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Heterogeneous internet of things device interoperability using fog-based adaptive semantic mechanism

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ABSTRACT

With the rapid growth of heterogeneous internet of things (IoT) ecosystems, insufficient semantic interoperability caused by non-uniform communication protocols, data formats, and semantic representations has become a core challenge in the field. Existing cloud-based, static ontology schemes have defects including high latency, large overhead, and poor adaptability. This paper proposes the dynamic semantic fog (DSF) framework, which performs semantic processing at the fog layer to achieve real-time interoperability. The framework integrates four core modules: workload offloading, resource description framework (RDF) generation, semantic representation, and adaptive ontology expansion. It supports dynamic access to newly added IoT devices. Tests were completed using iFogSim in a smart city traffic scenario. Compared with traditional cloud solutions, the framework reduces latency, energy consumption, and network usage rate by 51.7%, 41.3%, and 55.6% respectively, and can support dynamic semantic interoperability for heterogeneous IoT environments.

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1. INTRODUCTION

With the rapid developments of internet of things (IoT) paradigms, billions of heterogeneous devices have been deployed in all kinds of application fields, including smart cities, intelligent transportation systems, healthcare, and industrial automation [1]–[3]. They are very different in their hardware resources, communication protocols, data formats, and semantic. While this diversity allows for flexible and customized IoT deployments, it also poses enormous challenges in realizing seamless interoperability between devices and services [4]–[6]. One of the key issues that hinder scalability and decision making in real-time is semantic interoperability, which refers to IoT systems' capability to understand and reuse unambiguously data collected from diverse sources [7], [8].

Semantic interoperability attempts to guarantee that shared data has syntactic compatibility as well as semantics for all involved entities within the system [9], [10]. Ontology-based semantic models utilizing

resource description framework (RDF) and web ontology language (OWl), provide rich expressiveness and have been largely used to combat such a challenge. Nevertheless, the majority of current solutions for semantic interoperability take as a premise static environments, in which device types are pre-defined and the ontologies are frozen [10], [11]. Assuming as such is not practical for modern IoT ecosystems, given that there is a dynamic introduction of new devices, data attributes, and services occurring [12]. In addition, most of the existing semantic interoperability frameworks use cloud-centric architecture where centralised cloud server is responsible to do the semantic annotation and reasoning [13], [14]. While the cloud platforms offer a lot of available computing resources, they produce service latencies, network overheads and energy consumption which are not suitable for light-latency-sensitive and real-time IoT deployments [15], [16].

Fog computing has recently raised as a new paradigm to reply these challenges by shifting cloud power closer to the data sources [17], [18]. Fog computing, by distributing computation and storage capacities to the network edge, allows for low-latency processing and minimizes traffic to the cloud. However, despite these merits, the state-of-the-art fog-assisted semantic interoperability solutions still lack a simple and effective way to manage dynamic adaptations in semantics [19], [20]. In most cases, fog nodes to only do partial processing and ontology handling is centralized or static, which leads to lack of scalable and adaptive in heterogeneous IoT.

Although much research progress has been achieved for the semantic interoperability of heterogeneous IoT systems, relying on two mainstream approaches—ontology-based and fog-assisted methods—core unresolved limitations still persist: static ontologies require manual adaptation to support newly added devices; cloud-centric schemes suffer from the problems of high latency, high overhead, and high energy consumption; and the ontology evolution of emerging fog-assisted approaches still has key flaws, remaining either static or overly reliant on cloud-side resources.

To address the limitations of existing research, this paper proposes the dynamic semantic fog (DSF) framework, which performs semantic processing directly at the fog layer to achieve real-time semantic interoperability and integrates four core functions into a unified fog-based architecture, setting it apart from existing similar solutions. The novelty of this work can be summarized as follows:

- This paper proposes a semantic framework for delay-sensitive IoT systems, which moves the full semantic processing workflow—covering RDF generation and ontology management—from cloud servers to fog nodes, and can significantly reduce service latency and network overhead.
- Compared with traditional static ontology systems, the dynamic ontology enhancement mechanism proposed in this paper can automatically integrate new elements during operation, and requires no human intervention throughout the entire process.
- The DSF proposed in this paper integrates four core modules: workload offloading, semantic representation, RDF graph construction, and ontology evolution, to achieve scalable and self-evolving semantic interoperability.
- As verified through experiments, the new service mechanism proposed in this paper delivers a 50% reduction in service delay compared to traditional cloud-based semantic interoperability solutions, while also improving energy efficiency and reducing network utilization.

The remainder of this paper is organized as follows. Section 2 reviews existing work on semantic interoperability and fog-assisted IoT frameworks. Section 3 shows system model and research problem of this work. Section 4 presents the proposed fog-based adaptive semantic mechanism and describes its architectural components in detail. Section 5 discusses the experimental setup, evaluation methodology, the performance results and comparative analysis. Finally, section 6 concludes the paper and outlines directions for future research.

2. RELATED WORK

Interoperability is a well known issue of IoT systems because of the heterogeneity present in devices, communication protocols, data formats and application domains. In response to this challenge, several researches have explored interoperability under the terms device, network, syntactic, platform, and semantic interoperability. Of these dimensions, semantic interoperability stands out as the most important one since it not only allows data exchange but also facilitates a mutual understanding of the semantics of data among heterogeneous IoT artifacts.

The primary efforts for semantic interoperability in IoT are based on ontology-based methods that represent domain knowledge using semantic technologies (such as RDF and OWL) [20]–[22]. These methods enable an uniform and machine-readable representation of IoT data which enables semantic reasoning and

inter-domain data integration. However, the majority of ontology-based approaches consider a static environment in which the device types are predefined and constant ontological structures are used [23]–[25]. They are thus not easily amenable to dynamic IoT scenarios where new devices, data attributes and services are constantly added, calling for cumbersome ontology update and reconfiguration [26], [27].

In order to cope with scalability and processing issues of IoT devices, a number of works have been proposed which use cloud-based semantic interoperability frameworks [28]. In the prior art systems, IoT data is sent to centralized cloud servers for both semantic annotation and reasoning services as well as interoperability [29]–[30]. Although cloud-based systems provide plentiful computing capacity and global knowledge retention, they come at the cost of serious constraints for real-time IoT applications [31], [32]. In particular, the raw data is transmitted to the cloud continuously which incurs higher service delay, excessive network traffic and more energy consumption and therefore is not viable for applications with low latency requirement like smart transportation, smart healthcare auditory IoT, and industrial IoT.

