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Semantic based approach for modeling and reasoning in multi-agent systems

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ABSTRACT

Multi-agent systems (MAS) are increasingly applied to complex tasks such as autonomous delivery, where multiple vehicles must coordinate in dynamic environments. A major challenge lies in ensuring semantic interoperability, so that agents can interpret and share information consistently. This paper presents autonomous vehicles ontology (AVsOnto), a domain specific ontology for autonomous delivery vehicles (ADVs), integrated into a semantic framework for real time data annotation and reasoning. AVsOnto enables vehicles to coordinate tasks, reroute efficiently, and adapt to disruptions such as traffic changes or urgent deliveries. By linking semantic knowledge with dynamic planning, the framework advances beyond existing models, offering greater adaptability and reliability. Results indicate improved coordination and operational efficiency in ADVs based delivery networks.

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1. INTRODUCTION

Urban logistics and delivery services are rapidly changing with the growing adoption of autonomous technologies [1]. Among these technologies, autonomous delivery vehicles (ADVs), as a specific application of autonomous vehicles (AVs), have emerged as a promising solution for urban parcel delivery [2], [3]. ADVs use perception sensors, artificial intelligence (AI), and control systems to understand their surroundings, make driving decisions, and perform navigation and vehicle-control tasks with limited or no human intervention [4]. According to the Society of Automotive Engineers J3016 (SAE J3016) standard, driving automation is classified into six levels [5], ranging from Level 0, which involves no driving automation, to Level 5, which represents full driving automation [6]. Despite these advances, ensuring the reliable, safe, and adaptive operation of ADVs in dynamic urban environments remains challenging. Traffic conditions can change rapidly, unexpected obstacles may appear, and vehicles must interact with pedestrians and other road users while also responding to changing delivery priorities.

Multi-agent systems (MAS) [7] offer a suitable framework for addressing these challenges by representing each delivery vehicle as an autonomous agent capable of perception, decision-making, communication, cooperation, and negotiation. Through coordination, these agents can work toward common objectives, including task allocation, route optimization, congestion reduction, efficient resource utilization, and timely parcel delivery. In general, a MAS consists of autonomous and potentially heterogeneous agents that perceive and act within a shared environment, communicate using protocols such as Foundation for

Intelligent Physical Agents-agent communication language (FIPA-ACL) and knowledge query and manipulation language (KQML) [8], and pursue individual, collective, or sometimes conflicting objectives. However, conventional MAS approaches often depend on application-specific data structures and communication models. This can make it difficult for heterogeneous agents to share a common understanding of concepts and communicate effectively across different systems.

Semantic technologies [9] offer a promising way to address this limitation by providing formal and machine-interpretable representations of knowledge within MASs. Ontologies can be used to describe concepts such as vehicles, parcels, routes, destinations, tasks, and environmental conditions, while resource description framework (RDF) and web ontology language (OWL) provide standardized mechanisms for representing and exchanging this knowledge [10]. When semantic models are combined with logical rules and inference mechanisms, agents can derive implicit knowledge, interpret contextual information, assess possible strategies, and adapt their behavior accordingly. Nevertheless, existing ontology-driven agent architectures often focus mainly on knowledge representation and interoperability, without explicitly connecting semantic reasoning (SR) to planning and operational decision-making. Other approaches incorporate reasoning capabilities but may still face limitations related to dynamic knowledge updates, scalability, computational efficiency, or coordination among heterogeneous agents [11]. Recent developments in knowledge graphs, neuro-symbolic AI, explainable AI, and large language model-assisted reasoning have opened new opportunities for combining symbolic knowledge with data-driven approaches. However, these approaches do not always offer a unified semantic model for representing ADVs, delivery tasks, agent capabilities, environmental constraints, and coordination requirements. This gap shows the need for a more integrated approach that connects ontology-based knowledge representation, rule-based reasoning, semantic interoperability, and planning in multi-agent delivery systems. To address this need, this study introduce autonomous vehicles ontology (AVsOnto), a semantic framework that brings these elements together by combining domain knowledge representation, rule-based reasoning, linked data (LD) principles, and a limited planning component based on planning domain definition language (PDDL) [12], [13].

The main contribution of AVsOnto goes beyond simply developing an ontology for ADVs. The framework connects domain knowledge, semantic inference, and agent coordination within a common representation. It provides a structured way to describe vehicles, parcels, destinations, delivery tasks, environmental conditions, and the relationships between agents. The reasoning component allows contextual knowledge to be derived from explicitly represented facts, while the LD perspective supports the sharing and reuse of semantic information. In addition, the PDDL component is used to represent selected aspects of the delivery planning process. By bringing these elements together, AVsOnto provides a shared semantic foundation that can improve interoperability and support more transparent and coordinated behavior among heterogeneous agents.

The following structure is used for the remainder of this document. Section 2 reviews previous work on semantic interoperability in MAS and ADVs. Section 3 presents the proposed AVsOnto framework and describes the methodology used in this study. Section 4 presents the validation results and discusses key findings. Finally, section 5 concludes the paper and outlines possible directions for future research.

2. RELATED WORKS

Research on MAS and ontologies has been steadily expanding, especially in fields such as ADVs, transportation, and smart logistics. Yet, despite this progress, these two areas often evolve in parallel: MAS approaches typically emphasize coordination and optimization, while ontologies focus on interoperability and knowledge representation. The missing piece is a tight integration of SR into MAS coordination, particularly in ADVs contexts. This section reviews representative studies and compares them along five key aspects: ontology, SR, semantic querying (SQ), LD, and ADVs applications as shown in Table 1. The analysis highlights the absence of an integrated framework combining MAS and SR for ADVs coordination.

MAS have proven to be powerful tools for managing the complexity of AVs coordination. For instance, Nasr [14] demonstrated how MAS can solve pathfinding problems and compared their effectiveness with classical optimization methods such as genetic algorithms and swarm-based heuristics. Other works have gone further in designing architectures tailored for AVs: a hierarchical MAS for cooperative control of connected vehicles [15], frameworks for engineering applications [16], and socially attentive reinforcement learning policies for multi-agent driving [17]. These studies demonstrate the potential of MASs to support distributed decision-making, scalability, and adaptation. However, many of these approaches remain primarily procedural. Agents typically rely on predefined rules, optimization strategies, or learned policies, while the meaning of exchanged information and the relationships between domain concepts are not explicitly represented. As a result, their ability to support semantic interoperability and knowledge-based coordination remains limited.

