generated three integrated recommendations.

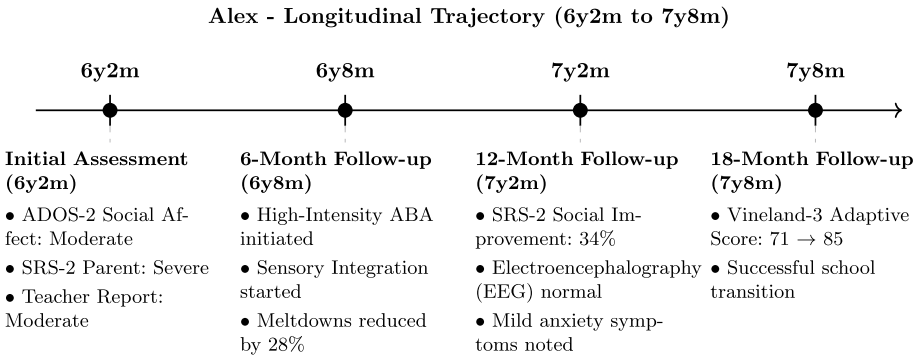

Fig. 4. Longitudinal trajectory of Alex from age 6y2m to 7y8m.

Application of Rule 1—Social Communication and Intervention Recommendation. The framework inferred moderate social-communication difficulties combined with net positive evidence for restricted and repetitive behaviors (despite some differences between home and school reports). Considering the expected developmental window and the possibility of emerging anxiety, the framework recommended a high-intensity applied behavior analysis ABA with regular monitoring (25–30 h per week).

Application of Rule 2—Sensory Sensitivity and Early Intervention Window. High sensory hypersensitivity and associated sleep difficulties were detected. The framework highlighted the importance of acting within the remaining critical developmental period and recommended daily sensory integration therapy (45-minute sessions).

Application of Rule 3—Comorbidity Risk and Ethical Shared Decision-Making. A moderate risk of intellectual disability was identified, along with a possible comorbidity of epilepsy. The framework produced a conditional recommendation for genetic testing (chromosomal microarray and epilepsy gene panel) only after a shared decision-making conversation with Alex's parents, while recommending regular EEG monitoring until age 8.

4.4 Longitudinal Evolution

The clinical team implemented the recommendations and monitored progress through regular follow-up appointments. At 6 months (age 6y8m), Alex had begun high-intensity ABA and daily sensory integration sessions. His social score on Social Responsiveness Scale, Second Edition (SRS-2) improved by 19%, and parent-reported meltdowns decreased by 28%. The results of EEG remained normal. The framework suggested a modest intensification of the social skills component within the existing plan.

At 12 months of follow-up (aged 7y2 m), the SRS-2 social improvement was 34%, and the meltdowns had decreased by 47%. Epilepsy was not identified.

Mild anxiety symptoms appeared, consistent with the possibility noted earlier. The framework updated the care plan accordingly.

At 18-months of follow-up (aged 7y8 m), all main goals had been met or exceeded. Alex's overall adaptive functioning (Vineland-3) increased from a standard score of 71 to 85. He successfully transitioned into the second grade with reduced support needs. The framework continued to provide ongoing guidance for the next stage of development.

This example illustrates how the HML-AutismOnt framework integrates heterogeneous, multi-source data into a coherent, adaptive decision-support process, enabling structured reasoning over evolving, potentially inconsistent information.

5 Discussion

In this work, we demonstrate that the HML-AutismOnt framework represents a significant methodological advance in the semantic modeling of neurodevelopmental disorders, with particular emphasis on ASD. By extending the well-established AutismOnt [14] through the concomitant integration of five complementary non-classical logics—modal, temporal, fuzzy, deontic, and paraconsistent—the framework addresses key limitations of classical Description Logic-based ontologies when applied to the complex, dynamic, and often contradictory reality of ASD.

The primary contribution we achieved lies in the ability to produce more nuanced and clinically relevant inferences. The hybrid rules demonstrated in Sect. 4 combine the graded severity of symptoms (fuzzy), the tolerance of conflicting evidence (paraconsistent), explicit temporal windows (temporal), the differentiation between possibility and necessity (modal), and normative/ethical constraints (deontic) within a single reasoning step. This integration enables us to generate personalized recommendations that better reflect the multifaceted nature of ASD presentations. The longitudinal case study of Alex we presented shows how these recommendations can be applied in practice, supporting more informed decision-making over time and facilitating smoother transitions across developmental stages.

