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RESEARCH

# Smart classroom ontology: enhancing interoperability in learning environments

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**Abstract**

Smart classrooms leverage advanced technologies to create interactive, data-driven learning environments that enhance educational experiences. However, interoperability remains a significant challenge, as many of these systems operate independently. This paper presents the Smart Classroom Ontology (SClassO), the very first holistic model designed to unify the key components of smart classroom environments, including people, context, and resources. By providing a semantic framework, SClassO enables seamless integration across heterogeneous systems, bridging gaps between sensing devices, learning management platforms, and classroom analytics. A proof of concept implementation demonstrates its ability to collect and integrate real-world data from both sensor devices and information systems using standard protocols such as MQTT and RESTful APIs. Data is stored both in OWL/RDF format and in a relational database to evaluate performance trade-offs. Finally, the study explores key architectural challenges, focusing on storage capacity, system performance, security, and data privacy.

**Keywords** Smart classroom · Ontology · Internet of Things · Interoperability · Semantics

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## 1 Introduction

The adoption of information and communication technologies (ICT) has brought transformative advancements to the education sector, reshaping traditional pedagogical methods. The use of laptops, tablets, and virtual learning platforms in primary and secondary education has fostered more personalized, inclusive, and collaborative learning experiences. More recently, cutting-edge technologies have enabled the collection and analysis of data from students, teachers, and the physical environment, providing deeper insights into classroom dynamics [1]. These innovations have paved the way for the development of smart classrooms, *i.e.,* intelligent systems designed to provide teachers with real-time, data-driven actionable insights that support informed and responsive decision-making [2].

However, the term "smart classroom" is often used indiscriminately to describe any learning space equipped with digital tools, such as interactive whiteboards, computers, or 3D printers. This overly broad usage risks overlooking a crucial distinction: while technology-enhanced classrooms integrate digital resources to facilitate teaching, truly smart classrooms employ advanced systems that sense, analyze, and adapt using real-time data [3]. Existing applications in smart classrooms typically focus on narrow use cases leveraging Internet of Things (IoT) devices and off-the-shelf Artificial Intelligence (AI) methods to address specific challenges. These applications include monitoring environmental conditions [4, 5], tracking student attendance [6, 7], detecting fatigue [8], and recognizing emotions in both students and teachers [9–11]. While these studies demonstrate the potential benefits of smart classrooms, they often remain narrowly focused, lacking holistic integration across environmental factors, student engagement, and pedagogical needs [12].

Formally, a smart classroom can be deployed as a context-aware system that integrates data from multiple sources to support adaptive teaching and learning (Fig. 1). Data acquisition is handled by a distributed network of Data Collecting Agents (DCAs), which operate either in the physical classroom environment or within related information systems. Environmental DCAs, equipped with IoT sensors, continuously monitor parameters such as ambient conditions [4], physiological status using wearable devices [13], and behavioral indicators of both students and teachers through video analysis [14, 15]. In parallel, DCAs embedded in information systems gather data from conventional learning management systems (LMS) as well as specialized tools such as the Smart Classroom Annotation Tool (SCAT), which allows teachers to record students' behavioral observations manually [16]. All collected data are transmitted to the Smart Classroom Central Server (SCCS), which serves as the ecosystem's data warehouse and as its decision-making hub, processing incoming information to generate actionable insights. These insights are delivered through the Smart Classroom Teacher Assistant (SCTA), a front-end interface that provides teachers with timely feedback on classroom dynamics, including environmental conditions, student behavior (*e.g.,* participation, attention), and teacher-related metrics (*e.g.,* stress levels, speaking time).

However, building such an integrated ecosystem inevitably raises interoperability issues, a challenge common to complex smart systems. The deployment of a smart classroom involves the continuous interaction of heterogeneous devices, platforms, and information sources, each producing data in different formats and at varying levels of granularity. Establishing a comprehensive data model that enables seamless integration across these diverse components is essential to ensure efficient functionality. While the network of distributed agents facilitates the collection of information from both the physical environment and institutional information systems, the proliferation of heterogeneous technologies generates significant challenges in terms of interoperability and semantic representation [17]. Standardized data

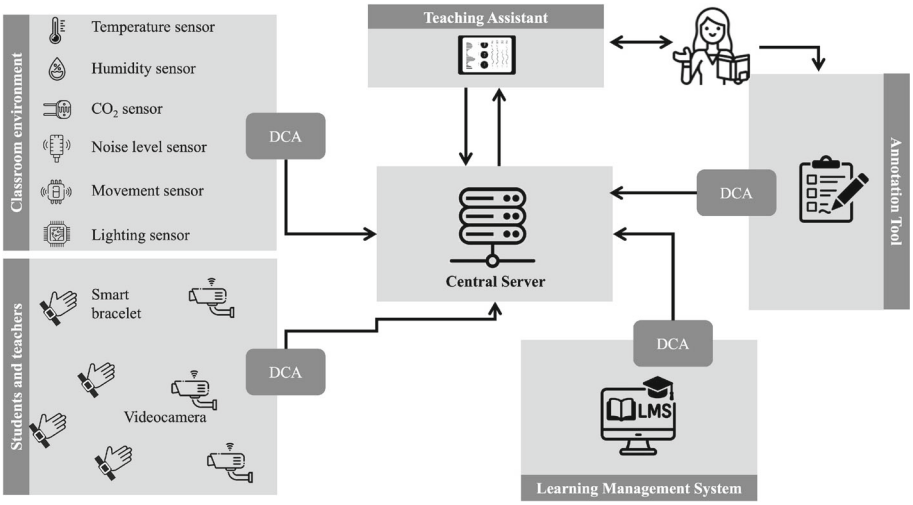



**Fig. 1** Example of a smart classroom as a context-aware system

models play a pivotal role in addressing these issues, as they not only structure the information being processed but also establish common frameworks that enable effective communication between agents and systems. In this way, data can be exchanged and, crucially, meaningfully interpreted across the different technological components of the ecosystem.

Ontologies provide a formalized and effective means of representing these data models within context-aware systems [18–21]. In complex environments such as smart classrooms, ontologies allow agents to rely on a shared catalog of data elements, ensuring consistency in data retrieval and integration. This common semantic framework mitigates interoperability issues while enhancing contextual awareness. Additionally, the AI-driven processes at the core of smart classrooms, which are responsible for detection, reasoning, and decision-making, require robust and well-structured data representations to operate reliably. Ontology-based modeling enhances contextual awareness, supports the accurate interpretation of heterogeneous data, and enables adaptive, context-sensitive responses to evolving learning environments.