At the same time, the ontology community has produced a rich body of work for transportation and logistics. Surveys on [18] transportation ontologies provide overviews of how semantic models can unify heterogeneous data sources and improve interoperability. More targeted contributions propose ontological frameworks for multimodal transportation systems [19], or even hybrid AI pipelines that combine ontology learning, knowledge graphs, and large language models to enhance data model translation in smart manufacturing and mobility domains [20]. These studies provide valuable foundations for representing vehicles, infrastructure, services, and transportation processes. Nevertheless, most of these ontologies remain mainly descriptive. They define concepts and relationships, but are not always directly connected to the reasoning, coordination, and decision-making processes of autonomous agents operating in dynamic delivery environments.

More recent wave of research is beginning to close this gap by exploring semantic collaboration among agents. For example, semantic collaboration for MAS [21] introduces a framework where agents communicate using semantically enriched messages, improving cooperation efficiency. Other works extend this idea to specific AV-related contexts, such as semantic-aware resource management in cellular vehicle-to-everything (C-V2X) platooning [22], which combines SR with multi-agent reinforcement learning. Broader surveys, such as semantic collaboration for multi-agent [23], point to a future where ontologies and even large language models enrich MAS with higher level reasoning. Although these approaches represent important progress, they are often conceptual, application-specific, or focused on particular coordination problems. They do not directly address the semantic representation and operational evaluation of autonomous delivery systems involving vehicles, packages, destinations, tasks, and environmental constraints. Taken together, these studies reveal three main limitations: MAS approaches often lack explicit semantic knowledge, transportation ontologies are not always connected to agent decision-making, and semantic collaboration frameworks have rarely been evaluated in autonomous delivery scenarios.

To address these gaps, this study proposes AVsOnto, an ontology-driven framework for autonomous delivery systems. It represents vehicles, packages, destinations, tasks, routes, and environmental conditions, while combining semantic interoperability, LD, rule-based reasoning, and a limited PDDL for selected planning aspects. Unlike general-purpose ontologies such as simulation of urban mobility (SUMO), sensor, observation, sample, and actuator / semantic sensor network (SOSA/SSN), and Industry 4.0 ontology (I4.0-Onto), AVsOnto is specifically adapted to autonomous delivery and connected to an agent-based operational scenario.

Table 1. Comparative analysis of recent contributions

Publication	MAS	ADVs	LD	SR	SQ	Onto
Nasr [14]	+	+	-	-	-	-
Liang *et al.* [15]	+	+	-	-	-	-
Kumar *et al.* [16]	+	+	-	-	-	-
Dai *et al.* [17]	+	+	-	-	-	-
Kudzh and Kurdyukov[18]	-	-	-	+	+	+
Tkachenko *et al.* [19]	-	-	-	+	+	+
Mohsenzadegan *et al.* [20]	-	-	-	+	+	+
Li *et al.* [21]	+	-	-	-	-	+
Zhang *et al.* [22]	+	-	-	-	+	+
Li *et al.* [23]	+	-	-	-	-	+
Proposed approach	+	+	+	+	+	+

3. METHOD AND PROPOSED APPROACH

The proposed framework introduces a multi-agent architecture to manage delivery operations in dynamic environments. It integrates three layers (ontology, planning, and simulation) to ensure consistency, adaptability, and effective evaluation. The ontology layer provides a shared representation of agents, packages, routes, and constraints; the planning layer uses PDDL to generate and update delivery plans; and the simulation layer (NetLogo and Python) models the vehicle's agents in a dynamic environment. Together, these layers enable agents to perceive, decide, communicate and cooperate effectively, with the aim of optimizing routes, improving service speed and improving resource utilization as shown in Figure 1.

3.1. Ontology construction and knowledge representation

In the context of AVs, knowledge representation is vital for ensuring that systems and agents share a unified understanding of their environment. This representation is often achieved through ontologies, which structure information by defining key concepts and the relationships between them. For example, an ontology for AVs may include classes, such as "Agent" "Sensor," "Environment," and "objective". Each class is defined with its specific sub-classes, such as "AVs" or "Camera," providing a precise and unified understanding of the different types of vehicles and the equipment they use.

Furthermore, the ontology defines relationships between concepts, such as the link between vehicles and sensors or their interactions with the environment. This structuring of knowledge enables AVs agents to communicate effectively, share data, and coordinate their actions intelligently. In summary, knowledge representation through ontologies provides a solid foundation for integrating and ensuring interoperability among different systems, thus facilitating safer and more coherent operations in the field of AVs. the requirements specification document is represented using the RDF language [24]. This representation organizes the specified requirements as a set of RDF triples in the form (subject, predicate, object).

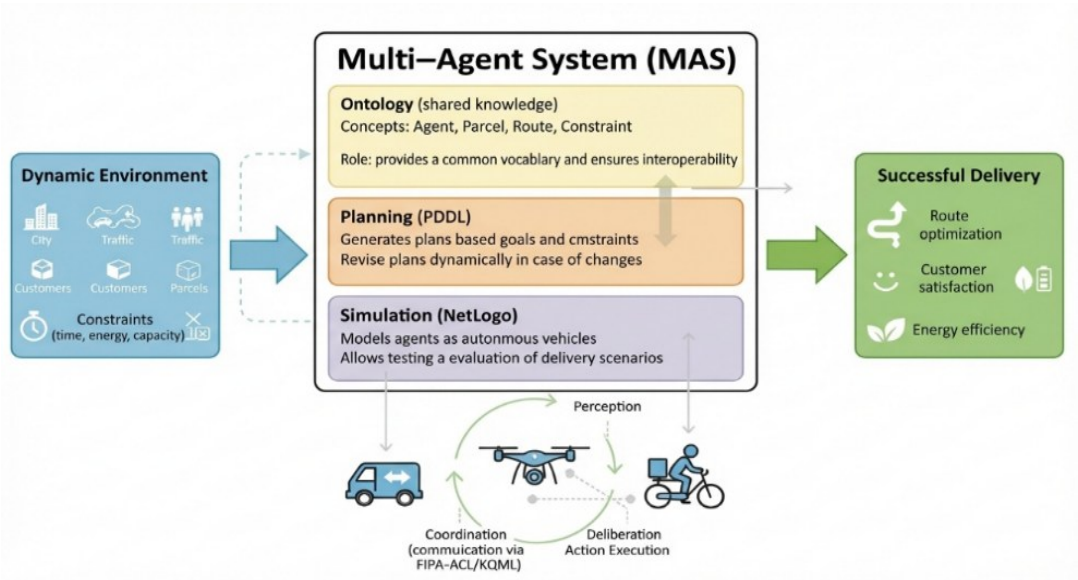

Figure 1. Architecture components

3.1.1. Ontology implementation

The ontology AVsOnto is built to represent knowledge and translate the conceptual framework into a functional system that can be used by various components within the vehicle's infrastructure. The first step in this process is defining the ontology using a suitable formal language, such as OWL [25]. This involves creating classes, properties, and relationships that accurately represent the key concepts of the domain, such as different types of vehicles, sensors, and environmental conditions.

