Journal of Information and Data Management, 2026, 17:1, doi: 10.5753/jidm.2026.5691

ActivEOn: An ontology for human activity modelling in smart spaces

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Received: 16 March 2026 • **Published:** 13 March 2026

Abstract One of the key challenges in smart environments is representing user context, as most applications need to collect and interpret data about their users. A crucial category of contextual information in these environments is user activity. This paper presents a literature mapping of recent research on human activity modelling using ontologies. Based on this analysis, we propose an ontology called ActivEOn, designed to represent human activities in smart spaces. This ontology provides high-level modelling of activities and related concepts, allowing for extensions into specific domains. The potential of the developed ontology was demonstrated through use cases in different smart environments modelled using Protégé software.

Keywords: Human Activity, Ontology, Smart Environment, Context

1 Introduction

Today, the advent of technologies such as mobile computing and the Internet of Things allows the spread of smart environments. Examples of such environments include smart cities, smart homes, smart buildings, and smart classrooms. These environments usually apply the ubiquitous computing concept, where computing must be present in environments to assist the user in performing their daily tasks efficiently. These environments advance otherwise passive surroundings to become active partners for their users. Equipped with technology that enables them to perceive and respond intelligently, smart environments integrate various technologies, including artificial intelligence, sensor networks, and ubiquitous computing. They offer possibilities to improve lives by providing assistance, convenience, and efficiency. Examples of applications include Ambient Assistive Living, which assists the elderly and people with disabilities in their daily activities, and Urban Environments. Smart environments also enable effective data-driven decision-making, trust communities, resource optimization, and interconnected environments.

Applications in smart environments must operate under dynamic conditions, as the availability and status of resources, as well as the behaviours and needs of users, are subject to frequent changes. Consequently, many of these applications and services can enhance their performance and effectiveness by leveraging context information. By incorporating contextual data in real-time, such as user preferences, environmental conditions, and resource availability, these applications can adapt their functionality to provide more accurate, relevant, and personalized results. This approach enables a more efficient and responsive interaction between users and the system, ultimately improving the overall experience and effectiveness of smart environments. Therefore, many of these applications and services can provide better results when using *context* information. The context is 'any useful information to characterize the situation of an entity (a person, object, or place) that may affect the interaction between users and systems' [Abowd *et al.*, 1999]. Therefore, context-aware systems use this information to provide services that are most relevant to their users.

An important aspect of context information is how to characterize them. There are several context dimensions identified by different researchers [Perera *et al.*, 2014]. When dealing with smart environments, a relevant context category is related to the actions or tasks performed by users, also known as *activities*. Examples of activities that context-aware systems can detect include walking, running, sitting, and using vehicles such as cars and buses [Nascimento *et al.*, 2021].

A central challenge revolves around the exchange of information between context-aware systems. The question arises: How can contextual information be shared among systems using a common representation pattern that all relevant agents can understand? This issue is fundamental for seamless communication and collaboration in context-aware environments.

In this context, the concept of ontology plays a central role in structuring and organizing knowledge within a given domain. An ontology provides a formal and explicit representation of concepts, relationships, and entities relevant to a particular field of study. By defining a common vocabulary, it facilitates shared understanding and interoperability among systems, applications, and stakeholders. Ontologies enable the systematic classification of information, support reasoning, and inference mechanisms, and enhance data integration across heterogeneous sources. As a result, they serve as a fundamental component in knowledge management, semantic computing, and intelligent system development, contributing to improved accuracy, consistency, and efficiency in data-driven applications. It includes a set of semantic definitions that are interpretable by computer programs, where the concepts of a domain and the relationships among them are defined [Noy *et al*., 2001].

This paper aims to present an investigation through a systematic literature mapping of recent solutions in representing human activities using ontologies. Based on the mapping results, we developed an ontology called *ActivEOn* (Activity in smart Environments Ontology) that allows semantically representing activities performed by users in smart environments. This paper is an extension of the work presented in Nascimento and Oliveira [2024].

The rest of this article is structured as follows. Section 2 analyzes recent studies identified through the systematic literature mapping. Section 3 introduces the proposed ontology, while Section 4 presents a fitness evaluation and use cases conducted to assess and illustrate its capabilities. Finally, Section 6 provides the concluding remarks.

2 The Systematic Literature Mapping

The systematic mapping study presented in this paper followed the steps proposed in Petersen *et al.* [2015] and answered the four Research Questions (RQ) presented below.

- RQ1: Which are the existing approaches for human activities modelling using ontologies?
- RQ2: What application domains were used?
- RQ3: How were the activities modelled?
- RQ4: Is there any specific approach for smart environments?
- RQ5: Was any specific methodology or third-party ontology used to develop the ontology?

Aiming to perform the search to answer our RQs, we defined the following search string: *("human activity" OR "activities of daily living" OR ADL) AND (ontology OR ontological OR "knowledge-based model" OR OWL OR RDF)*. We performed searches for primary studies using the following databases and search tools: *ACM Digital Library*, *IEEE Xplore*, *Science Direct*, and *Springer Link*. We also applied additional filters in the search tools to select just studies in English, from 2018 to 2023, studies in the computer science area, and papers published in journals or conference proceedings.

To filter studies, we applied some inclusion and exclusion criteria, enabling us to answer our RQs. We employed the following inclusion (I) and exclusion (E) criteria.

- I1: Studies published in English.
- I2: Scientific papers of conferences or journals related to Computer Science.
- I3: Studies from 2018 to 2023.
- E1: Papers that do not present a primary study.
- E2: Studies with less than 4 pages.
- E3: Papers that are duplicates of other studies.
- E4: Studies that do not discuss human activity modelling through ontologies.
- E5: Opening of proceedings.

