People's Democratic Republic of Algeria
Ministry of Higher Education and Scientific Research
Mohamed El Bachir El Ibrahimi University of Borj Bou Arréridj
Faculty of Mathematics and Computer Science
Department of Computer Science

THESIS
In order to obtain the Doctorate degree in LMD (3rd cycle)
Branch: Computer Science
Option : Information and Communication Technologies

THEME

At the heart of (Io)RT-E ecosystems

By: MAZA Abdelouahab

Publicly defended on: 18/12/2025

In front of the jury composed of:

Pr. ATTIA Abdelouahab	University of Bordj Bou Arreridj	President
Dr. Sabri Lyazid	University of Bordj Bou Arreridj	Supervisor
Dr. BELHADJ Foudil	University of Bordj Bou Arreridj	Examiner
Dr. MEDIANI Chahrazed	University of FERHAT Abbas SETIF 1	Examiner
Pr. AKHROUF Samir	University of M'sila	Examiner
Pr. CHIBANI Abdelghani	University of UPEC-PARIS France	Invited

2024/2025

Abstract

One of the major research areas in artificial intelligence focuses on designing and improving a robot's cognitive capabilities. This involves enabling robots to accurately interpret human behavior and intentions based on their perception of the environment. To achieve this, it is essential not only to understand human intentions, but also to anticipate the causal effects of elementary and complex actions and their consequences within a given context.

Modes of action preparation and emotions play an important theoretical role in this process. Frijda explains that the way individuals perceive and appraise events triggers different modes of action preparation. Similarly, psychologist James J. Gibson describes interaction with the environment through the concept of affordances, which guide action. Consequently, the contribution of artificial intelligence to modeling contextual understanding in (Io)RT-E ecosystems is undeniable.

Action recognition remains a critical research challenge, particularly in the field of human–robot interaction. Many questions remain unresolved, especially those related to understanding human behavior and anticipating future actions. This requires making spatio-temporal projections, predicting multiple possible futures, and inferring the effects of actions based on the current or inferred context. When a robot lacks information, it must adapt by enriching its knowledge through the properties of observed actions.

This process involves endowing robots with social cognitive capabilities that enable them to engage in joint actions with humans. In this context, we refer to joint human–robot agency.

This thesis proposes a hybrid framework that combines semantic annotation, spatio-temporal ontological modeling, narrative reasoning using NKRL, and reinforcement learning for adaptive human activity recognition. The proposed approach enables contextual, temporal, and causal interpretation of human actions. Experimental results conducted in Internet of Everything (IoE) environments demonstrate improved robustness, adaptability, and accuracy compared to classical activity recognition approaches.

Keywords: Artificial intelligence, spatio-temporal representation, cognition, intention recognition, joint action, machine learning, narrative reasoning, reinforcement learning, Internet of Robotic Things (IoRT), Internet of Everything (IoE), ecosystem.

Résumé

Parmi les travaux en intelligence artificielle est de concevoir et d'améliorer les capacités cognitives d'un robot. Il s'agit ici de permettre au robot d'interpréter avec précision le comportement et l'intention d'un humain à partir des perceptions de l'environnement. Il est donc crucial de non seulement faire une lecture de l'intention de l'humain mais d'anticiper les effets de causalité des actions/événements élémentaires/complexes et leurs conséquences dans l'environnement. Les modes de préparation à l'action et les émotions ont d'importantes implications théoriques. Frijda explique que la façon dont les individus perçoivent et apprécient les événements suscitent différents modes de préparation à l'action. Quant au psychologue James Jérôme Gibson qualifie l'interaction avec l'environnement en guidant l'action d'affordance. Par conséquent, l'apport de l'Intelligence Artificielle pour la modélisation du contexte des écosystèmes (Io)RT-E est sans doute indiscutable. La reconnaissance des actions est un problème de recherche important et de nombreuses questions demeurent non résolues, en particulier dans le domaine interaction humain-robot. Il s'agit donc d'appréhender le comportement de l'humain, d'anticiper ses actions, en effectuant entre autres des projections dans le temps et l'espace (plusieurs futurs à prédire) et des inférences sur les effets des actions en fonction du contexte en cours ou déduit. Un robot en manque d'informations devrait modifier ces connaissances en enrichissant ses informations manquantes à partir des propriétés des actions. Il s'agit ici de doter un robot de capacités cognitives sociales en vue de réaliser des actions conjointes. Nous parlons dans ce cas d'agentivité conjointe. Cette thèse propose un cadre hybride combinant l'annotation sémantique, la modélisation ontologique spatio-temporelle, le raisonnement narratif basé sur NKRL, ainsi que l'apprentissage par renforcement pour une reconnaissance adaptative des activités humaines. L'approche proposée permet une interprétation contextuelle, temporelle et causale des actions humaines. Les résultats expérimentaux obtenus dans des environnements IoE démontrent une amélioration de la robustesse, de l'adaptabilité et de la précision par rapport aux approches classiques de reconnaissance d'activités.

Mots Clés: Intelligence artificielle, représentation spatio-temporelle, cognition, reconnaissance de l'intention, action conjointe, apprentissage automatique, raisonnement narratif, apprentissage par renforcement, Internet des objets robotiques (IoRT), Internet de tout (IoE), écosystème.

الملخص:

يُعد تصميم وتحسين القدرات الإدراكية للذكاء الاصطناعي من المجالات البحثية الرئيسية. يتضمن ذلك تمكينه من تفسير سلوك الإنسان ونواياه بدقة بناءً على إدراكه للبيئة المحيطة. لذا، لا تقتصر الأهمية على قراءة نية الإنسان فحسب، بل تشمل أيضاً توقع الآثار السببية لأنشطته (البسيطة أو المعقدة) وعواقبها في المحيط. إن طرق استعداد الفرد للفعل وعواطفه لها آثار نظرية بالغة الأهمية. يوضح Fridja أن طريقة إدراك الأفراد للفعالية تستثير طرقاً مختلفة للتقويم. بينما يصف عالم النفس جيمس جيروم جيبسون التفاعل مع البيئة بأنه "توجيه الفعل" أو ما يُعرف بـ "الإمكانية" أو "الإتاحة .(Affordance) "وبالتالي، فإن إسهام الذكاء الاصطناعي في نمذجة سياق أنظمة إنترنت الروبوتات (IoRT-E) أمر لا يمكن إنكاره.

لا يزال التعرف على الفعالية مشكلة بحثية مهمة، وتحديداً في مجال التفاعل بين الإنسان والروبوت. إذا تعلق الأمر بفهم السلوك البشري، وتوقع أفعاله، فإن ذلك يتضمن القيام بتوقعات (قراءات) في الزمان والمكان (عدة احتمالات مستقبلية ممكنة) واستدلالات حول آثار الفعل بناءً على السياق الحالي أو المُستنتَج. ينبغي على الروبوت الذي يفتقر إلى المعلومات أن يعدل معرفته من أجل إثراء المعلومات المفقودة بناءً على خصائص الفعالية. وهذا يتضمن تزويد الروبوت بقدرات إدراكية اجتماعية لتمكينه من تنفيذ أفعال مشتركة. في هذه الحالة، نتحدث عن **الفاعلية المشتركة**.

تقترح هذه الأطروحة إطارًا هجينًا يجمع بين الوسم الدلالي، والنمذجة الأنطولوجية الزمانية-المكانية، والاستدلال السردي المعتمد على لغةNKRL ، بالإضافة إلى التعلم المعزز من أجل التعرف التكيفي على الأنشطة البشرية. يتيح النهج المقترح تفسيرًا سياقيًا وزمنيًا وسببيًا للأفعال البشرية. وتُظهر النتائج التجريبية المحققة في بيئات إنترنت الأشياء تطورًا ملحوظًا في المتانة، والقدرة على التكيف، ودقة التعرف مقارنة بالأساليب التقليدية للتعرف على الأنشطة.

الكلمات المفتاحية :الذكاء الاصطناعي، التمثيل الزمكاني، الإدراك، التعرف على النية، الفعل المشترك، التعلم، الاستدلال السردي، التعلم المعزز.

Acknowledgments

First and foremost, I would like to express my deepest gratitude to God Almighty for granting me the strength, clarity, and courage to pursue and complete this work. Without His guidance and blessings, none of this would have been possible. I would like to extend my heartfelt thanks to my supervisor, Professor Lyazid Sabri, whose encouragement was the turning point in my academic journey. He was the one who inspired me to return to my studies and embark on a career as a researcher. His guidance, patience, and unwavering support have been invaluable throughout this work.

My deepest appreciation also goes to my wife, whose love, understanding, and constant support have been my anchor in times of difficulty and doubt. She has always been behind me, motivating me to keep moving forward. I would like to thank my brother, Sofiane, for his continuous encouragement and faith in my abilities. His words of motivation have always reminded me to persevere and stay true to my goals. My deep gratitude to my colleague Nadia Agti for his encouragement and help.

Finally, I would like to express my sincere gratitude to all the members of the examination jury Professor Attia abdelouahab, Professor Akrouf Samir, Doctor BELHADJ Foudil and Doctor MEDIANI Chahrazed who have kindly accepted to evaluate and attend my defense. Their valuable time, insightful comments, and constructive suggestions are highly appreciated and will undoubtedly contribute to improving the quality of this work.

Dedication

I dedicate this work

To my beloved mother, **Malika**, whose constant prayers and unwavering wishes for my success have been a guiding light throughout my journey.

To my son **Aksel**

To my esteemed family in recognition of their continuous support and encouragement.

To my dear friends, especially **Rachid (the Saint)**, in appreciation of his sincere friendship and noble character.

Contents

List of Figures

List of Tables

Chapter 1

General Introduction

Psychological research has greatly enriched the field of artificial intelligence, and more specifically robotics, by providing foundations for human learning and reasoning through different schools of thought: behaviorism (Skinner, 1938 [?]), cognitivism (Piaget, 1952 [?]), and constructivism (Vygotsky, 1978, [?]). Behaviorism emphasizes the acquisition of knowledge through experience and the reinforcement of behaviors; cognitivism emphasizes the existence of internal structures that allow individuals to reason and learn independently of direct experience; while constructivism emphasizes the use of acquired knowledge to integrate new information. These perspectives offer essential insights for the design of artificial systems capable of learning and acting in a complex environment. In the context of robotics, and more specifically for human-robot collaboration (HRC), it is crucial that machines be able not only to perceive and interpret human behavior, but also to anticipate the effects of actions and events on the environment. Understanding intentions, predicting multiple future scenarios, and deducing the potential consequences of actions are all challenges for equipping robots with cognitive and social capabilities, enabling them to perform joint actions with humans. This approach raises fundamental questions: Why act in a given situation? What is the best action to perform? And how does the order of actions influence the achievement of objectives? Thus, drawing inspiration from psychological theories can guide the development of intelligent robotic systems capable of interacting fluidly and adaptively with humans, integrating perception, reasoning, and anticipation within a dynamic and contextual framework.

1.0.1 Research Motivation

The rise of smart environments, whether connected homes, assisted healthcare systems, or interactive robots, generates heterogeneous and dynamic data streams from sensors, cameras, mobile devices, or knowledge bases. To effectively exploit this information, systems must be able to understand not only individual events, but also the narrative, causal, and contextual relationships between these events.

In the field of artificial intelligence, one of the major challenges is to design and improve the cognitive capabilities of robots, enabling them to accurately interpret human behavior and intentions based on perceptions of their environment. This involves not only reading intentions, but also anticipating the causal effects of actions and events, whether basic or complex, and predicting their consequences on the environment. Action preparation modes and emotions play a crucial theoretical role: as (Frijda, 1987) [?] points out, the way individuals perceive and evaluate events influences action preparation strategies, while (James Jerome Gibson, 1977 and 1979) [?] and [?] introduces the notion of affordance, describing interaction with the environment as a guide to action. In fact, according to which the environment is not reduced to a set of objects, but constitutes a set of possibilities for action directly perceived by the agent. In our framework, contextual knowledge and observations from sensors can be seen as affordances guiding behavior and adaptive reasoning.

Human action recognition remains an open problem, particularly in the context of human-robot interactions, where many questions remain unresolved. It is therefore necessary to model human behavior by anticipating actions, performing multiple temporal and spatial projections, and inferring the effects of actions based on the observed or inferred context. When a robot has incomplete information, it must be able to update its knowledge by enriching its representations based on the properties of past, present, or projected actions. The ultimate goal is to equip the robot with social cognitive capabilities that allow it to perform joint actions with humans, a concept referred to as joint agency. In this context, the concept of the Internet of Robotic Things (IoRT) takes on its full importance. This paradigm extends the traditional concept of IoT and builds on the IoE (Internet of Everything) paradigm by providing any object with the typical functions of a robotic system: perception, actuation and control, and by allowing smart devices to monitor events, fuse data from multiple sources, decide on the best action and act in the physical world, sometimes by moving.

A fundamental aspect is symbolic anchoring, i.e. the ability to create and maintain associations between conceptual descriptions and perceptual information corresponding to the same physical objects. This thesis therefore proposes a generic framework for dynamic anchoring and narrative reasoning in (Io)RT-E ecosystems, structured on two levels: at the low level, the fusion of sensory data and the cooperative recognition of human intentions and activities via machine learning; At the high level, the conceptual representation of objects and events in a narrative model allows for the association of different types of descriptions with heterogeneous perceptual information. This framework aims to anticipate human actions, make inferences about their effects, and adapt robotic behavior for cooperative interactions, while laying the foundations for the introduction of NKRL (Narrative Knowledge Representation Language) for the representation of narrative and temporal knowledge in dynamic and complex environments. Thus, it is necessary to develop models combining sensory data fusion, conceptual representation, and narrative reasoning to enable robots to anticipate human actions and respond adaptively. These findings constitute the main motivation for this research.

1.0.2 Research Objectives

This thesis aims to propose a generic framework for dynamic grounding and narrative reasoning in (Io)RT-E ecosystems, articulating the following objectives:

1. Sensory Data Fusion and Processing: At the low level, implement machine learning-based approaches to fuse multi-sensor data and cooperatively recognize human activities and intention;
2. Conceptual Representation and Dynamic Grounding: At the high level, combine conceptual descriptions and heterogeneous perceptual information to represent narrative and contextual knowledge;
3. Action Anticipation and Prediction: Model human-robot interactions by integrating temporal and spatial projections, and reason about the effects of actions based on the current or inferred context;
4. Social Cognitive Capabilities and Joint Agency: Enable the robot to perform joint actions with humans, adjusting its beliefs and knowledge based on past, present, and future events;
5. Integrating Reinforcement Learning: Overcoming the traditional limitations of RL (training time, curse of dimension) by incorporating structured knowledge to guide learning and improve situation interpretation;

The ultimate goal is to provide a unified and interpretable model capable of handling the complexity of dynamic environments and human interactions, while laying the foundation for the introduction of NKRL as a narrative representation language.

1.0.3 Open Challenges and Limitations in the Research Domain

Current systems face several limitations:

- Traditional ontologies do not easily represent complex temporal and contextual relationships and generate redundant descriptions.

- Machine learning approaches offer good performance but remain uninterpretable and difficult to integrate into causal or narrative reasoning.

- Human action recognition and behavior anticipation remain an open problem, particularly in human-robot interaction. Humans can take unpredictable actions based on their beliefs or their physical and mental states.

- Fusing and integrating heterogeneous data from multiple sensors, videos, and knowledge bases represents a major technical challenge.

These limitations highlight the need for a model capable of representing and reasoning on narrative and dynamic knowledge, while integrating IoRT and IoE (Internet of Everything) to understand human behavior, anticipate actions, and guide interactions.

1.0.4 Research Challenges Addressed in This Thesis

To achieve the above objectives, several challenges must be addressed:

1. Representing narrative and dynamic knowledge: Defining an expressive model capable of managing the interdependencies between events, actions, and actors, taking into account the temporal and contextual dimensions.

2. Inference and reasoning about human intentions: Modeling the causal effects of actions and enabling the robot to adapt its decisions to unpredictable situations.

3. Fusion of heterogeneous and multi-level data: Combining sensors, video streams, textual descriptions, and ontologies to enrich context and improve predictions.

4. Integrating reinforcement learning with ontologies: Guiding robot learning by using symbolic knowledge to accelerate convergence and improve interpretability.

5. Developing joint agency: Enabling robots to act cooperatively with humans, adjusting their beliefs and plans for joint and adaptive actions.

   The use of NKRL as a model of narrative representation then appears as a suitable solution for combining expressiveness, reasoning about events, anticipation of human actions and integration of heterogeneous knowledge.

1.0.5 Thesis Contributions

This thesis makes several original contributions aimed at advancing the state of the art in human activity recognition (HAR) and automated decision-making. It proposes a framework where an intelligent agent, leveraging the narrative model of knowledge representation (NKRL), can interpret past and present events to anticipate human actions and suggest appropriate actions. By combining deep learning, semantic reasoning and cognitive modeling, this framework allows understanding the dynamic context, predicting multiple possible futures and generating adapted actions in complex IoRT and IoE environments:

- First, we propose a semantic annotation layer for describing evolving and interactive heterogeneous entities. This layer supports the semantic modeling of raw data from multiple sensors, thus facilitating analysis and reasoning on complex and dynamic information.

- The second contribution concerns the introduction of the NKRL (Narrative Knowledge Representation Language) narrative model in the field of ambient intelligence. This model enriches traditional HClass (generalization/specialization structure) concept ontologies with an HTemp (Temporal Hierarchy) event ontology for representing events and their spatio-temporal dependencies. NKRL thus overcomes the limitations of traditional web semantic languages by providing a contextual representation capable of reconstructing past and present situations and anticipating future interactions in IoE scenarios. The Query-Processing Mechanism (QPM), dedicated to human activity recognition and dynamic event and context management. QPM relies on hierarchical rules (transformations and hypotheses) to determine contexts and infer human activities and intentions. When explicit knowledge is lacking, the system combines these two types of rules to discover implicit information related to the initial context. Transformation rules automatically adapt initial queries into semantically close subqueries, improving query and reasoning capabilities. In addition, our method leverages ontology-based knowledge representation techniques to convert unstructured data into a structured semantic framework. Raw sensor data, such as those from the CASA Dataset (UCL), are translated into RDF triples, enabling detailed analysis of activity patterns, contextual events, and behavioral trends via SPARQL.

- Finally, we introduce a Deep Q-Networks (DQN)-based framework to treat human activity recognition as a sequential decision problem. A computationally low-cost agent monitors intervals of features extracted from sensors, predicts the corresponding activity, and adjusts its actions according to the received rewards. This approach improves adaptability, continuous learning, and reduces the dependence on labeled data, making the method particularly suitable for intelligent and dynamic environments.

1.0.6 Thesis Outline

Chapter 2: Literature Review

This chapter presents a comprehensive review of the state of the art in Human Activity Recognition (HAR), Internet of Robotic Things (IoRT), semantic knowledge representation, and cognitive modeling. It identifies current challenges, limitations of existing approaches, and research gaps that motivate the contributions of this thesis.

Chapter 3: Theoretical Foundations and Core Contributions

This chapter introduces the theoretical foundations underlying the thesis, including narrative knowledge representation (NKRL), semantic reasoning, and deep learning techniques. It details the core contributions, such as the semantic annotation layer, the integration of NKRL for context-aware reasoning, and the design of a Query-Processing Mechanism (QPM) for activity recognition and dynamic event modeling.

Chapter 4: Evaluation and Experimental results

This chapter describes the practical implementation of the proposed approaches. It includes a presentation of the datasets used, the experimental setup, the evaluation metrics, and the results obtained from comprehensive performance assessments. It demonstrates how the proposed framework can be applied in IoRT/IoE environments for context-aware activity recognition and action recommendation.

Chapter 5: Conclusion and Future Work

This final chapter summarizes the key findings of the thesis, discusses their theoretical and practical implications, and proposes potential directions for future research and applications in intelligent context-aware systems.

Chapter 2

Literature Review

2.1 Introduction

Inferring everyday human activities illustrates the intricate challenges of spatio-temporal modeling and high-level semantic reasoning. Intelligent systems in Internet of Everything (IoE) and Internet of Robotic Things (IoRT) environments are increasingly designed to assist and supervise dependent persons, handle objects, and perform complex actions autonomously. Such systems must process, analyze, and correlate events in time and space to enable accurate activity recognition, interpret user intentions, and make context-aware decisions. Understanding human behavior also requires identifying causal relationships between events, as Noël Carroll emphasizes: later events often depend on earlier occurrences [?]. This principle is fundamental for constructing predictive models and causal explanations in smart environments. Numerous frameworks have been proposed for OWL-based solutions to combine heterogeneous data sources and make informed decisions, but conceptual and practical issues remain regarding rule creation and processing, despite the benefits of semantic representations and reasoning tools [?]. Description Logic (DL) has become a standard in symbolic knowledge representation due to its completeness and support in reasoning tools such as Pellet. OWL 2 extends OWL 1 with additional practical features, and profiles like OWL 2 QL enable conjunctive queries resembling relational database operations, ensuring sound but potentially incomplete reasoning.

Human activity recognition (HAR) has been extensively explored using both classical machine learning and deep learning approaches. Onthoni and Sahoo [?] combined sensor-based data acquisition with a modified Gaussian Naïve Bayes classifier, achieving high predictive accuracy (≈0.885) in recognizing daily activities. Nan et al. [?] demonstrated that deep learning, particularly LSTM networks, effectively captures temporal dependencies in sensor data from pocket-worn smartphones, outperforming conventional models. Hayat et al. [?] compared multiple deep architectures (CNN 1D, CNN multichannel, CNN-LSTM, CNN-LSTM multichannel), finding that the multichannel CNN-LSTM model achieved 81.1% accuracy in classifying walking, sitting, and stair-climbing, although distinguishing similar activities remained challenging. The integration of HAR in smart homes also plays a critical role in energy management. Lissa et al. [?] and Rajuroy [?] explored systems leveraging HAR to optimize heating and hot water usage with photovoltaic self-consumption. Coupled with deep reinforcement learning (DRL), these approaches allow autonomous, context-aware energy management, dynamically shifting load to periods of high solar production while maintaining occupant comfort. These studies demonstrate that accurate activity recognition not only enhances healthcare services but also contributes to sustainable energy management.

The need to integrate heterogeneous data and enable reasoning has motivated the development of formal ontologies. Wang et al. [?] proposed AFOG, an algorithm that generates hierarchical and quantitative ontologies using deep learning, capturing semantic relations and clusters among concepts. Ontologies provide a structured and interpretable representation of objects, actions, and interactions, facilitating robot decision-making, workflow generation, and rule-based reasoning. They also underpin hybrid systems that combine symbolic reasoning with probabilistic or neural approaches. In this context, Recursive Reasoning Networks (RRN) exemplify the convergence of knowledge representation and machine learning, learning inference rules directly from data and enabling robust ontological reasoning even in the presence of incomplete or contradictory information. These approaches demonstrate high precision and resilience, although challenges remain regarding scalability and formal guarantees.

Cognitive robotics further extends these capabilities by enabling robots to model human beliefs, intentions, and social behaviors. Techniques such as dynamic epistemic logic (DEL) allow robots to reason about beliefs in real-time [?], supporting adaptive interaction and tasks requiring theory of mind. Similarly, reinforcement learning agents integrated with probabilistic models or large language models simulate realistic cognitive and emotional states, allowing personalized care strategies for individuals with dementia [?]. In addition, Bi-LSTM models guided by reinforcement learning can automatically generate executable action sequences from textual instructions, producing semantically coherent and functionally appropriate robotic behaviors [?]. These studies highlight the importance of combining deep learning, symbolic reasoning, and contextual knowledge to achieve autonomous and socially aware robotic systems.

Despite these advances, several challenges persist. HAR models often require large, labeled datasets and may struggle in multi-resident or sensor-diverse environments. Deep learning architectures demand significant computational resources, complicating deployment on edge devices. Ontology-based frameworks require careful design and integration to support real-time reasoning. Energy management systems, while promising, depend on accurate activity detection and environmental conditions. Future research directions include improving the generalization and interpretability of deep models, integrating richer contextual and semantic knowledge, and developing hybrid approaches that unify symbolic reasoning, probabilistic inference, and deep learning to enhance autonomous decision-making, predictive capabilities, and human-robot interaction. By addressing these challenges, intelligent systems can more effectively understand, anticipate, and support human activities in complex IoE and IoRT environments.

2.1.1 Deep Learning and Reinforcement Approaches for Human Activity Recognition for IoT and IoRT Applications

By automating feature extraction from raw sensor signals, deep learning has significantly improved human activity recognition (HAR). Hybrid networks combining CNN with recurrent layers like LSTM or GRU maintain robust performance. For example, Zhou et al. [?] proposed a multi-sensor fusion CNN-LSTM model achieving over 95% accuracy on WISDM, while the CNN-BiLSTM-GRU architecture of Genc et al. [?] reached nearly 99.7%. Ullah et al. [?] improved this approach with a cascaded dual-attention CNN and a Bi-GRU, demonstrating strong performance despite sensor noise and class imbalance.

Transfer learning has become popular in HAR, as it allows adapting pre-trained models to new users and devices; Abdulazeem et al. [?] and Shrestha and Pandey [?] showed that initializing with pre-trained weights improves generalization. Attention mechanisms, as used in PA-HAR (Position-Aware HAR) by Xu et al. [?] or via CBAM (Convolutional Block Attention Module) in CNN pipelines by Akter et al. [?], help focus the model on relevant channels and instants, improving accuracy.

Lightweight architectures like the attentive TCN by Wei and Wang [?] and the sparse Transformer by Cao and Wang [?] have been explored for fine-grained and real-time recognition. While lightweight architectures target efficiency, reinforcement learning shows potential for personalization and learning with few labels, as highlighted by Oleh et al. [?]. We propose a stateless DQN agent that learns from short-term sensor windows and continuously interacts via a reward loop, enabling scalable, autonomous, and personalized HAR without retraining, particularly suitable for dynamic IoT and IoRT environments.

Context-aware applications generally rely on three main components. First, context acquisition involves collecting contextual information using various sensors. Second, context processing interprets the acquired information and applies reasoning techniques to derive more general knowledge. Third, action corresponds to delivering personalized services or feedback to users based on their current context.

Recent developments in assisted living technologies (ALDs) have enabled accurate and non-intrusive activity recognition without requiring wearable devices. Such solutions improve the comfort, discretion, and privacy of elderly individuals while allowing continuous monitoring through environmental sensors integrated within smart homes. In this context, the authors developed a high-performance system tested in a controlled environment, where the AdaBoost model demonstrated superior performance compared to approaches relying on wearable sensors. However, the validity of these results is partially limited because the experiments were conducted on young participants simulating the behavior of older adults [?].

Activity recognition focuses on identifying the activities of daily living (ADL) of older adults in smart home environments. This capability enables continuous monitoring of health and allows sharing of relevant information with family members, caregivers, or healthcare professionals. However, recognizing ADL from raw sensor data remains challenging due to the inherent variability of human behavior. Context-aware applications generally rely on three main components :

- Context acquisition involves collecting contextual information using various sensors;
- Context processing interprets the acquired information and applies reasoning techniques to derive more general knowledge;
- Action corresponds to delivering personalized services or feedback to users based on their current context;

Recent developments in assisted living technologies (ALDs) have enabled accurate and non-intrusive activity recognition without requiring wearable devices. Such solutions improve the comfort, discretion, and privacy of elderly individuals while allowing continuous monitoring through environmental sensors integrated within smart homes. In this context, the authors developed a high-performance system tested in a controlled environment, where the AdaBoost model demonstrated superior performance compared to approaches relying on wearable sensors. However, the validity of these results is partially limited because the experiments were conducted on young participants simulating the behavior of older adults [?].

At the same time, data mining has become an essential tool in many scientific and industrial domains. Given the diversity of data sources and application goals, there is no universal procedure for mining data. One study [?] explored the discovery of behavioral rules from smartphone usage using a rule-based machine learning approach, aiming to provide intelligent contextual services. Smartphones, as central nodes of the Internet of Things (IoT), record a wide variety of contextual information—including temporal, spatial, and social data—as well as users' daily activities. In this scenario, association rule mining (ARM) is a widely used machine learning method for uncovering hidden relationships within datasets. ARM is particularly suitable for identifying connections between contextual elements and daily behaviors. Nevertheless, this approach often produces a large number of redundant or insignificant rules, which can hinder its effectiveness for contextual decision-making. Such redundancy complicates the interpretation of results and makes the decision-making process more cumbersome. To address this limitation, the authors propose the ABC-RuleMiner method, designed to identify and eliminate redundancy in associations. This approach allows discovering a set of non-redundant IF–THEN behavioral rules specific to each user, while taking into account the priority of relevant contexts. Concretely, the researchers developed an association generation tree integrating users' contextual data. The final rules are then extracted based on observed behavioral patterns and individual preferences for personalized services.

Furthermore, the problem of cross-domain action recognition, where training and test videos come from different distributions, remains largely underexplored. Some existing methods directly reuse cross-domain image recognition techniques, but these often suffer from significant temporal misalignment. To overcome this difficulty, the authors introduce the Temporal Co-Attention Network (T-CoAN), a model designed to improve cross-domain action recognition. This model is based on a cross-domain temporal co-attention mechanism that guides the network's learning by focusing attention on key frames shared between different domains, thus enhancing the robustness and generalization of the recognition process [?]. The approach presented in [?] aims to prevent injuries related to static joint overload by exploiting the variation of the human center of pressure (CoP) during physical interactions with a robot. The CoP is estimated online from the difference between a previously identified biomechanical model and measurements from an external device. Based on the CoP displacement and the subject's posture, the system estimates variations in joint torque under quasi-static conditions.

The robot's movement is then optimized to reduce joint torques while respecting task constraints. A human-robot collaborative transport experiment validated the effectiveness of the proposed control, demonstrating an improvement in ergonomic postures among participants. This method offers an interesting compromise between accuracy and complexity, since it does not require any complete identification of the human model. However, it has some limitations, including the quasi-static approximation and the need to use specific sensors (force plates or instrumented soles). Future work aims to extend this model to human-humanoid interactions, with the aim of improving mobility and collaborative workspace.