3.1.2. Key concepts of the ontology

Ontology [26] includes elements like classes, entities, relationships, characteristics, operations, and principles. Compiling a comprehensive inventory of all terms is essential, as it facilitates the articulation of concepts about AVs, irrespective of any class convergence, term interrelations, or class attributes that might exist. Some classes defined in the ontology are presented as follows:

i) Agent: represents all AVs in the system.
ii) Environment: represents the environment in which the vehicle operates (urban, rural, and highway).
iii) Obstacle: represents obstacles like pedestrians, other vehicles, and animals.

3.1.3. Defining the ontology classes and their hierarchy

Defining classes and their hierarchy involves organizing concepts from more general classes (superclasses) to more specific subclasses. In the proposed ontology, 'Obstacles' is defined as a superclass of 'Road Work' and 'Accident' is a subclass of the superclass 'Obstacles'. For example, each specific type of sensor is represented as a subclass of the general 'Sensor' class, as in Table 2.

Table 2. Classes and sub-classes

Class	First-level subclass	Second-level subclass
Obstacles	Accident	
----	Road_work	
----	RoadUser	Cars
----	----	Cyclists
----	----	Pedestrians

3.1.4. Defining ontology properties

Each class is associated with a set of properties that describe its characteristics. Figure 2 presents the main classes defined in AVsOnto, along with their data and object properties, as implemented in Protégé 5.6.4. [27]. The resulting model formalizes the key concepts, data sources, and outputs of the AVs domain, with a segment of the ontology's binary relationships shown in Figure 3.