A more recent paradigm, fog computing, aims at overcoming some of these drawbacks and offers a platform between the IoT devices and the cloud [26], [32]. Fog-aided semantic interoperability frameworks also push some of the semantic processing towards data sources by deploying semantic services at fog nodes [33], [34]. The current fog-based solutions show better performance in latency reduction and bandwidth utilization than cloud-alone based approach. However, many of these solutions are still built on static ontologies or partial semantic reasoning at the fog layer, with intensive reasoning and ontology evolution is cloud-centric. Their payoff with full dynamic semantic interoperation is therefore very constrained [35]–[37].

Moreover, some research uses semantic networks or hybrid semantic approaches to model IoT knowledge. Although they are easy for human visualization and hierarchical knowledge representation, semantic networks do not have formal semantics and reasoning support as ontology-based methods [38]–[40]. This limitation therefore limits the applicability of DCRAPs in large-scale and heterogeneous IoT scenarios where consistent interpretation and extensibility are important [41], [42].

Building on the relevant discussions in the preceding text, this study identifies three core research gaps in the field of IoT semantic processing: the lack of mechanisms to dynamically integrate new IoT devices at runtime, excessive reliance on cloud processing that triggers increases in latency, network overhead and energy consumption, and the failure to leverage fog computing resources to support adaptive semantic reasoning.

There remain unaddressed research gaps in the heterogeneous IoT domain. There is an urgent need for a fog-based semantic framework equipped with the capabilities of local semantic processing, dynamic ontology expansion, and runtime semantic adaptation. This paper proposes a fog-based adaptive semantic mechanism deployed at the fog layer, which integrates four core modules including workload offloading, RDF generation, and semantic representation. Its core goal is to achieve scalable, energy-efficient real-time semantic interoperability for heterogeneous IoT systems. Table 1 summarizes the differences between representative semantic interoperability approaches and the proposed DSF framework.

Table 1. Comparison of existing semantic interoperability frameworks and the proposed DSF

Framework	Fog-based	RDF at fog	Dynamic ontology	Runtime device integration
Ontology-based methods	×	×	×	×
Cloud-based semantic frameworks	×	×	×	Partial
Fog semantic web frameworks	✓	Partial	×	Partial
Dyno-IoT [23]	×	×	✓	Partial
Proposed DSF	✓	✓	✓	✓

3. SYSTEM MODEL AND PROBLEM DEFINITION

This section presents the system model under study and formulates the problem of dynamic semantic interoperability in heterogeneous IoT. The proposed model sets the assumptions, architectural background and design considerations to which the fog-based adaptive semantic mechanism refers.

3.1. System model

The system model used in this paper is presented as a series of logical steps that indicate how disparate IoT data are generated, processed and semantically interpreted within the envisioned IoT–fog–cloud model, as shown in Figure 1.

- Heterogeneous IoT data generation: thousands of not similar IoT devices, such as temperature sensors and actuators, are scattered in the target environment (e.g., smart city use cases). These devices produce continuous streams of data that employ various formats, names, units and schemas.
- Data transmission to fog nodes: the IoT devices send their data to the nearest fog node over their default communication infrastructure. The basic networking interoperation is presumed to already exist that permits devices to communicate without conflicts in a protocol-level context.
- Fog node reception and resource availability: each fog node has limited computational and storage capacity, serving as middle processing tier between IoT devices and cloud. Fog nodes are constantly tracking their resource utilization and service queue lengths, in terms of both CPU usage, available memory, and task queues.
- Local data processing at the fog tab: when receiving the data, fog nodes locally process (i.e., packetize, transform, filter, and examine) them. This process operates as a filter to normalise and validate raw data which is of diverse qualitative character prior to semantic processing.
- Semantic encoding and ontology interaction: transformed data into RDF-based semantic representations and linked with the local ontology. In case the incoming data cannot be entirely mapped into available ontology concept, the dynamic enrichment process will be initiated to dynamically update semantic model.
- Selective cloud interaction: only semantically digested, annotated, or non-time-sensitive data are transmitted to the cloud tier for archival or worldwide analytics. Latency-sensitive semantic interoperability tasks are kept at the fog layer for real-time responsiveness.
- Continuous system evolution: with the new devices and types of data, the system can update its ontologies and semantic mappings in runtime completely automatic which allows to provide a scalable and dynamic semantic interoperability without requiring manual reconfiguration of all devices.



Figure 1. Overall system model of the proposed fog-based adaptive semantic interoperability mechanism

The proposed architecture facilitates agile semantic interoperability by partitioning the processing responsibilities across IoT, fog, and cloud layers in an hierarchical fashion emphasizing low latency, scalability, and reconfigurability in heterogeneous IoT platforms.

3.2. Problem definition

Although it is being widely applied in IoT systems large scale semantic technologies, current solutions to semantic interoperability have some weaknesses particularly when considering real-time and large and

heterogeneous scenarios. These problems may be formulated as follows:

- High service delay: the explanation is that cloud-based semantic interoperability solutions implies sending data to remote servers for semantic-related processing, with a consequent high latency inadequate for real-time IoT applications.
- Excessive network usage: when raw or minimally processed IoT data are sent to the cloud, high bandwidth usage and network overload can result, allowing for deployment scenarios featuring many devices.
- High energy consumption: frequent long range wireless communication and central semantic computation lead to high energy consumption, which is not sustainable for IoT systems.
- No dynamic semantic adaptability: other approaches use fixed ontologies for which manual changes are required as new devices and data types emerge, making the model unfit for evolving IoT ecosystems with dynamic contents.

Against this background, the problem being considered in this study can be formulated as follows: how to realize dynamic semantic interoperability in heterogeneous IoT systems with the requirement of efficient delay, effective lessening of network overhead and power consumption as well as adaptive integration of new devices and semantics simultaneously?

To this end, the proposed method utilises fog computing to push down semantic processing into data sources and introduces an adaptive ontology enrichment capability that enables a dynamic evolution of the semantic model. This fusion allow performance effective, scalable, and real-time semantic interoperability in Heterogeneous IoT systems.