The research described in [?] is part of the context of intelligent monitoring of the elderly and patients with chronic diseases, in the face of increasing pressure on healthcare systems. Existing solutions often remain fragmented and insufficiently adapted to real-world use. To address these limitations, the authors propose a human activity recognition (HAR) system integrated into the SmartCare assistance platform, combining machine vision and deep learning. The system is based on a ZED 2 stereo camera and an Nvidia Jetson AGX Xavier card, enabling real-time analysis of interactions between humans and their environment. The approach integrates several lightweight detection models (YOLOv4, SSD-MobileNet, Inception) coupled with the iCAN model for human-object interaction (HOI) recognition. Identified activities (such as eating, drinking, sitting, or standing) are then transmitted via the MQTT protocol to the SmartCare platform, to automatically trigger alerts in the event of behavioral anomalies. Experimental results demonstrate good overall performance, although accuracy decreases for certain fine-grained actions, particularly those related to feeding. Future research focuses on enriching datasets and optimizing real-time processing for better adaptability in real-world conditions. The paper [?] addresses the challenge of accurately recognizing complex jumps in figure skating videos. The authors propose an improved deep reinforcement learning approach, integrating Internet of Things (IoT) technologies for video collection and analysis. Their method is based on three main components: target detection, joint feature extraction using a dense network (DSTG), and a trusted fusion strategy designed to enhance model robustness. Experimental results demonstrate high recognition accuracy, outperforming existing methods on several evaluation metrics and datasets. However, some limitations remain, particularly in recognizing specific jump types and in accounting for external factors that may influence performance. Two other studies, [?] and [?], focus on human activity processing and recognition. The first study focuses on human activity recognition (HAR) applied to home assistance systems (HAS) for elderly or dependent people. The authors propose a multi-view pipeline based on skeletal capture, combining data from multiple cameras to improve detection accuracy. Two models were evaluated:

1. M-LeNet, a lightweight and resource-efficient convolutional neural network (CNN);
2. Vision Transformer (ViT), a model based on attention mechanisms;

Experiments, conducted on the RHM-HAR-SK dataset (comprising 14 activities), indicate that ViT achieves 78% accuracy, while M-LeNet offers better computational efficiency. Although the overall accuracy remains moderate, this approach demonstrates interesting potential for computationally constrained HAS systems. The second study explores the detection of abnormal behaviors within nursing homes, using IoT sensors (movement, location, etc.). A machine learning pipeline analyzes data streams to identify deviant patterns likely to signal a risk or critical situation. The experimental results highlight effective anomaly detection, thus contributing to better responsiveness and safety of care. However, the approach remains highly dependent on a specific IoT infrastructure and requires broader validation in real-life conditions.

Finally, the study [?] examines whether home automation technologies can improve the quality of life (QOL) of older people, particularly those living alone. The experimental protocol is based on a 12-week personalized intervention, including the use of voice assistants (Google Home), connected lighting and switches. Sixty participants took part in this study, assessed using a pre-test/post-test protocol and the Personal Well-being Index (PWI). Statistical analyses (paired t-tests, ANOVA), carried out in SPSS, reveal a significant overall improvement in quality of life, particularly in terms of feelings of accomplishment and future security. These positive effects do not depend on the cohabitation status of the participants. The main limitations identified concern the small sample size and the potential influence of the COVID-19 pandemic on the results.

Authors in [?] addresse the challenge of real-time simultaneous recognition of multiple actions performed by multiple people, a task that most existing systems cannot handle. The proposed methodology uses YOLOv3 for person detection, Deep SORT for tracking, and an inflated 3D ConvNet (I3D) for action recognition on video segments from sliding windows. Key innovations include automatic zoom-in for distant people and a non-maximum suppression (NMS) technique to improve result consistency. However, a major limitation is a 2.5-second recognition time, and the system may struggle with visually similar actions or occlusions.

The smart home principle has existed for some time, but it has recently gained widespread popularity due to technological advances and the growing demand for convenience and efficiency. One of the main benefits of a smart home is the ability to control and monitor various aspects of the home remotely through the use of a Smartphone or other device [?], [?], [?], [?] and [?]. Since smart homes can be equipped with different sensors and intelligent devices, the idea of assisting older people or those requiring support has grown. Many researchers and companies have joined this promising domain and are trying to find solutions to some technical challenges like security and privacy, interoperability, connectivity and reliability, power management, complexity and user experience, cost and scalability and finally, legal and ethical issues. Combining the Internet of Things with green energy is a powerful way to enhance efficiency and performance, especially for designing sustainable Internet of Everything applications. Moreover, renewable energy sources like solar or wind power at home can ensure a reliable power supply, especially during power outages. This reliability is crucial for older adults who may rely on medical devices, such as oxygen machines or life-support equipment, which require constant power. Green energy can improve safety for older adults in several ways, especially when integrated into smart homes or assisted living environments.

Green energy solutions, such as upgraded air filtration systems, solar-powered heating, and air conditioning) systems, improve indoor air quality. This is especially important for older adults who may have respiratory problems. Clean, well-regulated indoor air helps ensure better overall health and reduces the risk of complications. As highlighted by [**?**], the IoT made it easier for people to transition from conventional houses to smart homes by monitoring, controlling, and managing energy usage according to their lifestyles.

Due to the increasing dependence on renewable energy and related systems, it is essential to closely monitor and identify the governing parameters for efficiency concerning environmental circumstances (temperature, irradiation, etc.). To maximize energy production, it is crucial to conduct an in-depth analysis emphasising the properties of photovoltaic and wind turbine devices. To obtain the parameters like Power, Energy and Efficiency, basic parameters are required, such as voltage, current, and system-specific (inverters and converters) parameters like losses and efficiency [**?**]. Green IoT will make significant changes in our daily lives and will help realize the vision of ”green ambient intelligence [**?**]. One of the most essential emerged techniques is what we call harvesting. The latter is the process by which energy is obtained from external sources (such as solar power, thermal energy, wind energy, salinity (changes in the saltiness of ocean water), and kinetic energy) to operate low-energy electronics. It is captured and stored for small, wireless autonomous devices, such as those used in wearable electronics and wireless sensor networks. This is the first time in Human History that it is economical to obtain small amounts of energy now because the newer small sensors need very little power to work, and it also eliminates the need for a battery.

Power management systems in smart houses lead to efficient and sustainable energy consumption. But there remain areas where many problems exist due to an ageing electricity grid, severe weather conditions, and the region’s isolation from central power generation sources; such issues present a danger for some vulnerable categories of persons whose dependence on energy and power is crucial. In [**?**] The authors addressed the challenge of powering Internet of Everything (IoE) applications in rural areas, where unreliable electricity limits the use of smart devices, especially for healthcare and monitoring. The solution is using green energy sources like solar and wind to create a sustainable and independent power supply for smart homes. It combines renewable energy with an intelligent system that uses sensors and an ontology-based method to understand and react to events. By converting sensor data into a structured semantic format (RDF triples) and querying it with SPARQL, the system can recognize patterns and contexts, such as power outages. For example, in a scenario where a power outage risks spoiling medicine in a freezer, the system can detect the outage, switch to a backup battery, and alert an elderly resident about the compromised medicine. The results show that this approach enables reliable, context-aware energy management, enhancing safety, efficiency, and quality of life in rural communities. The first aspect is a control energy power system which supplies sensors and intelligent devices at the smart home with electricity (energy) and brings emergency green solutions in case of electricity outage by some harvesting techniques based on wind and solar systems to keep the smart home always in power sufficiency.

Power sufficiency refers to the state where the smart home has enough energy to meet its needs, even during peak demand periods or in the event of an outage. This ensures continuous operation and comfort for the residents. The second one is to assist an elderly special needs one, where we present a scenario of an electricity outage at night, causing an invalidity of medicines in the freezer. This problem presents a risk for the assisted person and must be detected and notified before he takes his drug by relying on an intelligent system which uses sensor output.

The studies [**?**] and [**?**] are in the context of smart residential energy management, a field where activity recognition (AR) plays a key role. This work aims to optimize the control of heating and domestic hot water by leveraging photovoltaic self-consumption. By accurately identifying occupant habits, AR dynamically adapts temperature and energy demand based on context. Coupled with a Deep Reinforcement Learning (DRL) algorithm, this approach promotes autonomous and contextual equipment management, intelligently shifting the load to periods of high solar production. Experimental results indicate average energy savings of 8% (reaching 16% in summer), and load shifting of over 10%, while maintaining an occupant comfort rate of 99%. These performances illustrate the potential of AR as a lever for sustainable energy efficiency, although the results remain sensitive to weather and seasonal variations.

Table 2.1: Selected studies on HAR, IoT, Robotics, and Ontology

Paper	Approach	Problematic	Dataset / Tools / Field
Onthoni & Sahoo (2022) [?]	Machine learning	Daily living activity recognition for elderly	ARUBA dataset, Gaussian Naive Bayes, Smart Home
Nan et al. (2020) [?]	Deep learning	Activity recognition from smartphone sensors	CNN, CNN-LSTM, Multichannel CNN-LSTM, HAR
Hayat et al. (2022) [?]	ML and DL	Monitoring elderly daily activities	UCI HAR, AReHOP, RF, KNN, SVM, ANN, LSTM
Sridevi et al. (2020) [?]	Deep learning	Elderly behavior prediction in smart homes	ADL dataset, ADSCLD, RNN, LSTM, Smart Home/Healthcare
Wörgötter et al. (2020) [?]	Grammar-like event-based	Human action prediction for HRI	ESEC, VR-generated dataset
Hansen & Bolander (2020) [?]	Symbolic framework (DEL)	Theory of Mind for robots	Real-time sensor data, DEL, Robotics
Yuan et al. (2025) [?]	Reinforcement learning	Personalized autonomous care for dementia	Synthetic data, Q-learning, Probabilistic Markov chain, LLM, Robotics/Healthcare
Lissa et al. (2021) [?]	Deep Reinforcement Learning	Home energy management	Weatherbit.io, DQN, MDP, Smart Home/SHEMS
Kostovska et al. (2020) [?]	Knowledge representation	Making datasets findable	496 datasets, OWL-DL, RDF
Paischer et al. (2023) [?]	Knowledge representation	Interpretability of RL agents	CLIP, TransformerXL, data-driven semantics
Triboan et al. (2017) [?]	Knowledge representation	Segmenting sensor streams for HAR	Real-time sensor data, SWRL, SPIN, APACHE, JENA, RDF, SPARQL
Wang et al. (2017) [?]	Knowledge representation	Reducing manual effort for ontology creation	E-book logs, Moodle quiz, Wikipedia, OWL, RDF, SPARQL, Pellet
Zhang et al. (2021) [?]	Reinforcement learning	Generating action sequences for robots	Custom dataset, Policy gradient, Bi-LSTM, Robotics
Aggar et al. (2023) [?]	Statistical analysis	Improving elderly QoL with smart homes	Survey data, SPSS, Smart Home/Healthcare
Nguyen et al. (2017) [?]	Data mining / Knowledge representation	Accurate online disease info retrieval	Disease Ontology, Jena, SPARQL, MySQL, Apriori, Medicine
Sharif & Seker (2024) [?]	Reinforcement learning	Optimizing EV charging	EV charging data, Grid load, DQN, EV

The table **??** presented summarizes a selection of recent studies in the fields of human activity recognition (HAR), IoT, robotics, and knowledge representation. These works demonstrate the evolution of approaches, ranging from simple machine learning to deep models combining supervised learning, reinforcement learning, and hybrid architectures. Several studies focus on activity recognition for the elderly or people with reduced mobility, using wearable sensors, smart environments, or synthetic data to train robust models. This table also illustrates the diversity of datasets and tools used, reflecting the specific needs of each application. By highlighting the contributions of each study, it becomes evident that ontologies are a key component for linking raw data to reasoning capabilities. Finally, the integration of learning techniques and symbolic representations paves the way for more adaptive, personalized, and intelligent systems capable of understanding and reacting effectively to human behaviors. Other research uses ontologies to structure and organize knowledge, improving the interpretability and reusability of data. Ontologies facilitate the integration of different sources of information and ensure semantic consistency, essential for complex systems such as smart home environments or assistive robotics. Meanwhile, some approaches combine deep learning and symbolic representation to leverage both the power of data models and the richness of structured knowledge.

Numerous attempts have been made to determine methods to model human behaviour in IoE environments. Numerous frameworks for OWL-based solutions have been put forth to handle needs, such as combining data from disparate sources and making appropriate decisions in light of that data. However, some significant conceptual and practical issues still plague the use of W3C languages regarding the creation and processing of rules despite the important contribution these languages have made, for example, in simplifying the management and interpretation of contexts through the use of semantic representations and querying/reasoning tools. Description Logic (DL) has become a formalism in symbolic knowledge representation because it offers complete reasoning and is supported by tools (e.g., Pellet)). OWL 2 have extended the original OWL 1 with a few practical features. The three OWL 2 profiles can offer some advantages in particular application scenarios but are more restrictive than the full OWL 2 DL. OWL 2 QL becomes a good tool since it enables conjunctive queries to be answered similarly to the standard relation database principle. In this last case, reasoning will always be sound, but it may not be complete (that is, it is not guaranteed that all correct answers to queries will be computed). Researchers have explored expanding the DL is syntax to include the OWL language. However, it is important to note that significant alterations to current tools are necessary to effectively use these extensions and improve the standard version of the OWL language. In the following, we present the most significant works relate to knowledge representation and querying-processing framework for human activity recognition.

2.1.2 Synthesis of studies on intelligent systems and knowledge representation

Recent studies have addressed ontologies as a de facto solution for implementing intelligent systems for activity recognition and planning functions, tasks, and service composition ([?], [?], [?], [?]). Indeed, ontologies serve as the structural frameworks for knowledge representation about the world. They provide a vocabulary of concepts and properties, fostering a shared understanding of semantics among humans and machines. The ontology-based approach plays a crucial role in enhancing semantic understanding. It enables the definition of entities and heterogeneous sources and the insertion of new knowledge in accordance with logical axioms. Although various methods for representation and reasoning over temporal data ([?], [?], [?], [?]) developed, they only deal with specific time intervals or time points. Even so, time points and semantic relationships between two or a time interval and a time point are not what they are designed for. Furthermore, we must handle that connectivity, such as event causality and goal. Despite this, no proposals for n-ary relations are included in OWL1. Due to significant issues that remain unhandled by Ontology Web Language, it remains unsuitable for dynamic context/event recognition and spatiotemporal concept representation, expressing a chronological ordering between events and contexts. These points highlight the limitations of current methods ([?], [?], [?], [?]) and underscore the limitations of temporal description logic frameworks. One method to address this issue would be to use n-ary predicates to represent the evolution of knowledge and the chronological relationships between events and their contexts in both present and past. Narrative representation and reasoning, which are necessary to describe entities and a stream of events, play a crucial role in this context. A statement like: ”The robot observed that a person turned on the stovetop and left the kitchen towards the bathroom where he spent more than 25 minutes” is a complex task requiring consideration as a single indivisible entity. So, it can be challenging to fully describe this type of information using the usual binary Semantic Web languages such as Ressource Description Framework 2 and OWL. However, explanatory role properties should then be necessarily introduced to represent a context fully.

Key-value-based techniques have been proposed by [?] using a simple data structure to describe a sensor’s outputs and, therefore, trying to represent an activity. Moreover, [?] proposed hierarchical structures relying on deep neural networks. Unfortunately all those approaches are very limited in handling the interoperability in activity recognition systems. Various research for activity recognition approaches combining ontologies and rule-based models or machine learning, such as [?]. Authors have relied on naive Bayesian models to represent objects to infer the possible actions on these objects and, thus, deduce the associated activity. This approach is based on the semantic relations between everyday actions that can be executed through these objects. However, the authors did not use an ontology but a taxonomy of concepts and did not implement an ontology of roles. A symbolic representation of the user environment and ontological reasoning proposed by [?] have been presented to deduce activities according to a set of pre-selected actions using the OWL ontology. They exploited human-object interaction and, therefore, events using the flow of sensors for activity recognition. These systems are excellent at contextualising activities by establishing connections between objects, actors, and environments, a skill that is essential for accurately interpreting human behaviour. However, the ontology paradigm historically emphasises structure and lacks behavioural components such as role, as highlighted in [?].

In the context of monitoring patients returning home after hospitalization, the authors of [?] developed an innovative project aimed at designing an intelligent automated assistance system for home therapeutic monitoring. This system helps patients adhere to their treatment plan through personalized medication reminders and automatic alerts in case of medication errors. The proposed solution is based on a multi-agent architecture combining reinforcement learning algorithms and deep learning techniques, allowing the system to gradually adapt to the patient's behavior. In parallel, the authors introduce a knowledge representation ontology intended to formalize the scientific objects and processes involved in this type of research. In the field of data mining, several lightweight ontologies have been developed to describe the fundamental concepts, but few offer a complete modeling of the processes required to generate workflows.

To overcome this limitation, the authors propose a hierarchical ontology structured into four layers—phase, subprocess, action, and operator—to describe the data mining process in detail within the CRISP-DM framework [?]. The first three layers model the steps abstractly, while the fourth describes their operational implementation. This approach promotes a more complete semantic description of activities and facilitates queries and the generation of workflows tailored to specific user needs. However, despite a promising framework capable of adapting to patient skills, no guarantees are yet provided regarding the actual taking of medication after interaction with the pill dispenser. Future work will aim to automatically identify the physical actions associated with extracting and actually taking the pill. One of the major challenges in this area is dynamically adapting the system to the user's context and preferences. To address this challenge, the authors of [?] propose an approach based on a Markov Decision Process (MDP) to design the system's adaptation plan, and on a reinforcement learning algorithm (Q-learning) for its implementation. This mechanism allows the system to acquire, interpret and exploit contextual information (location, time, event, user state, etc.) in order to automatically provide appropriate services.

The system is based on a Dynamic Software Product Line (DSPL), divided into two phases:

- Domain engineering, performed during the design phase, where the system's essential functions and optional components are defined;
- Application engineering, executed in real time, where context changes can lead to changes in system functionality or configuration;

At the heart of this architecture is the adaptation engine, based on the Markov decision process and implemented via Q-learning. This engine learns through trial and error to adapt to the user and react dynamically to contextual variations, illustrating an advanced integration between IoT, artificial intelligence, and contextual modeling. The authors present an integrated knowledge management framework for a cognitive robotic system operating in a home environment. This framework leverages the VirtualHome dataset to extract behavioral information and integrate it into an ontology. An instance generation algorithm translates observed activities into ontological classes, allowing for the identification of relationships between actions and objects, as well as the semantic structure of household activities. The system also offers the ability to formulate SPARQL queries to suggest or plan the execution of activities in the home. Furthermore, it supports custom queries to its knowledge base, facilitating interaction between the user and the cognitive robot. Regarding future prospects, the authors plan to enrich the ontological schema by integrating spatial information about objects (e.g., indicating that soap is usually located near the sink, sponge, bathtub, or shampoo). They also plan to expand the knowledge base by leveraging open knowledge graphs such as DBpedia, and to improve the semantic matching algorithm by integrating data from other ontologies [**?**].

Deep learning models, while powerful and versatile, are becoming increasingly complex, combining multiple networks, heterogeneous objectives, and often non-intuitive learning methods. This complexity makes their design, documentation, and understanding difficult for researchers. To address this, the ANNETT-O system proposes a generic, machine-readable ontological vocabulary designed to describe deep learning configurations, procedures, and experiments. The ontology covers the topological, training, and evaluation aspects of complex neural networks, while remaining concise for peripheral entities. Knowledge bases built with ANNETT-O enable semantic queries and provide relevant information on neural architectures. Thanks to the expressiveness of the OWL language and the principles of the Semantic Web, ANNETT-O facilitates the creation of interoperable and reusable knowledge, promoting transparency and reproducibility in deep learning. Future work considers automatic knowledge extraction from code, integration with broader AI ontologies, and the development of interfaces accessible to non-experts. ANNETT-O thus constitutes the first ontology capable of modeling, linking, and reasoning about the design, training, and evaluation of neural networks. However, a major drawback of Semantic Web-based approaches lies in the considerable manual work required to build relevant ontologies [?]. To mitigate this constraint, the authors of [?] propose a hybrid approach combining the advantages of the Semantic Web for rule representation with the automation of their generation. The method relies on the CPAR (Classification Based on Predictive Association Rules) data mining technique to automatically extract rules, which are then translated into OWL. This approach significantly reduces the ontology engineering burden while maintaining knowledge readability, traceability, and reusability. Initial results are promising; Research perspectives focus on managing inconsistencies and integrating default actions to strengthen the robustness of the model.

The study presented in [?] proposes an activity recognition solution based on artificial intelligence, combining data acquisition techniques with a modified Gaussian Naïve Bayes classifier to build a supervised learning model. The feature extraction and data preprocessing mechanisms were specifically designed for this model. Experimental results show high accuracy compared to other supervised algorithms, with an average performance of 0.885 and an average loss of 0.461 over five training-to-test ratios. The model thus effectively identifies daily activities from raw sensor data. Future research prospects include extending the model to multi-resident home environments, involving multiple zones, sensor types, and activity categories . In the field of smart car navigation, study [?] introduces a reinforcement learning (RL) method designed to generate diverse and efficient driving policies in traffic simulation environments. The objective is to reproduce realistic driving behaviors—ranging from caution to aggression—while maintaining a high level of performance. The proposed algorithm relies on intrinsic rewards designed to encourage behavioral diversity and introduces two indicators: inter-policy diversity and global diversity. A greedy selection process then selects the most diverse and effective policies. An improved version of the Diversity-Driven Exploration (DDE) method, incorporating a reward based on Kullback-Leibler (KL) divergence, further enhances diversity without degrading performance. Experiments conducted in a traffic simulator demonstrate a significant improvement in behavioral diversity, paving the way for more realistic and rich driving simulations.

The research presented in [?] proposes a bio-inspired computational model for human action recognition, based on recurrent spiking neural networks (RSNNs). These networks reproduce the functioning of biological neurons, transmitting information in the form of temporal electrical signals. Thanks to their recurrent structure, they are able to memorize past inputs, making them suitable for analyzing action sequences. The model incorporates a delayed reinforcement learning mechanism, associating delayed rewards with previous actions, similar to the human learning process. This combination of temporal neural processing and delayed reinforcement aims to improve the accuracy and efficiency of action recognition in dynamic environments. Potential applications span robotics, cognitive neuroscience, and intelligent video surveillance. Finally, the study [**?**] highlights the abilities of agents trained using meta-reinforcement learning to understand and exploit causal structures. The authors observe the spontaneous emergence of causal reasoning, showing that agents can develop this skill without an explicit model. The agents also demonstrate effective use of counterfactual reasoning, improving their performance by formulating alternative predictions. The research highlights the essential role of interventional data, which can overcome biases related to simple observations and unobserved confounding factors. Agents learn to address these factors through active interventions, enhancing the accuracy of their causal inference. The study also highlights the importance of structured exploration, in which agents design and interpret their own experiments to collect more informative data. In conclusion, the results demonstrate that reinforcement meta-learning promotes the acquisition of advanced causal reasoning, paving the way for more autonomous, explanatory, and decision-making intelligent systems.

In the field of smart healthcare, accurate disease prediction and personalized medical recommendations remain complex tasks. This study [**?**] introduces MLtoGAI, an innovative approach integrating the Semantic Web and machine learning (ML) to improve diagnostic accuracy and the understanding of recommendations generated via ChatGPT. The system is based on three main components:

1. a reusable disease ontology enabling the semantic structuring of medical knowledge;
2. a diagnostic classification model leveraging symptoms to predict the most likely pathology;
3. a set of SWRL rules designed to generate personalized advice tailored to the patient's profile;

The MLtoGAI approach demonstrates improved predictive accuracy, increased explainability, and a richer user experience. By combining ontologies, logical reasoning, and explainable machine learning, it ensures recommendations that are both relevant and understandable, thus contributing to the development of smart and transparent healthcare solutions. For their part, the authors of [?] propose a context-aware healthcare system (CA-EHS) dedicated to the care of the elderly. The system is based on a three-layer architecture:

- Smart home monitoring;
- Health status prediction;
- Cloud-based alert services;

Using wearable sensors, it provides continuous monitoring, both indoors and outdoors, enabling proactive and personalized clinical care. The system also provides full data access for practitioners and families, improving care coordination. Experiments show that the adopted SVM classifier outperformed standard Random Forest (RF) in terms of activity detection accuracy, confirming the model's effectiveness in the context of connected and contextual healthcare. Study done in [?] focuses on time series prediction from combined semantic and temporal data. Traditional deep learning models, such as LSTM, typically focus on numerical values, neglecting underlying semantic relationships. To address this limitation, the authors present STBNet, a hybrid network combining contextual ontologies and real-time tweets to enrich semantic understanding. The model integrates a semantic attention mechanism coupled with a convolutional neural network (CNN) for textual feature extraction. Tested on S&P 500 financial data, STBNet outperforms ARIMA and LSTM models in terms of predictive performance. However, its reliance on noisy and structured textual data limits its generalizability, inviting the exploration of richer and more diverse linguistic sources in the future.

One of the major challenges in knowledge modeling lies in the manual construction of complex, often subjective and non-quantitative ontologies. The study [?] proposes an innovative solution through AFOG (Automatic Formal Ontology Generator), an algorithm for automatically generating formal ontologies. This approach combines the principles of deep machine learning and conceptual algebra, a mathematical framework for structuring and linking concepts according to their semantic similarities. AFOG autonomously generates hierarchical and quantitative ontologies from a set of concepts, while identifying semantic relationships and conceptual clusters within the data. The results demonstrate its ability to produce coherent and usable ontological structures. However, the quality and richness of the generated ontology remain highly dependent on the underlying cognitive knowledge base, constituting the main limitation of this approach.

Another related research area concerns the recognition of physical activities of older adults from smartphone-integrated accelerometer data. The researchers compared four deep learning models: 1D CNN, multi-channel CNN, CNN-LSTM, and multi-channel CNN-LSTM. The latter performed best, achieving 81.1% accuracy for classifying activities such as walking, sitting, or stair climbing. However, some confusions remain—particularly between sitting and lying down, or between walking flat and stair climbing. Despite these limitations, the model shows potential for real-time application, while highlighting a significant constraint: the training data comes from a specific smartphone position (pants pocket), thus limiting the model's generalization. Future work considers integrating additional sensors or personalized training to improve the system's robustness and accuracy. Recognizing physical activities in older adults using smartphone accelerometer data is a relevant area. Indeed, researchers compared four deep learning models: 1D CNN, multi-channel CNN, CNN-LSTM, and multi-channel CNN-LSTM. The best model, multi-channel CNN-LSTM, achieved an accuracy of 81.1% for classifying activities such as walking, sitting, and stair climbing. However, it struggled to distinguish lying down from sitting, and stair walking from flat walking. The model performs well enough for real-time use, but it was trained on data from a specific location of the smartphone (pants pocket), which could limit generalization. Future work could include additional sensors or personalized training. Authors in [**?**] a purely technical setting, in order to implement proposals and address the persistent technological gap between ontology engineering tools developed in Java and deep learning frameworks widely used in Python. To address this incompatibility, the authors introduce DeepOnto, a Python package designed to provide a unified pythonic interface to ontological operations and tools, thus facilitating the preparation and exploitation of ontological data in machine learning models. DeepOnto integrates several advanced techniques, including verbalization (conversion of formal logic into natural text), projection (transformation of ontologies into usable graphs), and language model refinement for tasks such as ontology alignment or merging. Experiments demonstrate the robustness and versatility of the system, validated both in industrial applications—such as medical concept mapping—and in academic research contexts for comparative analysis. However, the authors highlight some limitations, including the reliance on a Java backend, which complicates deployment, and the focus on ML-based approaches, to the detriment of other potential neural architectures [**?**].

The approach in [**?**] addresses the issue of monitoring the daily activities of older adults, which is essential to ensure their safety, independence, and health. The authors propose using smartphone sensors (accelerometer and gyroscope) to automatically recognize activities such as walking, sitting, standing up, lying down, and going up and down stairs. They applied both machine learning methods (random forest, k-nearest neighbors, support vector machine) and deep learning methods (artificial neural networks and long short-term memory networks). Data preprocessing included filtering and dimensionality reduction using PCA, and experiments were performed with UCI HAR and another dataset on older adults. The evaluation included accuracy, precision, recall, F1 score, and processing time, with two-fold and ten-fold cross-validation. The results show that LSTM achieved the best performance, with an overall accuracy of approximately 95%, outperforming other models. The SVM had slightly lower accuracy (89%), but was the fastest in terms of computation time. The study highlights that deep learning, and LSTM in particular, is particularly effective at recognizing temporal activity patterns. However, limitations exist: the size of the datasets, the difficulty in distinguishing between similar activities (e.g., going up and down stairs), and higher computational requirements than classical machine learning. The paper studies how humans predict actions and proposes a grammar-like model called Extended Semantic Event Chains (ESEC), which encodes actions as sequences of relational changes between objects. VR experiments with 49 participants showed that humans recognize actions at similar event times as ESECs, albeit slightly later. Robots using ESECs in chained tasks achieved up to 40% faster execution than non-predictive methods. Object-independent, efficient, and human-like, this approach is promising for human-robot interaction. Limitations include simplification of VR parameters, loss of fine temporal details, and modest predictive gains in complex action sequences [**?**].