We conducted the SMS from October 2023 to May 2024. The initial search returned 1334 papers. The authors carried out two revision rounds on the returned papers. The first round comprehended the first filtering based on the metadata analysis like title, keywords, and abstract. As a result, we obtained 86 papers. In the second round, we went deeper, analyzing the introduction, conclusion, and other sections where the authors explained their proposals. Table 1 presents the breakdown totals we got for each search engine after each filtering phase. Finally, we got a total of 32 papers shown in Table 2.

RQ1: Which are the existing approaches for human activities modelling using ontologies? The search results (Table 2) show that there are several recent approaches for human activities modelling through ontologies. The first analysis of these works was a counting of keywords present in the selected papers (Figure 1). Only words that appeared in three or more papers have been selected. *Ontology* and *activity* are obvious frequent words since these words are included in the search string.

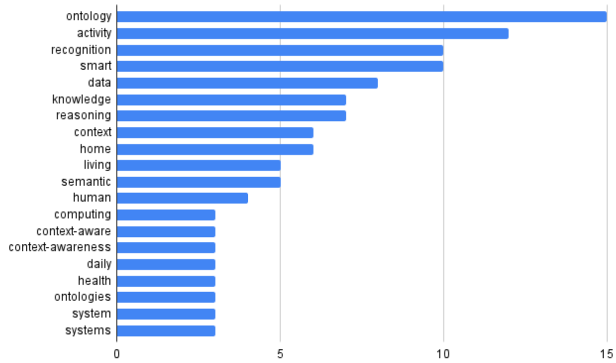

Figure 1. Counting of keywords in the selected papers.

The *recognition* word appeared in about a third of the papers, which indicates that most proposed ontologies were used in activity recognition solutions, as a component of a larger architecture. The presence of the word *smart* shows that several works present ontologies related to smart environments, such as smart homes, smart cities, and smart buildings.

The most common role of ontologies in such architectures is as a component of the inference process when, at least in part, it is knowledge-based (S5, S11, S15, S19, S25, S28, S31). A second case of ontologies usage in recognition processes is to semantically enrich activity labels provided by data-based machine learning inference methods. These inference engines usually generate activity related terms such as walking, running and standing. Ontologies can semantically describe these terms. This enriched information can be used for further knowledge-based analysis (S3, S27). Finally, S23 uses the knowledge about activities in the ontology to guide the training of data-driven recognition models.

The keywords *context*, *context-aware*, and *context-awareness* highlight the close relationship between the activity and context concepts. The activity modelling is included in ontologies that aim to model context (S1, S24). As described in other works in literature, activities are commonly used as part of the user's context. On the other hand, activities also have context. Several selected ontologies contain

Table 1. Number of results per database/search tool.

Database/Search Tool	Search results	1^{st} Filter	2^{nd} Filter
ACM Digital Library	87	27	13
IEEE Xplore	289	10	2
Springer Link	277	16	9
ScienceDirect	681	33	8
Total	1334	86	32

Table 2. List of selected papers.

Id.	Title	Year
S1	3LConOnt: a three-level ontology for context modelling in context-aware computing	2019
S2	A collaborative semantic framework based on activities for the development of applications in Smart Home living labs	2023
S3	A Context-aware Hybrid Framework for Human Behavior Analysis	2020
S4	A Framework for Constructing and Augmenting Knowledge Graphs using Virtual Space: Towards Analysis of Daily Activities	2021
S5	A Knowledge-Based Approach for Multiagent Collaboration in Smart Home: From Activity Recognition to Guidance Service	2020
S6	A novel ontology consistent with acknowledged standards in smart homes,	2019
S7	A Personalized Recommendation System to Support Diabetes Self-Management for American Indians	2018
S8	Activities of Daily Living Ontology for Ubiquitous Systems,	2018
S9	Activity recognition using wearable sensors for tracking the elderly	2020
S10	An approach to the acquisition of tacit knowledge based on an ontological model	2020
S11	CAVIAR: Context-driven Active and Incremental Activity Recognition	2020
S12	Context-aware Adaptive Recommendation System for Personal Well-being Services	2020
S13	Cyber Identity: Salient Trait Ontology and Computational Framework to Aid in Solving Cybercrime	2018
S14	Decision Support Systems to Promote Health and Well-Being of People During Their Working Age: The Case of the WorkingAge EU Project	2020
S15	Deriving human activity from geolocated data by ontological and statistical reasoning	2018
S16	Domain Ontology Construction with Activity Logs and Sensors Data – Case Study of Smart Home Activities	2022
S17	Exploiting a multi-device knowledge meshing to agent-based activity tracking	2020
S18	Exploiting Smart City Ontology and Citizens' Profiles for Urban Data Exploration	2018
S19	Fuzzy-Based Fine-Grained Human Activity Recognition within Smart Environments	2019
S20	HeLiS: An Ontology for Supporting Healthy Lifestyles	2018
S21	Heterogeneous self-tracked health and fitness data integration and sharing according to a linked open data approach	2022
S22	Hybrid approach for anticipating human activities in Ambient Intelligence environments	2022
S23	Hybrid Approach for Human Activity Recognition by Ubiquitous Robots	2018
S24	Intelligent context-awareness system for energy efficiency in the smart building based on ontology	2019
S25	Knowledge-Based Architecture for Recognizing Activities of Older People	2019
S26	Modeling a User-Oriented Ontology on Accessible Homes for Supporting Activities of Daily Living (ADL) in Healthy Aging	2019
S27	Multi-modal activity recognition from egocentric vision, semantic enrichment and life logging applications for the care of dementia	2018
S28	Probabilistic knowledge infusion through symbolic features for context-aware activity recognition	2023
S29	Probabilistic Ontology Reasoning in Ambient Assistance: Predicting Human Actions	2018
S30	Stream Reasoning approach for Anticipating Human Activities in Ambient Intelligence environments	2022
S31	TAO: Context Detection from Daily Activity Patterns Using Temporal Analysis and Ontology	2023
S32	Towards an Extensible Context Model for Mobile User in Smart Cities	2018

concepts describing activities context (S3, S11, S12, S28, S29).