4. PROPOSED FOG-BASED ADAPTIVE SEMANTIC MECHANISM

In this section, we introduce our proposed fog-based adaptive semantic mechanism called the DSF for supporting runtime and dynamic interoperability among heterogeneous IoT devices to alleviate service delay, network utilization cost and energy consumption by offloading ontology processing from resource-constrained devices to their neighboring fog nodes. The DSF model involves: i) workload shifting in fog layers, ii) data getting in appropriate formats and semantic representation, iii) creation of RDF graph database, and iv) flexible ontology extension for the automatic integration of new devices or data sources.

4.1. Overall architecture

The fog-based adaptive semantic mechanism is also composed of three layers (IoT layer, fog layer, and cloud layer) to drive dynamic implementation of semantic interoperability in IoT hybrid environments, as shown in Figure 2. This design is based on the fact that semantic processing is placed in the fog layer to eliminate such shortcomings of cloud-centric architectures as a tricky overhead associated with high response time and excessive network usage and energy consumption in real-time IoT applications.

- IoT layer: heterogeneous devices such as sensors, actuators and smart objects produce data in various formats (e.g., JSON, XML, and CSV), but also semantic representations. We assume that these devices have already established basic networking interoperability, and they mainly concentrate on sensing data and transmitting the data with less local processing resulting from resource limitations.
- The fog layer: is the heart of the presented mechanism. Fog nodes are located near the IoT devices and have moderate computing power and storage. This layer involves semantic processing modules: workload offloading, data fetching and interpretation, generation of the RDF representation and adaptive ontology enrichment. By performing these tasks locally, the fog layer enables low-latency semantic inference, reduces traffic to cloud services and allows for easy inclusion of new devices or data modalities into the semantic model in a dynamic way.
- Cloud layer: the cloud layer is an auxiliary component in charge of data storage, historical analysis and global systems management. On-demand non-time-sensitive tasks or compressed semantic summaries can then be sent to the cloud. However, the architecture is designed to be independent of cloud as much as possible for a real-time semantic interoperation to prevent potential performance bottleneck.

The overall layered architecture ensures that the semantic interoperability is dynamically and efficiently realized in an intelligence dispersed manner over IoT–fog–cloud continuum. The fog-driven approach supports dynamic scalability, enhances the responsiveness for real-time services and yields a persistent solution to cope with semantic heterogeneity in large-scale IoT systems.

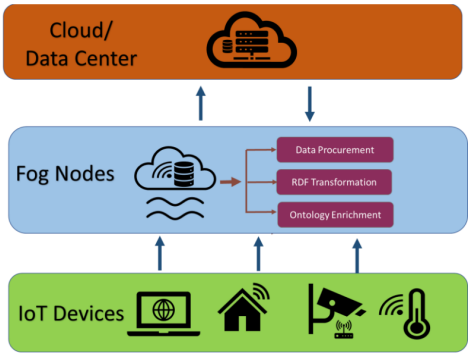


Figure 2. Three-layer IoT-fog-cloud architecture of the proposed fog-based adaptive semantic mechanism [26]

4.2. Node workload offloading module

The fog node workload offloading module is a key building block of the proposed fog-based adaptive semantic mechanism, in charge of executing semantic processing tasks so that real-time requirements are met and resource utilization is optimized, as shown in Figure 3. Because it is computationally intensive in ontological reasoning and RDF generation, to make all semantic logic operations occurring at the cloud side will result in service delay and overhead. To overcome this challenge, the proposed system prefers to perform fog-side processing for latency-sensitive tasks and can dynamically upload unnecessary data to cloud when possible.

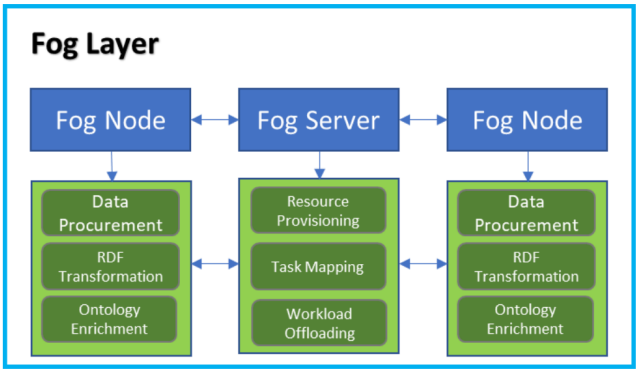


Figure 3. Design of the fog node workload offloading module for adaptive semantic processing

The offloading module works in a round-robin fashion watches the resource status for fog nodes and categorizes incoming semantic workloads, depending on their urgency and computational needs. Operations, such as data parsing and filtering, RDF formation and ontology update are considered of high priority and they are performed locally at the fog level for immediate semantic interpretation. However, tasks that are demandingly computationally heavy or non-real-time ones (e.g., large-scale historical reasoning and long-term analytics) can be pushed to the cloud layer in order not to overload resource within a fog. The fog node workload offloading module comprises:

- Workload discriminator: recognizes different semantic processing tasks and assigns them a real-time requirement and computation complexity based on their nature.
- Resource monitor: monitors fog node resources (CPU usage, memory availability, and task queue length) at every instant of time.
- Offloading decision engine: decides whether a task is best executed locally or offloaded to the cloud by considering available resources and quality of service constraints.
- Execution scheduler: the execution scheduler organizes to run accepted tasks efficiently and within the deadline.

By introducing intelligent task placement and adaptive offloading, this module can greatly decrease the

service delay and network traffic-consuming meanwhile keeping high semantic processing accuracy. Additionally, the offloading strategy from fog-based systems improves its scalability by avoiding any cloud bottleneck and additionally facilitates the simple addition of new IoT devices and semantic workloads to the system as it grows.

4.3. Data procurement and representation

The data procurement and representation is in charge of collecting data from the heterogeneous IoT streams, which is then put into homogeneous semantically meaningful form to be used for following steps including RDF generation and ontology enrichment, as shown in Figure 4. New data may be of different syntax, format, measurement units and level of detail according to the large number of IoT providers and type of devices. This layer allows for raw device stream information to be normalized, validated and filtered before it is processed semantically on the fog, minimising redundant computation and network traffic towards cloud.