2.1.3 Advances in Human Activity Recognition for IoT and IoRT Applications

With the rise of ubiquitous computing, ambient intelligence, and the widespread availability of wireless communication technologies—such as sensor networks, mobile networks, and smartphones—alongside software platforms (web services, middleware) and identification technologies (RFID, biometrics), a new generation of service robots, known as ubiquitous robots, has emerged. Networked robotics represents a highly promising research domain within robotics ([**?**], [**?**], [**?**]) with significant potential for growth, particularly in the service robotics market. Major technology companies, including Google, Microsoft, and Intel, have increasingly shown interest in this field. The goal is to seamlessly integrate these robots into smart environments, whether small-scale (smart homes) or large-scale (buildings, urban spaces), to deliver value-added services anytime, anywhere, and transparently. Such services may include cognitive assistance, security, comfort, entertainment, and more. In computer science, a service is understood as a function or resource provided to living beings, particularly humans, for convenience or assistance. A ubiquitous robot must be interoperable with objects or entities in its environment—such as sensors, actuators, other robots, or artifacts—rather than being statically pre-programmed. It should not only operate its own devices but also interact with external objects and dynamically adapt its services to changing contexts, a property known as context-awareness. The rise of cloud computing further supports this vision, allowing ubiquitous robots to enhance cognitive capabilities and share knowledge via cloud infrastructures [?], [?], [?] and [?]. Finally, in this new vision, a ubiquitous robot can also act as a human interaction embodiment. Research in affective computing explores the use of articulated facial models and, when combined with voice interaction, can create an almost human-like illusion of intelligence. Practical applications include integrating smart environment systems with a human-like interface or embodying them through everyday objects, enhancing user engagement and intuitiveness.

Programming robots for repetitive inspection and correction tasks is often slow and fraught with unexpected environmental variations. Authors in [?] propose an hybrid reinforcement learning approach to address this problem. This method combines the SARSA algorithm with a reference model of the appropriate environment to help the robot learn more efficiently by reducing unnecessary exploration. The research used a simulated 7x7 grid world where an agent had to find a misplaced block and put it back in its place. The agent's performance was tested under different levels of randomness in the block's starting position. The results showed that the robot learned effectively, but its performance decreased as the task became more variable; it learned quickly with predictable errors, but required more time and steps when the error locations were highly random. A major limitation is that the approach was only tested in a simple grid-based simulation, not with real robots or complex environments.

The learning effectiveness also depended heavily on carefully tuned parameters, which are difficult to define automatically. This suggests that the method may not be easily generalizable to more complex real-world tasks without further development. The research aims to equip robots with natural social skills for smooth human-robot interaction, even in the absence of explicit rewards. It introduces an intrinsically motivated deep reinforcement learning framework, where the robot learns from real-life experiences. Two networks are used: Qnet, for action selection, and Pnet, for predicting social events (handshake, smile, eye contact). Intrinsic rewards come from the accuracy of predictions, stimulating improvement in social behavior. Trained over 14 days of real-world interactions, the robot achieved 98.4% accuracy, outperforming conventional models, and demonstrated an ability to anticipate human intentions based on context [?].

A central issue for human-robot interaction concerns the ability of robots to understand human mental states, including beliefs, desires, and intentions—a field known as theory of mind (ToM). The study [?] proposes an approach based on dynamic epistemic logic (DEL) to model, in real time, the first- and second-order beliefs of human agents. The system combines perception neural networks and onboard cameras to identify actions and objects, and then updates the DEL symbolic models to track individuals' beliefs and false beliefs. Experiments show that the robot is able to correctly reason about the mental states of others, successfully completing classic first- and second-order false belief tasks. However, the method is highly dependent on stable visual perception, and its effectiveness can be compromised by low-light conditions or rapid movements of the observed agents. In the field of cognitive and emotional care, the work [?] focuses on the personalization of assistance for people with dementia (PVD). The main obstacle to this development lies in the scarcity of data from real interactions. To address this, the authors design a simulated environment combining a probabilistic model of human behavior and a large language model (LLM), capable of reproducing the cognitive and emotional states of PVD. A reinforcement learning (RL) agent plays the role of a care robot, learning to select optimal verbal assistance strategies according to the simulated state of the patient. The results demonstrate that the agent learns to provide effective personalized care, outperforming random strategies, while the LLM produces realistic and contextually appropriate interactions. Nevertheless, this approach remains limited by its dependence on simulation, the variable reliability of the LLM and the lack of clinical validation on real cases.

Finally, the research established by the authors in [?] addresses the problem of automatically generating robotic action sequences from complex textual instructions, a crucial issue for smart home automation. The authors propose a two-phase neural model (Bi-LSTM) coupled with hierarchical reinforcement learning, where rewards take into account a priori knowledge (object/action relationships), semantic similarity (via semantic role labeling), and action logic. The system generates action sequences annotated by functional labels (tool, location, target, etc.), producing logically coherent and semantically accurate plans. Experimental results confirm the superiority of the model over benchmark approaches. However, its strong dependence on preprocessed data and its difficulty in handling ambiguous spatial relationships limit its generalization to more complex physical environments. The authors used hierarchical reinforcement learning to simulate human activities and a Q-learning-based smart home. The results showed that the smart home could induce some simulated humans to switch activities more frequently and take longer to adjust parameters, especially if their internal reward structure differed from the learning model of the home. Interestingly, in the presence of two humans, some combinations behaved normally, while others exhibited these unexpected effects. A major limitation is that these results are based on simulations with simplified human models, not real users [?]. This research [?] borders on the challenge of performance variation introduced by human operators. Manufacturing processes are altered by collaboration with robots, disrupting efficiency. The authors developed a deep Q-learning network (DQN) agent in an AnyLogic-based simulation environment to enable a robot to adapt its speed to variations in human performance. The results showed that the RL agent successfully reduced system idle time by 18 to 25% and maintained production levels, demonstrating improved adaptability. A major limitation is that the study was conducted in simulation and used simplified models of human performance factors, rather than real-world data or complex scenarios. This paper addresses the challenge of automatically generating conflict-free smart home automation services without complex user intervention. The researchers proposed eight multi-agent reinforcement learning (MARL) architectures, collectively referred to as SHOMA, using techniques such as Q-learning and value decomposition. They simulated a home environment with lighting, temperature, and air quality services for evaluation. The results showed that the Equal Priority-based Architecture (EPbA) and Remove Shared Actuators-based Architecture (RSAbA) architectures performed best in optimizing user comfort and avoiding conflicts. A major limitation is that the study was conducted in simulation and requires validation in a real environment [?].

2.1.4 Query-processing mechanism

Few works have been done on developing query languages and inference rules based on temporal description logic, and Most of these works are based on Allen's temporal logic. Among these works, a temporal language TL-OWL 3an OWL-2 DL ontology of temporal concepts based on the idea of time interval and combing 4-D fluents [?]. Nevertheless, 4D-fluents maintain OWL expressiveness and reasoning support but still suffer from data redundancy [?]. Furthermore, unfortunately, TL-OWL ontology does not support temporal relations or consistency checking and is not compatible with OWL inferencing and querying tools. The authors of [?] have developed a semantic geospatial database system, intro ducing two sub-languages built on top of RDF and SPARQL query language. They have introduced t-SPARQL, an extension that can be directly mapped to standard SPARQL to express temporal queries. While t-SPARQL has not yet managed the temporal features, its potential for future development is promising. The principle of reification in ([?], [?], [?], [?], [?]), which depicts n-ary relations, has a significant problem of data redundancy. The authors in [?] propose knowledge reification as a solution for representing complex relationships and multilevel abstractions using the property graph model. The SWRL 4 and SQWRL [?] rules languages are employed in both approaches [?] and [?]. Using inference rules is a fundamental part of knowl edge management and a crucial component of the reasoning process. These rules are either written in the SWRL language or incorporate the Horn clause and an OWL DL. SWRL Temporal Ontology, a significant extension of the SWRL language, allows the annotation, reasoning and querying of temporal knowledge bases. This ontology's proposition, instant, and time interval concepts are crucial for presenting temporal knowledge. It is important to note that the representation knowledge may be com plex and better suited for describing temporal entities than the temporal context. Moreover, SWRL raises several limitations, such as the lack of negation. The OWL-Time5, a W3C recommendation since October 2017, is a powerful tool that provides a vocabulary for expressing facts about topological (ordering) relations among instants and intervals. OWL-Time does not support dynamic events for rep resenting object properties that change over time. To the best of our knowledge, no reasoning tools allow us to infer new temporal data. Despite these constraints, OWL Time is still a valuable resource for describing the temporal content of web pages and the temporal properties of web services. The main reasons are: 1) OWL and RDF language are based on binary relations that supply connect two instances, and 2) It cannot be combined with the existing OWL tools [**?**].

Furthermore, the issue of improving the search and reuse of data mining datasets through enriched semantic descriptions is of particular concern. The authors [**?**] developed an ontology-based annotation scheme combining provenance information, data mining-specific features (through extended versions of the OntoDT and OntoDM-core ontologies), and domain-specific knowledge. They applied this method to the semantic annotation of 496 datasets, demonstrating its usefulness in use cases involving neurodegenerative diseases and Earth observation data. The main results are a publicly available schema and annotations that improve dataset interoperability. A major limitation is the need for manual annotations and the availability of domain-specific ontologies. In order to overcome the interpretability issues of reinforcement learning agents operating in partially observable environments. The authors in [**?**] developed Semantic HELM (SHELM), a method that uses the pre-trained CLIP model to convert visual observations into human-readable language symbols (such as "miner" or "sword"), along with a pre-trained language model (TransformerXL) to compress the history of these symbols in memory. This approach achieved state-of-the-art performance on a memory-critical task (Psychlab continuous recognition), converging 100 times faster than previous methods, while providing human-readable memory for debugging. A major limitation is that the method relies on CLIP's ability to interpret synthetic visuals, which can be unreliable in abstract environments and increases computational costs. This research addresses the problem of segmenting real-time sensor data streams to recognize complex human activities in smart homes, which may be nested or concurrent. The method uses an ontology-based semantic approach with T-Box and A-Box reasoning, logical rules (SWRL/SPIN), and dynamic window sizing. Tools such as Apache Jena and SPARQL are used to reason and query RDF data streams. This approach successfully segments activities such as preparing tea or pasta with high accuracy. However, it has limitations, including a significant computational load due to the multiplication of reasoning threads and the difficulty of handling multi-user scenarios or dynamically updating the ontology with new activities [?].

This research [?] addresses the time-consuming problem of manually building ontologies for online learning. The method proposes a semi-automatic technique that leverages data from e-book reading logs, Moodle questionnaires, and Wikipedia articles to extract relationships between knowledge points (KPs) through association rule mining and a minimum spanning tree algorithm. The result is a system that suggests possible relationships between KPs to instructors for approval, thus simplifying ontology creation. A major limitation lies in the system's inability to automatically name higher-level concepts.

The problem of ontology matching, which involves aligning instances from different knowledge bases, is addressed in [?]. The authors propose PMOM, a method based on frequent pattern mining aimed at selecting the most relevant features and thus reducing the complexity of comparisons. Using the SSFIM algorithm, recurring patterns are extracted to identify key properties. Experiments conducted on OAEI and DBpedia demonstrate that PMOM outperforms benchmark approaches in terms of matching quality and execution time. However, the method remains sensitive to the size and complexity of the processed ontologies, and requires precise parameter tuning to achieve optimal performance. In the field of fall risk management, the study [?] highlights the lack of a formal knowledge structure. The authors designed the Fall Risk Management Ontology (FRMO) according to the Stanford methodology and implemented it in Protégé using OWL. The development is based on an extensive literature review and expert validation, resulting in a rich ontology with 890 classes, 43 object properties, and 28 data properties covering risk factors, prevention, and consequences of falls. The reasoning (Pellet) and verification (OOPS!) tools confirmed the model's consistency, completeness, and accuracy. However, its reliance on English and SNOMED CT limits its applicability in non-English-speaking contexts, and the creation of specific instances remains necessary for operational use. Smart monitoring of elderly people living alone is also an important research area [?]. The authors developed a smart home system using IoT sensors to collect data on activities of daily living (ADLs). The model is based on a recurrent neural network (RNN) with long-short-term memory (LSTM), which can model and predict behavioral patterns. The results achieved 97% accuracy in classifying activities such as meal preparation or sleep. However, practical limitations remain: the complexity of real-world deployment, the risk of false alarms due to changes in routine, and the need for large annotated datasets. The study [?]. explores improving the accessibility of smart homes for people with disabilities using AI predictive models. The methodology is based on defining user needs, modeling risk scenarios, and collecting data from smart sensors. A mathematical conceptual model structures this information into subsets related to health, incidents, and the environment. The results demonstrate the effectiveness of data categorization and the modularity of the system, but testing remains limited to experimental conditions without full field validation. Another particularly relevant study in the field of convergence between symbolic reasoning (KRR) and machine learning highlights the Recursive Reasoning Network (RRN), an innovative approach that seeks to combine the logical rigor of symbolic systems with the adaptive capacity of neural networks [**?**]. The RRN directly learns inference rules from data, allowing ontological reasoning even in the presence of incomplete or contradictory information. The experimental results, obtained on various datasets (DBpedia, UMLS, etc.), demonstrate remarkable accuracy (≈99%) and increased resilience to uncertainties. This approach represents a significant step forward towards hybrid AI, capable of combining statistical learning and explanatory reasoning, although it remains limited by scalability challenges and the lack of formal logical guarantees.

Table 2.2: Selected studies on intelligent systems, activity recognition, and ontology usage (Part 1)

Paper	Approach	Problematic	Datasets	Tools	Field	Ontology used
Arguello Casteleiro et al. A case study on Sepsis using PubMed and Deep Learning for Ontology Learning [?].	Combined approach between knowledge driven and data driven	Application of distributional semantics models for facilitating unsupervised extraction of biomedical terms from unannotated corpora	PubMed	LSA/LDA/CBOW/Skip-gram	Healthcare	OWL-DL
Wang et al. (2025). A Contactless Method for Recognition of Daily Living Activities for Older Adults [?]	Machine learning	Recognizing the daily activities of older adults	ARI (Activities of Daily Living Recognition Using Ambient Sensors)	Machine learning algorithms	Smart home	No
Man et al. (2021). A Hierarchical Data Mining Process Ontology [?]	Ontology and data mining	Introduces a hierarchical ontology to simplify and organize data mining workflows for easier querying and synthesis	OntoKDD DMWF	KNN, OWLAPI	Data-mining	OntoKDD DMWF
Muddasar Naeem et al. (2021). Reinforcement and deep learning based intelligent system for impaired patients [?]	Deep learning/Reinforcement learning	Tackles the problem of medication non-adherence and errors in home treatment for elderly and impaired patients	Medical box image dataset	Thompson sampling algorithm/Bayesian Reinforcement Learning/Vgg-16 (KNN)	Healthcare Smart home	No
Hallou et al. (2022). A DSPL and Reinforcement Learning Approach for Context-Aware IoT Systems [?]	Reinforcement learning, DSPL, MDP	Addresses how to automatically adapt IoT systems to user context using DSPL and reinforcement learning	N/A	UML (for context modeling)/Q-learning algorithm	Smart home/Context-awareness	No
Vassiliades et al. (2020). A knowledge retrieval framework for household objects and actions with external knowledge [?]	Knowledge driven ontology	Enhances household robotics with external knowledge graphs for better semantic reasoning	VirtualHome dataset, DBpedia, ConceptNet, WordNet	SPARQL, OWL, Semantic Matching Algorithm	Cognitive robotics/Smart home	OWL
Sarker & Kayes (2020). ABC-RuleMiner: User behavioral rule-based machine learning method [?]	Data driven, ABC-RuleMiner, Machine learning	Improve interpretability and context-awareness of discovered rules	Phone log dataset	Association Generation Tree (AGT)	Context-awareness	No
Pan et al. (2020). Adversarial cross-domain action recognition with co-attention [?]	Deep learning, adversarial training, co-attention, temporal feature alignment	Adresses the mismatch in action timing between domains, which reduces recognition accuracy	UCF101, HMDB51, Kinetics	Tcon	Video Action Recognition	No
Klampanos et al. (2019). ANNETT-O: an ontology for describing artificial neural network evaluation [?]	Ontology with deep learning, ANNETT-O	Deep learning models are complex and lack a standardized way to describe their topology, training, and evaluation, hindering understanding and reproducibility	N/A	OWL, SPARQL, DNN	Knowledge representation	Owl/SPARQL

Table 2.3: Selected studies on intelligent systems, activity recognition, and ontology usage (Part 2)

Paper	Approach	Problematic	Datasets	Tools	Field	Ontology used
Kim et al. (2017). Anticipatory robot assistance for the prevention of human static joint overloading [?]	Statically Equivalent Serial Chain (SESC)	Preventing human joint overloading during slow, heavy-load collaborative tasks with robots using real-time posture optimization	N/A	least-squares optimization + SESC	HRC	No
Onthoni & Sahoo (2022). AI-assisted activities of daily living recognition for elderly [?]	Machine learning	Recognizing elderly daily activities from variable sensor data sequences remains a challenge for accurate health monitoring	ARUBA	Gaussian Naive Bayes algorithms	Smart home/Action recognition	No
Shiroshita et al. (2020). Behaviorally diverse traffic simulation via reinforcement learning [?]	Reinforcement learning	Automatically generating a set of driving policies that are both highly skilled and exhibit diverse, distinct behaviors for realistic traffic simulation	N/A	greedy FPS-based sampling/Diversity-Driven Exploration	VAN / Traffic simulation	No
Nadafian et al. (2024). Brain-inspired Computational Modeling of Action Recognition with RSNN [?]	Reinforcement learning	Proposes a bio-plausible spiking neural network for effective action recognition	DVS-128 Gesture	Recurrent Spiking Neural Networks/Reinforcement Delay Learning	Action recognition	No
Chang et al. (2020). Building ontology-driven tutoring models using data mining [?]	Data mining for knowledge representation	Proposes a hybrid method for building pedagogical models in ITS by merging semantic ontologies with data mining	INF@NZIA DIGI.Tales 3.6	OWL, OWL Reasoner (Hermit), CPAR	Knowledge representation	OWL
Dasgupta et al. (2019). Meta-reinforcement learning of causal strategies [?]	Reinforcement learning	Introduces a hybrid ITS model combining semantic ontologies and data mining	N/A	RNN/causal Bayesian networks	Context awareness/reasoning	No
Chandra et al. (2024). MLtoGAI: Semantic Web with Machine Learning for Disease Prediction [?]	Machine learning with ontology and GAI	Disease prediction	Dataset created	ML Model, OWL, Protege, SWRL	Healthcare	OWL
Bl & Bhaskar (2021). Modelling of Context-Aware Elderly Healthcare Eco-System using ML [?]	ML (SVM) approach	Elderly activity recognition and healthcare	HAR dataset	SVM	Healthcare/Smart home	No
Steven Jiang et al. (2020). Multi-Ontology Refined Embeddings (MORE) for biomedical concepts [?]	Knowledge representation	Same medical concept can be written in many ways, complicating computer understanding	RadCore, MIMIC-III, MeSH	MORE	Healthcare	OWL

Table 2.4: Selected studies on intelligent systems, activity recognition, and ontology usage (Part 3)

Paper	Approach	Problematic	Datasets	Tools	Field	Ontology used
Xinran Li & Jun Zhang (2024). Context-aware Communication for Multi-agent RL [?]	Reinforcement Learning	Reduce context-aware communication budget in MARL tasks	N/A	LSQ/CTDE	Context-aware	No
Belhadi et al. (2020). Data mining-based approach for ontology matching problem [?]	Data mining/Knowledge representation	Use of data mining in ontology matching	DBpedia, OAEI	DMOM	Knowledge representation	No
Deng et al. (2018). Deep learning for knowledge-driven ontology stream prediction [?]	Deep learning / Knowledge representation	Integrates ontology streams and real-time text data to enrich semantic understanding	S&P 500, Wikipedia	STBNet, LSTM, CNN	Knowledge representation	No
Tsai et al. (2020). Deep learning-based real-time multiple-person action recognition [?]	Deep learning	Recognizing multiple actions simultaneously in real-time	NTU RGB+D	YOLOv3, Deep SORT, I3D ConvNet	Action recognition	No
Lissa et al. (2021). Deep reinforcement learning for home energy management system [?]	Deep Reinforcement Learning	Control heating and domestic hot water systems while improving comfort	Weatherbit.io	DQN, MDP, NN	Smart home (SHEMS)	Yes
Nan et al. (2020). Deep learning for activity recognition in older people using smartphone [?]	Deep learning	Activity recognition algorithm for older adults using smartphone accelerometry data	Built dataset	CNN, Multichannel CNN, CNN-LSTM	Human Activity recognition	No
He et al. (2024). Deeponto: Python package for ontology engineering with deep learning [?]	Deep learning/Knowledge representation	Gap between Java-based ontology tools and Python-based DL frameworks	Bio-ML Benchmark, OntoLAMA Probing, NHS	BERT, Prompt Learning, Graph-Based Learning, HermiT	Ontology/DeepOnto	Yes
Altuhaifa & Al Tuhaifa (2024). Developing an ontology for fall risk management [?]	Knowledge representation	Development of Fall Risk Management Ontology (FRMO) for clinical text mining	N/A	OWL, Protégé	Ontology FRMO	Yes
Sridevi et al. (2020). Elderly behavior prediction using deep learning in smart homes [?]	Deep learning	Monitoring elderly living alone to detect cognitive decline	ADL dataset, ADSCLD dataset	RNN, LSTM	Smart home/ Healthcare	Yes
Periša et al. (2025). Empowering people with disabilities in smart homes using predictive informing [?]	Modular system architecture	Improving smart home accessibility for people with disabilities	Built dataset	Set theory	Smart home/Healthcare	Yes
Rajuroy, A. Energy-Efficient Home Automation using Multi-Agent DRL [?]	Deep Reinforcement Learning	Optimizing energy consumption without sacrificing comfort	N/A	DQN, Actor-Critic	Smart home (SHEMS)	No

Table 2.5: Selected studies on intelligent systems, activity recognition, and ontology usage (Part 4)

Paper	Approach	Problematic	Datasets	Tools	Field	Ontology used
Alashti et al. (2023). Lightweight human activity recognition for AAL [?]	Deep learning	Recognizing human activities in AAL systems	RHMHAR-SK	CNN, ViT, Multi-view Fusion	Human Activity recognition	No
Lau et al. (2023). Location-based activity behavior deviation detection for nursing home [?]	Machine learning with IoT	Detecting abnormal/deviating activity behaviors of elderly people using IoT devices	Built dataset	K-means, Isolation Forest, Local Outlier Factor	Human Activity recognition	No
Hohenecker & Lukasiewicz (2020). Ontology reasoning with deep neural networks [?]	ML/Knowledge representation	Bridging symbolic KRR methods with ML approaches	DBpedia, Claros, UMLS, family trees, countries	RRN	Knowledge representation	OWL, DL
Kestel et al. (2019). Ontology-based approach for simulation knowledge acquisition [?]	Text mining, Data mining, Knowledge representation	Acquiring/providing simulation knowledge for FEA simulations	Creo Parametric, ANSYS Workbench, VDI 2230	SPARQL, OWL, DL, NLP, POS, NER, Regression	Knowledge representation	OWL, DL
Suman et al. (2021). Potential impacts of smart homes on human behavior [?]	Reinforcement learning	Investigate whether Q-learning smart homes affect human behavior	Built datasets	Q-learning, HRL, MDP	Smart home/Human activity recognition	No
Oliff et al. (2020). Reinforcement learning for facilitating HRI in manufacturing [?]	Reinforcement learning	Performance variation from human operators disrupts efficiency	Built dataset via AnyLogic simulation	DQL	Human-robot interaction in manufacturing	No
Qiu et al. (2022). RL-based architectures for dynamic generation of smart home services [?]	Reinforcement learning	Automatically generate conflict-free smart home services	Built dataset through simulation	Q-learning, Value decomposition	Smart home	No
Kostovska et al. (2020). Semantic description of data mining datasets [?]	Knowledge representation	Making data mining datasets more findable/reusable via semantic descriptions	496 datasets	OWL-DL, RDF	Knowledge representation	Yes
Paischer et al. (2023). Semantic Helm: A human-readable memory for RL [?]	Knowledge representation	Lack of interpretability in RL agents in partially observable environments	CLIP, TransformerXL	Data-driven, model-based semantics	Knowledge representation	Yes
Triboan et al. (2017). Semantic segmentation of real-time sensor data streams [?]	Knowledge representation	Segmenting real-time sensor data streams to recognize complex human activities	Real-time sensor data, Pre-collected data	SWRL, SPIN, APACHE, JENA, RDF, SPARQL	Human Activity Recognition/Smart home	Yes
Wang et al. (2017). Semi-automatic construction of ontology based on data mining [?]	Knowledge representation	High time cost and manual effort for constructing e-learning ontologies	E-book logs, Quiz data, Wikipedia articles	OWL, RDF, SPARQL, Pellet	Knowledge representation	Yes
Zhang et al. (2021). Service skill improvement for home robots via RL [?]	Reinforcement learning	Generating executable action sequences for home service robots	Custom-built, manually annotated dataset	Policy gradient, Bi-LSTM	Robotics	No
Aggar et al. (2023). Smart home technology to support older people's QoL [?]	Statistical analysis	Investigate whether SHT improves quality of life for older adults	Quantitative survey data	SPSS	Smart home/Healthcare	No

The work reviewed in Parts 1 to 4 (**??**, **??**, **??**, **??**) highlights the recent evolution of approaches to human activity recognition, health management and intelligent systems through the integration of artificial intelligence, deep learning and ontologies. In Part **??**, several studies combine data-driven and knowledge-driven approaches for the creation and use of ontologies in the field of health and home automation (, [**?**] and [**?**]). Reinforcement learning and deep learning applications for personalized patient assistance at home and contextual activity recognition are also observed ([**?**]), often coupled with knowledge representation frameworks such as OWL/DL and SPARQL. Part **??** extends these approaches to more dynamic and collaborative contexts, including multiple action recognition, joint overload prevention in robotics, and causal modeling via reinforcement learning ([**?**]). There is a growing use of hybrid models combining ontologies, machine learning, and generative intelligence to improve disease prediction and personalization of health recommendations ([**?**]). Home energy management and comfort improvement in smart home environments have also been addressed via deep reinforcement learning and multi-agent systems ([**?**]). Finally, the last two parts (**??**, **??**) show an intensification of work on context-aware communication for multi-agent systems, the integration of hybrid knowledge and deep learning models for action prediction, as well as the development of ontology frameworks and automated semantic engineering ([**?**]). The most recent research focuses on human activity assisted by IoT sensors and computer vision, the monitoring of deviant behavior in healthcare structures and the improvement of ontology interoperability via deep learning and reasoning architectures ([**?**]). This work illustrates a strong trend towards the hybridization of symbolic and neural approaches, the contextualization of intelligent systems and the consideration of human behavior in the design of automated and adaptive solutions.

This thesis seeks to overcome the limitations of traditional ontological approaches to the Semantic Web by introducing a model capable of representing contextual knowledge in a dynamic and narrative form. Its primary goal is to capture the interdependencies between events and contexts, addressing questions such as: Who initiates a given event? In what circumstances is an action carried out? Which entity is affected by the action? By integrating suitable inference mechanisms, the model can establish implicit semantic relationships between events—such as causality or purpose—thereby enriching context interpretation and supporting better adaptation to observed situations.

A significant challenge lies in managing dynamic and temporal knowledge, which remains constrained under conventional ontologies. While these ontologies are highly expressive, they often produce redundancy in temporal data and may necessitate extensive rewriting to accommodate updates. Moreover, reasoning about temporal relationships is not always achievable with standard OWL-DL engines, due to the difficulty of defining variable-arity predicates for representing temporal properties. To address these limitations, n-ary predicates provide a practical way to encode dynamic knowledge along with its chronological relationships. Within this framework, the NKRL (Narrative Knowledge Representation Language) model—introduced in the following chapter—proves especially suitable for recognizing complex, non-trivial temporal contexts [?] and [?]. Its expressiveness allows it to model narrative knowledge effectively, leveraging the HClass and HTemp ontologies, which define concept hierarchies and event hierarchies, respectively.

2.1.5 Critical Analysis and Research Directions

Throughout this chapter, we explored the various approaches to knowledge representation and context recognition in intelligent systems, whether based on traditional ontologies, machine learning techniques, or hybrid approaches combining symbolic reasoning and machine learning (Parts 1 to 3). Ontologies, while expressive, show their limitations for managing dynamic and temporal knowledge, particularly when it comes to reasoning about interconnected events or representing complex relationships involving multiple entities and contexts simultaneously. Models based on machine learning and deep learning provide power and efficiency for learning behaviors and recognizing actions in diverse environments, but often remain difficult to interpret and poorly suited to establishing explicit causal or narrative relationships.

This analysis highlights a crucial need: a model capable of representing narrative and contextual knowledge, integrating the temporal dimension and enabling semantic reasoning on implicit relationships between events. It is in this context that NKRL (Narrative Knowledge Representation Language) stands out as a suitable solution. By combining a high level of expressiveness with the ability to model narrative knowledge from hierarchies of concepts (HClass) and events (HTemp), NKRL offers a robust model for recognizing complex, non-trivial, and time-related contexts, while facilitating the inference of causal relationships and objectives. The introduction of NKRL therefore marks a crucial step towards more adaptive, interpretable intelligent systems capable of understanding the history of interactions and events in their environment.

Chapter 3

Theoretical Foundations and Core Contributions

3.1 Introduction

In this chapter, in the first part, we present the theoretical and methodological foundations of symbolic knowledge representation and reasoning, as applied to context-aware intelligent systems. We begin with a review of the main concepts of first-order logic and logical reasoning, which form the basis of all symbolic representation frameworks. Building upon these foundations, we introduce the Semantic Web ontologies, which provide formal structures for organizing, sharing, and reasoning about knowledge in a machine-understandable way.

We then presen, in the second part, the NKRL (Narrative Knowledge Representation Language) model, designed for representing and reasoning about contextual knowledge derived from observational histories. The chapter first provides the key definitions used throughout, then explores the principles of narrative knowledge modeling based on the HClass and HTemp ontologies, as well as the reasoning mechanisms implemented in NKRL.