RQ2: What application domains were used? Almost half of the works applied modelled human activities in the smart home domain (S2, S3, S4, S5, S6, S8, S9, S16, S19, S23, S25, S26, S27, S29, S30). The ontologies in these works describe *Activities of Daily Living* (ADLs) that mainly include activities of personal care (such as eating, drinking, sitting, walking, taking medicine, and using the toilet) and also activities related to housework (such as cleaning and food preparation). Most of the ontologies are used as part of a solution related to health care or elderly care contexts.

Other domains related to smart environments present in the selected works are *smart cities* and *smart buildings*. In these domains, activities are part of users' context (S24, S32), provide indicators that can provide relevant information about activities (S18), or related activities that can be done in certain Points of Interest (S15, S17).

Seven works present ontologies that are not related to a specific domain (S1, S10, S11, S12, S22, S28, S31). In general, these works present an upper-level ontological description of activities without specifying numerous activity subclasses. These high-level concepts can be specialized in domain ontologies. Other domains include the *physical activities modeling* (S7, S20, S21), *cybersecurity* (S13), and *working activities modeling* (S14).

RQ3: How were the activities modelled? Most works model activities from a main concept called *Activity*. There are several properties related to this concept. Each work used a different list of properties, most applicable to the problem modelled by each one.

Two works defined properties related to the identification and description of activities. The other two works defined properties of goals and motivation of activities. The selected activities are executed by people, and it is crucial to model information about actors who are directly involved in the activity execution and about other individuals who participate. Several works presented properties related to the activities' context. Most context properties specify the locations where activities take place. Location is important information to understand the context of activities. For example, if a person is *driving*, it can be important to know in which street the person is located. Other context information modelled as properties in the analyzed papers includes information such as social context, physiological context, and information about speed and number of steps.

A time when an activity occurred is another essential information. Most works define at least one property related to time. This information is modelled in different forms: some papers are concerned just with an instant of time of activity occurrence, while others are concerned with the time interval when an activity took place and the time duration of the activity development. In smart spaces, activities usually involve the use of one or more resources. These resources can include things such as sensors, objects, tools, devices, vehicles, or software systems. These resources can be essential to the development of the activity (for instance, a driving activity needs the resource car) or can affect the activity in some manner (a traffic light can affect the activity of driving).

Some works associate a type to an activity, model the situation before and after the execution of the activity (activities can change the environment state), and also define properties to specify the effects of an activity (such as changes in the environment or the event triggering). Some works are concerned with modelling the requisites of an activity (what is necessary or desirable for the activity development). Activities can need a specific place to occur, or they can need a specific resource. The activities also can require that actors are not in specific places or do not use a specific resource. Finally, there are fundamental properties related to the composition of activities, which play a crucial role in understanding their structure and organization. Various studies suggest that an activity can be broken down into smaller, more manageable components, often referred to as actions or tasks.

These subdivisions allow for a more detailed analysis of each segment, facilitating a clearer understanding of how activities function as a whole. Furthermore, these individual components can themselves be perceived as distinct activities, each possessing the potential to be further partitioned into even smaller units. This hierarchical decomposition enables a more systematic approach to studying activities, providing insights into their complexity and interdependencies. The parts compound a sequence of actions that is specified in a set of properties that define what are the next activities and/or what are the previous ones. Some properties were used to specify sequencing numbers or indexes to define what is the position of specific parts in the sequences.

RQ4: Is there any specific approach for smart environments? Most analysed approaches (62,5%) are applied to smart environments. As described in the response for RQ2, most solutions are related to smart homes. Four works are focused on smart cities (S15, S17, S18, S32), and one on smart buildings (S24).

Therefore, there are ontologies defined in the literature for activity modelling in smart spaces. However, they are specific for certain types of environments, and their application in other domains is restricted.

S1 and S22 present upper-level ontologies that contain a multi-domain specification for activities. However, these ontologies present a restricted set of properties (S1 provides properties for the specification of actors and the activity's environment, and S24 provides properties for location and objects used in the activity).

RQ5: Was any specific methodology or third-party ontology used to develop the ontology? Few works used a specific methodology. *Methontology*Fernández-López *et al.* [1997] has been used in two works (S1, S20) and *Ontology Development 101*Noy *et al.* [2001] was used in only one work (S8). About 16% of the works used third-party ontologies. High-level concepts from DOLCE and SUMO upper-level ontologies have been used in S1 and S20. S1 models activities as part of user context and uses generic context concepts modelled in CONON (COntext ONtology). ActivO is an ontology that models human activities and has been extended in S2, S11, S28. S4 extends Home Ontology to define several new properties to activities. The W3C Time ontology has been used to represent time concepts in S4 and S18. SSN has been reused in S6 and S19 to model information about sensors. Other reused ontologies are X3D ontology (S4), SMASH (S7), TrackPOI (S17), Schema (S18), RDF Data Cube (S18), Skos (S18), Scovo (S18), AGROVOC (S20), SEM (S27), Meeting Minds Ontology (S31), Domain Activity Ontology (S31).

3 Modeling Activities with the ActivEOn Ontology

The systematic mapping study showed common model decisions for human activities modelling using ontologies. The analysed works present an interesting set of different properties that can be associated with activities to model related information (as described in the discussion about RQ3). However, none of the analysed ontologies provide a comprehensive set of classes and relationships capable of fully representing activities and their contextual elements across various smart environments. While existing ontologies may address specific aspects of activity modelling, they often lack the breadth and depth required to capture the complexity and diversity of human activities in dynamically changing contexts. Moreover, the interdisciplinary nature of smart environments necessitates an ontology that can integrate diverse sources of information, account for variations in human behaviour, and adapt to different application domains. Therefore, to the best of our knowledge, there is currently no work in the literature that presents a fully developed ontology capable of modelling human activities across multiple smart environments in a holistic and adaptable manner. This gap highlights the need for further research and the development of a more comprehensive and flexible ontological framework that can effectively represent activities, their interrelations, and the contextual factors influencing them in smart environments.