Nevertheless, achieving semantic interoperability in smart classrooms remains a critical challenge. The lack of widely accepted vocabularies and semantic conventions often leads to ambiguity in the interpretation of shared information, limiting the full potential of these systems. To address this gap, we introduce the Smart Classroom Ontology (SClassO), a comprehensive ontology specifically designed to meet the data requirements of our envisioned smart classroom model. SClassO provides a structured and interoperable framework for seamless knowledge exchange and contextual reasoning. To the best of our knowledge, it is the first flexible and extensible framework for data integration and contextual awareness tailored to smart classrooms.

The rest of the article is organized as follows: Sect. 2 examines relevant literature on interoperability and semantic modeling within educational contexts. Section 3 describes the methodological approach used to design and implement the proposed SClassO, including expert involvement, ontology engineering practices, and implementation details. Then, Sect. 4 presents a proof of concept of SClassO, demonstrating the ontology's implementation through a testbed deployment. Section 5 discusses data collection strategies, performance consid-

erations, and security and privacy concerns. Finally, Sect. 6 summarizes key findings and pinpoints future research directions.

## 2 Related work

The successful implementation of ontologies in smart systems requires addressing interoperability challenges to ensure meaningful data exchange across diverse components. In smart classroom environments, achieving semantic coherence and adaptive behavior depends on the ability to standardize knowledge representation and facilitate integration across heterogeneous systems. This section provides an overview of interoperability as a foundational aspect of semantic modeling, followed by a review of relevant literature on ontology-based approaches, particularly those applied to learning environments.

### 2.1 Interoperability

Ensuring effective interoperability between hardware and software elements is essential for the development of flexible and scalable context-aware systems. Interoperability enables the seamless integration of diverse technologies while supporting system expansion and adaptation. This capability ensures autonomy in selecting manufacturers, technological platforms, and software solutions, allowing new components to be seamlessly integrated into existing infrastructures. The European Interoperability Framework, adopted in 2017, defines four interoperability levels: technical, semantic, organizational, and legal [22]. While organizational and legal dimensions primarily concern policy and administrative processes —beyond the scope of this work— technical and semantic interoperability operate in tandem to optimize data management and facilitate effective information exchange.

#### 2.1.1 Technical interoperability

Technical interoperability focuses on the encoding and transmission of data. It encompasses widely adopted standards, including character encoding (*e.g.,* UTF-8), data structuring formats (*e.g.,* XML, JSON), and communication technologies spanning various layers of the OSI (Open Systems Interconnection) model, such as IEEE 802.11 (Wi-Fi), Bluetooth, HTTP RESTful services [23], and MQTT (Message Queuing Telemetry Transport) [24]. Interestingly enough, MQTT is a lightweight messaging protocol optimized for constrained devices and networks with low bandwidth or high latency. It is one of the most widely adopted interoperability standards within the IoT ecosystem, and follows a publish-subscribe model (*i.e.,* clients publish messages to topics and subscribe to those of interest), typically operating over TCP. Thanks to the broad availability of these technologies, systems can transfer, collect, and interchange data, *e.g.,* between sensors and DCAs, and from DCAs to servers and information systems, supporting bidirectional communication.

#### 2.1.2 Semantic interoperability

Semantic interoperability ensures that exchanged data is consistently interpreted across interconnected systems, preserving its intended meaning. This aspect is particularly crucial for context-aware systems, where ontology-based models structure knowledge to support intelligent decision-making. Applications of semantic interoperability span multiple domains,

including healthcare records [25], smart city initiatives [26], IoT ecosystems [27], and educational technology [28].

To ensure reliability and effectiveness, semantic interoperability must meet several key system requirements [29]. First, high availability guarantees uninterrupted access to data resources. Second, continuous monitoring of service performance helps detect anomalies and maintain consistent quality of service. Third, support for real-time data analysis enables timely decision-making and adaptive system responses. Fourth, the infrastructure must be scalable, capable of accommodating an increasing number of interconnected devices and users without performance degradation. Lastly, robust security mechanisms are essential for protecting sensitive information, such as personal data, and ensuring that their transmission and storage are secure and compliant with privacy regulations.

There are several standards aimed at providing semantic interoperability in educational settings. Regarding learning materials, SCORM (Sharable Content Object Reference Model) [30] provides a robust framework supporting the portability, and reusability of web-based educational content. Moreover, the QTI (Question and Test Interoperability) [31] is focused on assessment items, quizzes, and evaluation outcomes. Regarding the conceptualization of students within their learning scenarios, SIF (Schools Interoperability Framework) [32] supports K-12 educational data exchange, defining structures for student records, teacher profiles, and course information, while also accommodating additional elements such as grading, attendance, and behavioral documentation. Finally, CEDS (Common Education Data Standards) [33] offers standardized data definitions spanning early education to lifelong learning. It defines a common vocabulary and data model for all the educational paths. For instance, for K12 students it specifies several attributes to be used beyond the students' identification, including health, family, and socioeconomic factors (*e.g.,* immigrant, homelessness, economic disadvantage…).

### 2.2 Ontologies in educational scenarios

Studies emphasize the importance of a common semantic framework to coordinate the interaction of learning management systems, collaboration tools, technology, and multimedia resources in smart educational environments [34]. Existing research on ontologies in educational scenarios falls into two categories: ontologies related to IoT (sensors, contextual monitoring,…) and those related to online learning and e-learning platforms (resources, evaluation,…).

#### 2.2.1 Ontologies in IoT for education

As context-aware systems, smart classrooms rely heavily on sensors and other IoT technologies, for which IoT-related ontologies can support meaningful integration and communication in educational settings.

Specifically focused on smart classrooms and, using the data collected from IoT devices, [35] addresses how human activities could be modeled to contextualize individuals for profiling and understanding classroom-specific interactions. Similarly, [36] extends the Semantic Sensor Network (SSN) ontology [37] ontology to incorporate key concepts such as user roles, classroom activities, and sensor data, with an emphasis on monitoring and analyzing student and teacher performances. However, this work remains largely theoretical, lacking practical implementation and real-world validation. Also, the notion of modeling context using an ontology is introduced in [38], which proposes an ontology for a context-aware classroom

considering basic factors such as the student's location and the ambient noise level. As a preliminary approach, however, the article does not provide further details about the data represented in the ontology.