Finally, we discuss how context-awareness in ambient intelligence and ubiquitous robotics relies not only on observable information from sensors but also on inferred knowledge about users' activities, intentions, and the global environment

Part 1: Semantic Web Languages for Context-Aware Knowledge Representation

3.2 Introduction

In this part, we present the foundations of the formalisms used for symbolic knowledge representation and the associated reasoning models. We begin with a review of first-order logic concepts and logical reasoning, which form the basic building blocks common to all symbolic representation and reasoning systems. We then examine various knowledge representation and reasoning models based on ontologies. The final section of the chapter is devoted to the foundations of temporal representation and the handling of dynamic knowledge.

3.3 Predicates and Propositions

In first-order logic, knowledge representation and reasoning require the use of predicates and propositions to formalize axioms, concepts, relationships between concepts, and inference rules. A proposition is a statement with a definite meaning and can be evaluated as either true or false. For instance, the assertion "The living room is heated" is true, whereas "The kitchen is empty" is false.

Propositional logic is the simplest and most decidable logical formalism [1]. A statement E is said to be satisfiable (or consistent) if there $\exists$ an interpretation I that makes it true, formally denoted $I \models E$. For example, the statement $(p \vee q)$ is satisfiable if the truth values of p and q are: $\{v(p) = true, v(q) = true\}$, $\{v(p) = true, v(q) = false\}$, $\{v(p) = false, v(q) = true\}$. Conversely, a statement is unsatisfiable if no interpretation can make it true. The conjunction of a proposition and its negation $(p \wedge \neg q)$ is an example of an unsatisfiable statement.

Predicates can be seen as a generalization of propositions, forming a more expressive logic than propositional logic. The use of universal $\forall$and existential $\exists$ quantifiers, functions, and

---

[1] A problem is decidable if a Turing machine can solve it in a finite number of steps.

variables increases the expressive power of first-order logic. Functions may have any arity, and the variables over which quantifiers apply represent objects in the domain. For example, to express "There exists at least one smoke detector in every room of the house," we can use the predicates Room(X), contains(X,Y), and SmokeDetector(Y). In predicate logic, the previous statement can be written as:

f1: $\exists Y(SmokeDetector(Y) \wedge \forall X(Room(X) \rightarrow contains(X,Y)) \wedge Space\_Region(X)));$

In natural language, f1 can be expressed as: "There exists a smoke detector that is present in all rooms of the house."

A fundamental characteristic of first-order logic is monotonicity, meaning that once an assertion is considered true, it can never be refuted. Formally, let $\{P1, ..., Pn, R, Q\}$ be a set of well-formed formulas. If Q remains derivable even after adding the formula R to the initial set. In other words, derivability is preserved when a set of formulas is extended.

3.4 Ontology-Based Representation and Reasoning

The term "ontology" refers to the study of the general properties of what exists. Borrowed from philosophy, it was first applied in computer science by John McCarthy in the 1980s [**?**], [**?**]. McCarthy highlighted the overlap between philosophical ontology and the definition of logical theories in artificial intelligence.

Many definitions of "ontology" have been proposed, yet they generally converge on a similar core meaning. The most widely cited definitions in the literature are those of Gruber [**?**] and Studer [**?**]. Gruber defines an ontology as an explicit specification of a conceptualization, representing an abstract and simplified view of the world to be modeled. According to Studer, an ontology is a formal and explicit specification, machine-readable, of a conceptualization shared by a group of individuals.

According to Uschold et al. [**?**], an ontology provides a framework for a structured and formal semantic description of a domain's concepts and their interrelations. It facilitates knowledge exchange both between users and systems, and among systems themselves. Ontologies are thus a powerful tool for formalizing the conceptualization of an environment and sharing knowledge across heterogeneous systems. They are often coupled with inference engines to enable automated reasoning over the knowledge they encode.

Ontologies can be classified into two types:

- **Lightweight ontologies:** these have a relatively simple structure, mainly composed of concepts and taxonomies. A taxonomy organizes concepts hierarchically according to subsumption relations[2]. These relations express Is-A links between concepts and their properties;

- **Rich ontologies:** these extend lightweight ontologies with semantic constraints on the domain, such as cardinality restrictions [**?**].

Currently, ontologies are central to many applications, including the semantic description of multimedia resources and physical objects in the context of the Internet of Things. They facilitate data search and mining, the deployment of semantic web services, and the design of ubiquitous systems. Besides establishing a consensus on concept descriptions for knowledge sharing, ontologies are also paired with inference mechanisms to automate reasoning over this knowledge.

Ontology-based representation and reasoning became feasible thanks, on one hand, to the emergence of the Semantic Web and associated languages and tools based on XML and RDF, and, on the other hand, to the development of inference engines exploiting these formats. The Semantic Web is one of the major projects aiming to use ontologies as a foundation for semantic interoperability among heterogeneous computing systems. Its original goal was to implement formalisms and tools for representing and processing symbolic knowledge that software agents could use to automatically search, process, and aggregate heterogeneous, multimodal knowledge scattered across the Web.

3.4.1 Foundations of Ontology Languages

Most ontology definition languages proposed in the literature are based on, or inspired by, first-order logic, representing knowledge as assertions (subject, predicate, object) (subject, predicate, object). These languages are designed to abstract away from data structures and focus primarily on the semantics of knowledge.

Among ontology definition formalisms, we can distinguish:

- structured ontology representation languages such as KL-ONE, LOOM, KIF-Ontolingua, Cyc, DAML, DAML+OIL, F-Logic, OWL, etc.;
- formalisms for formally describing knowledge, such as conceptual graphs or description logics.

In this context, schema-based languages (Frames), introduced in artificial intelligence as an alternative to semantic networks, have inspired much of the work on ontology formalisms

---

[2] This term, borrowed from philosophy, often replaces “generalization/specialization” in ontology research. For example, the concept *HumanBeing* is a specialization of the concept *Man*. Formally, $Man \sqsubset HumanBeing$ means that *HumanBeing* subsumes *Man*.

and languages. Frames, introduced by *Marvin Minsky* [?], are hierarchical data structures for representing stereotypical situations. They were designed to gather relevant knowledge about a given situation into a single object—the Frame—rather than dispersing this knowledge across multiple axioms.

A Frame consists of:

- *slots* (attributes or properties) defining the data structure;
- *facets*, which semantically describe the possible values for each slot;
- *relations*, usually of specialization/generalization type.

A Frame can be seen as a network of nodes and relations between nodes, similar to a semantic network. Knowledge encoded in Frames can be either explicitly described or inferred, primarily by inheriting attributes from parent Frames.

The Cycl language was one of the first ontology languages, initially based on Frames and later on first-order logic. It was used to describe the universal Cyc ontology, which comprises over three million assertions (facts, axioms, and rules) covering all aspects of the world, organized into 43 thematic domains (Time, Spatial Relations, etc.).

Semantic networks, originally introduced by Quillian [?], use graphs to represent knowledge. In these graphs, nodes represent objects (concepts, situations, events, etc.), and arcs represent relations between objects [?]. These relations are of two types:

- *"is-a-kind-of"* between concepts, e.g., *Seat* is-a-kind-of *Furniture*;
- *"is-a"* between a concept and an individual, e.g., a *chair* is-a *Seat*.

Reasoning in semantic networks relies on graph manipulation. The subclass/superclass hierarchy organizes concepts through specialization/generalization relationships. In this formalism, properties are generally primitive, whereas Frames support more complex properties. The graphical representation makes semantic networks both human-interpretable and machine-exploitable.

3.4.2 Description Logics

Structured Inheritance Networks (SIN)[3] were introduced in the 1970s by Brachman [?] and [?] to address ambiguities in semantic networks and Frames. Three key ideas from his work have strongly influenced the development of description logics:

---

[3] `http://www.ontotext.com/factforge/sin`

- The basic syntactic building blocks are atomic concepts (unary predicates), atomic roles (binary predicates), and individuals (constants);
- The expressiveness of description logic languages is intentionally restricted, using a limited set of constructors to build complex concepts and roles;
- Implicit knowledge about concepts and individuals can be automatically inferred using reasoning procedures, in particular, subsumption relations between concepts and roles (properties).

Early flagship projects in description logics include KL-ONE [**?**], LOOM [**?**], and KRIS [**?**]. KL-ONE is considered the ancestor of description logic-based systems [**?**], enabling the transition from semantic networks to a well-founded logical (terminological) representation. It introduced most of the key notions of description logics, such as concepts, roles, and the way they relate.

In recent years, a large research community has developed around tools for representation and reasoning in description logics, particularly for supporting the Semantic Web. Description logics allow structured and formal representation of domain knowledge through concepts, roles, and individuals. Knowledge representation in description logic generally relies on three main components:

- Intentional knowledge, represented as a terminology in the TBox component;
- Assertions describing the individuals (instances) of the domain, stored in the ABox component, also called the factual level;
- A set of constructors (conjunction, disjunction, negation, value restriction, existential quantifier, etc.) to combine concepts and roles.

Description logics come in several languages, distinguished by their expressiveness and complexity, mainly based on the choice of constructors. The logic $\mathcal{AL}$ (Attributive Language) is considered minimal, as shown in Table **??**. For example, the negation of a concept ($\neg Women$) can only be applied to an atomic concept, and the existential quantifier can only be used with the ($\top$) concept. Using the atomic role *wears*, one can express that a person wears a sensor as follows: $\textit{Person} \sqcap \exists$ wears.$\top$.

There are three main ways to increase the expressiveness of the $\mathcal{AL}$ logic:

- Adding role constructors;
- Adding concept constructors. For instance, $\mathcal{ALUE}$ is simply the $\mathcal{AL}$ logic extended with union ($\cup$) and the existential quantifier ($\mathcal{E}$);

Table 3.1: Description Logic $\mathcal{AL}$

C,D $\rightarrow$ A (atomic concept)
$\mid \bot$ *bottom concept*, represents the empty concept.
$\mid \top$ *top concept*, represents the individuals (instances) of concepts associated with entities in the environment.
$\mid \neg A$ negation
$\mid C \cap D$ concept intersection
$\mid \exists R.\top$ value restriction
$\forall R.C$ universal quantifier

- Defining constraints on the interpretation of roles.

The $\mathcal{AL}$ logic can be further extended using the following constructors, **??** $[U][E][N][C][I][F][H][Q][O]$.

To express concepts by enumerating named individuals, the letter $\mathcal{O}$ is added to $\mathcal{AL}$. Full concept negation is expressed by adding $\mathcal{C}$. The inverse of a role and role inclusion are represented by $\mathcal{I}$ and $\mathcal{H}$, respectively. Finally, the constructors $\mathcal{N}$, $\mathcal{F}$, and $\mathcal{Q}$ complete $\mathcal{AL}$ to express cardinality constraints on a role.

Table 3.2: Correspondences between constructors of different description logic languages.

Languages		Constructors	Concepts
$\mathcal{AL}$	$\mathcal{FL}0$	Atomic concept names	A, C
		Atomic roles	R_1, R_2
		Intersection (concept conjunction)	A $\cap$ C
		Universal quantifier (value restriction)	$\forall R.C$
	$\mathcal{FL}^-$	Existential quantifier	$\exists R$
		Top (subsumes all concepts)	$\top$
		Bottom (has no instance)	$\bot$
	$\mathcal{C}$	Negation	$\neg A$
	$\mathcal{U}$	Union (disjunction)	$A \cup C$
	$\mathcal{E}$	Typed existential quantifier	$\exists R.C$
	$\mathcal{R}$	Role conjunction	R_1, R_2
	$\mathcal{N}$	Cardinalities	$(\geq nR), (\leq nR)$
	$\mathcal{H}$	Role hierarchy	$R_1 \subset R_2$
	$\mathcal{I}$	Inverse role	R^-
	$\mathcal{Q}$	Qualified number restriction	$(\geq nR.A), (\leq nR.A)$

3.4.3 Reasoning in Description Logic

Reasoning in Description Logic involves performing inferences over the elements of the TBox and ABox components by applying the following operations:

- Subsumption: This operation establishes a hierarchy of concepts based on generalization and specialization. For example, consider the following axioms:

(4) monitoredSpaceRegion $\equiv$ Space_Region $\sqcap\exists$ equippedWith.Sensor ;

(5) monitoredSpaceRegion $\sqsubseteq$ Space_Region ;

Axiom (4) states that a space equipped with at least one sensor is a monitored space (*monitoredSpaceRegion*). Subsumption allows us to infer that every concept of type *monitoredSpaceRegion* is also a *Space_Region*. Therefore, the axiom: *Bath_Room* $\sqsubseteq$ *monitoredSpaceRegion* implicitly means that *Bath_Room* is a *Space_Region*, even if it is not explicitly stated in the TBox.

- Satisfiability: A concept A is satisfiable with respect to the TBox if there exists at least one interpretation of A, i.e., I(A) $\neq \emptyset$. For instance, the axiom *monitoredSpaceRegion* $\sqcap\neg$ *monitoredSpaceRegion* expresses that a space cannot be both monitored and unmonitored; the intersection of a concept and its complement is always empty.
- Equivalence: Two concepts A and B are equivalent if, for any TBox, there exists an interpretation I such that I(A) $\equiv$ I(B).
- Disjointness: Two concepts A and B are disjoint if they are semantically distinct with respect to the TBox, i.e., $I(A) \sqcap I(B) = \emptyset$.

For the ABox (factual component), inferences involve the following operations:

1. Consistency checking: Ensuring that the assertions in the ABox are consistent with the TBox.
2. Instance checking: Verifying that each instance satisfies the definition of its concept.
3. Role checking: Ensuring that the roles in an assertion R(a,b) properly relate valid individuals.
4. ABox realization: Determining the most specific concept associated with each instance.

3.5 Semantic Web Languages

3.5.1 RDF

The RDF language is based on three core primitives: class, property, and instance, which allow representing any information as a triplet. An RDF triplet consists of three components: the Subject, representing an IoE resource; the Predicate, corresponding to a binary property; and the Object, representing the value of that property. The predicate describes the relationship between the Subject and the Object, defining the domain and range of the property. Each IoE resource is uniquely identified by a URI (Uniform Resource Identifier).

For example, the statement "The smart lighting system turns on the living room light" can be represented by the triplet: Subject Smart_Lighting_System, Predicate turnsOn, Object Living_Room_Light. Similarly, "The temperature sensor measures the room temperature" corresponds to the triplet: Subject Temperature_Sensor_1, Predicate measures, Object Room_Temperature. Finally, for an autonomous vehicle detecting an obstacle: Subject Autonomous_Vehicle_1, Predicate detects, Object Obstacle.

3.5.2 RDF-S

Although RDF provides a framework for representing and sharing information, it does not provide semantic meaning. To address this, RDF is typically used with a predefined vocabulary called the RDF Vocabulary Description Language, forming RDF Schema (RDF-S).

RDF-S allows defining hierarchical classes and specifying relationships between properties, enabling simple inferences such as checking class or subclass membership. For example, Smart_Lighting_System and Temperature_Sensor_1 can be declared as subclasses of IoE_Device, and Obstacle as an instance of Physical_Object.

RDF-S also enables restricting the domain and range of predicates. For instance:

turnsOn : domain Smart_Lighting_System, range IoE_Light

measures : domain Environmental_Sensor, range Measurement

detects : domain Autonomous_Vehicle, range Physical_Object

Sub-property relationships can also be defined:

turnsOn is a sub-property of controls

measures is a sub-property of monitors

These mechanisms assign semantic meaning to IoE resources and allow automatic reasoning within connected environments.

3.5.3 Inferences in RDF(S)

RDF-S allows describing the semantics of shared information, but it has notable limitations in expressiveness. Key restrictions include:

1. Cardinality constraints: RDF-S cannot specify how many values a property can take. For example, it cannot express that a chair can be occupied by only one person at a time, or that a temperature sensor can measure only a single room.

2. Negation and disjunction: RDF-S cannot express the negation of a class or disjunction between two classes. For instance, it cannot represent that a person has not taken their medication, or that Robot and Human are mutually exclusive classes.
3. Default values: RDF-S does not support assigning default values to attributes, limiting the representation of implicit or hypothetical knowledge.

Therefore, inferences in RDF(S) are primarily limited to checking generalization/specialization relationships between classes and properties. To query RDF documents, several query languages have been developed:

- RDQL (RDF Data Query Language) [4]
- SPARQL (SPARQL Protocol and RDF Query Language) [5]

SPARQL is particularly powerful because it can query saturated RDF graphs, where all triples inferred from generalization/specialization relationships have been generated automatically. This saturation enables implicit inferences and simplifies complex queries in IoE environments—for example, identifying all IoE devices controlled by a central system or all sensors activated in a specific room.

For instance, in an IoE scenario, a Smart_Home_System could turn off all high-energy devices when the house is empty. SPARQL can automatically retrieve all instances of these devices using RDF triplet saturation,figure **??**.

3.5.4 The OWL Language

To address the limitations of RDF-S, the Semantic Web community developed OWL (Web Ontology Language), a more expressive language built on RDF. OWL is a standard for representing ontologies on the Semantic Web, allowing not only knowledge representation but also automatic reasoning over that knowledge.

In OWL, an individual represents an object, a property represents a binary relation between objects, and a class represents a set of objects sharing common characteristics. OWL originated from the fusion and extension of the DAML and OIL languages and adopts the syntax of RDF-S while providing a richer vocabulary for describing classes, properties, and relationships. OWL also provides constructors to define complex classes, such as class intersections, unions, or existential quantifiers.

OWL distinguishes two types of binary properties:

---

[4] `http://www.w3.org/Submission/2004/SUBM-RDQL-20040109/`

[5] `http://www.w3.org/TR/rdf-sparql-query/`

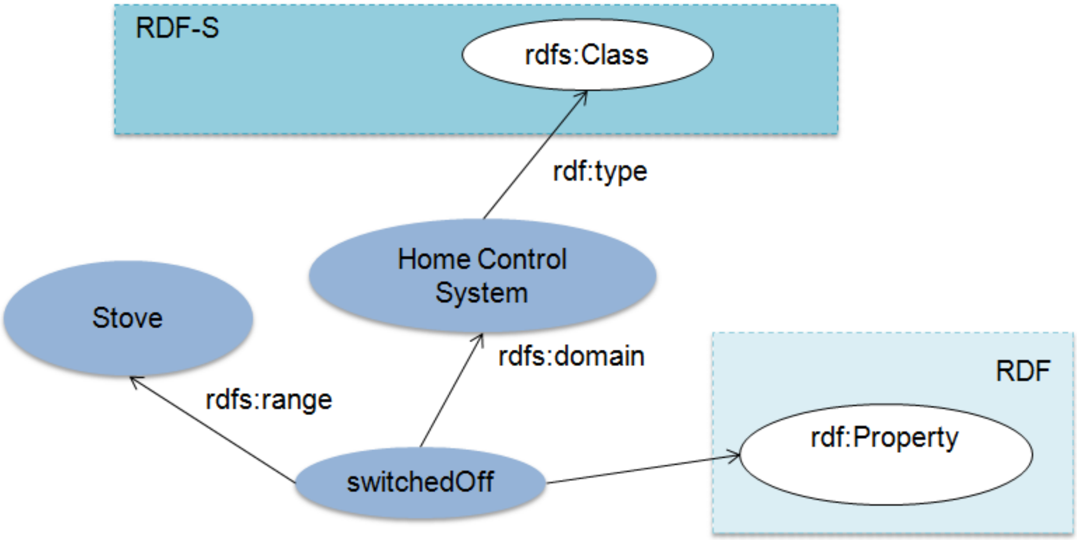


Figure 3.1: Graphical representation in RDF-S of the statement: *The system switches off the stove*

ObjectProperty: links individuals of different classes. The source class is defined using rdfs:domain, and the target class using rdfs:range.

DataTypeProperty: associates a class with a data type, such as integer, float, or XML Schema-defined types.

OWL properties may also have specific characteristics, including:

Transitive property (OWL Transitive Property): if a relation exists between individuals x and y, and between y and z, then a relation is inferred between x and z.

Functional property (OWL Functional Property): a property can have only one value for a given individual. If x is linked to y and z via the same functional property, then y and z represent the same individual.

OWL relies on a set of axioms and facts to describe a domain, based on the description logic $\mathcal{SROIQ}$ [?]. Several query languages exist to extract OWL knowledge:

* SPARQL, RDF-based, allows queries to be expressed as graphs and matches them against saturated RDF graphs.

* RQL (Racer Query Language), based on description logics, allows querying OWL-DL knowledge and performing inferences on TBox and ABox components.

* OWL-QL is a formal language proposed by the W3C to query semantic web knowledge bases, matching queries to annotations and generating responses based on predefined patterns.

In an Internet of Everything (IoE) context, OWL can model intelligent systems where a Smart_Home_System automatically controls connected devices, infers which sensors are active in each room, and detects anomalies, such as an appliance left on while the house is empty.

3.5.5 Reasoning in OWL

Reasoning in OWL can be performed at three levels:

1. Class level: checking inheritance (subsumption) and building the class hierarchy. For example, determining that all Smart_Light instances are IoT_Devices.
2. Property level: verifying relations between individuals across different types of properties. For instance, using transitivity, if a sensor is connected to a controller and the controller to a central system, a relation can be inferred between the sensor and the central system.
3. Individual level:
    - Consistency checking: ensuring that an instance of a class exists and satisfies ontology constraints.
    - Individual retrieval: identifying classes matching a partial or complete description of a given individual, useful in IoE systems to automatically detect devices that meet certain conditions or scenarios.

OWL thus enables automated reasoning over dynamic and heterogeneous IoE environments, combining ontological representation with powerful logical inference.

3.5.6 Rules and Inference in OWL Ontologies

Integrating rules into OWL ontologies significantly enhances expressivity and reasoning capabilities [?]. Description logic-based inference engines can:

check the consistency of concepts using the subsumption principle;

enforce cardinality constraints on classes and properties at the terminological level;

derive new knowledge from instances and axioms defined in the TBox and ABox components.

The most widely used rule language is SWRL [?], considered an extension of OWL DL. Based on logic programming and Horn clauses, SWRL allows manipulation of variables and instances in the rule body. Its fundamental principle is to apply rules when the antecedent is satisfied, without creating new concepts or relations.

However, SWRL is undecidable, which poses challenges when combining OWL and SWRL. A practical solution is to use Rete-based rule engines, such as Jess[6] or CLIPS-OWL [?], enabling efficient execution of rules in real-time systems or dynamic IoE environments.

3.5.7 Ontologies in Ambient Intelligence and Robotics

A major challenge in ambient intelligence and ubiquitous robotics is enabling agents to share a common understanding of the environment and entity interactions. Another goal is reusing existing models: new ontologies can be constructed by importing existing ones and adding only new entities or relations.

In ambient environments, facts are often dynamic: some information may change frequently or be unknown at a given time. Classical first-order logic and traditional ontologies are insufficient to represent such knowledge accurately.

Two reasoning assumptions are commonly used:

1. Open World Assumption (OWA): the absence of information in the knowledge base indicates that the fact is unknown, not false. This is standard in OWL ontologies and suits IoE applications where sensors or devices may not always be available.
2. Closed World Assumption (CWA): the absence of information is interpreted as the fact being false, useful in databases or certain robotic control rules.

For instance, in a smart healthcare system, OWA prevents drawing arbitrary conclusions when no patient data is available, while CWA allows verifying that a patient is not under a specific treatment by relying on missing data in the pharmaceutical database [?].

To express the negation of a fact in an OWA-based system, it is often necessary to introduce a new explicit role. For example, for the role present representing a person's presence in a room, its negation can be represented as notPresent or absent. In a CWA system, simply applying the negation operator to the existing role suffices.

In the IoE context, these principles enable intelligent systems to automatically infer complex situations, such as:

- Smart energy management: A system infers that multiple appliances are running simultaneously and automatically adjusts the energy allocation to prevent overloads.

---

[6] `http://herzberg.ca.sandia.gov/`

- Elderly care monitoring: A system detects that a patient has not taken their medication on time by combining sensor data (pillbox usage) and schedule rules, and triggers an alert to caregivers.
- Medical assistant robot: The system detects that a patient's room is unoccupied and automatically adjusts medical devices, lighting, and environmental controls, or reschedules routine checks and medication deliveries to optimize care and energy usage.
- Warehouse robotics coordination: Multiple robots share a map of inventory locations and tasks. The system infers potential collisions or task conflicts and reassigns paths or priorities to avoid accidents.
- Smart home security: If a window is open and no one is detected in the room, the system infers a potential security risk and triggers an alarm or locks other entry points automatically.
- IoE-based traffic management: Sensors detect vehicles on a road segment and infer congestion patterns. The system automatically adjusts traffic lights or recommends alternate routes to minimize delays.

3.6 Representation and Reasoning on Dynamic Knowledge

In Artificial Intelligence, two classical approaches for representing and reasoning about dynamic knowledge are those of *McDermott* [?] and *Allen* [?]. *McDermott* models two main aspects: uncertainty about the future and the continuity of time. In his "chronicle logic," a fact is defined as a set of states where a proposition remains true throughout. States are ordered by an antisymmetric and transitive relation denoted $<$. Hence, the future is represented as a branching tree of possibilities, each path corresponding to a chronicle.

In contrast, *Allen*'s temporal logic represents time along a continuous timeline, which is more suitable for reasoning about events and time intervals.

3.6.1 Allen's Temporal Logic

Allen models time using intervals, each defined by a start and an end point [?], [?], and [?]. He defines thirteen temporal relations: seven basic relations (*equal, before, during, meets, starts, overlaps, finishes*) and six inverse relations (*after, contain, met, overlapped, finished*),

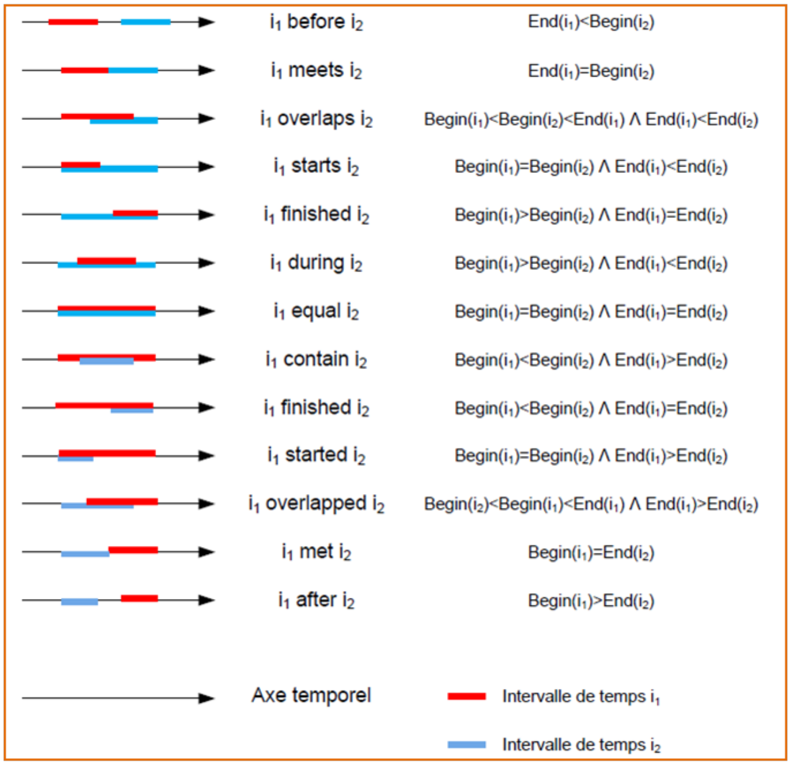


Figure 3.2: Temporal interval relations according to Allen [?]

as shown in Figure ??. This formalism is widely used to reason about events, actions, beliefs, or intentions over time.

For instance, the statement "a person watches TV" does not explicitly indicate a temporal dimension, but it can be implicitly represented by an interval corresponding to the duration of the activity.

Allen introduces three types of symbols: Property (*Holds*), Event (*Occurs*), and Process (*Occuring*), applied to a time interval during which an event or process occurs. The formalism allows us to:

- **Associate a property with a time interval** The binary predicate *Holds(p, i)* indicates that a property p is true throughout the interval i. This predicate is homogeneous: if p is true over i, it is true for any sub-interval i'. Example: *LightOn* is true during [2:00 PM, 3:00 PM], so it is also true during the sub-interval [2:30 PM, 2:45 PM].

- **Model the occurrence of an event** The predicate *Occurs(e, t)* indicates that an event e happens at instant t. Example: Event *PatientEntersRoom* occurs at 10:05 AM.

- **Model a process in progress** The predicate *Occuring(p, t)* represents that a process p is ongoing during interval t, useful for repetitive or continuous activities. Example: *MonitoringHeartRate* is ongoing from 10:00 AM to 12:00 PM.

3.6.2 Situation Calculus

The *Situation Calculus*, introduced by *McCarthy* [?] and formalized by *Levesque* [?] and *Reiter* [?], is a logical formalism in which time is reified. It is a second-order logic language used to axiomatize situations, actions, and temporal changes.

In this framework, the world is represented as a set of situations (or states). A situation is defined as a set of facts called *fluents*[7]. A situation can be seen as a time interval during which no change occurs in the environment. From an initial situation *s*, executing an action produces a new situation *s'*. Each action is represented symbolically; for example, *Open(door1, t1)* means that *door1* is opened at time *t1*.

Table **??** provides examples of fluents, events, and situations, including new sequences involving multiple individual, robot and intelligent home devices.

Although multiple sequences of actions can be executed, there is no guarantee that all fluents will be affected. Consequently, the implementation of the situation calculus gives rise to a well-known issue called the frame problem [?]. The frame problem concerns determining what does not change when an action occurs. This issue is considered a major challenge for modeling dynamic environments, as it requires specifying the properties whose values remain unchanged when an event or action takes place.