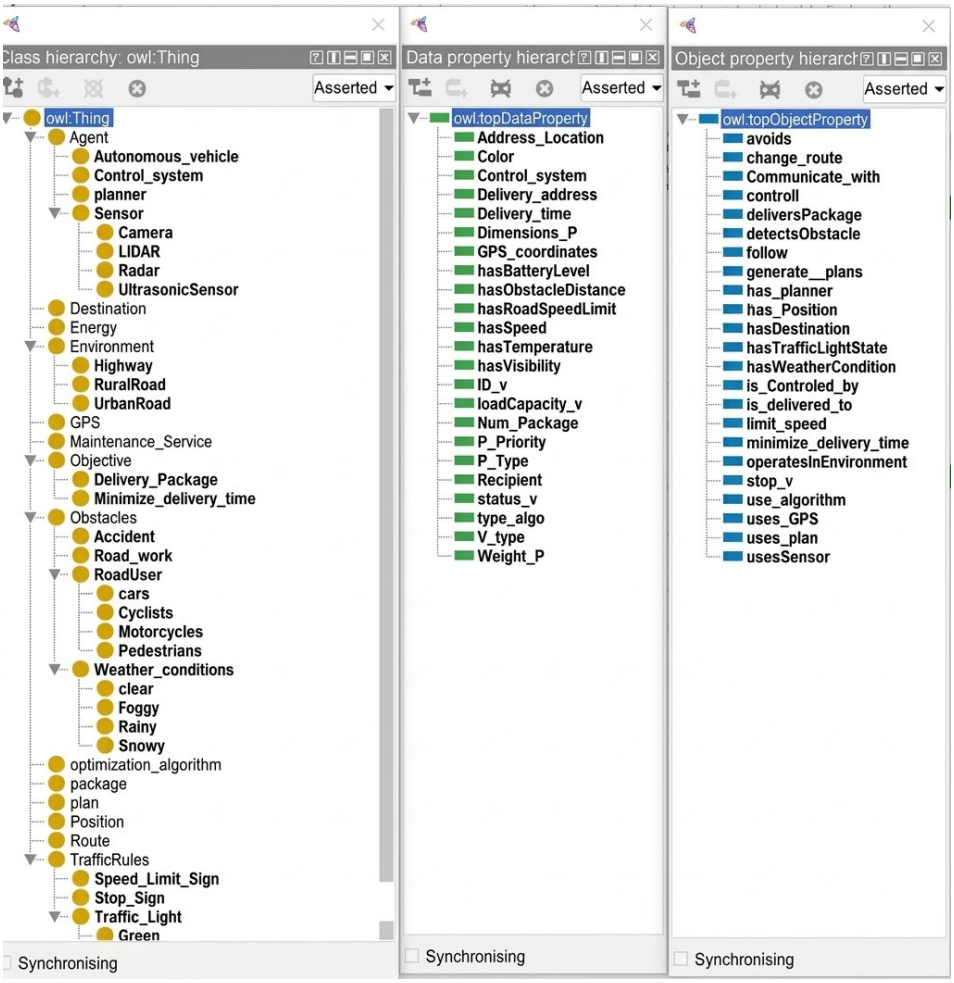

Figure 2. Classes and data/objects properties of AvsOnto

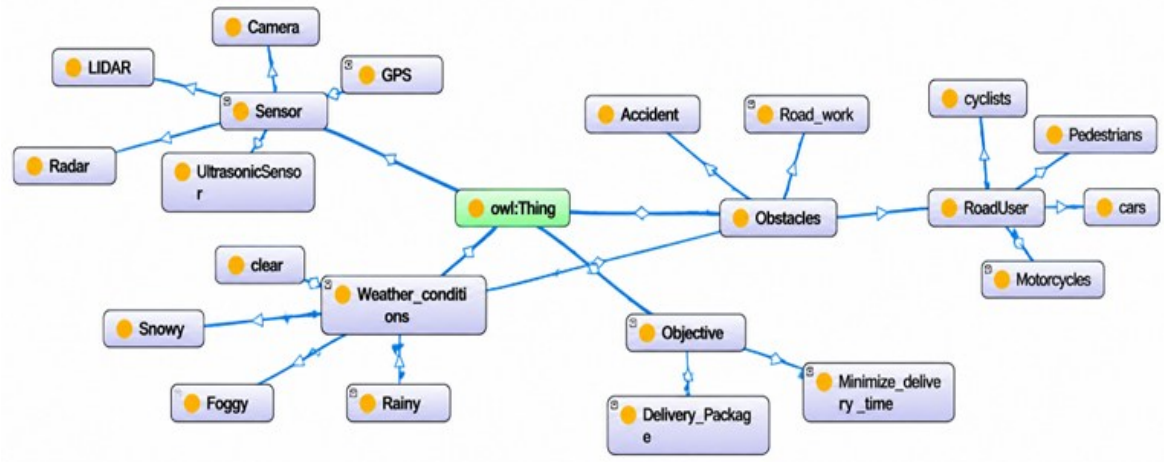

Figure 3. A part of AVsOnto ontology represented with OntoGraph

3.1.5. Defining data properties for ontology classes

Data properties are used to describe individuals through specific data values, are defined at the class level, and apply only to instances. Their definition requires specifying a domain (the class) and a range (the data type). Example types are shown in Table 3.

Table 3. Type of data properties

Data properties	Data types
Adress_Location	xsd:string
Weight_P	xsd:double/xsd:float
Delivery\time	xsd:dateTime

3.2. Semantic reasoning, rules, and querying

3.2.1. Ontology reasoning

The reasoning capability of the ontology is verified by inferring implicit logical relationships from predefined rules. The study employs the semantic web rule language (SWRL) [28], to define inference rules and the HermiT reasoning engine [29] to perform logical reasoning over the knowledge base. Representative SWRL rules and their inferred results are presented in Table 4.

- Rule S10: when two packages ?p1 and ?p2 assigned to the same vehicle ?v have different priorities (?prio1, ?prio2), the package with the higher priority must be delivered first.
- Rule S5: A package ?p is marked as urgent if its deadline ?d falls within 30-time units from the current time.

Table 4. Semantic rules exemples

Rule name	Rule
S10	UrgentPackage(?p1)ˆPackage(?p2)ˆassignedTo(?p1, ?v)ˆassignedTo(?p2, ?v) ˆ hasPriority (?p1, ?prio1)ˆhasPriority(?p2, ?prio2)ˆswrlb:greaterThan(?prio1, ?prio2) → DeliverFirst (?p1, ?v)
S5	Package(?p) ˆ hasDeadline(?p, ?d) ˆ hasCurrentTime(?s, ?now) ˆ swrlb:add(?limit, ?now, 30) ˆ swrlb:lessThan(?d, ?limit)→ UrgentPackage(?p)

3.2.2. Machine-readable verification

Ontologies support information retrieval by providing structured semantic representations that can be queried using semantic web technologies. In this study, SPARQL [25] is used to retrieve information from the RDF representation of the ontology. SPARQL enables queries over RDF triples and can return structured result sets or RDF graphs. An example SPARQL query for retrieving package-related information is presented in Figure 4.

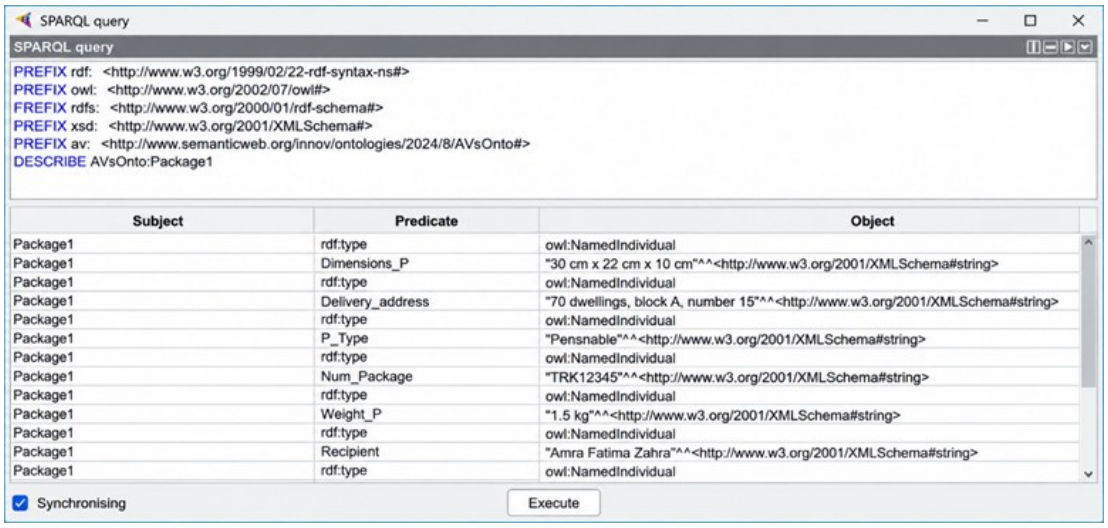

Figure 4. Result of execution of the DESCRIBE query

3.3. Integration with AI planning

Coordinating ADVs in a MAS requires connecting semantic knowledge with practical planning models. To achieve this, RDF/OWL ontologies are transformed into PDDL specifications, which can be processed by automated planners such as planning domains [30]. This allows the system to generate suitable delivery plans while taking into account vehicle capabilities, delivery tasks, and operational constraints.

3.3.1. Step 1: ontology-based knowledge representation

The ontology describes the key entities of the delivery domain, including vehicles, packages, locations, and contextual factors such as weather or obstacles. For instance, a vehicle v1 may be located at a depot, while a package p1 is waiting at a warehouse. These facts are represented in RDF triples and serve as the semantic backbone of the system. This process was implemented using a Python program that automatically maps ontology classes and properties to PDDL types, predicates, and objects, and formalizes actions relevant to delivery scenarios. For example: i) pickup: load a package onto a vehicle; ii) move: relocate a vehicle from one location to another under valid conditions; and iii) deliver: unload a package at its destination. An excerpt of the generated domain model is shown in Algorithm 1.