Beyond smart classrooms, ontology-based models have been applied to broader educational ecosystems. The work in [39] describes a context-aware architecture for smart campuses that dynamically composes IoT services using ontologies, enabling applications to adjust in real-time based on user preferences, roles, and environmental contexts in multi-campus environments. Regarding location tracking, [40] develops an ontology-based framework for modeling student movement across university spaces.

### 2.2.2 Ontologies in e-learning systems

Modern education increasingly integrates e-learning systems and online learning platforms, necessitating robust ontologies to structure semantic representations of learning components. In [41], the authors propose an ontology for ubiquitous learning, semantically modeling text, video, audio, and images to enhance accessibility and resource organization. Also focusing on e-learning environments, [42] presents an ontology tailored to the Sakai LMS. Specifically, the authors explore the data that can be obtained from this platform and model the corresponding ontology with the aim of improving personalization and recommendation. Moreover, the work in [43] presents an ontology designed to personalize education by managing personal information, cognitive skills, and preferred learning styles. A broader perspective on ontology-based recommender systems (OBRS) in e-learning is reviewed in [44], which highlights their ability to personalization through structured semantic models and hybrid techniques involving data mining and AI. Building on these ideas, the study in [45] introduces SLEek, an ontology specifically designed for learning environments that enables context-aware recommendations by linking learners, activities, and contexts, facilitating seamless integration of formal and informal learning scenarios.

### 2.2.3 Ontologies for smart classrooms

According to the literature, existing IoT ontologies for education [35, 36, 38–40] emphasize technical and environmental elements, such as location, temperature, sensors, and agents. Moreover, e-learning ontologies [41–43, 45] focus on pedagogical and learner-centered aspects, including learning, evaluation, feedback, personal profiles, and digital content. All these ontologies share common concepts (*e.g.,* person, time, class, resources, context, student, professor, and activities). In this line, Fig. 2 illustrates the intersection of concepts between the ontologies of both areas. However, our analysis of the literature reveals that there is no comprehensive ontology encompassing all the elements included in our conception of smart classrooms (depicted in Fig. 1).

Despite growing interest in ontology-based models in education, it is worth noting that most existing studies remain conceptual, with limited practical implementations that integrate essential components such as middleware, storage infrastructure, and real-time reasoning capabilities. The lack of operational frameworks hampers the coherent integration of diverse classroom elements, revealing a critical gap in the development of scalable, functional semantic models for smart classrooms.

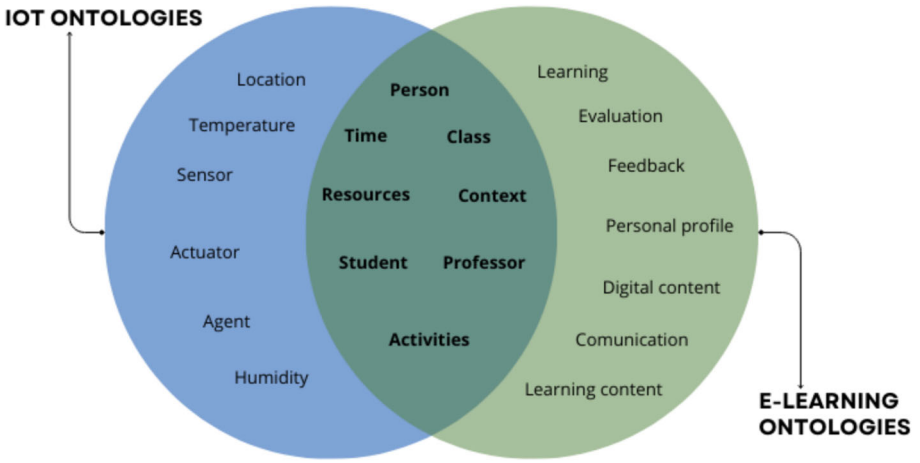



**Fig. 2** Most prominent terms found in the literature on ontologies in educational scenarios

## 3 The smart classroom ontology

This section presents the proposed Smart Classroom Ontology (SClassO), detailing its design, validation methodology, and key components. Additionally, it discusses essential aspects related to the design and implementation of SClassO in a real smart classroom system. This ontology includes concepts from both IoT and e-Learning domains found in the literature, aiming at providing a comprehensive approach to our concept of smart classrooms. This approach is validated by a group of experts, as described in Sect. 3.2.2.

### 3.1 Methodology

The development of SClassO followed the systematic Methontology process [46], which provides a structured approach to ontology development and consists of five main phases:

1. *Specification.* Defines the ontology's purpose, intended use, and target users.
2. *Conceptualization.* Structures informal domain knowledge into a structured, semi-formal conceptual model. In our approach, we have included a validation by experts in this step.
3. *Formalization.* Converts the conceptual model into a formal or semi-computable representation.
4. *Implementation.* Encodes the formal model using ontology languages.
5. *Maintenance.* Ensures ongoing updates and adjustments in response to evolving requirements or domain changes.

Throughout this process, particular attention is placed on leveraging existing ontologies, particularly those related to IoT and e-learning (see Sect. 2.2). Reuse strategies include integrating predefined classes and properties while establishing schema-level links for seamless interoperability. When existing ontologies do not address specific aspects of the smart classroom context, new terms are defined to ensure comprehensive modeling of its unique characteristics.

### 3.2 Proposal

The following describes the steps taken to develop SClassO, structured according to the aforementioned phases.

#### 3.2.1 Specification

This ontology serves as a data model for the smart classroom, facilitating interoperability among its various components, *e.g.,* DCA, SCCS, SCTA, and SCAT. The target users of the ontology fall into two groups: (i) technical developers responsible for implementing smart classroom systems in real-world settings, and (ii) teachers and education professionals to understand the types of information that can be leveraged within this framework.