In part, the frame problem has been addressed using the event calculus formalism, which allows reasoning about changes and non-changes in properties over time. For instance, if a medical assistant robot reminds John to take his medication, the robot's action changes the state of the MedicationTaken fluent, but other fluents, such as LightsOn in the living room, remain unaffected unless explicitly acted upon.

3.7 Synthesis

This chapter provided an overview of symbolic knowledge representation formalisms and associated reasoning models, contextualized within the scope of this thesis. We reviewed and analyzed ontology-based representation and reasoning approaches. Currently, RDF-S and OWL are the most widely used ontology languages for implementing knowledge management platforms in ambient intelligence and robotics. OWL extends RDF-S syntax by offering a richer vocabulary for describing classes, properties, and inter-class relations. Based on a decidable fragment of predicate logic, it supports constructors for complex class definitions, such as conjunctions or existential quantifiers. SPARQL is commonly used to query OWL

---

[7] Fluents are expressions whose values describe properties of objects that may change over time. A fluent is true in a state if the corresponding property holds at that moment. Events initiate or terminate fluents.

Table 3.3: Dynamic example of interactions with a medical assistant robot, including medication reminders, safety, and autonomous decision-making

(1) John is at home and it is 8:00 AM;
(2) The medical robot checks the prescription database and detects that John should take his antihypertensive medication;
(3) John is in the living room, busy on the phone; the robot sends him an audible and visual reminder;
(4) John ignores the reminder; the robot sends an additional reminder and proposes to place the medication on the kitchen table;
(5) John finally goes to the kitchen and takes the medication; the robot records the intake in the database;
(6) The robot detects that the insulin bottle is almost empty and notifies John that a refill is needed;
(7) John forgets to check his connected blood pressure monitor; the robot detects this and suggests measuring his blood pressure now;
(8) John agrees; the robot performs the automatic measurement and sends the results to the medical monitoring application;
(9) John moves to his bedroom to rest; the robot detects that the lights and TV are left on and proposes to turn them off;
(10) John does not respond; the robot automatically performs the action to save energy and reduce risks;
(11) The robot detects that the refrigerator door remains open after breakfast preparation; it suggests closing it to prevent loss of cold;
(12) The robot detects a fallen medication bottle on the bathroom floor; it informs John and secures it to prevent an accident;
(13) John receives an urgent call; the robot checks that all medications have been taken and notifies a relative or doctor if a dose was missed;
(14) The robot continues to monitor the environment and medication intake throughout the day.

knowledge bases represented as RDF triples.

This chapter highlighted the benefits of ontologies in context-aware ubiquitous applications. Ontologies enable a shared, intelligible semantic representation of contextual knowledge and support automated extraction and reasoning processes. OWL, in particular, provides sufficient expressivity for domains like robotics and ambient intelligence. However, its open-world foundation complicates dynamic reasoning in environments where real-time adaptation to changing conditions is required. W3C acknowledges that OWL's open-world and non-unique-name assumptions are incompatible with applications needing explicit truth values. Approaches combining OWL with closed-world assumptions, such as negation-as-failure, exist but are complex and difficult to implement.

Another key issue addressed is the management of dynamic contextual knowledge, which necessitates incorporating temporal aspects. Existing approaches typically rely on Allen's temporal logic and the fluent paradigm. Although expressive, these methods often produce redundant representations and require rewriting existing ontologies. Moreover, standard OWL-DL reasoners cannot process temporal semantics efficiently. A solution involves using n-ary predicates to represent dynamic knowledge and temporal relationships. The NKRL (Narrative Knowledge Representation Language) model, introduced in part 2, is particularly suited for recognizing non-trivial time-linked contexts supporting high expressivity and narrative knowledge modeling through HClass and HTemp ontologies describing concept and event hierarchies.

Part 2: Narrative Knowledge Representation for Dynamic and Temporal Reasoning

---

3.8 Introduction

In this part, we present the NKRL (Narrative Knowledge Representation Language) model for knowledge representation and reasoning, aimed at context recognition from observational histories. We first provide the definitions used throughout this chapter, and then we present, on one hand, the foundations of narrative knowledge modeling based on the HClass and HTemp ontologies, and on the other hand, the NKRL reasoning mechanisms.

3.9 Foundations of NKRL

In the following, we define the main notions used in the NKRL language:

Narrative Event: Two types of narrative events are distinguished: fictional and non-fictional (factual). The first type allows the representation of events in an imaginary world (simulated events), while the second represents events occurring in the real world [?].

According to *Bal*, a narrative event provides the classical theory of narratology [?]. Narratology is defined as a ternary structure composed of three entities: the fabula, the story, and the narrative. The fabula is a logically and chronologically ordered sequence of events. The story is a particular subset of the fabula, rearranged into a new sequence. Finally, the narrative concerns the way in which events are presented through a specific medium (e.g., text, image, video, film).

Elementary Event: An elementary event is considered a manifestation of specific attitudes towards living beings or abstract objects. It may have a spatial and/or temporal dimension, as illustrated by examples such as: "moving a chair," "sending a text message in the evening," or "starting the coffee machine early in the morning."

Static Entity: Represents a physical or immaterial object (e.g., wall, ceiling, tap) that does not change over the lifespan of the application.

Dynamic Event: Represents a sequence of elementary events describing the behavior of an entity (person, object). Examples include: a person uses a remote control to open a door, a system moves a robot following a fall, etc.

Concept: An NKRL concept can be assimilated to the notion of a class in the semantic web. It is associated with a set of properties or attributes. NKRL distinguishes two categories of concepts: directly instantiable concepts (sortal_concept) and concepts that cannot be instantiated directly (non_sortal_concept).

Directly Instantiable Concept: For example, instances such as CHAIR_125, BED_2012, TAP_45 are created from the concepts chair_, bed_, tap_.

Non-Directly Instantiable Concept: For instance, the concept Color cannot have a direct instance. Values like RED_120 or YELLOW_1 are meaningless on their own. NKRL solves this by introducing the concept color_appearance, a specialization of the instantiable concept physical_appearance. This allows associating a color with an instantiable concept, e.g., RED_TABLE, YELLOW_CUP.

Predicate: NKRL is not a universal formalism but is designed for representing non-fictional events. It defines seven basic predicates to determine the specific category of an event and identify its type (action, state, situation, etc.), as shown in Table **??**.

Table 3.4: NKRL Basic Predicates

Predicate	Description
BEHAVE	Represents knowledge such as: a person or an abstract/concrete object adopts a particular attitude or plays a specific role (concretely or intentionally) to achieve a result. For example: a person is having a meal, a group of people are conversing, etc.
EXIST	Represents the presence of an entity in a given space. For example: a person is in the living room, a person has died in a hospital.
EXPERIENCE	Indicates that an entity is affected by events. For example: the light intensity decreases in a room, a person feels unwell, etc.
MOVE	Represents the movement of an entity, e.g., moving a robot, sending a text message, etc.
PRODUCE	Represents the execution of a task or activity by an entity. For example, a temperature sensor produces information about a specific space.
OWN	Represents possession or ownership relationships between entities. For example, a house belongs to a person, the area where a person fell is part of the house, a door is closed, etc.
RECEIVE	Represents events related to receiving information. For example, a person receives a phone call.

Role: NKRL defines seven conceptual roles: SUBJECT, OBJECT, SOURCE, BENEFICIARY, MODAL, TOPIC, and CONTEXT. A role is used to:

semantically represent a functional relation between a predicate and its arguments, identify the actors of an event.

NKRL was originally designed to formalize, manage, and process knowledge expressed in natural language, particularly contained in non-fictional documents such as reports, memos, or medical records. Narrative knowledge processing in NKRL aims to provide an expressive representation for both elementary events and the temporal relations linking them. The conceptual representation of narrative knowledge is performed through the HClass ontology, which is similar to traditional ontology languages such as OWL and DAML+OIL. For dynamic events, NKRL uses a second ontology called HTemp, which efficiently represents n-ary relations. NKRL also relies on inference mechanisms to automatically establish implicit or explicit semantic relations between knowledge. It provides means to combine predicates and conceptual roles to adequately encode narrative information, and to construct semantic links (causality, purpose, etc.) between elementary events.

3.10 Narrative Knowledge Representation in NKRL

The conceptual representation of narrative knowledge relies on four components:

1. **Definitional Component**: Represents concepts such as desk, house, robot, sensor, etc. Concepts can be general (e.g., human_being) or specific (e.g., chair). In NKRL naming rules, a concept identifier is a lowercase string ending with an underscore.

2. **Enumerative Component**: Enumerates the instances of all concepts defined in the definitional component. NKRL naming rules for individuals are the same as for concepts. For example, DAVID_ and JOHN_ are instances of human_being, and ROBOT_KOMPAI is an instance of robot_.

3. **Descriptive Component**: Represents the structures (templates) of elementary events. An elementary event in NKRL consists of a predicate, one or more roles, and associated arguments. Table **??** shows the general structure of a template:
    (a) PREDICATE: One of the seven basic predicates (PRODUCE, MOVE, EXPERIENCE, EXIST, OWN, RECEIVE, BEHAVE)
    (b) Argument: Attributes associated with each role (SUBJ, OBJ, SOURCE, MODAL, TOPIC, CONTEXT, BENEFICIARY)
    (c) Location: The space where the event occurs
    (d) Modulators and Temporal attributes: Parameters for temporal representation of knowledge

Table 3.5: General structure of an NKRL template

```
PREDICATE SUBJ { <argument > : [location] }
          OBJ { <argument> : [location] }
          SOURCE { <argument> : [location] }
          BENF { <argument> : [location] }
          MODAL { <argument> }
          TOPIC { <argument> }
          CONTEXT { <argument> }
          {[ modulators ]}
          {[ temporal attributes]}
```

4. **Factual Component**: This component represents all instances of all elementary events. An instance of an event is called a predicative occurrence. The instantiation of a predicative occurrence follows the rule (**??**):

$$(L(P(R_1a_1)(R_2a_2)\dots(R_na_n))) \tag{3.1}$$

where:

L: The semantic label (generic symbol) used to uniquely identify a predicative occurrence, according to the Unique Name Assumption (UNA);

P: An NKRL predicate;

R_k (k=1,...,n): The set of roles (SUBJECT, OBJECT, SOURCE, BENEFICIARY, MODAL, TOPIC, CONTEXT);

a_k (k=1,...,n): The set of arguments associated with each role.

Table **??** presents the MOVE template. The symbol NLDescription provides a natural language description of the template. Any role or variable enclosed in square brackets [] is considered optional.

In the MOVE template:

The roles SUBJ and OBJ, as well as the variables var1 and var3, are mandatory.

The roles BENF, MODAL, and CONTEXT, along with the variables var2, var4, var5, var6, and var7, are optional.

The variables var1 through var7 represent constraints that ensure the values assigned to each variable, when creating a predicative occurrence, are specific to the terms (concepts or instances) defined in the definitional component. Consequently, the constraints specified in the templates of the HTemp ontology are linked to concepts defined in the HClass ontology.

The knowledge consistency verification process relies on HClass to establish a concept and instance hierarchy based on the generalization/specialization principle.

Table 3.6: Structure of the MOVE template

```
NLDescription: 'Transmit Structured Information'
PREDICATE: MOVE
              SUBJ var1 : [(var2)]
              OBJ var3
              [BENF var4 : [(var5)]]
              [MODAL var6]
              [CONTEXT var7]
              {[modulators] != abs}
              {[temporal attributes]}
var1 = <human_being> | <artefact_>
var2 = <location_> var3 = <symbolic_label>
var4 = <human_being> | <artefact_>
var5 = <location_>
var6 = <media_> | <information_support>
var7 = <situation_>
```

3.11 The HClass and HTemp Ontologies

Knowledge representation in NKRL relies on two ontologies: HClass (Concept Hierarchy) and HTemp (Event Hierarchy). The definitional and enumerative components are defined within HClass, while the descriptive and factual components are defined in HTemp.

HClass is composed of three main branches: nkrl_grammar, non_sortal_concept, and sortal_concept. The concepts and instances within these branches are organized according to a subsumption-based taxonomy (see Figure **??**).

Concepts subsumed under non_sortal_concept are generally used with the SPECIF operator. This operator allows associating a list of properties, expressed as concepts or instances, with NKRL roles. For example, the conceptual representation of two different spaces (living room and bedroom) in NKRL is expressed as follows:

Example 1:

(SPECIF LIVING_ROOM_1 (SPECIF different_from ROOM_1))

(SPECIF HALL_1 (SPECIF between_ BATH_ROOM_1 LIVING_ROOM_1))

In Example 1, a binary relation is used between the arguments LIVING_ROOM_1 and ROOM_1. Example 2 illustrates a ternary relation (between_) associating three arguments: HALL_1, BATH_ROOM_1, and LIVING_ROOM_1.

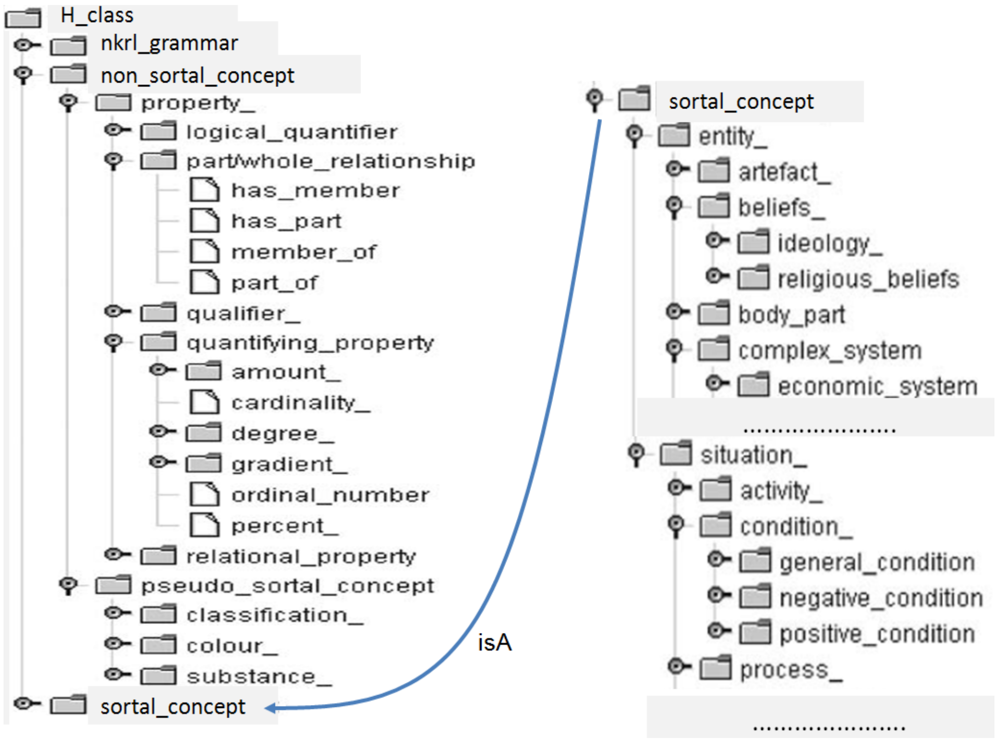


Figure 3.3: Tree representation of the HClass ontology

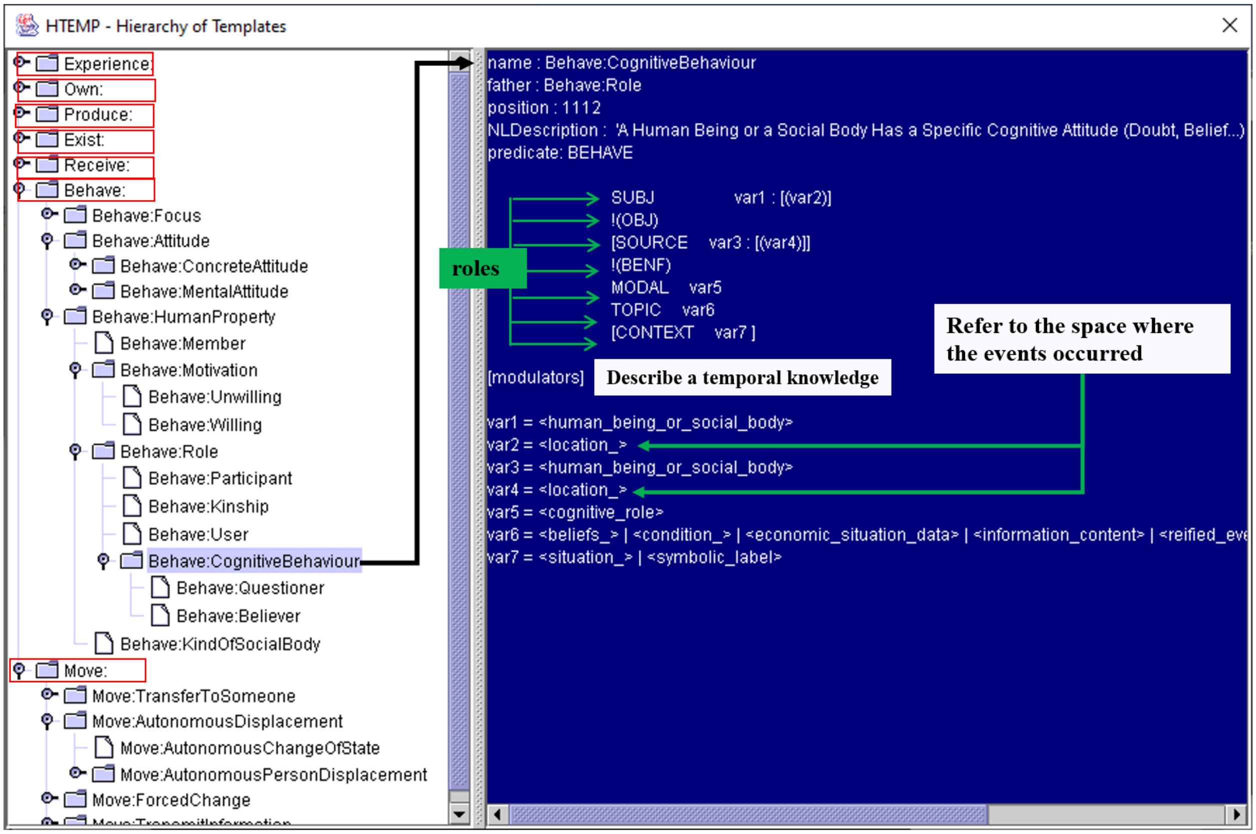
Originally containing over 2,700 concepts, the HClass ontology has been extended to meet the needs of ambient intelligence applications developed within the scope of this thesis.

The nodes in HTemp are hierarchically connected as n-ary structures. This ontology is defined as the formal depiction of elementary events. Our approach distinguishes between an elementary event and a complex event, which describes an entity's behaviour (motions, actions, temporal events, etc.). For example, turning on the coffee machine early in the morning and opening the door are elementary events. However, if the robot moves towards the space where a human is located and interacts with him, it is a complex event.

Figure **??** depicts the general structure of HTemp ontology divided into seven branches called templates or predicates (MOVE, PRODUCE, RECEIVE, EXPERIENCE, BEHAVE, OWN, EXIST). The BEHAVE predicate, a crucial concept in our understanding of actions and behaviours, represents the actions or behaviours of one or more individuals. On the other hand, EXIST indicates an entity's presence in a given space. EXPERIENCE is typically employed to describe an event that affects an individual, like illness, success, accident, etc. MOVE, a versatile predicate, describes many actions like moving, sending, etc. The OWN predicate can represent the notion of ownership between entities or the state of an entity. The PRODUCE predicate describes the execution of a task, activity, or other action. RECEIVE describes events related to the reception of information.

Table 3.7: Elementary events vs complex vents (ioe.m156).

Description	narrative event
The robot gives its assistance by moving itself towards the bathroom where a human is localized and tries to interact with him.	ioe.m156) MOVE SUBJ ROBOT_KOMPAI: (KITCHEN_1) OBJ ROBOT_KOMPAI: (BATHROOM_1) MODAL speech_interaction CONTEXT potential_risq date-1: 2024/11/25/15:25 date-2: Move:AutonomousDisplacement
On 2024/11/25, at 14:35, the system observes that a stovetop in the kitchen is turning on in the kitchen denoted respectively by the symbols STOVETOP_1 and KITCHEN_1.	ioe.o145) OWN SUBJ STOVETOP_1:(KITCHEN_1) OBJ property_ TOPIC TURN_ON {*obs*} date-1: 2024/11/25/14:40 date-2: Produce:Assessment/Trial
On 2024/11/25, at 14:58, the system observes that the temperature on the kitchen stovetop has risen	ioe.e85) EXPERIENCE SUBJ (SPECIF temperature_ KITCHEN_1) OBJ growth_ {*obs*} date-1: 2024/11/25/14:58 date-2: Experience:GenericSituation



```
name : Behave:CognitiveBehaviour
father : Behave:Role
position : 1112
NLDescription :  'A Human Being or a Social Body Has a Specific Cognitive Attitude (Doubt, Belief...)
predicate: BEHAVE

            SUBJ          var1 : [(var2)]
            !(OBJ)
            [SOURCE    var3 : [(var4)]]
            !(BENF)
            MODAL    var5
            TOPIC    var6
            [CONTEXT    var7 ]

[modulators]

var1 = <human_being_or_social_body>
var2 = <location_>
var3 = <human_being_or_social_body>
var4 = <location_>
var5 = <cognitive_role>
var6 = <beliefs_> | <condition_> | <economic_situation_data> | <information_content> | <reified_eve
var7 = <situation_> | <symbolic_label>
```

roles

Describe a temporal knowledge

Refer to the space where the events occurred

Figure 3.4: General HTemp ontology structure and CognitiveBehaviour structure.

Each Template can be customized to derive the new templates that could be needed for a particular application. HTemp ontology contains 165 templates. Each branch of template contains seven generic roles (subject(SUBJ), object(OBJ), SOURCE, MODAL, TOPIC, CONTEXT, Beneficiary (BENF)). The space where an event/situation occurs and temporal knowledge are respectively described by location and modulators (described in more detail in the next section). Modulators represent the (start, end, duration) of a given event/context. A role or a variable defined in square brackets ([ ]) are optional elements. In Figure **??**, the SUBJ, MODAL and TOPIC roles and (var1, var3, var5 and var6) are mandatory, while SOURCE, CONTEXT, roles, and variables (var2, var4, var7) are optional. The variables var1, ..., and var7 represent constraints allowing us to check that the values assigned to each variable when a CognitiveBehaviour Template is instantiated correspond to (concept, sub-concepts) defined in the HClass ontology. Therefore, the consistency checking process is based on ontology HClass, which establishes a hierarchy of concepts/instances based on the generalization/specialization principle. Furthermore, the MOVE template is divided into four categories that describe how to transfer something to someone, send information, and move autonomously (e.g., a robot moves itself).

Table 3.8: NKRL Temporal Modulators

Acronym	**General Description**
begin	Represents the start of an event
end	Marks the end of an event
obs	Used when there is no temporal information about the start or end of an event. For example, the system observed that the temperature began to rise at 11:32 PM.

The Table **??** depicts three examples of elementary events and complex vents. Where each template has a unique symbolic label (SymL) identifying a given template, some examples of SymL : (ioe.m156), (ioe.o145).

3.11.1 Representation of Time Points and Time Intervals in NKRL

In NKRL, temporal knowledge is represented by adding temporal annotations, also called temporal modulators, which provide information about the start and end of an event or indicate that the event occurs on a specific date, as shown in Table **??**.

3.11.2 Binding Occurrence Structures

These structures allow the definition of semantic links between elementary events. Unlike predicative occurrences, binding structures do not use the symbols PREDICATE and ROLE to express semantic relationships.

The construction of binding structures using operators such as COORD, GOAL, CAUSE, etc., follows the syntax:

$$(\text{operator} \;\; [arg_1 \;\; arg_2 \;\; ... \;\; arg_n]) \tag{3.2}$$

where $arg_1, ..., arg_i$ represent predicative occurrences.

Example. Suppose John is detected in the corridor (HALL_1) and the system switches on the lights in that area. The predicative occurrences corresponding to these two pieces of knowledge, MOVE and EXIST, are as follows:

aal.c6) MOVE SUBJ: HOME_CONTROL_SYSTEM_1
OBJ: lighting_: (switch_off, switch_on)
TOPIC: HALL_1

date-1: 11/08/2024/22:36
date-2:

aal.c7) EXIST SUBJ: JOHN_: (HALL_1)
date-1: 11/08/2024/22:34
date-2:

The CAUSE binding operator can then be used to link these two occurrences, expressing that the elementary event represented by occurrence aal.c6 is caused by occurrence aal.c7. Formally:

(CAUSE aal.c7 aal.c6)

3.12 Rule Matching and Representation Mechanisms

The NKRL reasoning mechanisms rely on a question (query)-answer principle. Processing a question (query) is performed through a set of modules: the Filter Unification Module (FUM) and the inference module for hypothesis rules and transformation rules.

3.12.1 Matching Module: Filter Unification Module (FUM)

This module uses the HClass ontology to match (unify) predicate occurrences from the knowledge base with a query written in the form of a predicate occurrence. This operation is also based on the generalization/specialization principle between concepts/instances defined in the HClass ontology. Any predicate occurrence matched with the query is then considered a plausible answer.

3.12.2 Hypothesis Rule – Transformation Rule

A hypothesis rule consists of a premise and one or more conditions. Each condition corresponds to a reasoning step, as shown in Figure **??**. A hypothesis rule allows explaining the causes that led to the recognition of a context by reconstructing semantic links between events. For example, it can explain why an air conditioner stopped working during a given time interval, despite high temperatures. The underlying idea here is to prove the existence of a predicate occurrence in the knowledge base indicating that a person stopped the power supply to the air conditioner.

If it is impossible to find an answer to a query associated with a hypothesis rule, it is always possible to obtain a response by transforming the query into a new one. This transformation is carried out through one or more transformation rules.

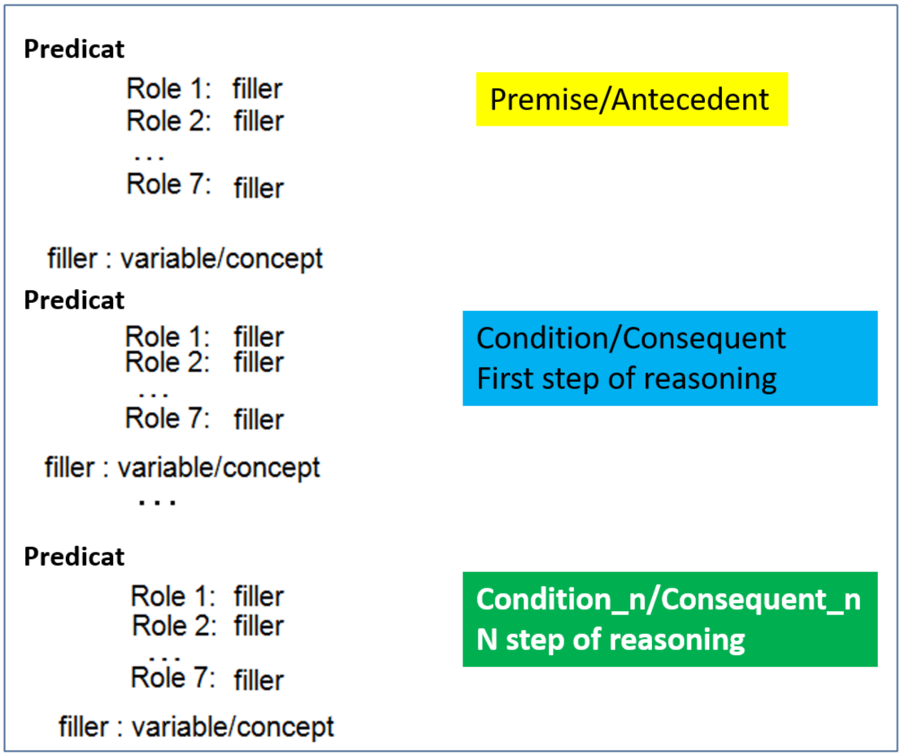


Figure 3.5: General schema of a hypothesis or transformation rule.

A transformation rule consists of an antecedent, which corresponds to a generalization of the initial query created from the conditions of a hypothesis rule, and one or more consequents, as shown in Figure **??**.

Both hypothesis and transformation rules consist of a predicate, role(s), attribute(s), and a set of constraints.