From the collected information, we developed an ontology called ActivEOn (Activity in Smart Environment Ontology) that models high-level concepts and properties related to activities and can be extended to represent specific domain terms.

An overview of the ontology is shown in Figure 2. The presented diagram uses OntoUML [Guizzardi *et al.*, 2018] language to model the ontology.

The main concept in the ontology is *Activity*. This concept is a context entry related to an activity that occurred or is occurring and that can be part of the contextual history of an entity. Some related works presented in 2 modeled activities as subtypes of events. Events are entities that have limited duration and do not have a persistent identity. However, in this work, an activity as a part of an entity context can be persisted for historical purposes.

Each activity is associated with a unique numerical identifier (ID) and a description. We considered an activity as part of the user's context. Therefore, use modelled the Activity class as an extension of the *ContextValue* concept, defined in the SpaceCOn [Nascimento and de Oliveira, 2023] ontology. The goal of SpaceCOn ontology is to model context information in general. An activity is a context category and, therefore, is related to a subset of context information. The SpaceCOn ontology is not concerned with the representation of activities but defines general concepts that can be extended to model activities. The extension of SpaceCOn *ContextValue* concept allows an activity to be part of contextual information related to an entity.

A human activity is performed by one or more people. We decided to use the concept *Person* of the FOAF ontology[1]. FOAF defines a set of several properties that can be used to describe an activity's actor.

Each activity can contributes to their actors goals. A goal can be modelled using the *Goal* concept of UFO-C[2]. For instance, an activity *driving* contributes to his actor's goal to arrive at some specific place. Thus, we modeled an Activity as a relator the mediates the achievement of people goals.

The property "*occurred in*" allows us to specify the time information related to the activity. We chose to use the *TemporalEntity* concept from W3C Time ontology[3], which was reused by some analysed ontologies. The *TemporalEntity* concept is generic enough to allow the inclusion of time intervals, time instants, or duration specifications in different ways.

Resources can be associated with activities through the use of property. The detailed modelling of resources can be different for each domain. For example, in a smart home domain, the SSN ontology can be used to model sensors, and home objects can be modelled using domain-specific concepts. In smart cities, it is necessary to model resources such as vehicles, smartphones, and parking lots. Smart classroom resources can be modelled, for example, using the PLOM ontology [Atif *et al.*, 2015].

Each activity can have a context that can be specified through one or more instances defined by the *ContextualElementInstance* concept from SpaceCOn. A contextual element instance is an attribute value of the activities' context. These attributes can be the location related to the activity, social context, environment context, and so on.

The situation before and after the activity can be specified through the "*has initial situation*" and "*has final situation*" properties. Situations are individuals of *Situation* concept defined in gUFO[4] ontology as a particular configuration of a part of reality which can be understood as a whole and in which entities stand in relations. A situation may be counterfactual or actual. An actual situation (or in other words, a "fact") "obtains" in a certain time instant or during a time interval.

Activities can also be related to each other. An activity may have another activity that occurred immediately after (property *next*). It is also possible for an activity to be composed of other activities specified by the "*has sub activity*" property. The order of activity in a sub-activities sequence can be specified in the *sequenceNumber* property.

An activity has a type (for instance, walking, running, or driving), modelled in the *ActivityType* concept. This concept can be extended to model a specific taxonomy of activities used in a domain.

A type can have one or more requirements, represented by the *Requirement* concept. We decided to relate requirements to activity types and not to Activity concepts because requirements are conditions that should be true before an activity starts. As the Activity concept models an activity that occurred or is occurring, it is supposed that all the requirements have already been provided. Furthermore, all activi-

[1] http://www.foaf-project.org/
[2] https://dev.nemo.inf.ufes.br/hcion/UFO.html
[3] https://www.w3.org/TR/owl-time/
[4] http://purl. org/nemo/doc/gufo

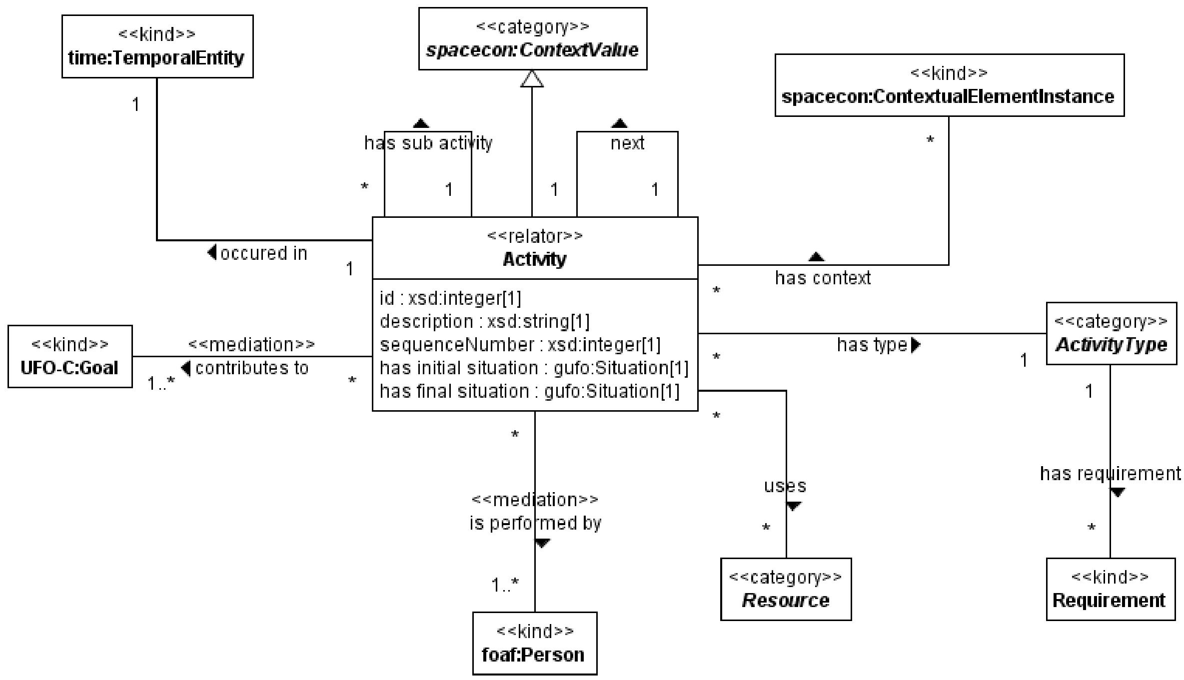

Figure 2. ActivEOn ontology concepts and properties.