#### 3.2.2 Conceptualization

The proposed ontology is structured around three main concepts: people, context, and resources. In a smart classroom environment, several key actors work together to support teaching and learning. Students and teachers are the main *people* involved. Teachers lead instruction, whereas students engage in learning activities. Additionally administrators help manage and maintain the classroom's technological and physical infrastructure. Beyond the people, *context* plays a crucial role in shaping what happens in the classroom. For example, physical context, such as temperature, noise, and lighting, can affect students' focus and comfort, and these factors are monitored via sensors. Emotional context, including indicators of stress or engagement, influences how both students and teachers interact and perform and is assessed through wearables and IoT devices. Recognizing and responding to these factors can make teaching more responsive and supportive. An extensive analysis of the contextual elements within the smart classroom and their relationship with learning effectiveness can be found in [47]. Finally, *resources* include both traditional and digital learning materials, such as textbooks, printed materials, and online learning platforms. Moreover, the annotation tool used by teachers to record observations on classroom insights, and will complement the ones monitored from the physical and emotional contexts.

To validate our conceptualization, we conducted an expert assessment process based on the Delphi method [48]. In a nutshell, this method aims to gather a collective expert perspective on a given topic through repeated rounds of questioning and can be regarded as a systematic approach designed to elicit, refine, and synthesize group judgments. Expert selection was based on their knowledge of the subject matter and prior participation in projects related to the IoT in the context of smart classrooms, as well as their availability and willingness to participate. Potential experts self-assessed their suitability through an online questionnaire, and those who achieved the highest expertise index were selected. The final panel included five experts, all of whom were primary or secondary school teachers with demonstrated proficiency in educational technology and the use of e-learning platforms. Prior to the consultation, participants were presented with an overview of the smart classroom concept (as described in Sect. 1) and a visual representation of the proposed ontology. The evaluation was conducted via anonymous questionnaires, without any open meetings, and participants were unaware of each other's identities. Consensus was defined *a priori* as agreement among at least three of the five experts. The experts were asked to respond to the questions described in Table 1. The response options for Q1-Q4 are designed to capture both the teachers' interest in accessing the data and their perception of its relevance to their teaching practice, whereas Q5 asks

**Table 1** Questionnaire on Smart Classroom Data and Perceived Impact

| Questions |
|---|
| Q1. One of the key elements of the smart classroom is environmental conditions. Do you believe that having real-time data on temperature, humidity, air quality, and noise could influence your teaching practice? |
| Q2. Imagine you have a smart classroom information system that provides relevant, contextualized data about students (such as assessments, behavior, attendance, participation, etc.). Do you believe that having access to such data could influence your teaching practice? |
| Q3. Imagine you have a system that evaluates students' state (*e.g.,* detecting signs of fatigue or stress) and provides real-time relevant information. Do you believe that having access to such data could influence your teaching practice? |
| Q4. Imagine you have a system that evaluates the teacher's state (*e.g.,* detecting signs of fatigue or stress) and provides real-time relevant information. Do you believe that having access to such data could influence your teaching practice? |
| Q5. After analyzing the different elements in the data model proposed, do you think that it adequately includes all the elements you consider relevant for your teaching practice? |

about the elements in the data model. Consensus was reached on all five questions, reflecting a high level of alignment among the experts regarding both the usefulness of contextual data and the completeness of SClassO.

### 3.2.3 Formalization

We next describe the key classes defined in the proposed SClassO (see Fig. 3), organized according to the aforementioned core components.

The class `Person` represents individuals who participate in the smart classroom ecosystem. This class is specialized into the following subclasses:

- `Student`: Models individuals who engage in learning activities within the smart classroom. In our scenario, this refers primarily to children in primary or secondary education.
- `Teacher`: Models individuals responsible for delivering educational content in the smart classroom, including teachers and other educators.
- `Administrator`: Models individuals responsible for configuring and maintaining the smart classroom infrastructure, including hardware, software, and system settings.

The class `Context` is used to capture the various factors that shape participants' experiences in the smart classroom. This class is specialized into three subclasses that represent distinct dimensions of context, each associated with temporal metadata to reflect their dynamic nature. To reflect this, the ontology supports time-dependent representations, allowing context instances to be linked to specific timestamps or time ranges. This temporal dimension enables the smart classroom system to analyze trends, adapt interventions, and monitor changes across different time scales. Importantly, the ontology models the influence of context differently for students and teachers. Students are associated with three types of context—physical, emotional, and social—as their learning process is shaped by environmental conditions, personal affective states, and broader social indicators. Teachers, in contrast, are primarily influenced by physical and emotional contexts, since social aspects are not considered a direct attribute of the teaching role. Specifically, the three subclasses of `Context` are defined as follows:

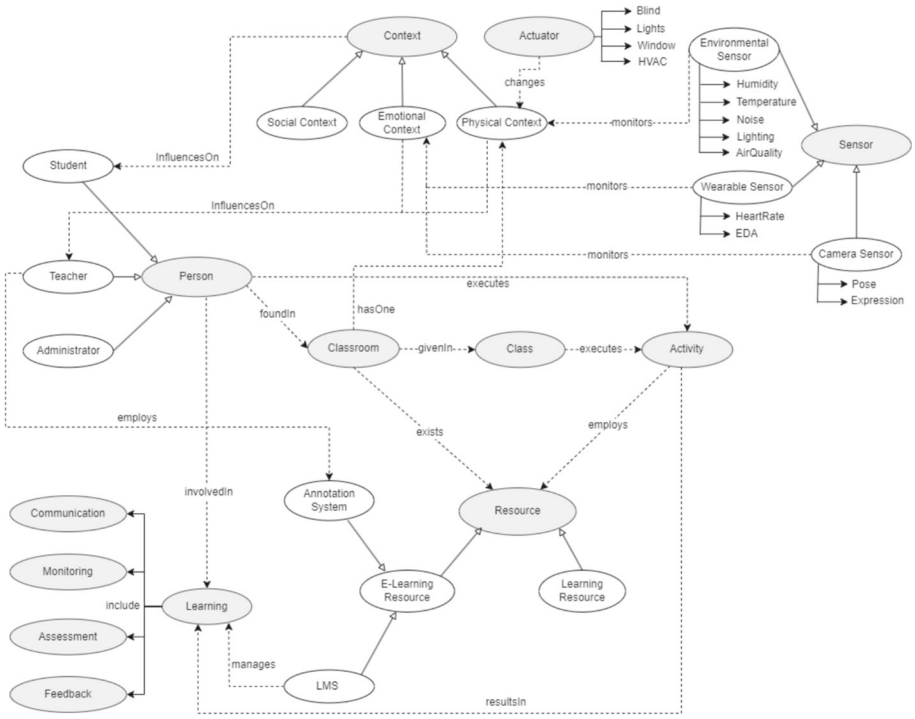



**Fig. 3** Visual representation of the proposed SClassO

- `Physical Context`: Represents measurable environmental conditions within the classroom, such as temperature, light, and noise levels. These data are typically gathered through sensors deployed in the classroom. Physical context reflects a shared environment that influences both students and teachers, and is generally collected at regular intervals (*e.g.,* every few minutes).
- `Emotional Context`: Models the affective states of individuals based on multimodal input. This may include facial expression analysis via video cameras, physiological signals collected from wearable devices, and self-assessment tools such as short surveys. Emotional context applies to both students and teachers, as emotional engagement is critical for all participants in the learning process.
- `Social Context`: Provides broader socioeconomic and health-related indicators relevant to students. This type of context is more static compared to the others and is typically collected at longer intervals (*e.g.,* once per academic term).

The class `Sensor` represents the technological mechanisms through which contextual information is collected and integrated into the smart classroom ontology. Hence, the ontology explicitly connects sensors to the contextual dimensions they monitor. This design emphasizes the role of sensing devices as the primary source of data that model high-level contextual constructs over time. More concretely, three main types of sensors are distinguished:

- `Wearable Sensor`: Devices such as smart bracelets or wristbands that collect physiological signals (*e.g.,* heart rate, electrodermal activity…). These data are analyzed to infer the emotional context of both students and teachers, providing individualized monitoring of affective states.

- `Camera Sensor`: Devices that capture visual information in the classroom. Through techniques such as facial expression recognition or pose estimation, camera sensors also contribute to modeling the emotional context, complementing physiological signals with behavioral indicators.
- `Environmental Sensor`: Devices deployed in the classroom to measure shared environmental variables such as air temperature, humidity, pollution, noise, movement, and lighting levels. These data directly inform the physical context, which influences all participants present in the classroom.

Complementing the sensing layer, the class `Actuator` represents the devices that can modify the classroom environment in response to contextual knowledge. While sensors capture data to model the different types of context, actuators enable the system to close the loop by adapting physical conditions to better support teaching and learning. Examples include automated control of lighting, blinds, heating, ventilation, and air conditioning systems.

The class `Resource` represents the educational materials available within the smart classroom ecosystem, supporting both teaching and learning activities. These resources are categorized into specialized subclasses:

- `E-Learning Resource`: Includes digital learning materials accessed through local or remote LMSs, including quizzes, video lectures, slide decks, and other online learning content.
- `Learning Resource`: Encompasses tangible educational materials, such as textbooks, printed handouts, and physical manipulatives. Although these are physical in nature, they are represented in the system and may be linked through metadata records, *e.g.,* entries in a classroom resource catalog database.
- `Annotation System`: Refers to the tool used by teachers to annotate and track student progress for ongoing assessment and relationship tracking. This includes recording observations, monitoring social states, and annotating achievements or areas of concern.

Resources can also be linked to physical classrooms and instructional activities. To support this, the ontology incorporates auxiliary classes that model various aspects of the learning environment and its structural components:

- `Classroom`: Represents the physical space where teaching takes place. This class may include attributes such as room size, floor location, and availability of specialized physical equipment (*e.g.,* smartboards, sensors).
- `Class`: Models a teaching session or lecture. It can include metadata such as subject, duration, and participating students and teachers.
- `Activity`: Refers to specific learning activities conducted within a class. Activities make use of one or more `Resource` instances and may involve collaboration, problem-solving, or assessments.

Learning activities are central to the ontology's instructional model. Formalized under a `Learning` class, various components of classroom interactions involving both students and teachers. By modeling these components, the ontology supports a holistic understanding of classroom processes and facilitates intelligent feedback loops that can enhance personalized education and instructional decision-making. It is worth noting that such learning is the result of a specific learning activity. The following sub-classes are considered:

- `Communication`: Captures interactions between teachers and students, as well as among students themselves.
- `Monitoring`: Refers to real-time observations of student engagement, behavior, and progress.

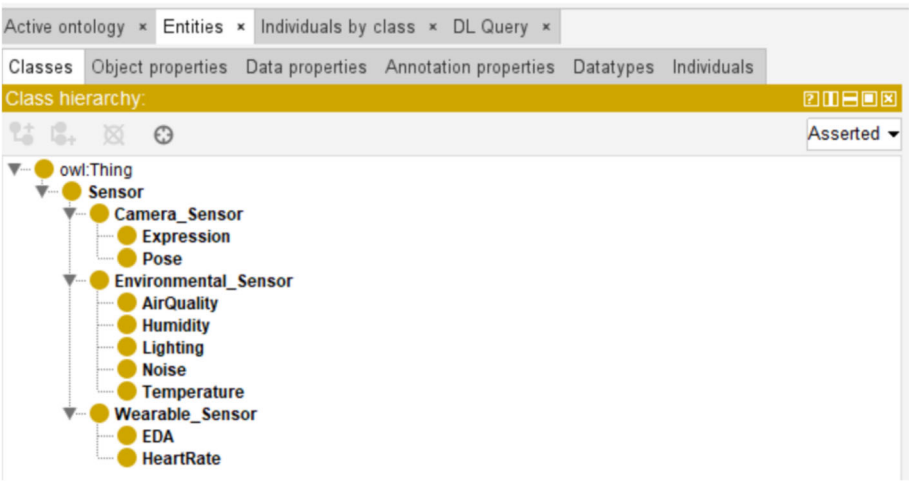



**Fig. 4** The `Sensor` class of SClassO implemented in Protégé

- `Assessment`: Represents the evaluation of learning outcomes, including both formative and summative assessment mechanisms.
- `Feedback`: Refers to the information provided to students (and potentially teachers) to guide learning. It can result from assessments or direct observations and is a key element in adapting teaching strategies and supporting student progress.