3.12.3 Reasoning over Observation History

Before describing the NKRL inference procedures, we provide the following preliminary definition:

Definition 1: All inference procedures are triggered according to the rule:

$$X \quad \text{iff} \quad Y_1 \text{ and } Y_2 \text{ ... } Y_n. \tag{3.3}$$

where X represents the context to be inferred, and $Y_1, \ldots, Y_n$ are the reasoning steps required to perform all matching operations with predicate occurrences stored in the knowledge base. The reasoning foundations introduced in this chapter will be further detailed in the "next chapter, Querying and Processing Mechanisms section", where the inference and contextual

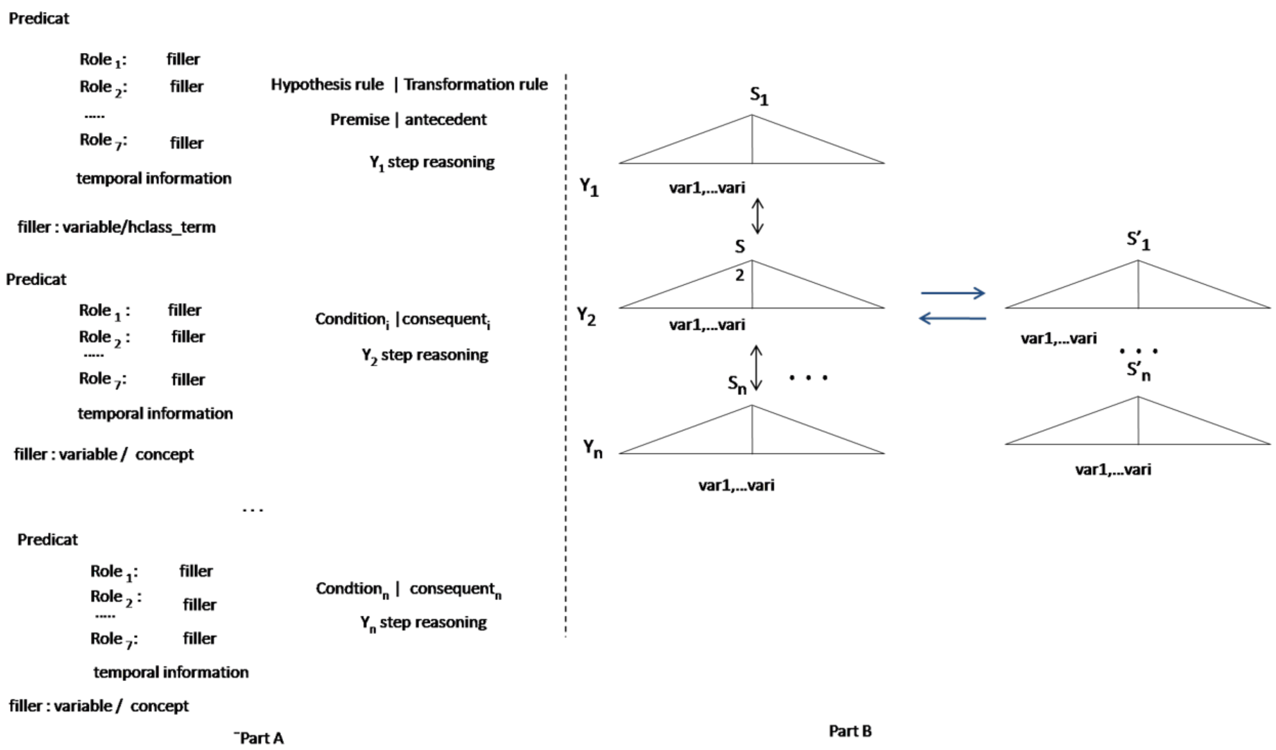


Figure 3.6: NKRL Inference Process.

knowledge processing models are described. We will also show how these inferences intertwine with the HTemp ontology, linking temporal dynamics with the contextual reasoning process.

Figure **??** illustrates the inference process for context recognition. The process works as follows:

- For each constraint assignment to a variable *vari* in each premise/antecedent, a predicate occurrence is instantiated. This occurrence, called a search pattern, represents a query that the inference engine attempts to unify with predicate occurrences in the observation history. Each condition or consequent of a hypothesis or transformation rule corresponds to a reasoning step, denoted as Y_i (Figure **??**).

- When an answer is found for a search pattern, it means that the condition/consequent is satisfied. The inference continues by processing the next condition/consequent. Successive queries over the observation history proceed until the final reasoning step Y_n (Figure **??**).

Two cases can occur:

1. In the case of a transformation rule, the search pattern constructed from the hypothesis

rule can be substituted by another pattern X' to continue processing the hypothesis rule.

2. In the case of a hypothesis rule, a plausible answer explaining the context X_1 has been inferred.

From an implementation perspective, an NKRL query corresponds to a SPARQL query over an OWL knowledge base. For example:

Query 1:

```
PREDICATE EXIST
SUBJ: human\_being : location\_
```

Query 2 (with temporal constraints) :

```
PREDICATE EXIST
SUBJ: human\_being
date-1: 11/4/2024/11:30
date-2: 11/4/2024/11:40
```

3.13 Toward Dynamic and Narrative Knowledge Representation

In this section, we presented the NKRL (Narrative Knowledge Representation Language) knowledge representation and reasoning model. Knowledge representation in NKRL is based on the HClass (Concept Hierarchy) ontology and the HTemp (Event Hierarchy) ontology. The latter is well-suited for representing n-ary relationships. NKRL relies on inference mechanisms to establish implicit or explicit semantic relationships between knowledge. It allows the combination of predicates and conceptual roles to adequately encode narrative information and to construct semantic links (causality, purpose, etc.) between elementary events. The NKRL reasoning process is based on the question (query)-answer principle and a matching mechanism for processing hypothesis and transformation rules. To exploit this model, an approach for annotating elementary and dynamic events was proposed. Àcross this part of the chapter, we have shown that the high expressiveness and narrative reasoning of the NKRL model makes it particularly well suited for the recognition of non-trivial contexts that may be related to time.

Chapter 4

Evaluation and Experimental results

4.1 Introduction

This chapter presents the experiments conducted to evaluate the contributions of this work. Three main areas are explored.

The first concerns the semantic annotation layer, which allows for the representation of heterogeneous entities evolving over time and interacting with each other, while facilitating the analysis of raw sensor data.

The second area focuses on the NKRL narrative model, applied for the first time to ambient intelligence, combining the HClass concept ontology and the HTemp event ontology. This approach integrates the temporal dimension and represents events and contexts hierarchically for more precise reasoning.

The third area explores the recognition of dynamic activities and events via a query processing mechanism (QPM) and reinforcement learning methods (DQN), capable of analyzing spatiotemporal data, predicting future situations, and adapting in real time to intelligent environments.

The following sections detail each of these contributions, their methods and the experimental results obtained.

4.2 Experimental Datasets for Activity Recognition in Ambient Intelligence Environments

Washington State University's Center for Advanced Study in Adaptive Systems (CASAS[1]) is now an international reference in research on smart environments and ambient intelligence. Its ambient sensor datasets, such as CASAS Aruba or MIT PlaceLab[2]. The CASAS project aims to create "off-the-shelf" smart home environments (smart home in a box) for re-

---

[1] `https://casas.wsu.edu/datasets/`

[2] `https://www.media.mit.edu/about/overview/`

search in ambient intelligence, activity recognition, elderly care, health, etc. These datasets leverage event-driven sensors—motion detectors, pressure mats, switches—to infer activities from asynchronous event sequences. Modeling temporal dependencies and managing sparse and irregular data is essential. Unlike datasets like WISDM[3] , which are based on inertial sensors and low-frequency continuous streams, event-driven datasets like CASAS Aruba rely on discrete activations. They therefore require learning models capable of capturing non-uniform temporal patterns and reasoning about incomplete sequences. CASAS Aruba focuses on a single individual, which facilitates model customization but also increases the risk of overfitting related to a particular environment or user. In a dataset such as CASAS Aruba, the sensor architecture demonstrates strong adaptability and robustness in the face of heterogeneity in sensory modalities and activity contexts. Integrating real-world data from the CASAS project validates the practical relevance and generalizability of the proposed framework for capturing the temporal, spatial, and contextual nuances of human activities.

4.2.1 CASAS–Aruba dataset

1. The site lists more than 20 main smart home datasets (with residents, sensors, multi-residents, families, etc.) as well as mobile (smartwatches).
2. For each dataset, we find metadata such as: testbed (location), number of residents and participants, description (ADL = activities of daily living, daily life, etc.), whether annotated or not, and date of last update.

The set contains annotations for eleven distinct activities: meal preparation, relaxation, eating, work, sleep, washing dishes, going to bed or using the toilet, entering and leaving the home, cleaning, breathing, and others. The "Other" category represents nearly 50% of the instances, corresponding to unannotated or ambiguous periods typical of natural environments. This sensory diversity makes it possible to assess the robustness of reasoning models in real-world contexts, where data scarcity and sensor heterogeneity represent major challenges.

4.2.2 WISDM Dataset

Unlike ambient sensors, smartphone-based datasets such as WISDM rely on continuous inertial sensors. The full dataset includes 1,098,209 instances divided into six activities: walking, jogging, standing, sitting, and climbing and descending stairs. The classes are unbalanced:

---

[3] `https://archive.ics.uci.edu/dataset/507/wisdm+smartphone+and+smartwatch+activity+and+biometrics+dataset`

walking represents 38.6% of the total, while standing represents only 4.4%. Due to the large volume of the CASAS Aruba dataset (approximately 1,048,576 rows), preprocessing is a critical step. To ensure computational feasibility, only the first four days of data (20,897 events) were retained for the experiment, while preserving the representativeness of the activities and sensors.

Data were recorded from 36 participants wearing an Android smartphone and included accelerometer and gyroscope on both devices (thus 4 sensor streams in total) at a frequency of 20 Hz (1 measurement every 50 ms). These smartphones were placed in the front leg pocket during their daily activities. The main sensor was a triaxial accelerometer sampled at 20 Hz, complemented by an integrated motion sensor. Due to its popularity, this dataset has become a reference in the HAR community, facilitating comparison between approaches and strengthening the reproducibility of studies [?].

Robust preprocessing is essential to ensure model quality. Key steps include:

- Encoding activity labels into numeric values;
- Linear interpolation of missing values;
- Normalizing features between 0 and 1;
- Segmentation into fixed time windows (80 time steps);

4.2.3 Justification and Suitability of the Selected Datasets

The use of rich, structured, and well-documented datasets is essential for the development and evaluation of intelligent systems in robotics and ambient intelligence. Such data enables the modeling of residential environments, human activities, and contextual state transitions, which are critical for reasoning, perception, and decision-making processes. In this context, datasets combining ambient sensors and wearable devices provide a valuable experimental framework for studying activity recognition, context-aware reasoning, and human-centered interaction. The following points highlight the main advantages and research opportunities offered by the considered dataset, particularly in terms of data representation, model evaluation, system generalization, multi-modal sensing, temporal dynamics, and reasoning efficiency.

1. Robotics & Ambient Intelligence: This data allows for modeling residential contexts, state transitions, and activities, which can be used to power reasoning systems, robotic agents, and smart homes.

2. Enables testing of activity recognition models derived from wearable sensors, which complements ambient data (environmental sensors) such as those from CASAS Aruba.
3. Offers a standardized and well-documented format, which helps focus on modeling (e.g., segmentation, windowing, encoding) rather than raw data collection.
4. The diversity of activities and participants allows for testing system generalization or comparing customized vs. global models.
5. The "multi-sensor, multi-model" nature (smartphone + smartwatch, accelerometer) offers the opportunity to explore sensor fusion, multi-modal processing, or hybrid architectures.
6. Significant temporal data: Since these are sequences of events captured over time, the dynamic aspect is essential. If reasoning must be based on the evolution of a context or activity, this data is very useful.
7. In an experimental case, about 200 SPARQL queries were executed on the CASAS Aruba game, with a very satisfactory average execution time (around 200 ms) and a complexity classified as medium, confirming the system's effectiveness for moderately complex query scenarios.

Given that this thesis explores narrative representation, dynamic reasoning, ubiquitous robotics, and ambient intelligence, the following outlines how such datasets can be effectively integrated:

- Real-world context: These data come from real-life smart home environments with residents, allowing us to test reasoning models on scenarios close to the real world.
- Temporal & contextual evolution: The event sequences capture transitions, activities, and residents changing state, which supports the narrative approach (evolution over time, changing context).

4.3 Semantic and Temporal Modeling for Context-Aware Activity Recognition

The first axis concerns the semantic annotation layer, which enables the semantic description of heterogeneous entities evolving over time and interacting with each other. This layer also supports the semantic modeling of raw data from various sensors, facilitating analysis and reasoning on this data. The second axis highlights the use of the narrative model of NKRL, applied for the first time in the field of ambient intelligence [?]. This model enriches the classic concept ontology (HClass), structured according to the principles of generalization/specialization, with the event ontology HTemp, allowing events to be represented hierarchically and the integration of the temporal dimension into contextual analysis. The third axis focuses on the design of a query processing mechanism (QPM) for activity recognition and dynamic event and context management, illustrated in Figure ??. This mechanism leverages the hierarchical structures of semantic predicates and functional roles defined in HTemp. Ontological querying based on chronological events improves activity recognition and predicts future situations. Combining spatial and temporal data with contextual awareness provides adaptive analysis, the ability to predict events, and dynamically adjust context evaluation. Unlike classical approaches based on temporal description logic, our spatiotemporal query method refines system responsiveness, improves efficiency, and personalizes human-machine interaction. The use of ontologies allows for managing, analyzing, and understanding the semantic context of data generated by interconnected devices, sensors, and individuals in the Internet of Things ecosystem, and provides early warnings of potential risks, such as health degradation or dangerous behaviors.

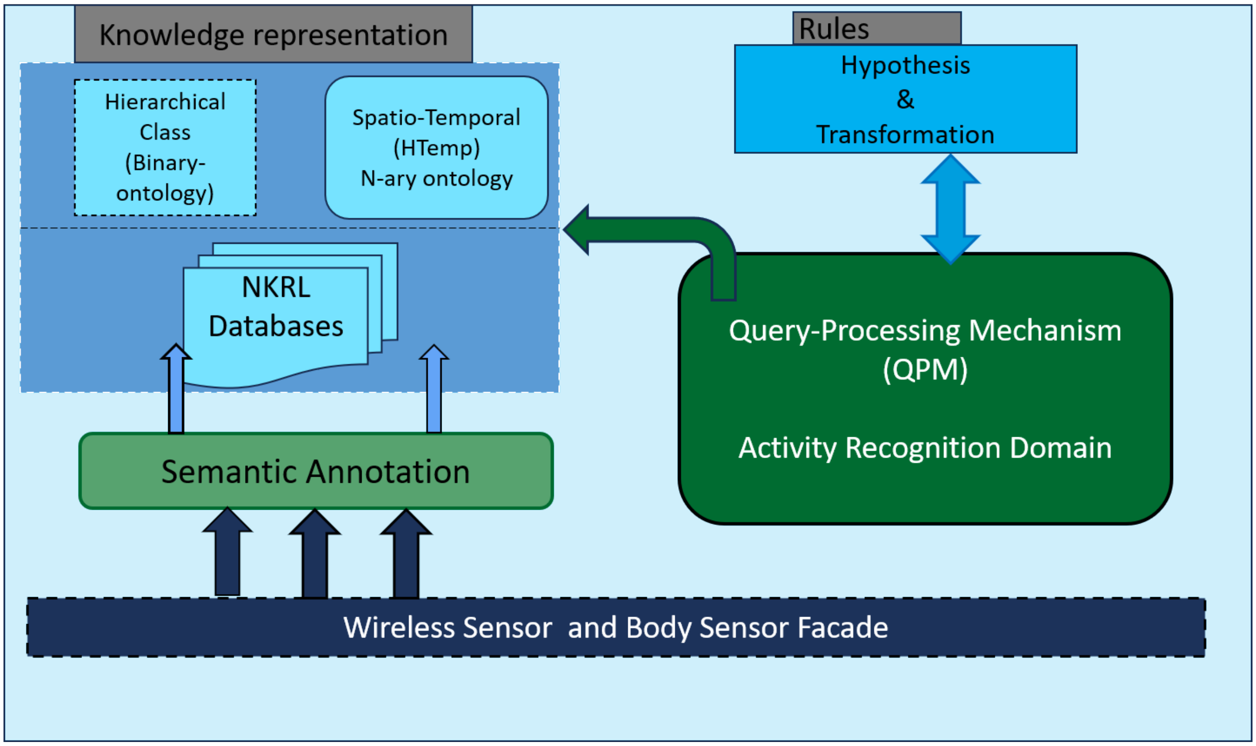


Figure 4.1: General activities and intentions recognition platform.

4.3.1 Spatio-temporal representation

According to [?] narrative events are those that take place in reality. As for [?], a narrative event provides the classical theory of narratology. The author defines narratology as a ternary structure consisting of three entities: The fable (Fabula in Latin), the story (story) and the narrative (narrative). A logical and chronological sequence of events makes up the fabula entity. The story entity is a fragment of fabula arranged into a new sequence. Finally, the narrative describes how events are narrated in a given language, media, signal, etc.

In our approach, the Allen interval's logic can be recreated relying on two properties (date 1) and (module):

1. The property (date 1) represents the event that begins at timestamp t1.;
2. Date 2 is the property that signifies the maximum time limit for the event at timestamp t2;
3. Temporal attributes can be associated with temporal modulators like begin, end, and observe (obs) to mark the start or end of an event;
4. Point time is a time stamp that indicates that the date associated with date-1 is solely a specific point in the temporal interval associated with the event. The second property, date-2, is empty;

Table 4.1: The location where the scenario takes place is depicted in this narrative event. The house referred to as HOUSE_1 here belongs to INDIVIDUAL_PERSON_1.

narrative event
ioe.b148) BEHAVE SUBJ DAVID_1: (BATH_ROOM_1) MODAL user_ TOPIC SHOWER_TAP_1 date-1: 2024/11/25/15:03 date-2: **Behave:CognitiveBehaviour**
ioe.o25) OWN SUBJ INDIVIDUAL_PERSON_1 OBJ HOUSE_1 date-1: 2024/05/25/10:00 date-2: Own:ConcreteResources

Table **??** shows two examples, the narrative event denoted by (ioe.b148) expresses that the symbol DAVID_1, which is used as filler of the SUBJ(ect) role, represents a human who is localized at the bathroom denoted with the symbol BATH_ROOM_1, the user_ filler of the Modal role describes that INDIVIDUAL_PERSON_1 is performing the activity (using the bathroom's shower tap) described in the TOPIC role as SHOWER_TAP_1. The property (date 1) depicts a specific time-point within the temporal interval corresponding to an event. As for (ioe.o25), throughout the scenario, DAVID_1 is the house owner denoted with HOUSE_1.

4.3.2 Chronological Knowledge representation

Binding narrative, a structure used to link together several events/contexts, taking into account semantic linking, are formalized by the binding operators. These operators, such as GOAL, COORD(ination), and CAUSE, play a crucial role in formalizing the logical semantic link between the narrative events using their symbolic labels (SymL). Furthermore, they allow describing complex IoE scenarios. The binding narrative can be expressed as follows:

$$(bind.operator\ [\ SymL_1\ o\ SymL_2\ o\ SemL_3...\ SemL_i]) \tag{4.1}$$

Formula **??** denoted a binary structure under the list of arguments SemL. The SymL corresponds to a symbolic label or recursively to sets of labelled lists. For instance, the narrative event ioe.b148 allows the robot to determine David's presence in the bathroom. Simultaneously, the narrative ioe.e85 indicates that the oven is in use, Figure **??**. In response, the robot sends a proposal to turn off the stovetop, a crucial action to prevent a potentially hazardous issue. This decision depicts a complex event that should be separated into three formal elementary events (derived from three different templates of the HTemp ontology):

- The temperature on the kitchen stovetop has risen (ioe.e85, Table **??**);
- The robot takes note that David is not in the kitchen since he is in the bathroom (ioe.b148, Table **??**););
- Provide an early warning, the robot moves towards BATHROOM_1 where the person is localized (ioe.m156 depicted in Table **??**);

Using the COORD operator, the narrative events (ioe.m148) and (ioe.e85) can be linked to represent the entire narrative described by (ioe.c1), Figure **??**. So, the full description of these events is represented by the unique narrative event (ioe.s2).

Table 4.2: Binding narrative events.

It is clear that there is a logical connection between ioe.e85 and ioe.b148.	ioe.c1) (COORD ioe.b148 ioe.e85)
ioe.c1 triggers the narrative event that is described in ioe.m156	ioe.s2) (CAUSE ioe.c1 ioe.a156

4.4 Experiment and results

This section provides a detailed explanation of how the inference process is implemented. We, therefore, exclude aspects such as modelling and rule editing tools that are not necessary for the system to run, as they are mostly used during the design phase. We explain thorough knowledge acquisition methods, the process of integrating perceptual information into the knowledge base, and general query processing. Context recognition requires the fundamental knowledge provided by HClass and HTemp ontologies. The HClass ontology comprises 2700 concepts, while the HTemp ontology features 165 templates.

4.4.1 A use case scenario

The following will describe a scenario demonstrating the proposed approach in a practical, real-world context. Identifying situations and providing customized assistive and monitoring services in elderly healthcare can be challenging for any system if it cannot capture and comprehend chronologically related events.

In our scenario, the robot not only gathers real-time information about the senior citizen's actions but relies on narrative querying-processing, demonstrating the effectiveness of a high level of understanding of the activities. The system is responsible for identifying the activity the person is engaged in and interpreting the associated risks. Let us now assume that David, a senior citizen living alone, wishes to prepare a meal which involves using appliances such as a stovetop and various kitchen utensils like pots and baking dishes. After 20 minutes, David heads to the bathroom and opens the shower tap. A sensor installed on the shower tap confirms when it's open, which allows the robot to determine David's presence in the bathroom. At the same time, the oven's temperature sensor detects an increase in temperature, which indicates that the oven is in use and there is no one around. The robot concludes that David cannot be in two different locations simultaneously since

David is taking a shower in the bathroom and the stovetop is turning on. The robot, acting as a vigilant companion, moves towards where David is localized and tries interacting with David by sending an audio notification to suggest turning the stovetop off. David did not respond immediately.

Two minutes later, the robot tries to ensure everything is okay and tries to confirm David's health condition. Establishing dialogue-based interaction with David will help collect information about his health. If David does not interact with the robot, he is considered unconscious, and consequently, the current context corresponds to an emergency. This contextual information is not directly measurable and, therefore, obeys complex processes in which multiple events/actions must be correlated and analyzed as they occur in time and space to determine a user status and assess the current context/situation.

Let us clarify why these analyses are crucial.

1. Chronological analysis involves understanding the sequence of events, such as moving from the kitchen to the bathroom and the time spent there;

2. If the person stops moving, the system will recognize a potential issue and react accordingly;

3. Consider suggesting or taking action, like turning off the stovetop, based on a time interval (e.g., after a long cooking session or be a while in the bathroom);

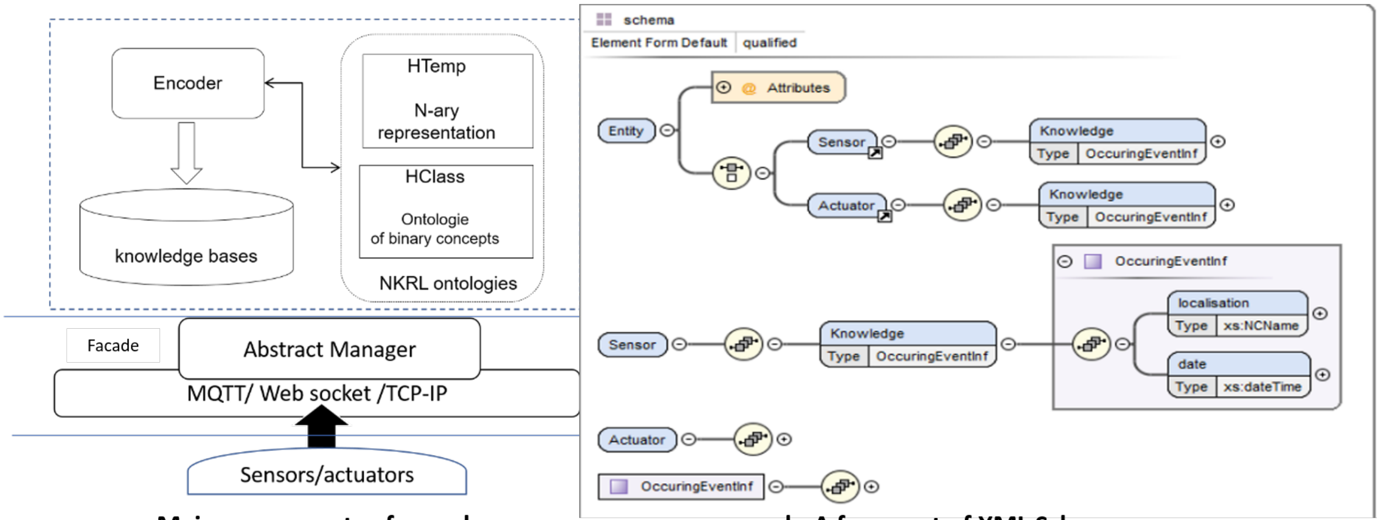
4. The chronological analysis significantly enhances safety by proactively preventing forgotten cooking sessions, thereby ensuring a secure environment free from potential fires or accidents;

4.4.2 The narrative knowledge processing

This section explains the thorough knowledge acquisition methods and the process of integrating perceptual information into the knowledge base, along with general query processing.

4.4.3 Annotation processing

The interface communication component allows communication with real-world entities through heterogeneous protocols Figure **??**. The interface transforms low-level events of virtual or physical entities generated by sensors into higher-level abstraction. The Encoder component is responsible for adding new narrative events to the knowledge base. The interface communication component (i.e., Facade) allows communication with real-world entities through MQTT protocols. Ensuring the homogeneity of the knowledge base and classifying each



a. Main components of encoder **b. A fragment of XML Schema**

Figure 4.2: Semantic annotation architecture.

entity according to its role allows for efficiently aggregating spatial-temporal events. For example, when the sensor sends information such as the shower tap open in the bathroom, the Abstract Manager performs the mapping with the narrative model to transmit it to the Encoder. In this case, the open_ property with parameter (agent (SUBJ); location; TOPIC and timestamp); see ‘Figure **??** which presents a fragment of an XML Schema that describes the content of a narrative event. Then, based on the HClass and HTemp ontologies, the data gathered from the XML file is used to generate a knowledge base representing the raw data.

4.4.4 General Querying-processing mechanism

For clarity, it is important to recall that the inference process within the NKRL framework is governed by a general rule schema that formalizes the logical structure of all reasoning operations. This schema expresses the relationship between a conclusion S and a set of premises $Y_1, Y_2, Y_3, ..., Y_n$, which must all hold for the conclusion to be inferred. The following equation defines this fundamental inference pattern:

$$S\ iff\ Y1\ and\ Y2\ ::\ Yn$$

Where S is the event/context to infer and Y_1,..., Y_n represent the reasoning steps. X, Y_1,..., and Y_n are modelled as instances of the template (narrative event). Y_1 is called condition in hypothesis rules and called antecedent in transformation rules.

var_i = h_class_term_1, h_class_term_2, . . ., h_class_term_n, var_i are constraints on variables, $S_1..Y_n$ S_1', S_n': search patterns, where S' semantically equivalent to S.

A hypothesis rule contains a premise and one or more conditions.

$Y_1..Y_n$ represent successive reasoning steps, formula **??**.

A transformation rule contains an antecedent (i.e., a left-hand side) representing the search query to transform and one or more consequents (i.e., right-hand sides) representing search patterns for which a QPM will substitute the query.

Key Points:

- The knowledge base includes individual facts that are referred to as narrative events;
- The search pattern defines the conditions that are used to retrieve a set of narrative events;
- The search pattern's conditions must be matched with the narrative events during unification;
- The set of events that meet the patterns' conditions will be the answer to the query;

The reasoning step Yi is started once the reasoning step Yi-1 has succeeded. The Yn (Equation **??**) denotes the leaf in the tree structure, which symbolizes the success of the reasoning process.

A QPM (Figure **??**) component converts during a reasoning steps a search pattern derived from the variables and their values into search patterns S_i that attempt to match and unify these queries with the knowledge stored in the knowledge base. The ontology HClass which represents a higher-level abstraction within the system allow adapting each concept/individual that occurs in the query to all subsumed concepts/indivduals.

Query Formulation: In this context, the antecedent refers to the condition or situation that prompting the system to create a query to understand the situation better. For example, the senior person has not moved from the bathroom for an unusually long time. This would involve applying semantic and chronological analysis, as well as correlating other factors, such as health status, time, and location.

4.4.5 Chronological and Semantic Analysis of Events

David's failure to hear the audio notification message results in his unawareness of the robot's interaction. This breakdown in communication disrupts the robot's on David's interaction, leading it to assume that David is in danger and the situation is an emergency. This scenario underscores the need for deep reasoning about spatiotemporal events, semantic analysis, and past and ongoing events. It also reiterates the importance of human-robot communication in the robot's decision-making process, as it is a key takeaway from the scenario.

Table 4.3: Generic hypothesis and transformation rule to understand what is happening after an alarm has been triggered

Hypothesis rule:	**Transformation rule 1:**
X1) PREMISSE: PREDICATE PRODUCE SUBJ var1 OBJ triggering_ TOPIC alarm/control_tool var1 = robot_ **Y1) CONDITION 1:** PREDICATE OWN SUBJ var1 OBJ control_ BENF var2 var2 = human_being **Y2) CONDITION 2:** PREDICATE BEHAVE SUBJ var1 MODAL user_ TOPIC var3 CONTEXT (SPECIF control_ var2) var3 = robot_ **Y3) CONDITION 3:** PREDICATE PRODUCE SUBJ var2 OBJ button_pushing TOPIC var4 { oblig } var4 = emergency_button **Y4) CONDITION 4:** PREDICATE OWN SUBJ var4 OBJ property_ TOPIC (SPECIF part_of (SPECIF var5 var3)) var5 = alarm/control_tool **Y5) CONDITION 5:** PREDICATE PRODUCE SUBJ var2 OBJ button_pushing TOPIC var4 { negv }	**ANTECEDENT:** PREDICATE OWN SUBJ var1 OBJ control_ BENF var2 var1 = robot_ var2 = human_being **CONSEQUENT 1:** PREDICATE PRODUCE SUBJ var1 OBJ detection_: (var3) TOPIC var2 var3 = building/area_component **CONSEQUENT 2:** PREDICATE OWN SUBJ var3 OBJ property_ TOPIC (SPECIF part_of (SPECIF var4 var2)) var4 = house_ **Transformation rule 2:** **ANTECEDENT:** PREDICATE BEHAVE SUBJ var1 MODAL user_ TOPIC var2 CONTEXT (SPECIF control_ var3) var1 =home_ control_system var2 = robot_ var3 = human_being **CONSEQUENT 1:** PREDICATE MOVE SUBJ var3 OBJ information_content BENF var1 MODAL (SPECIF var4 var2) var4 = alarm/control_tool

4.4.6 Extraction of implicit observations

The Table **??** contains hypotheses rules and transformation rules for causal reasoning and knowledge base querying, which search for causal links explanations by extracting and transforming relevant information from the knowledge base. The first query is adjusted to obtain relevant information or infer new causal relationships from existing data, enabling the creation of a narrative that explains the triggering alarm.