ties of a given type have the same requirements. For example, the *driving* activity type requires a resource *car*, while "*having breakfast*" must occur in the morning.

4 Evaluation

The ActivEOn evaluation occurred in two stages: (1) we implemented the ontology and developed two use cases in distinct scenarios to demonstrate its capability to represent different types of human activities within diverse smart environments; and (2) we applied an ontology fitness evaluation approach[Tatarintseva *et al*., 2013] to assess its structural consistency, semantic richness, and overall adequacy for supporting activity modeling.

4.1 Use Cases

The ontology was implemented in OWL language using Protégé software [Musen, 2015], version 5.5.0. The implementation used gUFO as base ontology. The implementation of each class is summarized below.

- *Activity*
  - Subclass of *gufo:Kind*, *spacecon:ContextValue*
  - Restrictions:
    - ∗ activeon:isPerformedBy **min** 1 foaf:Person
    - ∗ activeon:hasInitialSituation **exactly** 1 gufo:Situation
    - ∗ activeon:hasFinalSituation **exactly** 1 gufo:Situation
    - ∗ activeon:hasGoal **min** 1 activeon:Goal
    - ∗ activeon:hasType **exactly** 1 activeon:ActivityType
    - ∗ activeon:next **exactly** 1 activeon:Activity
    - ∗ activeon:occuredIn **exactly** 1 time:TemporalEntity
- *ActivityType*
  - Subclass of *gufo:Category*
- *Resource*
  - Subclass of *gufo:Category*

To evaluate the capacity of the ontology to represent real-world situations, we used two use cases.The first one is based on the following scenario: *A visitor is staying at a hotel in a city's central area. Around midday, the visitor feels hungry. They open a restaurant recommendation application on their mobile device and spend several minutes searching for vegetarian dining options nearby. The application suggests a few restaurants, and the visitor selects one of them. The visitor then uses a private vehicle and a navigation application to travel from the hotel to the selected restaurant. The restaurant is located near a public parking facility that displays real-time information about available parking spaces. Using this information, the visitor finds an available spot and parks the vehicle. The trip to the parking facility takes about fifteen minutes, and parking takes an additional two minutes. Afterward, the visitor walks for about a minute to reach the restaurant. Once inside, the visitor spends approximately thirty minutes having lunch.*

The visitor was modeled as an individual of the class *Person* of FOAF ontology. We modeled five subclasses of *Resource*: *Smartphone*, *App*, *Car*, *ParkingLot*, and *InformationPanel*. We created individuals for each of these classes, representing resources used in the use case: *Visitor*, *RestaurantRecommendationApp*, *NavigationApp*, *VisitorsCar*, *PublicParkingLotNextToRestaurant*, and *InformationPanelAtPublicParkingLot*. We also created three subclasses of *ActivityType*: *Eating*, *Movement*, and *UsingApp*.

An additional subclass of *Movement* was created called *Driving*. Six activity types have been modeled as individuals of these classes: one individual of class *Eating* (*HavingLunch*), two individuals of the class *Movement* (*GoingToPlace* and *Walking*), two individuals of the class *Driving* (*DrivingACar* and *Parking*), and one individual of the class *UsingApp* (*UsingRestaurantRecApp*).

We modelled three main activities in the scenario as instances of *Activity* class: "*searching for a restaurant*", "*going to the restaurant*", and "*having lunch*". These activities definitions in the Protégé software are shown in Figures 3, 4 and 5. The activity "*going to the restaurant*" has been divided in three parts: "*driving to the restaurant*", "*parking*", and "*walking to the restaurant*". These activity properties can be viewed in Figures 6, 7, and 8.

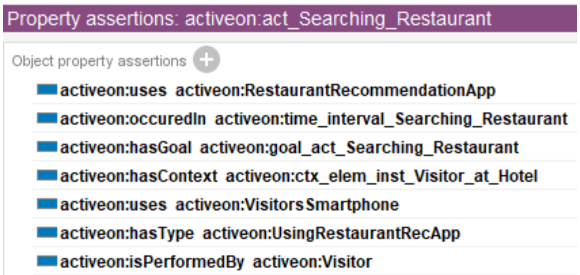

Figure 3. The modelling of the "searching for a restaurant" activity.

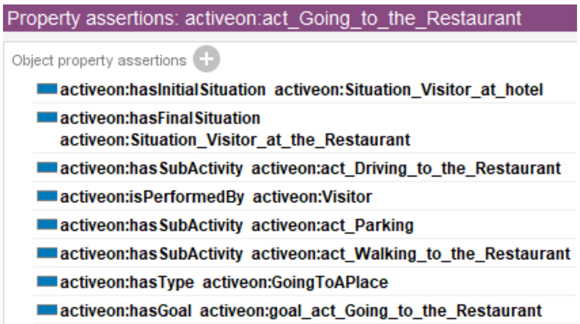

Figure 4. The modelling of the "going to the restaurant" activity.