### 3.2.4 Implementation

Protégé [49] is a widely used open-source ontology editor and knowledge-base framework developed by the Stanford Center for Biomedical Informatics Research. It provides tools for creating, visualizing, and managing ontologies across various formats, offering a user-friendly interface, powerful reasoning tools, and extensibility through plugins. These features make it an essential resource for researchers and practitioners working on semantic web technologies and knowledge representation for a wide range of domain-specific applications.

The development of SClassO involved defining a structured taxonomy in Protégé. Figure 4 exemplifies the class hierarchy of the `Sensor` class. There, subclass relationships are established to organize domain-specific concepts, object properties are introduced to model interactions between classes, while data properties captured specific attributes of individuals. Example individuals are then created to validate real-world applicability and assess the ontology's practical feasibility. To ensure semantic interoperability, existing standard vocabularies are reused where applicable. For instance, student-related data properties are adopted from the CEDS standard, while LMS resources are aligned with the data structure of Moodle, a widely used platform, referencing its interoperable API.

Protégé allows exporting ontologies in widely accepted formats, including OWL (Web Ontology Language) [50] and RDF (Resource Description Framework) [51]. RDF-ontologies can be queried using SPARQL, enabling efficient retrieval and manipulation of structured data. As an illustrative example, Fig. 5 presents an excerpt of RDF/OWL definitions for several datatype properties associated with the `Sensor` class. These properties formally represent sensor data captured by physical environment monitoring devices within the smart classroom. Each property is linked to the `Sensor` class as its domain, and specifies a

```
<owl:DatatypeProperty rdf:about="http://smartclassroomontology.edu/sclasso#hasSensorID">
    <rdfs:domain rdf:resource="http://smartclassroomontology.edu/sclasso#Sensor"/>
    <rdfs:range rdf:resource="http://www.w3.org/2001/XMLSchema#string"/>
</owl:DatatypeProperty>

<owl:DatatypeProperty rdf:about="http://smartclassroomontology.edu/sclasso#hasSensorLocation">
    <rdfs:domain rdf:resource="http://smartclassroomontology.edu/sclasso#Sensor"/>
    <rdfs:range rdf:resource="http://www.w3.org/2001/XMLSchema#string"/>
</owl:DatatypeProperty>

<owl:DatatypeProperty rdf:about="http://smartclassroomontology.edu/sclasso#hasSensorStatus">
    <rdfs:domain rdf:resource="http://smartclassroomontology.edu/sclasso#Sensor"/>
    <rdfs:range rdf:resource="http://www.w3.org/2001/XMLSchema#string"/>
</owl:DatatypeProperty>

<owl:DatatypeProperty rdf:about="http://smartclassroomontology.edu/sclasso#hasSensorTimeStamp">
    <rdfs:domain rdf:resource="http://smartclassroomontology.edu/sclasso#Sensor"/>
    <rdfs:range rdf:resource="http://www.w3.org/2001/XMLSchema#dateTimeStamp"/>
</owl:DatatypeProperty>

<owl:DatatypeProperty rdf:about="http://smartclassroomontology.edu/sclasso#hasSensorUnit">
    <rdfs:domain rdf:resource="http://smartclassroomontology.edu/sclasso#Sensor"/>
    <rdfs:range rdf:resource="http://www.w3.org/2001/XMLSchema#string"/>
</owl:DatatypeProperty>

<owl:DatatypeProperty rdf:about="http://smartclassroomontology.edu/sclasso#hasSensorValue">
    <rdfs:domain rdf:resource="http://smartclassroomontology.edu/sclasso#Sensor"/>
    <rdfs:range rdf:resource="http://www.w3.org/2001/XMLSchema#float"/>
</owl:DatatypeProperty>
```

**Fig. 5** RDF/OWL snippet showing datatype properties of the `Sensor` class

range using standard XML Schema datatypes, such as `xsd:string`, `xsd:float`, or `xsd:dateTimeStamp`. Defined properties include `hasSensorID` (unique sensor identifier), `hasSensorLocation` (physical placement in the classroom), `hasSensorStatus` (operational status), `hasSensorTimeStamp` (reading's timestamp), `hasSensorUnit` (measurement unit), and `hasSensorValue` (measured value). This semantic structure ensures a formal, machine-readable, and reusable representation of sensor data, supporting interoperability with reasoning engines and educational data analysis systems.

RDF defines elements using triples, each consisting of a *subject*, *predicate*, and *object*. The first snippet in Fig. 5 defines the datatype property `hasSensorID` using two RDF triples. The first triple (`hasSensorID`, `rdfs:domain`, `http://smartclassroomontology.edu/sclasso#Sensor`) specifies that the domain of `hasSensorID` is the class `Sensor`, meaning that this property is intended to be used with individuals that belong to the `Sensor` class. The second triple (`hasSensorID`, `rdfs:range`, `xsd:string`) indicates that the values assigned to this property must be string literals.

It is worth noting that implementation goes beyond simply introducing the model into tools like Protégé and verifying it for inconsistencies. In our view, fully implementing the model also requires designing and developing interoperability functionalities through middleware capable of operating across the smart classroom infrastructure. This functionality could be embedded within DCAs, responsible not only for data collection but also for processing and structuring it according to the defined ontology. By doing so, DCAs would ensure that the SCCS receives semantically consistent and interoperable data, bridging the gap between raw inputs and structured knowledge representation. The implementation of the ontology is publicly available [52].

### 3.2.5 Maintenance

Ontology maintenance is a continuous process of updating and refining the model to accommodate new requirements or changes in the domain. As smart classroom evolve, new concepts or properties may need to be added, and existing ones adjusted or even removed. These revisions should be carried out in collaboration with the domain experts involved in the original design to ensure consistency and relevance. To this end, version control plays a crucial role in tracking updates and maintaining transparency. Clear documentation and detailed change logs should accompany each release, allowing users to reference specific versions and understand modifications made over time.

## 4 Proof of concept

To assess the practical applicability of the proposed SClassO model, we have developed a proof of concept using a subset of components within the smart classroom, focusing on data acquisition and storage. This implementation does not include the AI-driven reasoning components that would ultimately leverage this data to support smart classroom functionalities, as their development lies beyond the scope of this study.