X1) Initial request (search pattern)
PRODUCE
SUBJ(ect): robot_
OBJ(ect): triggering_
TOPIC: alarm/control_tool

Table 4.4: Since David did not respond, the robot triggered an alarm

Description	narrative event
Narrative event representing the initiator (agent) who triggers the alarm	ioe.p158)PRODUCE SUBJ ROBOT_KOMPAI OBJ triggering_ TOPIC emergency_alarm CONTEXT EMERGENCY_SITUATION_1 date-1: 2024/11/25/15:28 date-2: is instance of Produce:PerformTask/Activity

The NKRL search patterns operate like database queries in conventional systems, such as those used in information retrieval (IR). Similar to database query (e.g., in SQL), a pattern in NKRL enables systems to query and obtain answers directly from the knowledge base. Nevertheless, in our approach, a pattern is a formalized representation of a query that may involve logical relationships, constraints, and conditions expressed in a knowledge representation language as instances of HTemp ontology. The pattern is used to search for information, facts, or relationships within a semantic or knowledge-based system. Therefore, when the reasoning process is performed, the explicit variables in the template are replaced with concepts (abstract categories like "person," "robot," or "location") or individuals (specific entities like "DAVID_" "BATH_ROOM_1," or "STOVETOP_1"). The constraints imposed on these variables ensure that the substitute is consistent with the knowledge base. For instance, if a template has a variable "vari" that represents a "location," only concepts or individuals classified as a location in the knowledge base would be valid replacements for this variable. In a narrative-based knowledge base, all events might be represented as structured statements or facts, often involving temporal or causal relationships (e.g., David be present in the bathroom since 15h03, The temperature increase, David heads to the bathroom and opens the shower tap). For example, if the search pattern asks for events involving David, the system will also check if the symbol "DAVID_" is a valid instance of the person_ concept or any of its subclasses (like human_being, owner_, etc.).

The query (X1) plays a crucial role in defining the event. The search pattern defined by the conceptual predicates (PRODUCE with the roles of SUBJ and TOPIC) will result in a set of narrative events that match with the specified concepts (i.e., the output of the query will consist of all instances where the robot_ is associated with the production of an alarm/control_tool).

The system symbolised by (ioe.p158, Table **??**) depicts that ROBOT_KOMPAI is the agent responsible for triggering the alarm. The consistency-checking mechanisms validate the symbol robot_ in Table **??** by relying on the HClass ontology and the constraint associated with variable var1 in the hypothesis rule. This component checks that the robot_ symbol is an instance of the alarm/control_tool concept and establishes a hierarchy of concepts from the generalisation/specialisation relationship between the emergency_ alarm concept and the alarm/control_tool concept. The inference process continues its reasoning by attempting to verify the step indicated by Y1, which corresponds to condition 1 of the hypothesis rule. The new pattern is produced (see pattern (Y1)) by utilising the value var2 = human_being and the var1 = robot_ symbol. Condition 1 is used to check that the filler represented by ROBOT_KOMPAI is an agent (i.e., subconcept of control_tool) and monitoring system.

Y1: condition 1) PREDICAT: OWN
SUBJ(ect): ROBOT_1
OBJ(ect): control_
BENF: human_being

4.4.7 Using a transformation rule

Based on an ontology-based system, the query (Y1), the robot tries to find direct matches or relevant data. Since the direct search might not yield a valid or concrete result, the robot employs a transformation rule from Table **??**. This rule infers implicit knowledge not directly available in the knowledge base but can be derived logically. Applying the transformation rule, the system finds a form of knowledge not directly queried as implicit knowledge. The narrative event (ioe:p159), Table **??** denotes a specific event where someone is in the bathroom. The property detection_ is a role that holds the "object" of the event as a filler of the OBJ(ject) role. DAVID_ represents an individual human being. So, DAVID_ is the filler of the Topic. Thus, the querying processing infers that DAVID_ (a human being) is in the bathroom. The latter knowledge is not directly found through the query but is derived through implicit knowledge inferred from the system's transformation rule.

Table 4.5: Results for transformation rule 1

Description	narrative event
Narrative event specifying that DAVID is located in the bathroom.	ioe.p159)PRODCE SUBJ ROBOT_KOMPAI OBJ detection_: BATH_ROOM_1 TOPIC DAVID_ date-1: 2024/11/25/15:03 date-2: is instance of is instance of Produce:Assesment/Trial

The first condition of the hypothesis rule has been satisfied, and the reasoning process can now proceed with the processing of condition 2. In this step, the inference engine tries to find within the knowledge base any information indicating that the robot has attempted to establish a dialogue with DAVID_ (i.e., David as a person), thereby creating the search pattern (Y2).

Y2) PREDICATE BEHAVE
SUBJ(ect) :ROBOT_KOMPAI :
MODAL(ity) : user_
TOPIC : robot_
CONTEXT : (SPECIF control_ DAVID_)

Table **??** captures the core meaning of the robot_David interaction. The whole semantic meaning that reflects the relationships and actions is described as follows:

Actions/Relations: Semantic Representation

- **Communication (Robot, David**: The robot plays a crucial role in the communication process, being the entity responsible for interacting with David;
- **Modality (Robot, Touch Screen, David)**: The robot's touch screen serves as a powerful tool, enabling DAVID to communicate effectively;

- **Notification (David, Touch Screen, Help)**: A message was sent to David to inform him that he can request assistance using the robot's touch screen.

Transformation Rule 2 (Table ??)

The following formal representation provides a clear and concise explanation of how the message is transmitted, who receives it, and the communication mode.

- MOVE(ROBOT_KOMPAI, DAVID_, "You can use the touch screen to request help"): DAVID_ is being notified by the robot that he can use the robot's touch screen to request help;
- BENF(ROBOT_KOMPAI) : It is evident that ROBOT_KOMPAI is the intended recipient of the message if DAVID_ responds;
- MODALITY(touch_screen) : states that the robot's touch screen is the communication mode;

Table 4.6: Results for transformation rule 2

David can use the touch screen to interact with the robot	ioe.m145) MOVE SUBJ DAVID_:BATH_ROOM OBJ confirmation_statement BENF ROBOT_KOMPAI TOPIC (SPECIF assistance_ ROBOT_KOMPAI) date-1: 2024/11/25/15:25 date-2: Produce:Assessment/Trial

The querying-processing checks that the ROBOT_KOMPAI symbol is an instance of the robot_ concept and the touch_screen concept is a sub-concept of alarm/control_tool. The purpose of the third and fourth steps is to provide more information about the message that was notified to DAVID_. It is about finding explicit proof that the robot moves towards the location where David is localized to propose to him its assistance. The inference engine uses patterns (Y3, Y4) by utilizing the value var4 = emergency_button in (Y3). The search pattern (Y3) is designed to explore past events (according to their temporal interval) and find narrative events that indicate DAVID_ should press the emergency button. The search pattern (Y4) aims to retrieve explicit knowledge indicating that the emergency button is an actuator embedded in the robot.

Y3) PREDICATE PRODUCE
SUBJ(ect) : DAVID_
OBJ(ect): button_pushing
TOPIC: emergency_alarm

Y4) PREDICATE OWN
SUBJ(ect): SOS_BUTTON_1
OBJ(ect): property_
TOPIC:(SPECIF part_of (SPECIF alarm/control_tool ROBOT_KOMPAI)

The search pattern (Y3) derives the answer depicted in Table **??**. The oblig(action) modulator expresses obligations, permissions, and prohibitions in formal logic to validate an emergency situation. The narrative event (i.e., ioe,o24) indicates that the SOS_BUTTON_1 button is part of the robot's touch screen, and this relationship is established using a "part_of" property. After treating condition 5 of the hypothesis rule, the inference engine will verify that David did not press the emergency button to explain why the alarm was triggered. The

Table 4.7: The result for condition 3 and condition 4, hypothesis rule

Description	narrative event
Narrative event specifying that David Must push the emergency button annotated with SOS_BUTTON_1 symbol	**The result for condition 3** ioe.p160)PRODUCE SUBJ DAVID_1 OBJ button_pushing TOPIC SOS_BUTTON_1 {oblig} date-1: 2024/11/25/15:26 date-2: is instance of Produce:PerformTask/Activity
The emergency button is part of the robot's touch screen	**The result for condition 4** ioe.o24) OWN SUBJ DAVID_:BATH_ROOM OBJ property_ BENF ROBOT_KOMPAI TOPIC (SPECIF part_of (SPECIF touch_screen ROBOT_KOMPAI)) {obs} date-1: 2024/11/25/14:55 date-2: is instance of Own:CompoundProperty

(Y5) search pattern below is used to infer this knowledge.

Y5) PREDICATE PRODUCE
SUBJ(ect) : DAVID_
OBJ(ect): button_pushing
TOPIC: SOS_BUTTON_1
{negv}

Table 4.8: Formal narrative mark of negative events in our querying-processing system

Description	narrative event
narrative event specifying that the emergency state has been trigged because David did not push the emergency button after the fall has been observed.	ioe.p161)PRODCE SUBJ DAVID_ OBJ button_pushing TOPIC DAVID_ CONTEXT LIVE_SAVING_BUTTON_1 {negv} date-1: 2024/11/25/15:05 date-2: is instance of Produce:PerformTask:Activity

A crucial aspect of our work is the reasoning process, which is significantly driven by a formal narrative representation. Modulator {*negv*} is a formal narrative mark of negative events in our querying-processing system. It represents negation denoting an event's negation (in this case, not pushing the emergency button). The rule processing hypothesis, derived from the (X1) initial request, plays a pivotal role in recognizing the emergency context situation. The successive reasoning process, crucially involving the consideration of missed actions and the overall chronological of events, is instrumental in understanding the sequence of events that led to the triggering an emergency situation.

4.5 Evaluation and Scalability

The purpose of the use case is to assess the proposed framework's performance in real-time, with a focus on response time and emergency context processing as follows:

- **Detecting Inactivity**
  1. **Goal**: Determine if the system can recognize when someone has left an activity, interrupted it, or been inactive for a specified period, and categorize it as a potential emergency;

    2. **Expected Action 1**: In order to respond, the system should activate an emergency protocol;
    3. **Expected Action 2**: To ensure user safety and prevent accidents, the system should recommend preventative safety measures (such as turning off the stovetop;

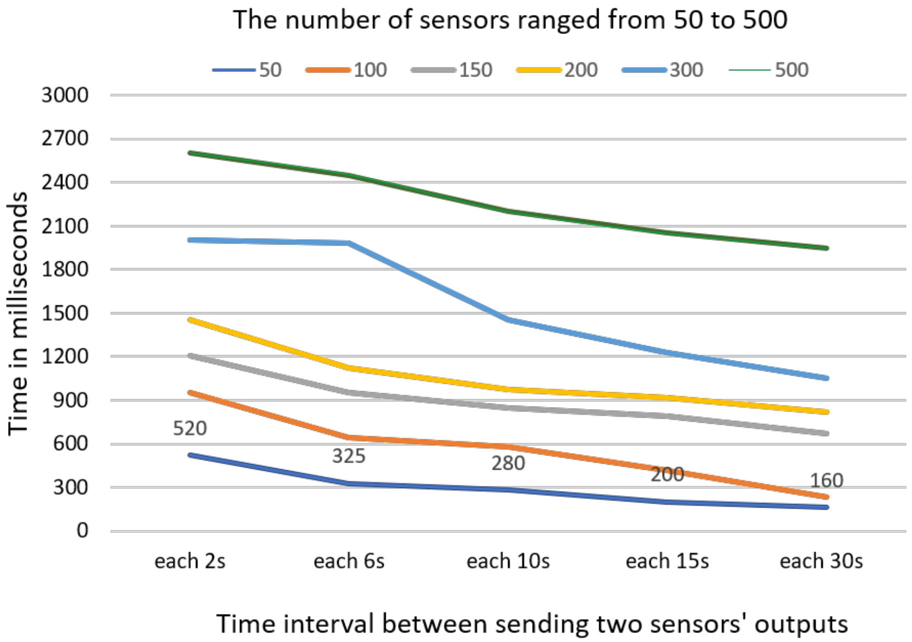
- **The Framework's evaluation criteria**
    1. **Real-Time Responsiveness**: What is the system's response time to recognizing inactivity or dangerous contexts and taking action?
    2. **User Trust and Intervention**: User Trust and Intervention : The system's ability to suggest or take preventive actions without constant user intervention is dependent;

Through our narrative querying-processing approach, the system can be both responsive and able to prevent accidents in real time, while also taking into account the safety of the user.

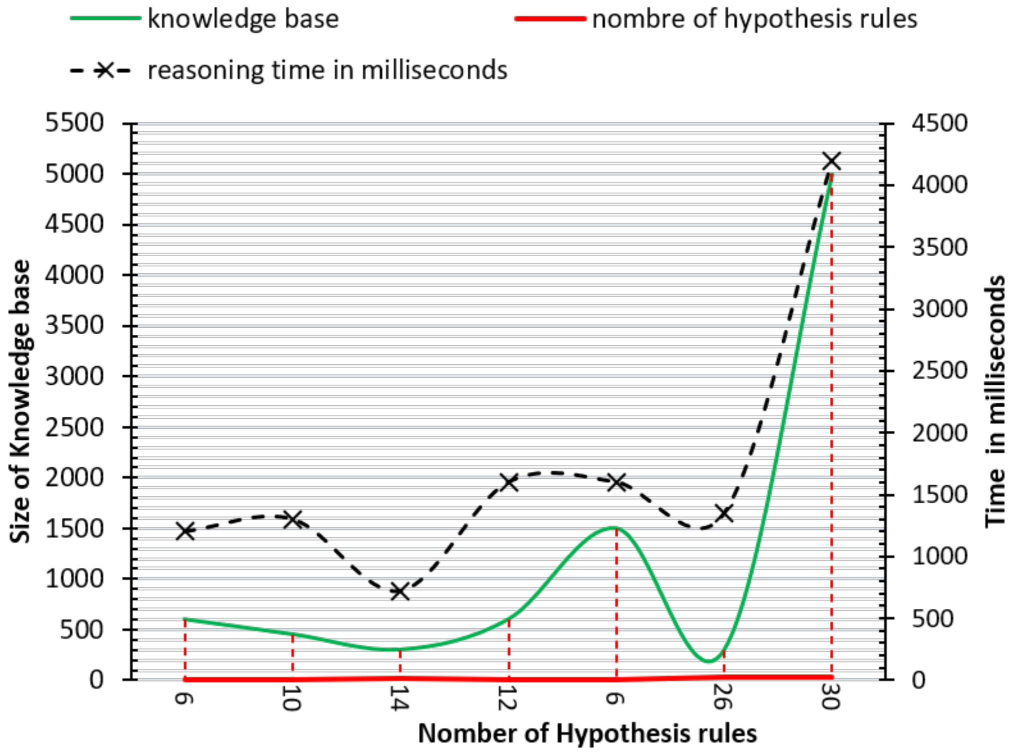
The narrative model balances a trade-off between reasoning time and the amount of context knowledge inferred. The model can infer a broader and deeper understanding of implicit knowledge while taking more time to combine hypothesis rules with transformation rules. Recognizing complex situations or removing doubts is crucial in emergency management. The effectiveness of this approach lies in its ability to recognize complex and specific contexts, particularly in scenarios that do not require immediate response times but require deep contextual understanding. Emergency management and doubt removal require a response time of 3.8 seconds to recognize context **??**. The querying-processing approach operates efficiently for real-time applications because it falls within an acceptable range. The response covers the time it takes an Abstraction Layer to process sensor outputs, encode them, and add facts to a knowledge base.

Our evaluation of scalability regarding sensor outputs was comprehensive. We developed a set of synthetic scenarios that incorporate HClass concepts and up to 30 hypothesis rules. We also included 24 transformation rules. The number of sensors ranged from 50 to 500. We conducted rigorous testing of the platform multiple times for each scenario and measured the average execution time across various parts of the architecture. The effectiveness of the proposed representations is measured by relying on both time intervals and points to recognize an activity effectively. Therefore, elementary events containing points and intervals were exploited to measure the response times of the reasoning process. First, we sought to infer contexts based solely on hypothesis rules. Subsequently, the semantic relationships extracted from the hypothesis rules were combined with transformation rules. The experiments were conducted on a PC with the Intel Core i5 processor, Dell Latitude 5550 15p, 16GB of RAM, and a 500GB SSD. It is crucial to point out that all the executions were done in a single-threaded way. Each test run was designed to contain 6-30 hypothesis rules and 12-24 hypothesis and transformation rules.

The figure serves as a comprehensive visual guide to the essential transformation process from sensor perception to NKRL knowledge representation (i.e., narrative event). This interface is not just a tool, but a vital communication channel that aligns real-world sensor data with predefined knowledge templates. This alignment is key to ensuring that real-world situations are consistently and coherently mapped to the knowledge bases. This approach is versatile and can be applied across domains where sensor data plays a pivotal role in decision-making. For instance, a system with around 250 sensors dispersed in a home automation environment can maintain adequate context awareness without causing a bottleneck, thanks to the short time interval between sending two sensors' outputs, Figure **??**. The figure also illustrates how data annotations in semantic representation enable actions to be executed in near real-time, ensuring the system's responsiveness. The annotation process is significantly influenced by each sensor's signal transmission time differences; the time annotations decrease when there is a longer gap between two sendings. For example, a door/window sensor may not need to transmit a signal every second, as it only matters when the state changes (open/closed). Similarly, for human health monitoring, wearable sensors can transmit updates every 180-300 seconds, providing sufficient data for the application without overburdening the system.

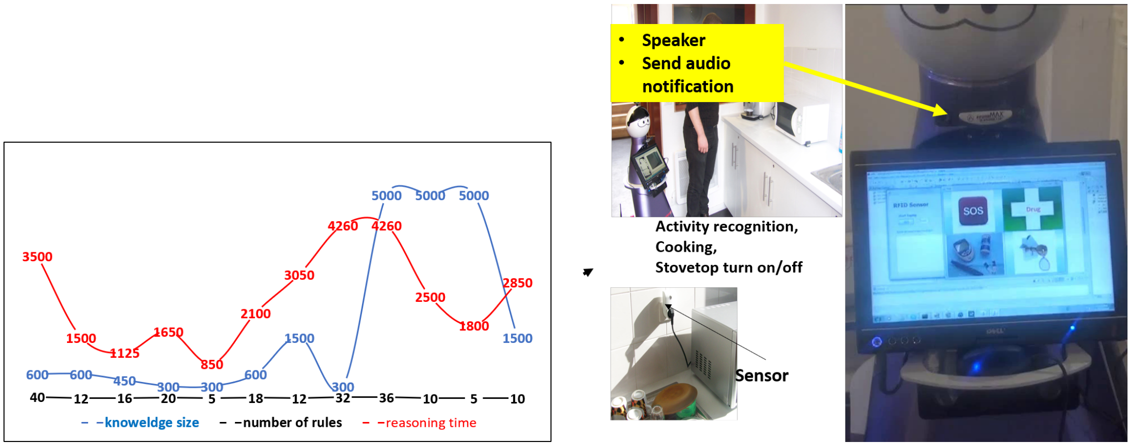


(a) Real time Semantic Annotation



(b) Average reasoning time with hypothesis rules

Figure 4.3: Evaluate the scalability of a system concerning sensor outputs while considering only hypothesis rules



(a) Average reasoning time combining hypothesis and transformation rules

(b) Robot and push button are used to detect and confirm early warning contexts.

Figure 4.4: A simulation: Assess the proposed framework's performance in real-time. Response time to recognizing inactivity or dangerous contexts and taking action?

4.6 Reinforcement Learning with DQN for Real-Time Activity Recognition

To enhance system adaptability, we explore reinforcement learning (RL) methods. Deep Q-Networks (DQNs), capable of handling sequential decision-making problems, are used for real-time sensor-based human activity recognition (HAR) [?]. Our approach considers HAR as a sequential decision problem, where a resource-efficient agent observes short intervals of sensor features, predicts the corresponding activity, and adjusts its actions based on the rewards received from the environment. By using the WISDM dataset to simulate sensor inputs in real time, this method improves continuous learning, reduces dependence on labeled data, and effectively adapts to intelligent and dynamic environments. Thus, the chapter illustrates how the combination of semantic modeling, narrative reasoning, and reinforcement learning techniques enables the design of a robust system capable of recognizing, predicting, and reacting to events in complex and changing ambient environments.

4.6.1 Power Energy Analysis

The first aspect is a control energy power system which supplies sensors and intelligent devices at the smart home with electricity (energy) and brings emergency green solutions in case of electricity outage by some harvesting techniques based on wind and solar systems to keep the smart home always in power sufficiency. Power sufficiency refers to the state where the smart home has enough energy to meet its needs, even during peak demand periods or

Table 4.9: Examples of sensor description and output data in RDF.

Subject	Predicate	Object
http://ioeActivity.univ-bba/event25	http://ioeActivity.univ-bba/date	"2024-10-28"
	http://ioeActivity.univ-bba/time	"04:26:18.557461"
	http://ioeActivity.univ-bba/device	"BedroomABed"
	http://ioeActivity.univ-bba/status	"On"
	http://ioeActivity.univ-bba/activity	"Sleep"

in the event of an outage. This ensures continuous operation and comfort for the residents. The second one is to assist an elderly special needs one, where we present a scenario of an electricity outage at night, causing an invalidity of medicines in the freezer. This problem presents a risk for the assisted person and must be detected and notified before he takes his drug by relying on an intelligent system which uses sensor output.

Our method utilizes ontology-driven knowledge representation techniques to translate unstructured sensor data into a structured semantic framework. We use the CASA (Center for Advanced Spatial Analysis) Datasets related to environmental monitoring developed and shared by the CASA research group at University College London (UCL). This process involves converting raw sensor readings into RDF triples, a key step that captures the data's semantic meaning and enables us to derive detailed insights into activity patterns, contextual elements, and behavioural trends. We achieve this by employing SPARQL, a query language for querying RDF datasets. Our goal is to comprehensively understand the motivations and contexts surrounding various events by analyzing the relationships between activity events, the time intervals between their occurrence, and contextual factors such as power outages. Using a querying and processing system, our approach facilitates high-level data integration and reasoning. As shown in the Table **??**, each event is translated into an RDF triple, consisting of a Subject, Predicate, and Object.

One of the primary advantages of this integration is the achievement of energy savings and enhanced efficiency. Real-time monitoring capabilities provided by IoT devices enable users and systems to promptly identify and address energy wastage. Based on real-time occupancy and pre-set schedules, automated adjustments to lighting, HVAC systems, and appliance usage ensure that energy is only consumed when and where it is needed. In smart grids, the integration facilitates the optimization of energy distribution and load balancing, ensuring that electricity is delivered efficiently across the network. Furthermore, this integration plays a crucial role in efficiently utilising renewable energy sources, allowing for better management of their intermittent nature and maximizing their contribution to the energy supply.

Our research, inspired by numerous studies, demonstrates the effective transformation of raw sensor outputs into knowledge descriptions using semantic models such as RDF and

SPARQL. The key contribution of our work is the development of a novel framework for ontology-based energy analysis. This framework, which leverages RDF knowledge representation and SPARQL query processing, has the potential to significantly impact the field by enabling in-depth exploration of events based on their temporal sequences, spatial locations, and contextual timing.

A symbolic representation of the user environment and ontological reasoning are excellent at contextualising activities by establishing connections between objects, actors, and environments, a skill that is essential for accurately interpreting human behaviour and any power outages.

The data is transformed into RDF triples, semantically encoding the relationships between actions, their occurrences, and contextual elements within the smart home environment through structured ontology mapping. This semantic model supports the inference of activity patterns and behaviours, enabling the execution of advanced SPARQL queries. Figure **??** provides an overview of the ontology-based knowledge base. The complete source code is available on our GitHub repository [4].

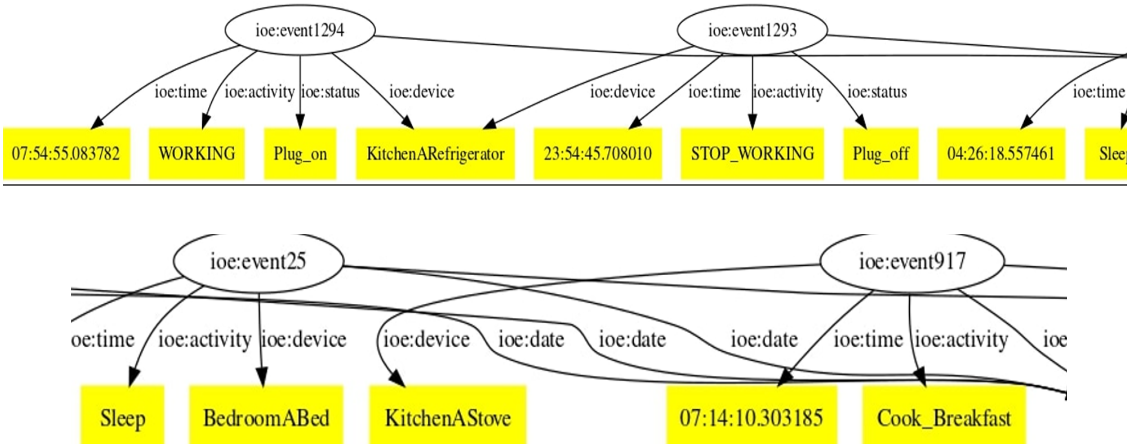


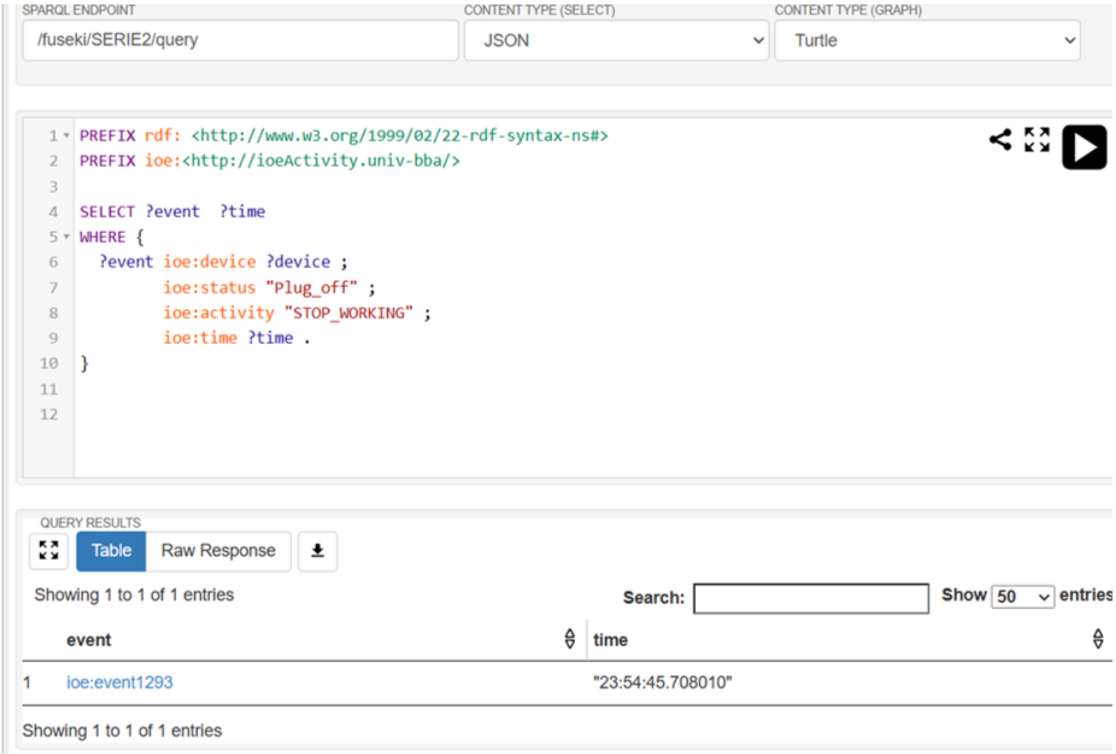
Figure 4.5: A fragment of the RDF ontology generated from the signal sensors' output of the casa dataset `https://casas.wsu.edu/datasets/`.