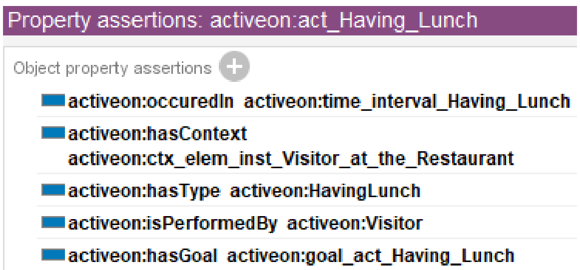

Figure 5. The modelling of the "having lunch" activity.

The second use case is based on a smart home scenario described in Roggen *et al*. [2010] and shown in Figure 9. The "Opportunity Scenario" refers to an experimental environment created to collect complex data on human activities in a sensor-rich space. This scenario was designed to study and model human activities at different levels of granularity, from atomic gestures to more complex and composite activities. It is widely used in the literature to test activity recognition systems and ontologies due to its layered structure and the richness of the collected data.

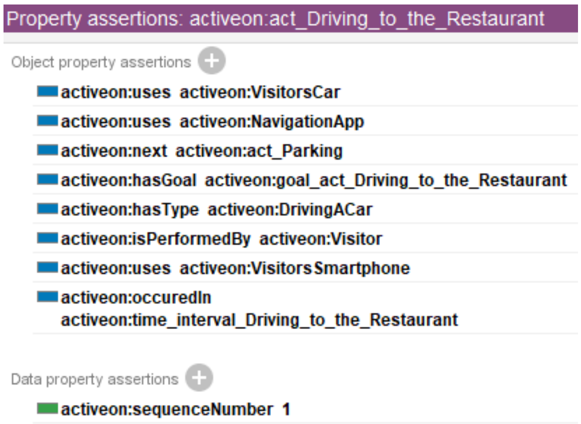

Figure 6. The modelling of the "driving to the restaurant" activity.

Figure 7. The modelling of the "parking" activity.

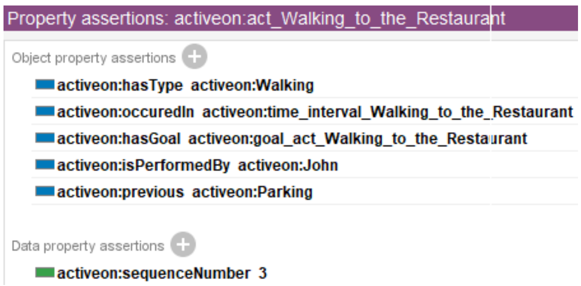

Figure 8. The modelling of the "walking to the restaurant" activity.

The described scenario has four levels of activities. Level I is the highest activity level available in the setup. Each activity can be decomposed into other high-level sub-activities. Level III contains activities related to modes of locomotion and manipulative gestures that compose higher-level activities in level II. Finally, level IV encapsulates atomic gestures forming the manipulative ones of level III.

We modelled the activities shown in levels III and IV, and also the activity "Get Bread" shown in level II. Figure 10 shows the modelling of the first *Reach Drawer* activity. This activity is related to two types specifically created for this example: one for level IV activities and another to describe *reach* activities. The activity is performed in a context where the volunteer is located in the scenario's kitchen. The context is modelled as a *SpaceCOn* contextual element instance. The activity also occurred during a time interval specified using a *W3C Time* interval instance. The actor that performs the activity is described as a *FOAF* and *DUL* person instance. The activity uses a resource (the drawer located in the kitchen), and it is also a sub-activity of *Open Drawer*.

The *next* and *sequenceNumber* properties are used to spec-

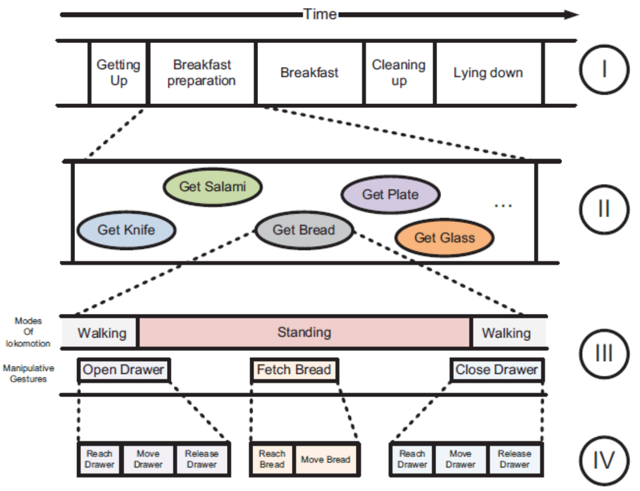

Figure 9. The layered organization of activities in the Opportunity scenario [Roggen *et al.*, 2010].

Figure 10. The modelling of the first activity "Reach Drawer" in the Opportunity scenario.

ify a sequence of sub-activities of *Open Drawer*. The next activity in the temporal sequence is the *Move Drawer* action (the property *sequenceNumber* specifies that the showed activity is the first sub-activity in the sequence). Thus, the *Reach Drawer*, *Move Drawer*, and *Release Drawer* form a sequence of activities that compose the higher-level *Open Drawer* activity. Other level IV activities were modelled similarly.

Figure 11 shows the modeling of *Fetch Bread* activity. This is a level III manipulative gesture that is composed of two sub-activities: *Fetch Bread* and *Move Bread*. The *hasSubActivity* property was used to model the relationships between these activities. As stated before, the temporal order of each activity is defined in the *sequenceNumber* and *occuredIn* properties in each sub-activity. The other two level III activities related to manipulative gestures are modeled similarly.