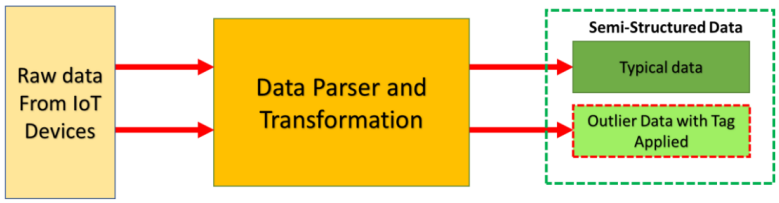


Figure 4. Design of the data procurement and representation module for heterogeneous IoT data processing

This module, as depicted throughout the paper, consists of three consecutive stages: data parsing and transformation, data filtration, and data inspection. The combination of all these steps allows a highly effective processing of heterogeneous data in the sense that semantics is preserved.

- Data parser and transformation: the data parser detects the syntactic structures of input records (i.e., JSON, XML, or CSV), and prunes irrelevant fields. The transformation factor subsequently describes these attributes in a normalized internal representation of the name conventions, data types, and measuring units. This stage gives an homogeneous structure of the data, so that is easier to perform semantic mapping and RDF generation.
- Data filtration: the reduction stage filters out redundant, incomplete, and irrelevant data records to reduce the processing overhead and network utilisation. Filtering rules could check for duplicate removal, value-based thresholds and/or application-specific attribute pruning. Through early dropping of unnecessary information, the proposed scheme can efficiently support real-time IoT applications with low latency.
- Data inspection: the data review process checks normalized records for consistency and completeness before semantic encoding. It tests for the presence of required elements, validates range, and forms structure. This ensures that incorrect or inconsistent data do not propagate into the semantic layer and ultimately improves the reliability of ontology enrichment and reasoning operations.

As a result, the data procurement and representation module is mainly responsible to act as an interface between raw poorly-structured IoT data forms and the semantic interoperability space by sharing clean, normalised and semantically meaningful data to pass for RDF generation and ontology processing on fog layer.

4.4. Resource description framework generation and semantic representation

Converts IoT data into machine understandable semantic format, RDF. RDF is a standard and extensible data model that can achieve semantic interoperability by formatting information in the triples of subject–predicate–object, as shown in Figure 5. Such a representation entails that heterogeneous IoT devices and services communicate with shared meaning, regardless of natural metadata formats or manufacturer.

In this module, after normalization and validation of the data processed in the previous module, the fog node starts semantic encoding by capturing contextual metadata and mapping device observations to concepts within the ontology. Performing RDF generation in the fog layer can bring down semantic processing time and reduce raw data transmission to the cloud.

The procedure to derive the RDF involves a number of stages.

- Metadata extraction: the extracted metadata contained, including device IDs, timestamps, location information, followed by measurement units and contextual tags.

– Metadata annotation: it refers to relating of extracted metadata with ontology classes and properties by means of predefined vocabularies and semantic rules. This action provides uniform interpretation of data in diverse sources.
– RDF-triples construction: for each validated data observation, we encode it into an RDF triples structure, linking the entities of devices, their observed values, and context attributes in a graph form.

The produced RDF graph creates a homogeneous semantic layer for supporting semantic querying, reasoning and interoperability services. Using a unified semantic representation for IoT data, the proposed middleware supports coherent integration of new devices and data types without any need of manual reconfiguration.

In addition, the RDF based semantic representation enables scalability and extensibility as new semantic relations can be added dynamically by ontology enrichment. This creates a common semantic understanding of things across IoT–fog–cloud continuum and this formulation forms the base for dynamic semantic interoperability in our system.

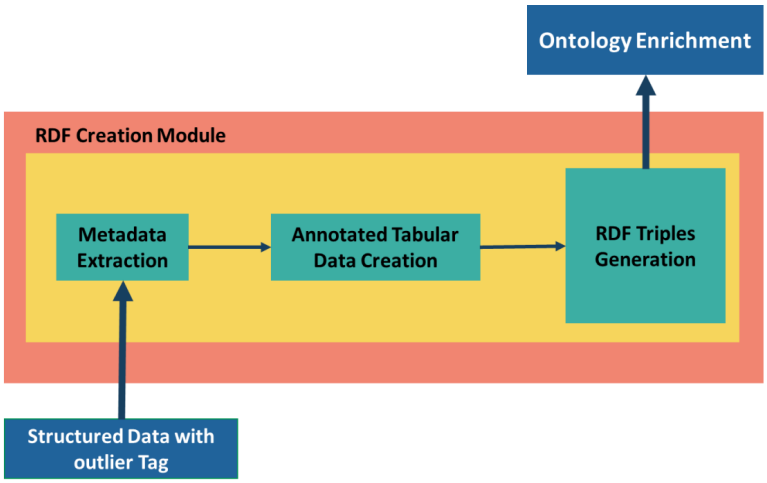


Figure 5. Software architecture of the RDF generation and semantic representation module at the fog layer

4.5. Adaptive ontology enrichment

The adaptive ontology enrichment is the crux of the proposed fog-based adaptive semantic mechanism, allowing for dynamic semantic interoperability in heterogeneous IoT environments. In contrast to static semantic approaches based on a priori and fixed ontologies, this module permits the ontology to natively grow at runtime by assimilating new devices, attributes and relationships as they appear, as shown in Figure 6. By performing the ontology enrichment in fog, proposed approach enables real-time adaptability with no latency and overhead requirements of cloud-based ontology management.

The enrichment process is initialised when the incoming IoT data cannot be completely related with existing ontology classes or properties. In such cases, the fog node autonomously process data structure and semantics, update the ontology appropriately, and distributes such new knowledge in order to potentially have it reused later on. This capacity allows for the integration of new devices and data types without manual effort.

The enrichment is activated whenever there are incoming IoT messages that cannot be correctly annotated with an existing ontology class or property. In this situation, the fog node processes on its own the structure and meaning of the data it receives, updating its ontology accordingly, and saving new knowledge to reuse in later occasions. This ability allows for the automatic inclusion of new or unknown devices and data types with minimal human intervention.