Algorithm 1. PDDL domain specification for AVs delivery planning

```
(define (domain avs-delivery)
  (:requirements :strips :typing)
  (:types Vehicle Package Location Weather)
  (:predicates
    (at ?v - Vehicle ?l - Location)
    (package-at ?p - Package ?l - Location)
    (loaded ?p - Package ?v - Vehicle)
    (good-weather ?w - Weather)
    (blocked ?from - Location ?to - Location)
  )
  (:action move
    :parameters (?v - Vehicle ?from - Location ?to - Location ?w - Weather)
    :precondition (and (at ?v ?from) (good-weather ?w)
                       (not (blocked ?from ?to)))
    :effect (and (not (at ?v ?from)) (at ?v ?to))
  )
)
```

3.3.2. Step 2: problem instantiation

Instances extracted from the ontology are injected into the PDDL problem file. A simplified example is given in Algorithm 2. These instances represent the delivery environment, including vehicles, packages, destinations, and relevant constraints. This transformation allows the planning system to use the semantic knowledge provided by AVsOnto to generate appropriate delivery plans.

Algorithm 2. PDDL problem definition for autonomous delivery planning

```
(define (problem avs-delivery-problem)
  (: domain avs-delivery)
  (: objects
    v1 - Vehicle
    p1 - Package
    depot warehouse destination - Location
    sunny - Weather
  )
  (: init
    (at v1 depot)
    (package-at p1 warehouse)
    (good-weather sunny)
  )
  (: goal (package-at p1 destination))
)
```

3.3.3. Step 3: execution on planning platforms

The generated PDDL files can be uploaded and tested using platforms such as planning. domains [30]. This helps check whether the semantic information has been correctly translated into planning models. The platform then generates delivery plans based on the available information and environmental constraints, as illustrated in Figure 5. The generated plans can also be examined to verify whether the defined actions and environmental constraints are properly represented.

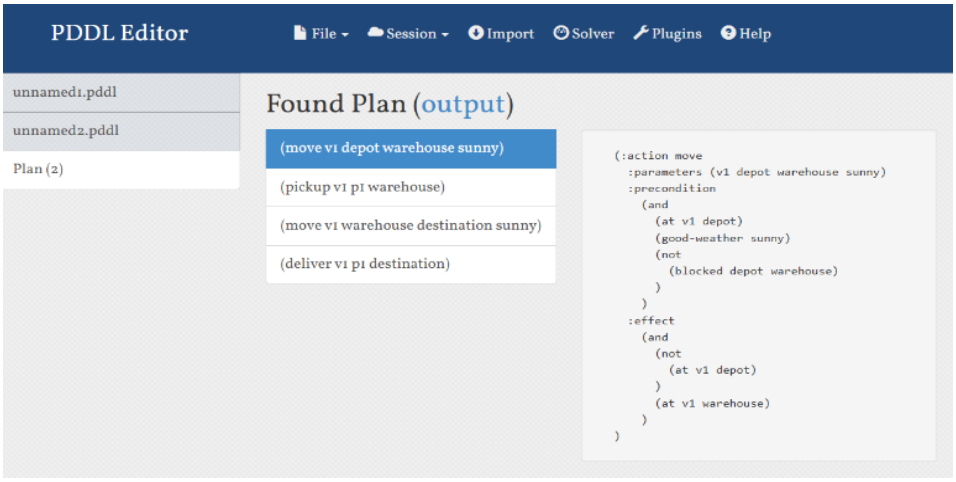

Figure 5. Result of execution of the DESCRIBE query

4. RESULTS AND DISCUSSION

This section presents the validation and experimental results of the proposed AVsOnto framework. The evaluation focuses on the consistency of the ontology, SR and applicability of the proposed knowledge representation in autonomous multi-agent delivery scenarios. The framework is first validated by ontological consistency tests, followed by NetLogo and Python simulations to demonstrate semantic task allocation, navigation, obstacle avoidance, and delivery coordination. Finally, a reinforcement learning scenario is presented as an additional validation of the use of semantic constraints in adaptive decision making by agents.

4.1. Ontology consistency check

Izquierdo and Castro [31] describe Themis as a tool for validating ontologies against predefined functional requirements through tests based on a glossary of terms. These tests produce four possible results [32]: correct, indefinite, conflicting information, or missing relation, as shown in Figure 6. This process helps detect inconsistencies and verify whether the ontology meets the expected requirements. In this study, it is used to evaluate the reliability of AVsOnto.

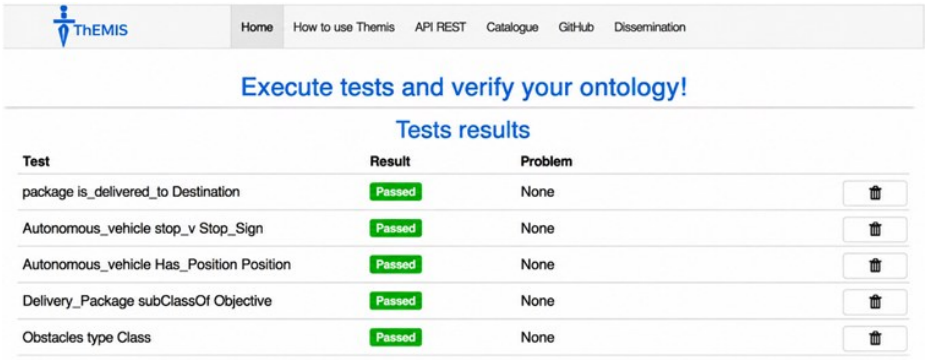

Figure 6. Tests and results

4.2. Simulation setup and results

To evaluate AVsOnto, a multi-agent simulation was implemented using NetLogo 6.4.0 [33]. The simulation represents a grid-based delivery environment in which AVs transport packages from randomly generated pickup locations to their designated destination homes. At the beginning of each simulation, the environment is configured as a two-dimensional grid. Obstacles are randomly generated on approximately 5% of the grid cells. Eight AVs are then created and placed at random free locations. Each vehicle is assigned a starting position from which it performs delivery tasks. Twenty packages are randomly distributed among

the free cells of the environment. Each package is associated with a specific destination home, resulting in a one-to-one association between packages and destination homes.