The modes of locomotion are organized in a separate sequence, parallel in time to the manipulative gestures sequence. Figure 12 shows the modeling of the first *Walking* activity. We choose to use the *hasFinalSituation* property to specify that after the conclusion of the activity, the volunteer will be located in the kitchen. This fact is the context of the *Standing* activity (Figure 13) and the initial situation of the second *Walking activity* (Figure14). The *sequenceNumber* property was set to 1 because this activity is the first of the

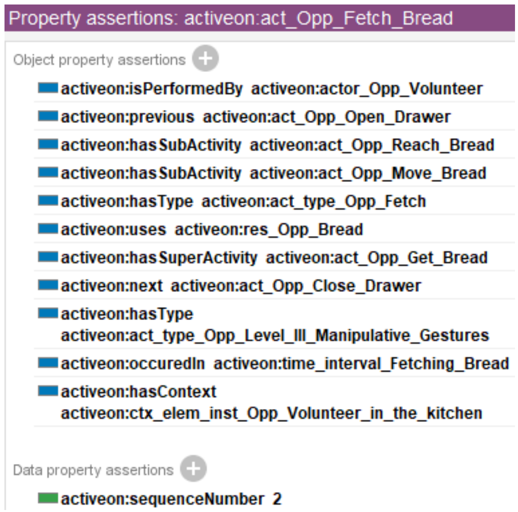

Figure 11. The modeling of "Fetch Bread" activity in the Opportunity scenario.

parallel sequence of modes of locomotion.

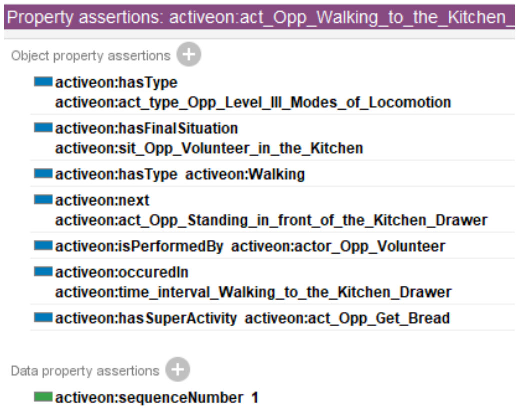

Figure 12. The modeling of "Walking to the Kitchen" activity in the Opportunity scenario.

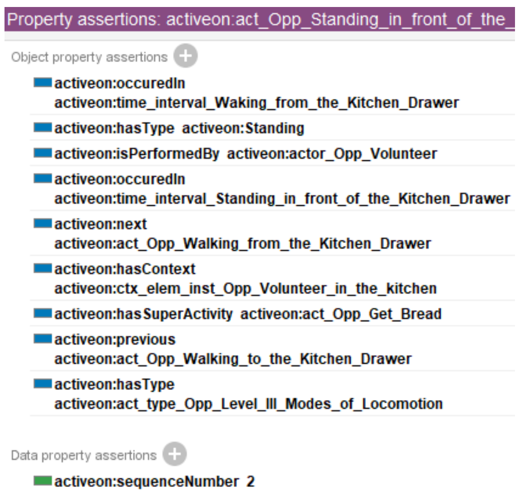

Figure 13. The modeling of "Standing" activity in the Opportunity scenario.

Finally, Figure 15 shows the modeling of the level II activity *Get Bread*. This activity has six sub-activities (three manipulative gestures and three modes of locomotion that perform in parallel) modeled using the *hasSubActivity* property. The actor and resources associated with this activity are the same as specified in the sub-activities. Other activities in layers I and II can be specified similarly.

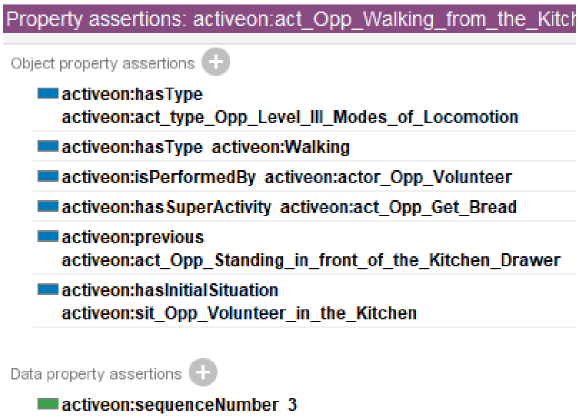

Figure 14. The modeling of second "Walking" activity in the Opportunity scenario.

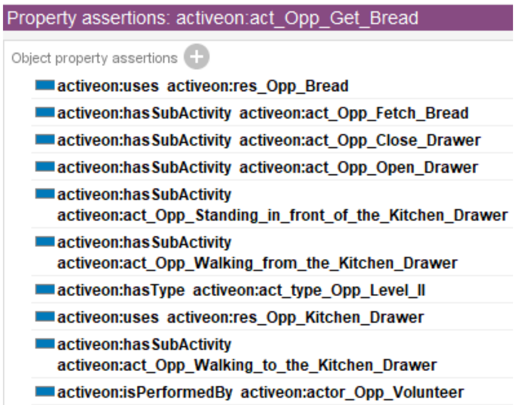

Figure 15. The modeling of "Get Bread" activity in the Opportunity scenario.

The two use cases presented in this paper show that ActivEOn can be successfully used to model activities in different smart spaces. It is also clear that different information related to each activity can be modeled as well. The model supports the modeling of different levels of granularity for activities.

4.2 Ontology Fitness Evaluation

In order to assess the ontology's fitness for the human activity domain, we adopted an approach adapted from the vote-based method proposed by Tatarintseva *et al*. [2013]. The first step consisted of extracting terms from the ontologies described in the papers selected through the systematic mapping presented in Section 2. These terms included the classes and properties defined in each ontology that are related to activity description. The final list of terms comprised only those mentioned in more than one study, as they were deemed to be highly specific to a given domain or scenario. We considered that the selected terms represent key aspects that should be taken into account when modeling activities in smart environments.

The second step involved comparing each identified term with the elements of every ontology. All terms that matched were counted as positive votes for an ontology. A match was defined as any term corresponding to the name of an equivalent element (a class or a property) within an ontology. The name comparison also accounted for synonyms. For instance, some ontologies describe a person who performed an activity using the property *hasActor*, while others use *involvedIn*. Therefore, the terms *hasActor* and *involvedIn* were considered to refer to the same concept.