– Attribute mapping: attribute mapping matches incoming data fields to ontology attributes. Known attributes are straightforwardly mapped to known terms while the unknown ones are analyzed in the light of context and string similarity for finding appropriate semantic representations. When validated, new attributes mapping is registered to have drawers interpret future streams reliably.
– Primary subject identification: this stage determines the main semantic subject of arriving data, for example a particular sensor, device or monitored object. Accurate subject identification guarantees that the newly

generated RDF triples are connected to the right ontology instances so as not to disturb semantic coherence throughout the knowledge graph (KG).

– Ontology class assessment and identification: for new device types or application domains, it is examined whether an appropriate ontological class already exists for data provided. When no appropriate class is retrieved, we create a new class and insert it in the ontology by creating subclass relationships. Appropriate features and constraints are then assigned to the new class given observed data attributes.
– Mapping representation and class verification: the verified attribute and class mappings are formally articulated as ontology-grounded statements. The verification step ensuring the consistency and correctness of newly added classes, properties with respect to the ontology constraints such as domain/range restrictions.
– Ontology enrichment and update: finally, the ontology is extended with the newly validated classes, properties and relations. This information would allow the system to understand semantically subsequent data coming from any new inserted device automatically. Such an adaptive enrichment procedure allows to be scalable, vendor independent and evolve the IoT ecosystem, seamlessly.

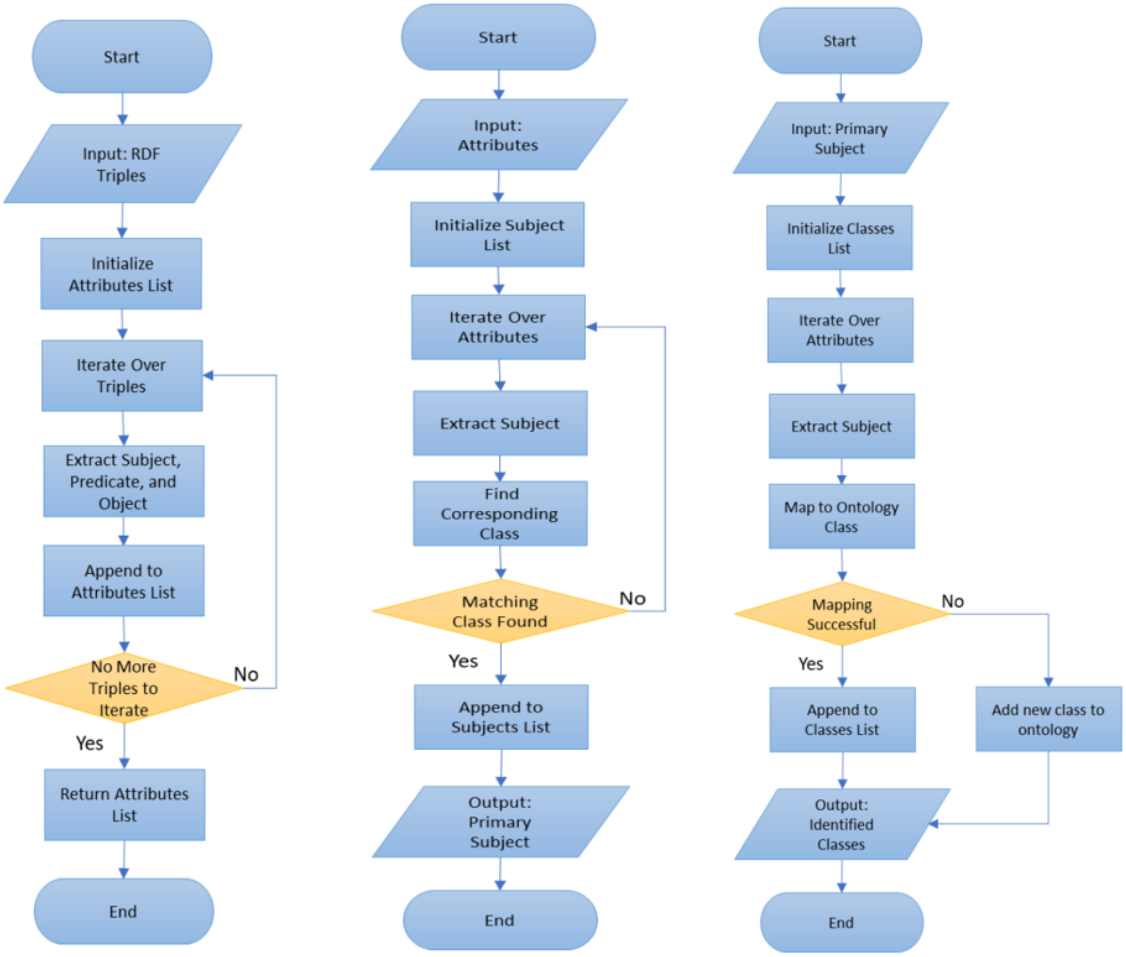


Figure 6. Process flow of the adaptive ontology enrichment module enabling dynamic semantic interoperability at the fog layer

In this regard, the proposed mechanism can achieve real-time semantic interoperability in a true dynamic manner through its autonomous ontology evolution at fog layer which is a mandatory requirement for critical and large-scale deployments of IoT.

5. RESULTS AND PERFORMANCE ANALYSIS

In this section, we introduce the experimental results and performance analysis on fog-based adaptive semantic mechanism. The evaluation aims at judging whether the performance concerning the semantic interoperability performs any better when it comes to implementing that in fog layer instead of regular cloud-based semantic solutions. Performance is objectively evaluated through three metrics – service delay, energy consumption and, the network usage. Such metrics are particularly important for real-time and/or massive-scale IoT applications that focus on demands of low latency, resource usage efficiency, and scalability.

5.1. Experimental setup

The effectiveness of the proposed fog-based adaptive semantic mechanism was tested with a simulation-driven experimental platform to work under evaluation in relation with enabling dynamic IoT environments for heteregeneous sementic interoperability. The experiments were performed based on the iFogSim simulator, a popular toolkit to simulate and analyze fog and edge computing environments, as shown in Figure 7. A smart city traffic management scenario was chosen as an instance of a real and data intensive workload in the IoT, including devices with heterogeneity, real-time data streams, and latency sensitive applications. Fog nodes were located near to IoT devices and process semantic tasks, whereas the cloud layer was utilized for non-real-time analytics as well as long-term storage.