Compared with previous work, we believe that the proposed framework offers clear advantages. Foundational ontologies such as ADAR [23] and AutismOnt itself excel at structured representation and basic phenotype inference, but remain limited by the assumptions of classical logic. More recent hybrid approaches incorporate machine learning [5], case-based reasoning [18], or individual non-classical logics [3], yet none achieves the full concomitant integration of the five logics we present here. This unified approach allows HML-AutismOnt to handle the full spectrum of challenges encountered in real-world ASD care—graded severity, temporal evolution, conflicting data, epistemic uncertainty, and ethical obligations—within a single coherent system.

From a clinical perspective, we consider the framework to have the potential to improve both diagnostic precision and intervention planning. The explainable

nature of hybrid rules facilitates shared decision-making with families and supports longitudinal monitoring with clear, measurable goals. In research settings, it can contribute to a more accurate definition of phenotypes, more powerfully designed studies of developmental trajectories, and improved data harmonization between international cohorts.

Several limitations should be acknowledged. First, the computational cost of full hybrid reasoning increases with the number of active logics and the size of the data set; optimization will be important for large-scale deployment. Second, fuzzy membership functions and evidence thresholds currently rely on expert input and may benefit from data-driven refinement in future versions. Third, although the illustrative case study provides an initial demonstration of feasibility, large-scale prospective validation across heterogeneous system configurations remains necessary to rigorously establish real-world performance and generalizability. Finally, successful implementation will require targeted education and training of practitioners, as well as systematic consideration of the ethical, legal, and regulatory dimensions of AI-enabled decision support platforms. A comprehensive quantitative evaluation and benchmarking against alternative reasoning systems remain important directions for future work.

Looking ahead, several promising research directions emerge. Integration with machine-learning pipelines could enable automated parameter optimization and systematic discovery of novel reasoning rules based on a hybrid ontology. Extension of the framework to additional application domains, such as ADHD and intellectual disability, would substantially enhance its generality and scalability. The development of user-centric interfaces and seamless interoperability with existing information systems through FHIR-compliant standards constitutes a key system engineering challenge for practical deployment.

6 Conclusion

In this paper, we propose HML-AutismOnt, a hybrid multi-logic framework that we developed to extend the established AutismOnt ontology by integrating five non-classical logics: modal, temporal, fuzzy, deontic, and paraconsistent. The proposed approach addresses important limitations of classical DL-based ontologies when applied to the complex, dynamic, and often contradictory nature of ASD and other neurodevelopmental disorders.

By combining graded symptom representation, tolerance of conflicting evidence, explicit temporal modeling, differentiation between possibility and necessity, and formalization of normative and ethical constraints, we enable more nuanced, clinically relevant, and longitudinally consistent reasoning. The illustrative case study of Alex demonstrates how these capabilities can be translated into practical, personalized care recommendations that evolve with child development and respond to new information over time.

Compared to the literature, we believe that HML-AutismOnt offers a more comprehensive solution. Although foundational ontologies such as ADAR [23] and AutismOnt [14] provide robust taxonomic structures, and more recent hybrid

systems have incorporated individual non-classical logic or machine-learning elements, none has achieved the full concomitant integration of the five logics we present here. This unified architecture represents a significant step forward in ontology-based modeling for ASD.

The framework offers several system-level benefits. Enhances decision-support processes, enables richer system workflows, and improves longitudinal data integration across heterogeneous information systems. In research environments, it provides a robust foundation for more precise phenotype modeling, scalable trajectory analysis, and advanced data harmonization across large-scale knowledge bases. From a broader perspective, the approach demonstrates how non-classical logics can effectively bridge the gap between formal knowledge representation and the inherent complexity of real-world application domains.

Naturally, challenges remain. Large-scale validation across diverse contexts remains required, as is computational optimization for large datasets, data-driven refinement of fuzzy membership functions and evidence thresholds, and the development of user-centric interfaces. The ethical, legal, and regulatory considerations surrounding AI-supported decision support systems will also require continued attention.

In conclusion, we consider that HML-AutismOnt demonstrates that the principled integration of non-classical logics can yield a more expressive, flexible, and computationally powerful knowledge representation system. By addressing vagueness, temporality, inconsistency, and normativity within a unified hybrid architecture, the framework advances ontology-driven modeling and opens new avenues for scalable and semantically rich information systems in neurodevelopmental care.

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