During the simulation, each idle vehicle selects the nearest available package as its target. The vehicle moves from its current position toward the selected package while avoiding obstacles. When the vehicle reaches the package, it picks it up, and the package follows the vehicle during transportation. The vehicle then changes its destination to the specific destination home assigned to that package and transports the package to the designated location. Once the package reaches its destination, it is marked as delivered, and the vehicle becomes available to perform another delivery task after returning to its original starting position.

The simulation continues until all 20 packages are successfully delivered to their destination homes. The simulation setup and overall workflow are illustrated in Figure 7. During the simulation, the system records the number of packages delivered, delivery success rate, total delivery distance, average delivery distance, and performance metrics related to obstacles. Figure 8 shows the evolution of the number of parcels delivered, illustrating the gradual completion of delivery tasks and the delivery success rate, which reaches 100% when all packages are delivered.

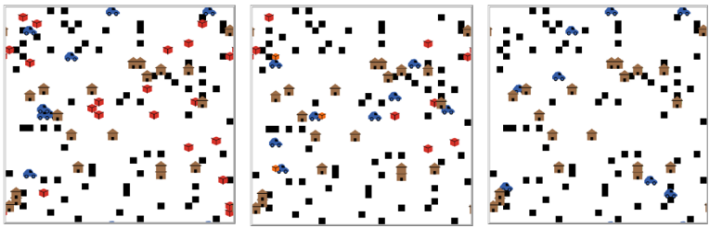

Figure 7. Simulation of the delivery process with planning and obstacle avoidance

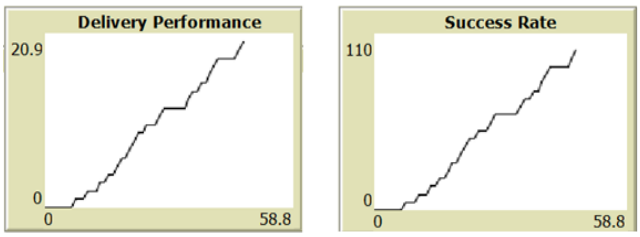

Figure 8. Evolution of delivery performance and success rate during the simulation

Finally, Figure 9 show that SR improves coordination efficiency rather than simply reducing individual delivery time. Compared to the non-semantic configuration, this reduced the total distance by 10.4% and reassigned tasks by 63.6%, while maintaining a 100% delivery success rate and no formatting conflicts. Although the average delivery time increased slightly, the overall duration of the simulation increased from 54 to 51 clicks, indicating more effective overall coordination among agents.

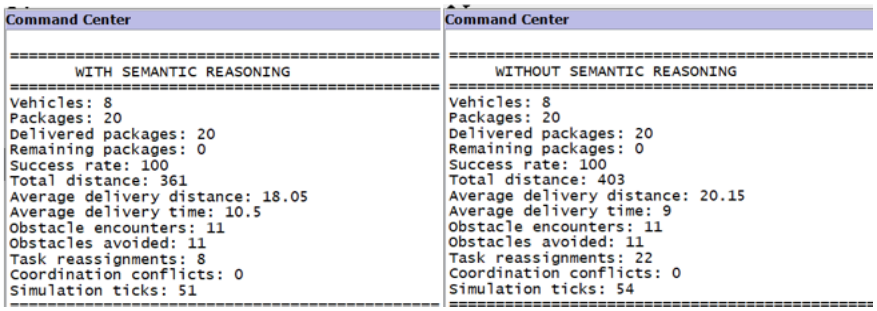

Figure 9. Summary of the final simulation results

Python-based simulation was used to validate the applicability of the AVsOnto framework in a 20 × 20 grid environment containing AVs, delivery parcels and obstacles. Vehicles perform task allocation and route planning using ontology-based information, while adapting their trajectories to environmental constraints. Two scenarios were considered: 8 vehicles with 20 packages and 50 obstacles, and 14 vehicles with 40 packages and 70 obstacles. Both scenarios reached a 100% delivery success rate, with low reasoning latency, demonstrating the practical applicability of AVsOnto for semantic task allocation and coordinated autonomous delivery as shown in Figures 10 and 11.

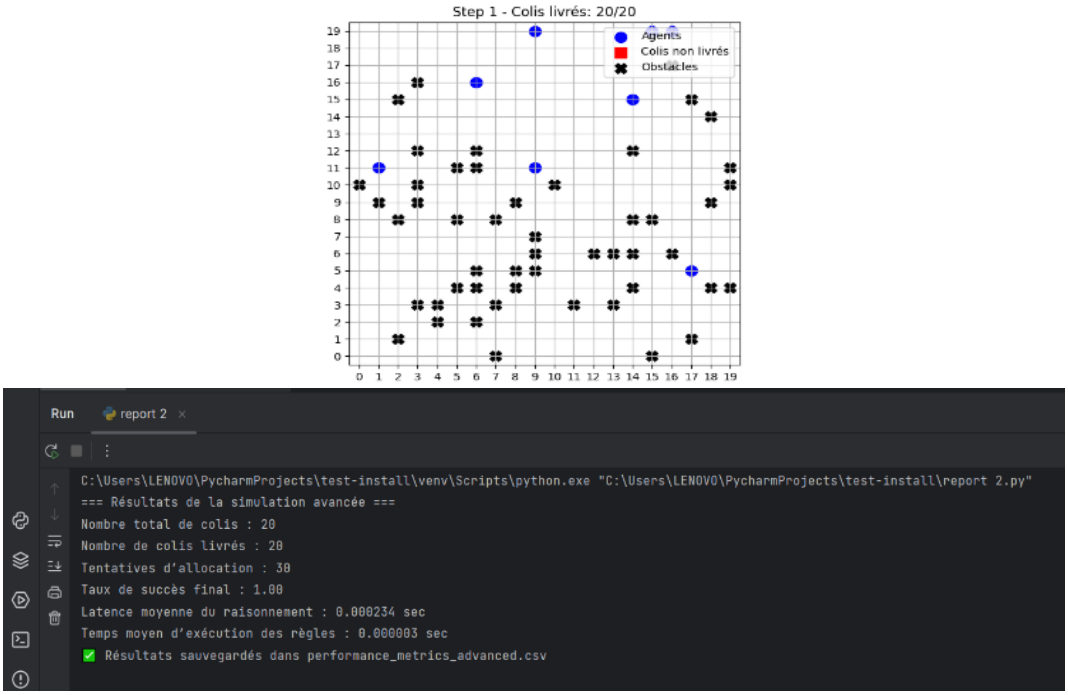

Figure 10. Dynamic coordination and performance metrics of 8 agents in a 20-parcel and 50-obstacle