### 4.1 Components

The components selected for this proof of concept are illustrated in Fig. 6. The setup includes two physical environment monitoring units, each equipped with multiple sensors. Originally developed for the ACTUA project [4] and tested across more than one hundred primary schools in Catalonia (Spain), these units contain sensors for measuring air temperature, humidity, and $CO_2$ concentration, among other parameters, managed by a Raspberry Pi 4. The monitoring units connect to the smart classroom infrastructure via Ethernet and require a continuous power supply. Each unit acts as an Environmental DCA: collecting contextual sensor data using Python scripts and transmitting them to an MQTT broker. In parallel, Moodle LMS, running on a dedicated local server, is connected to the infrastructure via a Python-based LMS DCA. This agent communicates using RESTful API POST requests, retrieving learning-related data such as course completion and assessment records, which are then stored in the SCCS's back-end. The SCTA, implemented as a simple front-end element, interacts with this integrated model to provide basic visualization of the collected data.

For testing purposes, the collected data is stored into two systems within the SCCS: one managed through Protégé, representing the semantic knowledge base, and another using an SQLite relational database. This dual-storage approach facilitates comparative analysis of different data management strategies under high data volume constraints typical of smart classroom environments. A thorough discussion on data volume issues is later provided in Sect. 5.1. Additional hardware used in the proof of concept includes a router/access point for network connectivity, and a PC hosting several core components, including the environmental DCA, the Protégé ontology management software, and back-end services.

Figure 7 depicts the hardware components deployed in our research laboratory as a proof of concept of the proposed model.

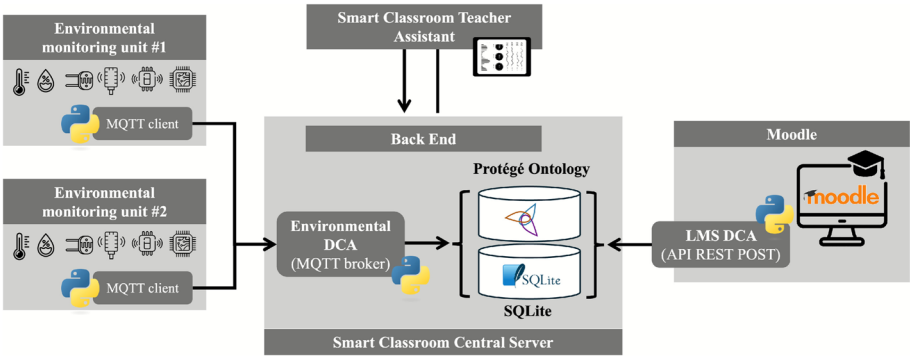



**Fig. 6** Components schemes implemented in the proof of concept

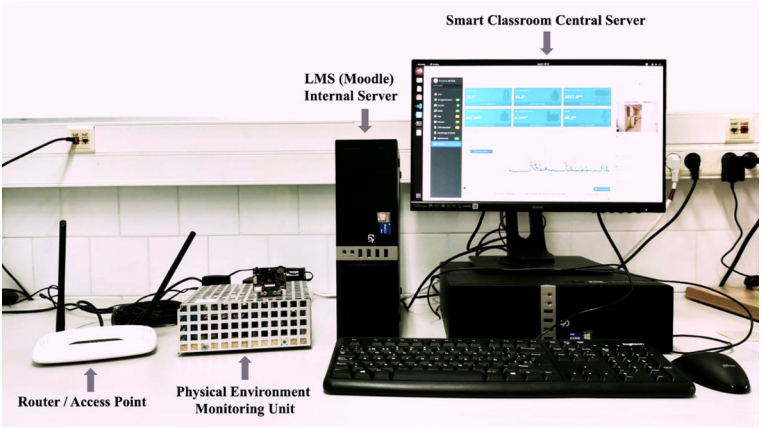



**Fig. 7** Components in our proof of concept. From left to right: the Wi-Fi router providing components wired and wireless connectivity, the monitoring unit for measuring the physical context of the smart classroom, the LMS server running Moodle, and the computer hosting the SCCS and providing basic front-end functionality. A second physical context monitoring unit was placed in another area of the laboratory

## 4.2 Data collecting agents

The Environmental DCA Python script operates as an MQTT client, subscribing to sensor data topics while additional MQTT client scripts run on the monitoring units. All scripts use the `paho-mqtt` library, which provides the standard Python interface for implementing the MQTT protocol. On these monitoring units, sensor values are read at regular intervals (every 5 min for testing purposes) and published to predetermined topics, such as `temperature`, `humidity`, and $CO_2$, using the `publish()` method. These messages are sent to an MQTT broker running at a specified IP address within the local smart classroom network (in our proof of concept, as shown in Fig. 6, this corresponds to the SCCS). The Environmental DCA connects to this broker using the `connect()` function and subscribes to the relevant topics via `subscribe()`. This connection specifies both the broker's IP address and the designated TCP port (1883). Upon receiving a message, the `on_message()` callback is triggered, allowing the DCA to extract the sensor value from the payload and store it in the back-end data infrastructure.

To store extracted data within the semantic model managed in Protégé, we use the `rdflib` library for Python. The RDF/OWL ontology file is loaded and updated by creating individuals and asserting properties that reflect the extracted data, such as new triples involving `hasSensorTimeStamp` and `hasSensorValue`. For storage in SQLite, the Python script establishes a connection to the database using the `sqlite3` library using the `connect()` function, while data insertion is performed with the `execute()` method. Each sensor reading is stored in a corresponding table, *e.g.,* `temperatures`, `humidities`, or `co2_levels`, with two columns: `value` (representing the measured value) and `timestamp` (recording the time of acquisition).

The LMS DCA retrieves and integrates learning-related data by connecting to Moodle's RESTful APIs. To illustrate this process, we describe the extraction of student grades from a Moodle course. The API function `gradereport_user_get_grade_items()` returns a structured JSON response containing a student's grade records. This request includes key parameters, such as an authentication token for accessing the Moodle web service, the function name to be invoked, the desired response format, and the identifiers of the target course and student. When a successful response is received (*i.e.,* HTTP 200 return code), the LMS DCA parses the JSON payload to extract relevant details: the grade item's name, the student's grade, and any associated teacher's feedback. Each entry is timestamped to ensure temporal traceability. The extracted information is then stored in both Protégé and SQLite using similar procedures as for environmental data.