Table 3 presents the ten most voted ontologies. The complete list of evaluated ontologies and terms is available at this link[5] . ActivEOn was the ontology containing the highest number of terms related to human activities. The works S11, S28, and S3 present ontologies that achieved vote counts close to ActivEOn. These ontologies include an extensive set of properties related to activity requirements. However, they do not include concepts associated with goals or activity decomposition, and their representation of activity context is limited to location information (S3 does not include any property for location specification). Therefore, it can be concluded that ActivEOn provides a more comprehensive framework for modeling activities in smart spaces compared to other ontologies described in the literature.

Table 3. Number of term ocurrences in the most voted ontologies.

Work	Term Ocurrences
ActivEOn	25
S11	21
S28	19
S3	18
S1	11
S10	11
S29	9
S4	8
S8	8
S21	6

5 Discussion

The research question that guided this study was: "How can contextual information be shared using a common representation pattern that all involved agents can understand?" Ontologies are a form of semantic representation of information that can be understood by different software agents. Therefore, an ontological modeling of activities would be a response to the question posed.

An extensive analysis of recent literature was conducted through a systematic mapping study. This analysis revealed that there are several ontological approaches for modeling human activities; however, none of them allows for sufficiently comprehensive modeling of these activities across different situations and scenarios. For this reason, the decision was made to develop the ActivEOn ontology, which is presented in this article.

Most ontologies identified in the systematic mapping study have been designed for specific domains: smart homes (S2, S3, S4, S5, S6, S8, S9, S16, S19, S23, S25, S26, S27, S29, S30), smart cities and smart buildings (S15, S17, S18, S24, S32). These classes and properties defined in these ontologies are useful to model activities that are specific to these domains, but that cannot be extended to other smart

[5] `https://docs.google.com/spreadsheets/d/1jKr8EpDc7XGPN5DpAT95WL3iUzp3Yiihkj0jSdzyhyQ/edit?gid=2139652455#gid=2139652455`

domains. For example, ontologies in smart homes are limited to modeling activities that occur inside homes and relating them to resources and locations that can be found in houses. Ontologies for smart cities relate activities to locations such as points of interest, and cannot be applied to domains where it is necessary to represent locations inside buildings, such as rooms. Furthermore, most of these ontologies have been designed with specific applications in mind, such as health care, elderly care, activities of daily living modeling, energy efficiency, mobile user context modeling, physical activities modeling, and work activities modeling. The use cases demonstrated that ActivEOn can be extended to model activities in different smart environments.

Seven analyzed ontologies are domain-independent (S1, S10, S11, S12, S22, S28, S31). Despite the possibility of application in different domains, these works lack properties for the representation of different resources (the focus is physical entities such as tools or objects) or different contexts (the focus is on location contexts) in a unique ontology. ActivEOn allows the association of activities with different resources (including non-physical ones, such as digital documents) and different contexts (such as user preferences, and weather conditions).

Few analyzed ontologies reuse others to model concepts such as time, context, or upper-level concepts. ActivEOn reuses ontologies such as W3C Time (for time-related concepts), SpaceCOn (for context-related concepts), gUFO (upper-level concepts), and FOAF (for actors modeling).

There are several practical uses of ActivEOn. As observed in Section 2, activities can be viewed as part of the user's context, and ActivEOn can be integrated with context modeling ontologies (such as SpaceCOn) to complement context modeling. ActivEOn is also an important tool to semantically describe activity-related terms in systems where there is data exchange, and it is crucial to ensure the correct interpretation of such concepts by all agents.

There are several solutions for human activity recognition that can semantically enrich their results using ActivEOn. For instance, the Opportunity scenario used in the second use case presents four semantic levels for activities. Activities in level IV and modes of locomotion in level III can be inferred from machine learning models trained from low-level sensor data. These activities' information is modeled as ontology instances, as shown in this paper. Reasoning approaches like SWRL rules can use such instances to infer properties of higher-level activities (for instance, start and end time instants, contexts, and used resources). However, the time involved in processing the ontology can be an obstacle to the ActivEOn application in time-critical systems.

6 Conclusion

This paper presented a systematic literature mapping and an ontology called ActivEOn. The systematic mapping study analysed recent literature on human activity modelling using ontologies. The analysis found several research papers that used ontologies to model human activities in smart environments, especially smart homes. The proposed ontologies defined several concepts and properties for activities, but each ontology failed to be generic enough to be applied to different smart environments, or the set of concepts and properties is limited. Therefore, the ActivEOn ontology has been proposed. The ontology defines a main concept called *Activity* and properties based on properties and concepts defined in the literature. The ontology is also extensible, and it allows the addition of new activity classes.

Use cases were developed using the Protégé software. The developed scenarios had reached the intended purpose of consistently representing context information. ActivEOn can be successfully used to represent activities in a smart environment scenario. Furthermore, domain ontologies can extend ActivEOn to represent domain-specific concepts.

In future work, we plan to expand our research by conducting a series of comprehensive tests on the ontology across diverse usage scenarios. These tests will aim to evaluate the ontology's robustness, scalability, and adaptability in various real-world contexts. By doing so, we seek to identify potential areas for improvement and validate its applicability in different domains. Additionally, we intend to extend the ontology to better model activities within specific smart environments, such as smart campuses. This extension will involve incorporating domain-specific knowledge and refining the ontology to capture the unique characteristics and requirements of these environments. Through these efforts, we aim to enhance the ontology's utility and contribute to the development of more intelligent and context-aware systems in smart environments.

Acknowledgements

This study was supported by the National Council for Scientific and Technological Development (CNPq) through CNPq/MCTI Nº 10/2023 Universal grant n. 402086/2023-6 and Nº 10/2022 Pq Sr. grant n. 306695/2022-7.

Availability of data and materials

The ontology is available in `https://github.com/lvnascimento/activeon/blob/main/activeon.owl`.

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