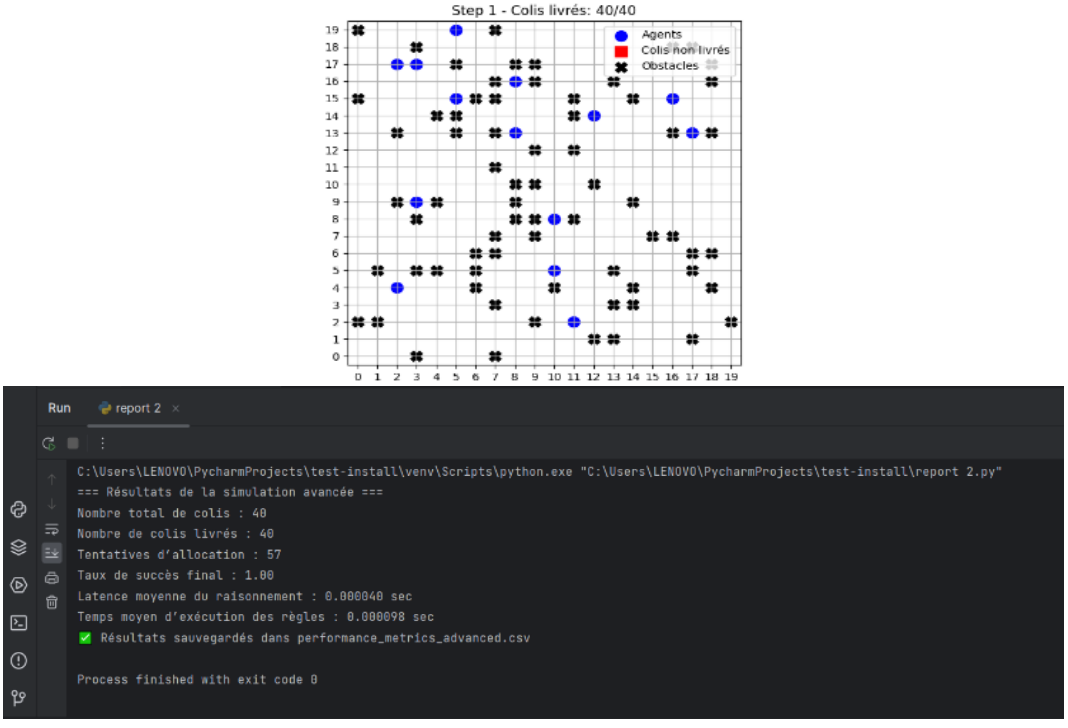

Figure 11. Dynamic coordination and performance metrics of 14 agents in a 40-parcel and 70-obstacle

4.3. Learning agents

To improve adaptability, the proposed Python-based SMA integrates reinforcement learning [34] into ontology-driven reasoning. Agents learn optimal delivery strategies through Q-learning while respecting the semantic constraints defined in AVsOnto. The approach was evaluated in a 5 × 5 discrete grid environments with delivery tasks, obstacles, and restricted areas.

4.3.1. Simulation setup

Five agents (AVs) were initialized on the top row of the grid ([0, 0] to [0, 4]), each having a delivery goal on the opposite side ([4, 4] to [4, 0]). Ontological constraints such as forbidden zones (e.g., [1, 1], [2, 2]) and speed limits were extracted via Owlready2 and integrated as semantic penalties. The reward function was defined as follows:

- Step cost: −1
- Forbidden zone entry: −10
- Collision between agents: −5
- Successful delivery: +10

The Q-learning parameters were set to $\alpha = 0.1$, $\gamma = 0.9$, and an ϵ-greedy policy decaying from 1.0 to 0.01 (decay factor 0.995). Each agent was trained for 100 episodes, sequentially, in an environment with randomly moving peers.

4.3.2. Learning dynamics and reward analysis

The results show a gradual improvement in agent performance. During the first episodes, rewards were mostly negative (between -40 and -60), mainly due to exploration and frequent constraint violations. After around 50 episodes, rewards increased to between -5 and +1, suggesting that agents became better at avoiding forbidden areas and reducing collisions (Table 5). Overall, this improvement indicates that agents gradually learned from their interactions with the environment.

Table 5. Empirical performance of agents over 100 episodes

Agent ID	Mean reward (Ep. 1–0)	Mean reward (Ep. 81–100)	Avg. steps (final)
0	-52.3	1.2	9.4
1	-48.7	1.4	8.9
2	-61.2	0.8	10.2
3	-45.9	1.5	8.7
4	-49.1	1.3	9.1

The Q-values converge toward higher positive values near goal states (e.g., Q[3, 3, 3] ≈ 3.5 for rightward action toward [3, 4]) and remain negative near restricted cells (Q[1, 1, :] ∈ [-2, -5]). For example, the optimal trajectory of agent 0 avoids the semantic constraints defined in AVsOnto:

$$[0, 0] \rightarrow [0, 1] \rightarrow [0, 2] \rightarrow [0, 3] \rightarrow [0, 4] \rightarrow [1, 4] \rightarrow [2, 4] \rightarrow [3, 4] \rightarrow [4, 4]$$

This demonstrates that semantic constraints guide the agents toward safe and efficient paths.

4.3.3. Discussion and implications

The simulation validates that reinforcement learning can effectively integrate ontological reasoning within an MAS. Agents adapt their behavior to respect semantic constraints while optimizing delivery time. Despite the limited 5 × 5 grid, convergence was achieved after approximately 50 episodes, illustrating the feasibility of scaling this hybrid neuro-symbolic approach. Performance metrics collected during training include: i) reasoning latency per step: ≈0.015 s; ii) rule execution time (Owlready2 reasoning): ≈0.08 s; and iii) agent coordination success rate: ≈92%. These results demonstrate that integrating semantic ontologies as dynamic priors enhances decision interpretability and coordination efficiency in autonomous delivery scenarios as shown in Figure 12.