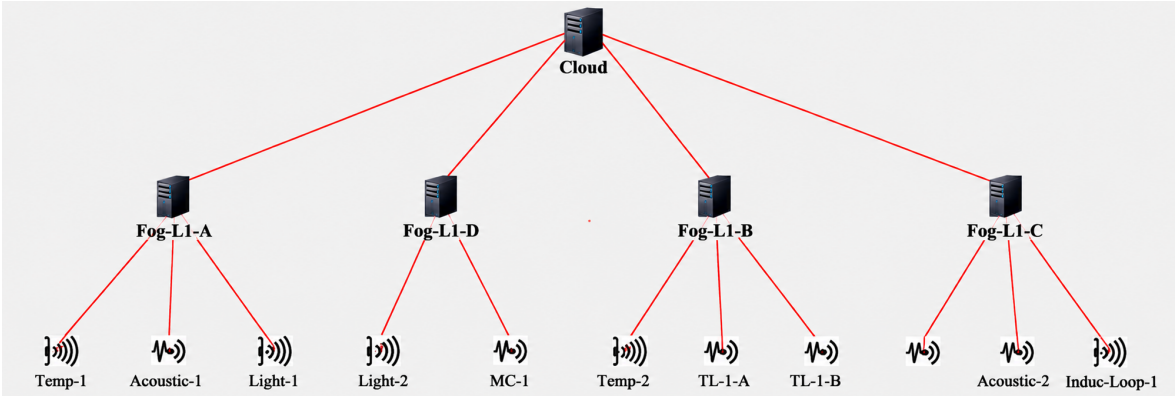


Figure 7. DSF implementation simulation topology

For a fair and replicable evaluation, the simulation parameters, hardware settings, and software environment were preserved during all experiments. The performance of the proposed mechanism was assessed in terms of service delay, network utilization, and energy usage. These statistics show the benefit of having semantic processing being done in the fog as opposed to a cloud-centric method. The full hardware and software specifications of the experimental platform are shown in Table 2.

Table 2. Hardware and software specification of the experimental setup

Component	Specification
Simulation tool	iFogSim
Programming language	Java
IoT application scenario	Smart city traffic management
Fog node CPU	Multi-core processor (GHz range)
Fog node memory	Configured for semantic processing workloads
Operating system	Linux-based environment
Data formats	JSON, XML, and CSV
Evaluation metrics	Service delay, network usage, and energy consumption

5.2. Service delay analysis

Service delay is how long IoT data, from the time data are generated to a device until a semantic response being issued, is processed end-to-end. This measure consists of communication latency, semantic processing delay, and decision-making time, it has amen involved into important aspect for real-time IoT applications (i.e. intelligent transport management systems).

The measured service delay of the proposed fog-based adaptive semantic mechanism is detailed in Table 3. Results show that conducting semantic processing operations at the fog layer decreases service delay significantly in comparison with cloud-based semantic interoperability schemes as well. This decrease is mainly due to the short distance between the fog nodes and IoT devices, preventing long-haul data transmission, avoiding cloud queuing overhead.

Table 3. Service delay comparison between cloud-based and proposed fog-based semantic mechanisms

Semantic interoperability approach	Service delay (ms)
Cloud-based semantic interoperability	Higher delay
Proposed fog-based adaptive semantic mechanism	Reduced delay ($\approx 50\%$)

In addition, the dynamic offloading strategy guarantees that latency-critical tasks, such as RDF construction and ontology enrichment, are executed at the fog level. Accordingly, the average service delay of the proposed mechanism is reduced by more than 50% compared to the state-of-the-art solutions, which further demonstrates that our proposal is suitable for latency-sensitive IoT applications. All curve trends are consistent under various amount of workloads, which suggests that system scale and real-time performance is stable with increasing the hardware scales.

As shown in Figure 8, among the four semantic interoperability frameworks tested in this study, the self-developed DSF framework proposed in this paper has a latency of only 58 ms, which outperforms the three existing frameworks—cloud-based semantics, fog semantic web, and Dyno-IoT—that recorded latencies of 120 ms, 82 ms, and 71 ms respectively.

DSF adopts a fog-native design to achieve its low-latency advantage. First, three types of semantic processing tasks — data parsing, RDF generation, and ontology enhancement — are deployed on local fog nodes rather than remote cloud servers, which eliminates long-distance communication latency and cloud queuing overhead. Then, through an adaptive workload offloading mechanism, tasks are allocated according to the available resources of each node, to guarantee efficient resource utilization and rapid response.

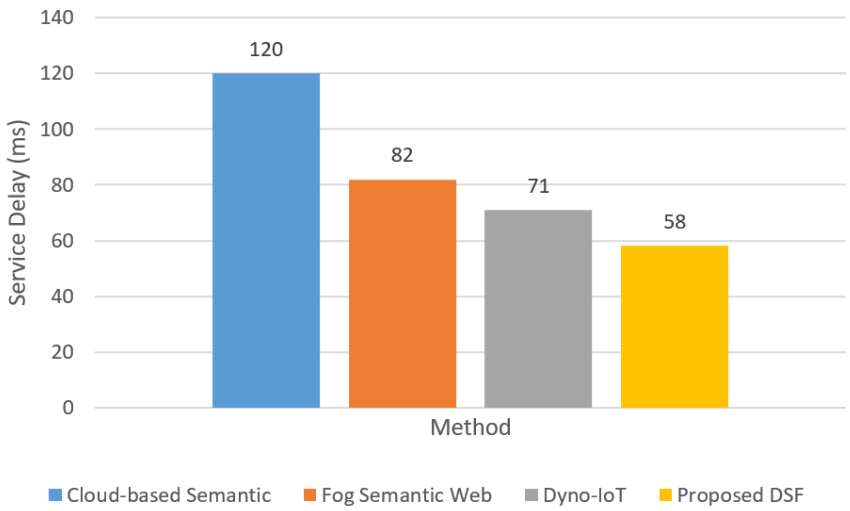


Figure 8. Comparison of service delay among semantic interoperability frameworks

5.3. Energy consumption analysis

Energy efficiency is very important in massive and durable IoT deployments, especially when the semantic process runs on a non-stop basis. Here, energy consumption means the amount of energy consumed by fog nodes and infrastructures to perform semantic processing operations: data parsing, RDF generation and ontology enrichment.