## 5 Discussion

The development of SClassO demonstrates not only its technical feasibility but also its potential to transform smart classroom environments. By reusing and extending existing ontologies and validating new domain-specific concepts with experts, we have structured an interoperable framework that integrates diverse classroom data sources. Our proof of concept highlights the practical implementation of SClassO using Protégé to formalize and populate the ontology with relevant elements. Additionally, Python's flexibility and extensive library support allowed us to develop DCAs capable of operating across different hardware platforms. Leveraging interoperability standards such as MQTT for sensor data transmission and `rdflib` for managing RDF/OWL-based ontologies further reinforced the model's adaptability. Beyond the technical validation, our modular and hierarchical design, comprising distributed sensors, environmental-specific DCAs, and additional DCAs interfacing with other information systems like LMS, provides a scalable and extensible approach. This design supports dynamic adaptation to varying smart classroom technologies and use cases, ensuring versatility in deployment.

### 5.1 Data volume issues

In addition to validating the semantic modeling capabilities of SClassO, our testing highlighted a critical challenge inherent to data-intensive IoT environments: managing storage capacity and maintaining acceptable performance when handling RDF/OWL files. This challenge becomes particularly pressing in real-world smart classroom deployments, where high-frequency data from heterogeneous sources (*e.g.,* environmental sensors, wearable devices, and learning platforms) must be persistently stored, queried, and potentially reasoned over, without compromising efficiency.

Experiments with smart classroom prototypes have revealed that combined wearable and environmental sensor streams can easily reach few gigabytes of raw data per week for a single classroom [13, 53]. Scaling this to multiple classrooms or across an entire academic term results in data volumes that quickly surpass what RDF/OWL-based persistent storage can efficiently handle. The bottleneck stems from how Protégé and RDF/OWL files handle individual data values. While Protégé allows direct modeling and storage of instances, numeric values (*e.g.,* integers or floats) are encoded as text literals using XML Schema datatypes such as `xsd:int` or `xsd:float`. For example, the value "30" is encoded in UTF-8, where each character consumes one byte. However, the real overhead arises from the RDF structure itself: every reading is represented as a triple, significantly increasing processing time and file size to hundreds of bytes. Prior studies confirm that OWL is not optimized for storing time-series sensor data, making scalability a serious limitation in sensor-rich environments [54]. In contrast, relational databases offer a far more efficient solution. In our proof-of-concept implementation using SQLite, the data type `REAL` uses 8 bytes, while timestamps can be stored as strings. At larger scale, databases like MariaDB use `FLOAT` (4 bytes) and `DATETIME` (8 bytes), requiring only 12 bytes per entry [55], a dramatic reduction compared to RDF/OWL. These findings reinforce the widely recognized recommendation to separate high-volume, transient sensor data from the semantic layer. In hybrid data management architectures, the ontology provides integration, contextualization, and reasoning, while raw sensor data is managed by relational back-ends such as SQLite or MariaDB [56, 57]. In this approach, the ontology defines 'what data means' and 'how it related across contexts', while the database ensures efficient storage and retrieval.

Additionally, two complementary strategies could be used to further optimize storage: (i) event-driven recording, where new sensor values are stored only if they differ significantly from the previous reading (*e.g.,* surpassing a predefined threshold), thus avoiding redundant entries, and (ii) context-sensitive recording, where data are logged selectively when values exceed predefined comfort zones, prioritizing conditions with pedagogical or contextual relevance. Together, these mechanisms reduce storage requirements without sacrificing essential information.

Finally, life-cycle management policies are crucial to avoid uncontrolled data growth. For smart classrooms, retaining sensor data beyond two academic years is rarely necessary, making automated deletion or archiving an effective long-term strategy.

### 5.2 Security and privacy

Given the sensitive nature of some of the collected data, security and privacy are essential concerns. Ensuring data integrity is critical, as AI-driven decision-making in the SCCS depends on accurate and untampered information. To this end, we recommend protecting data at rest through selective encryption. This can be implemented either at the application level, *i.e.,* encrypting individual records within the SCCS before storage, or at the database level, where the database management system handles encryption autonomously. The latter option minimizes complexity in application logic while mitigating risks such as eavesdropping or unauthorized access to sensitive information. Additionally, applying Role-Based Access Control (RBAC) within RDF/RDFS knowledge bases presents a promising approach for controlling access at the semantic and knowledge level [58].

## 6 Conclusions

In this article, we have presented a comprehensive semantic model for smart classrooms, referred to as SClassO. The proposed ontology was developed through a structured methodology, validated by domain experts, and implemented in a proof-of-concept scenario involving real data acquisition and semantic integration. The model successfully integrated diverse information sources, namely the people involved, their context (physical context in the classroom, and emotional context of students and teachers), and the learning activities. The ontology's semantic structure was formalized using OWL/RDF and implemented in Protégég1, ensuring interoperability and supporting future reasoning capabilities.

To validate the ontology's practical applicability, we implemented it within a selected set of information sources. In this line, a distributed network of DCAs was developed to capture and process data using standard interoperability protocols such as MQTT and RESTful APIs. Our implementation demonstrated the feasibility of Python-based DCAs in semantically structuring and transmitting smart classroom data. However, it also highlighted critical challenges in the practical deployment of such systems, particularly in handing large volumes of real-time data in relation to OWL-based persistent storage. Hence, hybrid data management architectures are encouraged to decouple semantic modeling from high-volume, time-series sensor data storage, recommending relational databases for efficient back-end support.

Future research should prioritize the development of lightweight, modular ontologies and context-aware reasoning mechanisms optimized for smart classrooms equipped with resource-constrained IoT devices. Furthermore, integrating ontologies with machine learning models, running on the SCCS to understand classroom dynamics, presents exciting opportunities for enhancing semantic interoperability and adaptive decision-making. This synergy will pave the way for smarter, more responsive educational environments that can continuously evolve based on classroom dynamics and student needs.

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**Data Availability** The proposed ontology is publicly available on the website of the research group.

## Declarations

**Conflict of interest** The authors declare no Conflict of interest.

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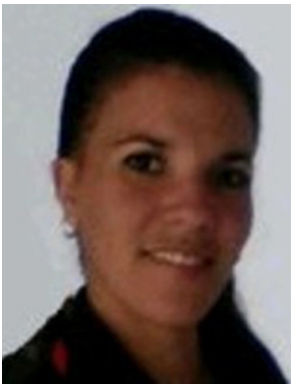
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