The experimental results show that SR improves agent collaboration by providing a shared understanding of vehicles, packages, tasks, destinations, and environmental conditions. Through AVsOnto and SWRL rules, agents can infer contextual information, reduce ambiguity, and make more consistent decisions for task allocation, obstacle avoidance, and coordination. This is particularly useful when obstacles or multiple delivery requests are present, as agents can adapt their actions to the current situation. However, SR introduces additional computational overhead, making scalability with larger numbers of agents and more complex knowledge bases an important direction for future work.



Figure 12. Learning curve of multi-agent reinforcement learning (5 agents)

4.4. Data publication

Semantic publishing relies on RDF and OWL standards to make data machine-readable and interoperable on the web [35]. In this work, the RDF ontology and dataset are published as Linked Open Data (LOD) Cloud [36], enabling public access, querying, and reuse via a direct web link, as shown in Figure 13. This approach facilitates knowledge sharing and integration with other semantic applications. It also supports the extension and reuse of AVsOnto in different autonomous delivery scenarios.

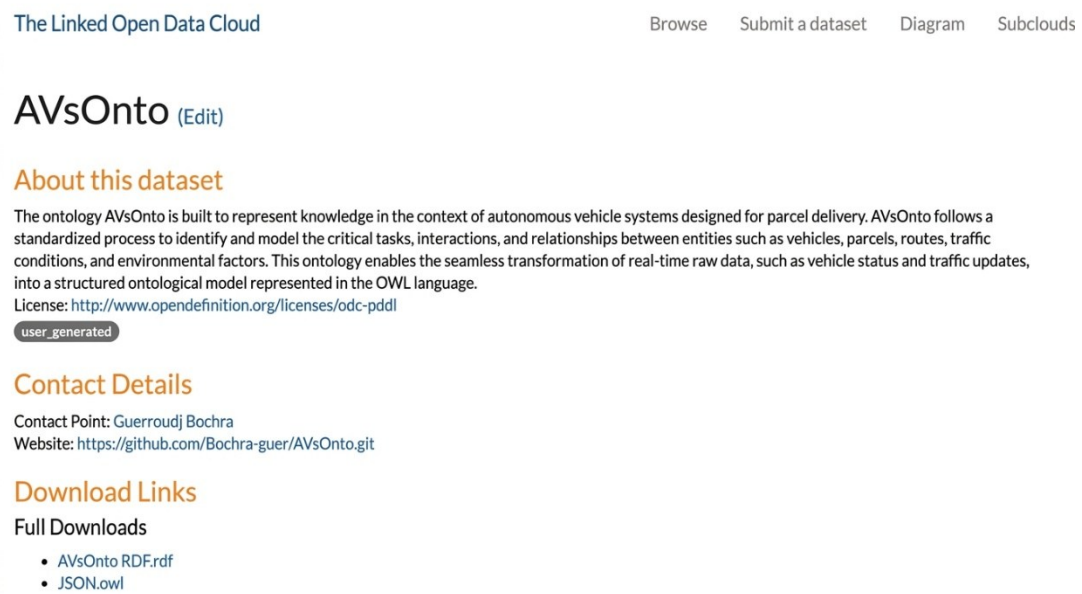

Figure 13. LOD Cloud model

5. COMPARATIVE ANALYSIS WITH EXISTING ONTOLOGIE

To evaluate the originality and robustness of the proposed ontology, AVsOnto was compared with representative ontologies, such as SUMO, SOSA/SSN, and I4.0-Onto, focusing on three main criteria: expressiveness, reasoning depth, and interoperability. What sets AVsOnto apart is that it doesn't just capture static info about traffic or sensors. It combines task related concepts with behavior rules using SWRL. Unlike SUMO or SOSA/SSN, which mainly describe physical things and observations, AVsOnto models how agents interact dynamically, considers context-based rules, and organizes goals in layers. This helps support smarter decision-making in multi-agent setups. Ontologies like SOSA/SSN handle basic inferences, like "a

sensor observes a property." AVsOnto goes further by mixing traditional reasoning with neuro-symbolic methods based on graph neural networks. That means it can draw deeper conclusions like figuring out the best vehicle task matches, route limits, or which tasks need immediate attention instead of just following simple class hierarchies.

Interoperability was a key focus when building AVsOnto. It builds on concepts from SSN, DOLCE, and Industry 4.0 ontologies and supports standard RDF/OWL formats. This makes it easy to use with tools like SPARQL and Protégé, as well as multi-agent platforms such as Java agent development framework (JADE), NetLogo, and Python agents using Owlready2. Because of this, AVsOnto can act as a shared semantic foundation that links different intelligent agents and external AI planning tools like PDDL based planners.

6. LIMITATIONS AND FUTURE WORK

Despite the advantages of the proposed framework, its scalability and computational efficiency remain significant challenges. As the size of the ontology and the number of agents and knowledge states increase, SR may require higher computational resources and lead to increased latency in reasoning. The present study does not provide a comprehensive assessment of ontological scalability, memory consumption, computational complexity and thought latency under large-scale conditions. As a result, future work will examine the scalability and computational performance of the framework across broader sets of agents and ontological instances, while assessing reasoning time and resource utilization. In addition, future work could develop a unified framework that integrates symbolic reasoning (OWL/SWRL) with graph-based models such as graphical neural networks (GNNs). This hybrid approach would combine logical reasoning and relational learning, potentially improving adaptive path planning, task coordination, and decision-making in large-scale dynamic delivery environments.

7. CONCLUSIONS

This study has highlighted the significant role of semantic approaches in improving efficiency and adaptability within multi-MAS, particularly in the context of dynamic planning for smart delivery using AVs. This paper has shown that leveraging semantic technologies enables rich data representation and reasoning, which substantially enhances decision-making in complex and unpredictable environments. The integration of ontologies and LD provides a coherent framework for agent interaction and collaboration, allowing the system to process real time information and promptly adjust route planning, resource allocation, and task management. This semantic-driven methodology paves the way for more reliable, scalable, and intelligent solutions in smart delivery systems, supporting the development of fully autonomous logistics networks. Future work may focus on combining advanced reasoning mechanisms with machine learning models to further improve predictive capabilities and adaptability to changing conditions. The findings of this study demonstrate the potential of semantic approaches not only to redefine autonomous delivery but also to extend efficient multi-agent coordination to other dynamic and complex domains.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article in GitHub at https://github.com/Bochra-guer/AVsOnto.

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