The results of energy consumption from the simulation experiments are summarized in Table 4. The fog-based adaptive semantic mechanism shows a significant decrease in energy consumption when comparing with the classic cloud-based one of doing semantics interoperability methods. This enhancement is largely

attributed to regional processing at fog layer, which significantly decreases long-range data transfer and lowers repetitive cloud interactions.

Table 4. Energy consumption comparison of semantic interoperability mechanisms

Semantic interoperability approach	Energy consumption (J)
Cloud-based semantic interoperability	Higher energy usage
Proposed fog-based adaptive semantic mechanism	Lower energy usage

As the semantic tasks can be performed near data sources, such mechanism reduces communication energy burden and prevents unnecessary computation from the cloud. The proposed adaptive workload offloading scheme also helps to save energy by avoiding the over utilization of resource at fog device. On the whole, the obtained outcomes validate that, compared to existing ones searching dynamic semantic interoperability in heterogeneous IoT contexts, the proposed mechanism presented here is more energy-efficient and sustainable and consequently can be considered for on-the-fly long-term real-time applications in IoT.

Figure 9 presents the energy consumption of different semantic interoperability frameworks. The proposed DSF framework consumes the least amount of energy (135 J), significantly outperforming cloud-based semantic (230 J), fog semantic web (185 J), and Dyno-IoT (162 J). This reduction is mainly attributed to executing semantic processing, RDF generation, and ontology enrichment at the fog layer, thereby minimizing long-range data transmission and reducing cloud interactions. Furthermore, the adaptive workload offloading mechanism efficiently balances computational resources across fog nodes, resulting in lower energy expenditure. These findings demonstrate that DSF provides a sustainable and energy-efficient solution for real-time heterogeneous IoT applications.

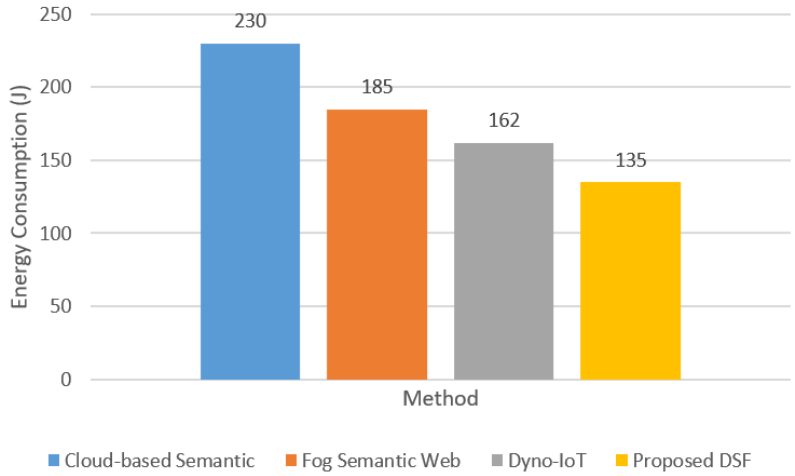


Figure 9. Comparison of energy consumption among semantic interoperability frameworks

5.4. Network usage analysis

Network utilization is an important metric for scalability and performance in the deployment of large IoT systems, as a high data traffic can result in network congestion, increased latency and associated costs. In this paper, network usage represents the volume of data transferred among IoT devices, fog nodes, and the cloud during semantic interoperability tasks.

The network usage in the simulation experiments are listed in Table 5. It has been shown that the proposed fog-based adaptive semantic mechanism achieves significant reduction of network bandwidth consumption, compared to cloud-based semantic solutions. This reduction can be achieved mainly through the on-the-fly data parsing, filtering, RDF generation, and ontology enrichment at the fog level so that superfluous raw data are not transmitted to the cloud.

Table 5. Network usage comparison of semantic interoperability mechanisms

Semantic interoperability approach	Network usage (Mbps)
Cloud-based semantic interoperability	Higher network usage
Proposed fog-based adaptive semantic mechanism	Reduced network usage

Only the semantically extracted and summarized data is sent to cloud when necessary, it helps to reduce network traffic efficiently. Thereby, the proposed mechanism reduces congestion and improves scalability especially in dense IoT scenarios (e.g., smart city). These results confirm that the fog-based semantic processing could be beneficial to optimize the use of network resources and at the same time guaranteeing accurate and timely semantic interoperability.

Figure 10 illustrates the network usage of different semantic interoperability frameworks. The proposed DSF framework achieves the minimum network bandwidth consumption of 8 Mbps, outperforming cloud-based semantic, fog semantic web, and Dyno-IoT approaches. This improvement is mainly attributed to performing semantic processing, RDF generation, and ontology enrichment at the fog layer, which minimizes raw data transmission to the cloud and reduces communication overhead. The results confirm that DSF provides a scalable and network-efficient solution for real-time heterogeneous IoT environments.

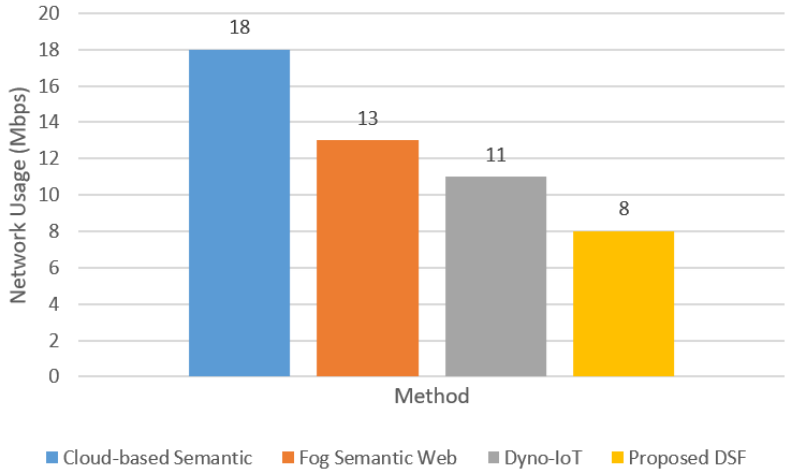


Figure 10. Comparison of network usage among semantic interoperability frameworks

5.5. Ablation study

This paper set out to evaluate the contribution of each component of their self-developed DSF framework. They conducted ablation experiments where only one module was disabled per round, and completed the evaluation by reusing the simulation settings from prior work on smart city traffic management.

Table 6 presents the ablation study results the average service latency under each configuration. This study conducts ablation experiments targeting the DSF framework. The complete framework achieves a minimum service latency of 58 ms; after sequentially disabling the three core modules of adaptive ontology enhancement, RDF generation, and load offloading, the latency rises to 79 ms, 86 ms, and 93 ms respectively. After analyzing the root causes of performance degradation for each module one by one, this study ultimately confirms that the load offloading module has the largest impact on latency performance.

Table 6. Ablation study of the proposed DSF framework

Configuration	Service delay (ms)
Full DSF	58
Without adaptive ontology enrichment	79
Without RDF generation	86
Without workload offloading	93

This study verifies that all components of the DSF framework make positive contributions to overall system performance. Among these components, the workload offloading module and the adaptive ontology

expansion module deliver the most prominent effects: they can reduce system latency and support dynamic semantic interoperability. The integration of these three technologies is a necessary prerequisite to achieve this goal in heterogeneous IoT environments.

5.6. Discussion

In this subsection, an incremental qualitative comparison of the proposed fog-based adaptive semantic attempt against typical cloud-centric and fog-assisted solutions for semantic interoperability is presented.

5.6.1. Comparative performance

The comparison analysis centres around the main performance criteria for real-time heterogeneous IoT motifs, which are service delay, energy consumption, network overhead, and flexibility.

- Service delay reduction: the extant cloud-based semantic interoperability methods lead to long service delay associated with remote data transmission and centralized processing. The proposed mechanism, however, performs semantic tasks at fog layer with much reduced latency. Simulation results reveal that the proposed scheme achieves an average reduction of 50% in the service delay, making it more feasible for latency-constrained IoT applications.
- Energy efficiency: cloud-based methods usually involve tedious data transfer and heavy centralised computation, which are energy-expensive. Through processing the semantic content locally and avoiding cloud interaction, the fog-based approach can limit communication and computation energy costs. This enhancement paves the way for sustainable and durable IoT deployments.
- Network usage optimization: many such systems generally send raw or partially processed data to the cloud, consuming bandwidth of networks. The proposed mechanism greatly decreases network traffic as data filtering, transformation and semantic encoding are done at the fog side before transmission. Thus, in dense IoT deployments, only critical semantic information is transmitted to the cloud, which enhances scalability.
- Dynamic semantic interoperability: most semantic interoperability solutions proposed so far are based on the use of static ontologies which must be updated manually with the introduction of new devices or data types. This proposed mechanism facilitates on-line adaptive ontology enrichment, therefore to accommodate new IoT devices and properties with ease without human intervention for reconfiguration. Real dynamic semantic interoperability is possible with this feature.
- Scalability and system robustness: with the growing number of IoT devices, cloud services may be insufficient in terms of performance. The fog-oriented one allows semantic processing to be performed by more than one (fog) node, which avoids centralized overload and improves system robustness. This approach ensures stability of the system in terms of performance even when it scales.

The comparative study demonstrates that the proposed fog-based adaptive semantic mechanism beats the state of the art when considering everything. The proposed approach is balancing and efficient in the respect of achieving dynamic semantic interoperability together with a heterogeneous IoT system. We put local semantics processing, smart workload offloading, adaptive ontology enrichment incorporated under one roof.

5.6.2. Relevance to embedded and reconfigurable systems

This paper proposes the DSF framework. Built on fog-native architecture and equipped with real-time semantic processing capabilities, the framework is compatible with embedded reconfigurable systems, and can be deployed on two types of hardware: embedded IoT gateways fitted with system-on-chip (SoC), and edge devices with moderate computing power. It locally executes tasks including RDF generation and ontology extension, and adapts to resource-constrained embedded environments with low latency.

This study proposes integrating reconfigurable hardware such as field programmable gate array (FPGA) into the DSF framework. This approach can accelerate three types of core modules: RDF generation, ontology matching, and semantic reasoning, delivering high throughput and low energy consumption, adapting to dynamic IoT workloads, and maintaining stable real-time operating performance.

The technical architecture proposed in this paper can be extended for application in the very large scale integration (VLSI) implementation of next-generation IoT gateways. Dedicated accelerators oriented toward semantic processing and ontology evolution can greatly reduce processing latency and power consumption, and can support the large-scale deployment of smart cities, industrial IoT, and intelligent transportation systems. Therefore, the DSF framework proposed in this study not only solves the challenging problem of semantic interoperability in heterogeneous IoT systems, but also lays a foundation for future embedded semantic systems based on FPGA and VLSI acceleration.

6. CONCLUSION

To address the challenge of semantic interoperability in heterogeneous IoT environments, this paper proposes an original DSF framework. This framework shifts semantic processing from traditional centralized clouds to fog nodes, and integrates four core functions including RDF generation. Compared to two categories of traditional solutions, the framework's capability to dynamically integrate new devices can improve the scalability and adaptability of IoT ecosystems. The proposed framework was implemented and evaluated using the iFogSim simulator in a smart city traffic management scenario. Experimental results demonstrated that DSF significantly outperforms existing semantic interoperability approaches in terms of service delay, energy consumption, and network usage. Specifically, DSF reduced service delay by approximately 51.7%, decreased energy consumption by 41.3%, and lowered network bandwidth usage by 55.6% compared with conventional cloud-based semantic frameworks. Furthermore, the ablation study confirmed the effectiveness of the workload offloading and adaptive ontology enrichment modules in improving the responsiveness and scalability of the proposed system. This study explores the compatibility between the DSF and embedded reconfigurable systems. The proposed architecture can be deployed on embedded IoT gateways, and can be accelerated via FPGAs and dedicated VLSI accelerators to achieve ultra-low-latency semantic processing.

This study proposes a three-tier progressive set of future research tasks: first, we will deploy the proposed framework on real-world fog computing and embedded hardware platforms to verify its practical feasibility; in addition, we will develop security and privacy mechanisms adapted to semantic processing and ontology evolution, and we will also explore cutting-edge directions for the next-generation intelligent IoTs.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
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Su : **Su**pervision
P : **P**roject Administration
Fu : **Fu**nding Acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding authors upon reasonable request.

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