Consider the following scenario for a smart home powered by solar energy. Imagine a senior living alone in a smart home equipped with solar panels, home batteries, and a network of devices connected to the IoT. The house generates its own electricity during the day and stores excess power in batteries for use at night. Without an intelligent system, energy might be wasted—devices could run during low-production hours, and excess midday solar energy might go unused. However, with an intelligent energy management system, this case study could be managed as follows:

---

[4] `https://github.com/wahab-maza`

1. Power Outage Detection: When the smart freezer detects a power outage, it immediately sends an alert to the smart home's central control system;
2. Diagnostic Request: Upon receiving the alert, the control system uses a SPARQL querying processing to request a detailed diagnostic to identify the cause of the power interruption, Figure **??**;
3. Switch energy: Simultaneously, the control system queries the power management system to quickly identify and switch to an alternative energy source available within the smart home (e.g., battery backup or solar storage);
4. Contextual Awareness: During this event, an assisted person in the smart home moves toward the kitchen to take a scheduled insulin shot. The control system recognizes this action based on time, location, and user behaviour patterns. Given the detected power outage, the control system sends an urgent notification warning that the insulin may no longer be valid due to improper refrigeration;



SPARQL ENDPOINT: /fuseki/SERIE2/query
CONTENT TYPE (SELECT): JSON
CONTENT TYPE (GRAPH): Turtle

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX ioe:<http://ioeActivity.univ-bba/>

SELECT ?event  ?time
WHERE {
  ?event ioe:device ?device ;
         ioe:status "Plug_off" ;
         ioe:activity "STOP_WORKING" ;
         ioe:time ?time .
}
```

Showing 1 to 1 of 1 entries

Search: Show 50 entries

	event	time
1	ioe:event1293	"23:54:45.708010"

Showing 1 to 1 of 1 entries

Figure 4.6: SPARQL Query allows us to get knowledge about power outages and it's time occurring, see Figure **??**.

4.6.2 Data Preprocessing & Feature Extraction

To improve system adaptability, we leverage reinforcement learning (RL), employing Deep Q-Networks (DQNs) to address real-time, sensor-based human activity recognition (HAR). In this framework, HAR is treated as a sequential decision-making problem: a resource-efficient agent monitors short intervals of sensor-derived features, predicts the corresponding activity, and updates its actions based on environmental rewards. Using the WISDM dataset to simulate real-time sensor inputs, this approach enhances continuous learning, minimizes reliance on labeled data, and adapts effectively to dynamic intelligent environments.

Overall, this chapter demonstrates how integrating semantic modeling, narrative reasoning, and reinforcement learning enables the development of a robust system capable of recognizing, predicting, and responding to events in complex, evolving ambient settings.

To prepare the data for learning, the cleaned sensor stream was segmented into fixed-size time windows of 50 samples each, corresponding to roughly 2.5 seconds of activity. For each window, we computed simple yet informative statistical features commonly used in HAR literature: the mean and standard deviation for each axis (x, y, z). This resulted in a six-dimensional feature vector per window: $\mu_x, \mu_y, \mu_z, \sigma_x, \sigma_y, \sigma_z$. Each feature vector was tagged with the corresponding activity label and served as the observation input for the reinforcement learning agent.

We modeled the activity recognition problem as a Markov Decision Process (MDP), where each observation (feature vector) represents a state, and the agent's action corresponds to selecting an activity label. The agent receives a reward of +1 for a correct prediction and -1 otherwise. Importantly, each step is treated as an inde pendent decision, with no temporal dependence between successive states. This design simplifies the problem and allows the agent to focus on learning accurate single-step classifications. The state space is continuous, composed of six real valued features, while the action space is discrete and includes all possible activity classes in the dataset.

4.6.3 Reinforcement Learning Environment Design

To support the learning process, we created a custom environment following the OpenAI Gym interface. Within this environment, the agent receives randomly sampled feature vectors from the training set, selects an activity label as its action, receives a reward based on the correctness of its prediction, and then proceeds to the next sample. This setup enables online learning by continuously exposing the agent to diverse activity instances, allowing it to learn progressively from both correct and incorrect predictions.

The learning agent is implemented using a Deep Q-Network (DQN), which estimates the value of each possible action in a given state. The network architecture consists of two fully connected hidden layers, each with 64 neurons and ReLU activation functions, followed by an output layer with one neuron per activity class to produce a Q-value for each action. The DQN is trained to minimize the temporal difference (TD) error using the mean squared error loss function. Optimization is performed with the Adam optimizer, which is well-suited for reinforcement learning due to its adaptive learning rates and efficient convergence properties.

4.6.4 Training Strategy

The agent is trained over a series of episodes, with each episode involving multiple interaction steps with the environment. We adopt an ε-greedy exploration policy: the agent starts with a high exploration rate ($\xi = 1.0$) to encourage diverse experiences and gradually reduces it to 0.01 as learning progresses, shifting toward more exploitation of known good actions. To improve sample efficiency and stability, we use a replay memory buffer that stores past experiences (state, action, reward, next state). During training, random mini batches are drawn from this buffer to update the network, preventing the model from overfitting to recent transitions. We also employ a target network that is periodically synchronized with the main DQN to further stabilize learning.

In a smart home environment that combines energy management and health monitoring, the system state is modelled through a set of dynamic contextual vari ables. On the energy side, relevant states include bat tery charge level (battery_level), real-time solar produc tion (solar_output), current electricity consumption (en ergy consumption), grid status (grid status), and time of day (time_of_day). On the health side, key variables include the person's location (person_location), current activity (activity_type), medical refrigerator temperature (insulin_temperature), and the possible presence of a critical alert (emergency_alert). An activity recognition module can identify physical exertion such as walking, climbing stairs, or rapid movement, which can lead to low blood sugar levels in people with diabetes. In the absence of recent food, these signals can indicate a risk of hypo glycemia. The intelligent agent, based on reinforcement learning (such as Q-learning), can then react by activating medical devices, triggering an alert, or adapting energy management—for example, by prioritising the supply of insulin to the refrigerator or suspending non-essential equipment. This intersection of physiological and energy dimensions allows for a balanced decision-making pro cess that ensures both the well-being of the individual and the energy efficiency of the home, providing a sense of security to the users.

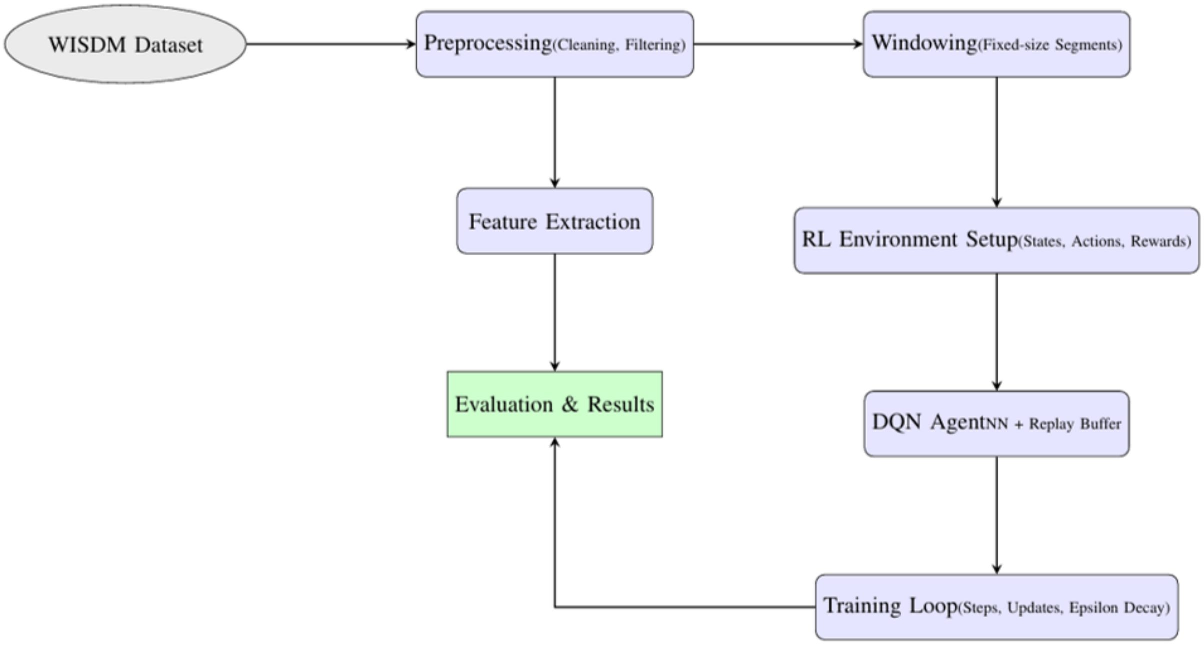


Figure 4.7: Overview of the proposed reinforcement learning-based framework for human activity recognition.

4.6.5 Scenario : Intelligent Cross-Energy Management and Health

Smart home management systems are evolving beyond comfort to integrate critical functions related to the health of vulnerable individuals. Key challenges include respon siveness in the event of a power outage, preservation of sensitive medications (such as insulin), and optimization of energy consumption. The reinforcement learning ap proach allows a software agent to learn to adapt to multi ple contexts without explicit supervision. Consider a smart home equipped with solar panels, batteries, and an IoT sensor network. The resident is an elderly diabetic woman living alone and following a regular insulin schedule.

- The home is equipped with motion sensors, thermal cameras, solar panels, batteries, and a connected refrigerator storing insulin.
- The Q-learning agent begins without knowledge of the user's behavior or critical priorities. Adaptive response over time: During the first few days (initial episodes), the system behaves inefficiently: it some times fails to anticipate power outages, leaves the freezer without power while insulin is stored there, or fails to send urgent alerts. This results in low or negative rewards, as shown in the curve. But by observing the consequences of its actions, the system learns:
    - Power outage detected: Immediate switch to backupbattery

- Potentiallycompromisedinsulin:Sendapriority alert tothecaregiver'sphone
- Entering the kitchen at treatment time: Pre check the power supply to critical equipment

4.6.6 Experimental Setup

Table 4.10: Key hyperparameters of the DQN model.

Parameter	**Value**
Episodes	10
Steps per Episode	200
Batch Size	64
Replay Buffer Size	3000
Learning Rate	0.001
Discount Factor (γ)	0.95
Exploration (ϵ)	$1.0 \rightarrow 0.01$

The dataset was processed as described in section above. We used 80% of the data for training and reserved the remaining 20% for testing. The reinforcement learning environment was implemented using a custom Gym-style interface, and the model was developed and trained with TensorFlow within a Jupyter Notebook running under the Anaconda distribution. All experiments were performed on a personal computer equipped with an Intel Core i5 processor and 16 GB of RAM, using CPU computation. The key hyperparameters are summarized in table **??**. Furthermore, table **??** presents the total rewards obtained by the agent across the training episodes. A general upward trend in the reward values can be observed, indicating effective learning and a gradual improvement in the agent's ability to correctly classify activity samples.

Table 4.11: Total reward obtained by the agent across episodes.

Episode	**Total Reward**
1	114
2	132
3	97
4	81
5	54
6	36
7	19
8	10
9	36
10	58

4.6.7 Classification Performance

The final model was tested on the held-out test set. Table **??** reports the precision, recall, and F1-score for each activity. The results show that the agent achieves strong performance across most activity classes, with particularly high accuracy for static activities such as "Sitting" and "Standing."

Table 4.12: Classification report on the test set.

Activity	Precision	Recall	F1-Score	Support
Walking	0.91	0.89	0.90	320
Jogging	0.88	0.90	0.89	300
Upstairs	0.85	0.81	0.83	280
Downstairs	0.80	0.76	0.78	250
Sitting	0.93	0.92	0.92	310
Standing	0.92	0.90	0.91	290
Average	0.88	0.87	0.87	1750

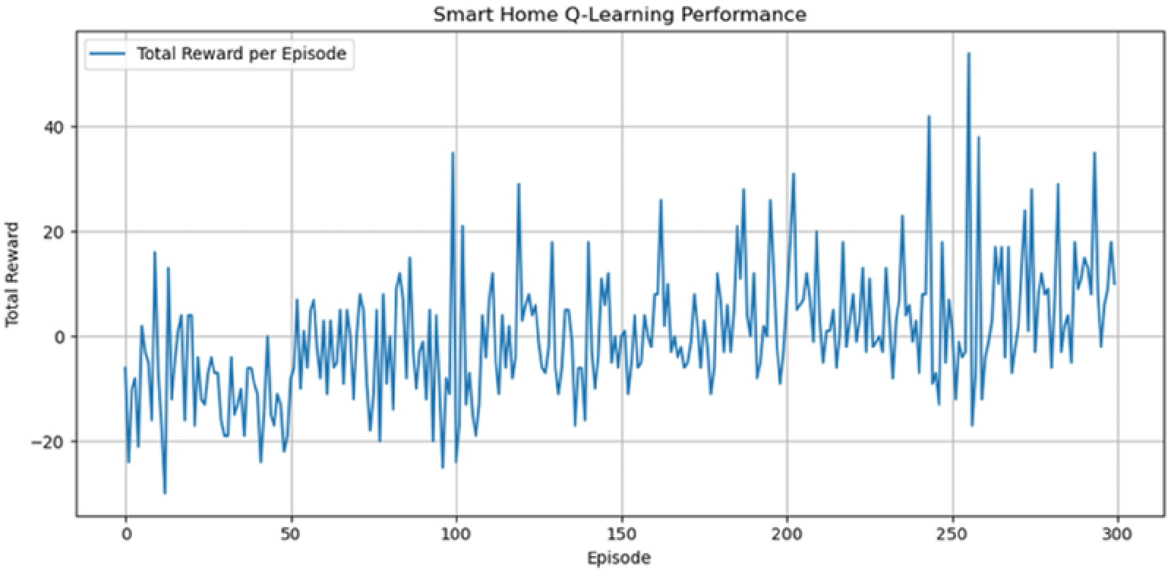


Figure 4.8: The smart Home Q-learning Performance for prediction in a smart home energy management system..

Figure **??** illustrates the total reward obtained by the reinforcement learning (Q-learning) agent per episode, highlighting the progressive improvement in its behavior. Each of the 300 episodes represents a simulation in which the agent makes decisions, such as activating a backup battery or sending an alert during a power outage in a smart home environment.

Initially, rewards fluctuate widely, reflecting the agent's exploratory phase. Over time, positive reward peaks occur more consistently, indicating that the agent is learning from its experiences and adjusting its actions to better handle critical situations (e.g., preserving insulin during a power outage). The overall upward trend in rewards demonstrates that the agent is gradually developing an effective policy aligned with the system's objectives.

The results show that the DQN-based agent successfully learns to classify human activities through interactive feedback. Static activities, such as "Sitting" and "Standing," are recognized with high confidence, while dynamic transitions like "Upstairs" and "Downstairs" remain more challenging due to overlapping sensor signals.

4.7 Comparative Analysis

we provide a comparative perspective that situates our approach within recent advances in Human Activity Recognition (HAR). Specifically, we treat HAR as a sequential decision-making problem and train a Deep Q-Network (DQN) agent that observes temporal sensor streams (from the WISDM dataset) and iteratively refines its predictions through interactive feedback and environment-based rewards. This comparative framing emphasizes our focus on adaptability in dynamic contexts, minimal dependence on labeled data, and robust generalization to unseen scenarios. Several recent studies have explored the integration of deep learning and reinforcement learning (RL) for human activity recognition (HAR), each addressing the issues of adaptability, supervision reduction, and temporal reasoning from a different perspective. In [?], a semi-supervised framework uses a DQN module to auto-label weakly annotated sensor streams before classifying them using an LSTM network. While reinforcement learning is used solely for automatic labeling, our approach uses it as the central decision-making mechanism, where an adaptive agent iteratively refines its predictions through interactive feedback and rewards from the environment.

Similarly, [?] presents the BAROQUE method, a multi-agent framework combining DQN and bee swarm optimization for feature subset selection in wearable sensor HAR. Although both approaches rely on DQN, theirs focuses on feature optimization, while ours prioritizes online sequential classification, interactive refinement, and generalization to new data. For its part, [?] proposes a hybrid optimization framework for HAR in IoMT environments, combining a DQN-based auto-labeling module and an LSTM classifier. Unlike these approaches, where the DQN is introduced upstream in the pipeline, our DQN acts as the primary classifier, responsible for real-time decision-making and progressively refining predictions.

Table 4.13: Comparison of recent HAR methods vs. our proposed DQN-based RL agent.

Reference	**Year**	**Method / RL twist**	**Datasets**	**RL**	**Feedback**	**Online/adaptive**	**Our work vs others**
Zhou et al. [?]	2020	Semi-supervised LSTM + DQN auto-labeler	Smartphone HAR (IoHT)	Yes (DQN for labeling)	No (auto-labels)	Semi-supervised	We use RL as the *classifier agent* that iteratively refines predictions.
Fan & Gao [?]	2021	BAROQUE: BSO + multi-agent DQN for feature selection	Wearable HAR benchmarks	Yes (DQN for FS)	No	Offline/selective	DQN used for feature selection; ours for sequential classification and interactive refinement.
Khalid et al. [?]	2023	Hybrid optimisation + DQN auto-labeling	IoMT sensor sets	Yes (DQN for labeling)	No	Pipeline semi-supervised	Their DQN is for labelling; ours is the decision-loop RL classifier with online refinement and generalisation.
Ismail et al. [?]	2023	Adaptive / semi-supervised deep model	UCI-HAR / Opportunity etc.	Some adaptive components	Limited human feedback	Adaptive (not RL)	Focus on adaptive supervised; ours casts HAR as sequential decision-making with explicit rewards.

Continued on next page

Table 4.13 continued from previous page

Reference	**Year**	**Method / RL twist**	**Datasets**	**RL**	**Feedback**	**(On/off)line**	**Our work vs others**
Kumrai et al. [?]	2020	DQN controls camera viewpoint to maximise HAR confidence	Vision/skeleton datasets	Yes (DQN for sensing)	Indirect (via reward)	Online control	They control sensors; ours uses RL to refine classification on accelerometer streams (different action space).
Mekruksavanich & Jitpattanakul [?]	2024	Deep learning (Att-ResBiGRU) for position-independent HAR	PAMAP2 / REALWORLD16	No	No	Offline	High offline accuracy; not designed for RL-style, streaming, incremental refinement.
Navakauskas et al. [?]	2025	FIRNN, LSTM, GRU comparison for HAR	Various wearable HAR datasets	No	No	Offline	Compares architectures; we apply RL as the core agent for sequential decision-making.
Mao et al. [?]	2023	Hybrid IMU sensor-based pose recognition	IMU sensor datasets	No	No	Offline	Focuses on pose recognition; we focus on sequential classification using RL.
Irfan et al. [?]	2021	Hybrid LSTM, BiLSTM, CNN model for HAR	Public HAR datasets	No	No	Offline	Employs hybrid deep learning; we employ RL for sequential decision-making.

Continued on next page

Table 4.13 continued from previous page

Reference	Year	Method / RL twist	Datasets	RL	Feedback	(On/off)line	Our work vs others
Our Work [?]	2025	DQN-based RL classifier	WISDM	Yes (DQN)	Yes (environment feedback)	Online / adaptive	Sequential decision-making with iterative prediction refinement; generalizes to unseen data.

Work [?] introduces an adaptive semi-supervised deep learning model aimed at reducing the reliance on fully annotated datasets. Both approaches share the desire for greater autonomy from labels, but their model remains essentially supervised. Instead, we propose an approach where the classification process is entirely formulated as a sequential decision task based on environmental feedback and continuous learning.

Other work, such as [?], uses a DQN agent to control the position of a mobile camera and improve activity recognition based on vision and skeletons. Although DQN is equally used in both cases, their action space is at the sensor level, whereas ours acts directly on classification decisions from wearable accelerometer streams. Similarly, [?] presents a deep bidirectional residual GRU model with attention mechanism (Att-ResBiGRU) for activity recognition independent of sensor position, achieving excellent offline performance. Our approach stands out by enabling interactive and scalable learning, capable of adapting to context variations in real time.

The study [?] systematically compares three dynamic neural architectures—FIRNN, LSTM, and GRU—to assess their relevance for HAR. While their work analyzes architectural performance, our approach integrates decision logic via RL, thus linking perception and adaptive reasoning. For their part, [?] and [?] propose hybrid models combining LSTM, BiLSTM, and CNN networks, or using IMU sensors for pose recognition. These approaches achieve excellent supervised results, but remain static and offline, unlike our DQN agent, which continuously learns, interacts with its environment, and refines its decisions with each learning episode. Beyond these algorithmic contributions, our research extends the HAR problem to a cognitive and semantic paradigm by integrating narrative knowledge representation (NKRL) into the reinforcement learning process. This fusion allows the system not only to recognize physical activities, but also to understand their narrative and causal context: for example, determining why an activity occurred or why it did not. By combining symbolic narrative reasoning from NKRL with dynamic RL adaptation, the system gains the ability to abstract events, perform causal inference, and generate appropriate responses. This synergy between symbolic reasoning and interactive learning paves the way for truly intelligent systems capable of linking perception, understanding, and action.

In summary, while existing work integrates reinforcement learning primarily as a secondary component for labeling or optimization, our framework makes it the primary cognitive agent, capable of learning from its interactions, generalizing to new situations, and aligning its decisions with narrative semantic representations derived from NKRL ontologies. This convergence of semantic modeling, narrative reasoning, and adaptive learning represents a significant step toward cognitive ambient intelligence, capable of recognizing human activities while reasoning about the intentions, dependencies, and contextual meaning of actions in dynamic, real-world environments.

Beyond these algorithmic contributions, our research extends the HAR problem to a cognitive paradigm. This allows the system not only to recognize physical activities, but also to understand their narrative and causal context: for example, determining why an activity occurred or why it was not performed.

Compared to traditional supervised classifiers, the reinforcement learning (RL) approach offers two main advantages:

1. Minimal supervision: Complete labeled sequences are not necessary.
2. Adaptability: The agent continuously learns from new data without requiring retraining.

In a smart home combining energy management and health monitoring, RL enables dynamic adaptation to daily routines and critical events. The environment is modeled via contextual states, including battery charge, solar production, power consumption, time of day, and the occupant's recognized activities, such as walking, resting, taking medication, or climbing stairs. These activities serve as key indicators of health, especially for vulnerable populations like elderly or diabetic users.

The RL agent selects actions—such as switching energy sources, deferring non-essential loads, or maintaining power to medical equipment—based on these states. Each action is evaluated through rewards reflecting energy efficiency and user safety. For example, if physical activity is detected before meals, the system can anticipate a glucose drop and respond by ensuring critical devices remain powered or issuing alerts.

By integrating activity recognition with energy and health variables, the agent optimizes decisions aligned with personalized care and sustainable energy use. Using a Deep Q-Network (DQN) architecture eliminates the need for complex mathematical modeling, allowing the agent to learn from experience without explicit system models or formal Markov decision processes.

This strategy enables dynamic adaptation, though it requires sufficient training and high-quality historical data. Compared to fixed-rule heuristics, it provides greater robustness against unexpected events, such as emergencies or system failures. Unlike the approach in [**?**], which relies on edge-cloud architectures for computation, our scenario uses a local DQN agent embedded in the home IoT environment. This setup allows progressive learning over episodes and real-time adaptation, without dependency on remote cloud resources, while integrating medical constraints at a fine-grained, real-time level.

4.8 Discussion

Reasoning in OWL primarily relies on description logic inference mechanisms and Horn-like rules expressed in SWRL. In practice, SWRL is limited to asserting new instances of concepts or properties. Due to the open-world assumption underlying OWL and SWRL, negation of facts is not supported, preventing modification or deletion of instances during inference. Consequently, SWRL is ill-suited for reactive reasoning over dynamic knowledge whose truth values evolve over time. Attempts to extend OWL with SWRL or temporal reasoning often lead to redundancy, increased complexity, and significant modifications to existing ontologies. Furthermore, defining predicates of arbitrary arity to capture temporal properties remains a challenging task, limiting OWL's ability to fully represent dynamic contexts.

Dynamic interactions in ambient intelligence and ubiquitous robotics often require n-ary relations to model semantic links between events. High-level knowledge representation models that account for both time and space are essential to capture context interdependencies and answer questions such as: Who initiated an event? In what context did it occur? Who was affected? Using such models, reasoning systems can establish semantic correlations between events, enhancing context recognition, analysis, and prediction. For instance, in scenarios where elderly individuals misplace objects like mobile phones, spatio-temporal reasoning can infer the likely location of items by analyzing sequences of events and constructing temporal and causal links, akin to human narrative reasoning.

OWL excels in concept classification and hierarchical reasoning but remains static, limiting its capacity to handle real-world phenomena that evolve over time. Its lack of variables and support for negation restricts its ability to manage dynamic, context-dependent knowledge. While constructs like owl:NegativePropertyAssertion provide some support for expressing negation, they are limited to simple subject-predicate-object relations and do not generalize to more complex dynamic scenarios.

To address these limitations, combining ontologies with narrative or high-level temporal reasoning models—such as NKRL (Narrative Knowledge Representation Language)—enables reasoning akin to human storytelling. This approach captures semantic, spatio-temporal context and supports non-monotone reasoning, allowing modifications and deletions of knowledge, which is crucial for reactive systems.

In addition to ontological reasoning, reinforcement learning (RL) offers an adaptive approach to managing dynamic environments. In smart homes, for example, RL agents leveraging Deep Q-Networks (DQN) can integrate contextual states—including energy consumption, solar production, battery levels, and recognized human activities—to optimize decisions that balance efficiency and safety. RL agents continuously learn from interactions, adapting to changing routines without complete retraining, and can anticipate critical events such as health risks. This adaptive, data-driven approach complements symbolic reasoning by handling temporal and dynamic aspects that are difficult to capture solely with ontologies. Experimental results on human activity recognition (HAR) demonstrate that DQN-based agents can recognize static activities with high confidence and gradually improve recognition of dynamic transitions, although challenges remain in representing temporal sequences and reward design. Future work could integrate temporal learning components (e.g., LSTMs) and richer state representations to further enhance adaptive reasoning.

Overall, our discussion highlights that while OWL provides a robust foundation for static knowledge representation, its limitations in temporal reasoning and dynamic contexts necessitate hybrid approaches. By combining ontologies with narrative reasoning, n-ary relations, and adaptive RL techniques, it is possible to create intelligent systems capable of understanding and predicting complex spatio-temporal interactions in ambient intelligence and ubiquitous robotics applications.

Chapter 5

General Conclusion and Future Directions

This thesis explored an integrated framework combining semantic modeling, narrative reasoning, and reinforcement learning for activity recognition and prediction in smart ambient environments. The main contributions can be summarized as follows:

Semantic Modeling and Annotation of Heterogeneous Data

We introduced a semantic annotation layer capable of representing heterogeneous, dynamic, and interactive entities, as well as raw data streams from various sensors. This approach facilitates automatic data comprehension and fine-grained analysis in complex and evolving contexts. The HClass ontology formalized concepts and instances according to a generalization/specialization hierarchy, while the HTemp ontology structured temporal events and the relationships between them.

5.0.1 Narrative Reasoning with NKRL

The use of Narrative Knowledge Representation Language (NKRL) in an ambient intelligence context has made it possible to link elementary events through linking structures (CAUSE, GOAL, COORD), providing the ability to reconstruct logical and causal sequences between occurrences. This mechanism has demonstrated its usefulness for interpreting complex contexts from observation history and for generating plausible answers to queries about activities and events. The narrative approach has proven particularly well-suited to managing temporal uncertainty and representing causal and contextual relationships.

5.0.2 Activity Recognition and Reinforcement Learning

For human activity recognition (HAR), we proposed a framework based on Deep Q-Networks (DQN), considering HAR as a sequential decision-making problem. The resource-efficient agent observes time windows of sensor data, predicts the corresponding activity, and adjusts its actions according to the rewards received. Experimental results on the WISDM dataset show that the model learns efficiently, particularly for static activities, while remaining adaptable to dynamic transitions. Integrating HAR with energy management and health monitoring in a home automation environment enabled the system to make contextually appropriate decisions, maximizing safety, comfort, and energy efficiency.

5.0.3 Summary of Results

The combination of three axes—semantic modeling, narrative reasoning, and reinforcement learning—made it possible to design a system capable of:

1. Recognizing and predicting human activities in dynamic and complex environments.
2. Maintaining knowledge consistency and relevance through the HClass/HTemp ontological architecture and NKRL rules.
3. Optimizing real-time decision-making via an RL agent, reducing reliance on labeled data and adapting system behavior to contextual changes.

Thus, this thesis contributes to the advancement of ambient intelligence by proposing a hybrid methodology combining knowledge representation, symbolic reasoning, and machine learning, capable of addressing the challenges of complexity and uncertainty in interactive and connected environments.

5.1 Perspectives and Future Directions

Several areas of development and improvement can be considered to extend the work of this thesis:

Improving dynamic activity recognition

Fast activity transitions and complex events remain a challenge, particularly when sensor signals overlap. The use of recurrent neural networks (RNN, LSTM, or GRU) in addition to DQN could improve the capture of long-term temporal dependencies and the accuracy of transitions.

Extending semantic modeling

The integration of new specialized ontologies (health, security, mobility, energy) could enrich the semantic layer, allowing for the processing of multi-domain scenarios and improved service personalization. The formalization of more refined adaptive and contextual rules in NKRL, combined with non-monotonic reasoning mechanisms, would provide better uncertainty and exception handling.

Optimizing RL Agents for Edge Computing

Although local DQN has proven effective, large-scale deployment in IoT environments requires lighter, more distributed agents capable of learning in real time on resource-constrained devices. Integration with edge and fog computing architectures would help balance performance, latency, and energy consumption.

Multi-sensory Fusion and Online Learning

Exploiting multiple sensor sources (video, audio, biometrics, IoT) combined with online learning techniques would enhance the system's robustness and adaptability to new situations. Transfer learning methods could also facilitate adaptation to new environments or users without requiring complete retraining.

Applications to Healthcare and Smart Environments

The proposed approach can be applied to personalized monitoring of vulnerable people, home incident prevention, and energy optimization. A promising avenue is to integrate proactive prediction of critical events, combining HAR, physiological data, and energy management, to create truly autonomous and safe environments.

Towards Explainable Ambient Intelligence

Finally, the combination of symbolic reasoning and reinforcement learning paves the way for explainable systems (XAI) in ambient intelligence, capable of justifying their decisions, improving user confidence, and facilitating integration into critical contexts such as healthcare and home security.

Exploiting Knowledge in Cognitive Psychology

A recent thesis entitled “Cognitive Psychology in Service of the Machine: Towards the Study of Human Cognition,” defended by Nadia AGTI, demonstrates that understanding human cognitive mechanisms, particularly the reasons behind an unperformed action, constitutes a valuable contribution to ambient intelligence. Integrating this knowledge could enable the system not only to recognize activities, but also to propose appropriate interventions or recommendations, taking into account users’ intentions, limitations, and motivations.

In summary, this thesis demonstrated the feasibility and effectiveness of a hybrid framework combining ontologies, narrative reasoning, and reinforcement learning for activity recognition and prediction in smart ambient environments. The opportunities opened up allow the development of more robust, adaptive, and explainable systems capable of meeting the growing challenges of dynamic environments and the Internet of Things.

Publications

- Maza Abdelouahab and Sabri Lyazid (2025). **Green Energy for Enhancing the Internet of Everything Applications in Rural Areas**. *Proceedings of the First International Conference on Green Engineering*, Algeria.
- Maza Abdelouahab and Sabri Lyazid (2025). **Spatio-Temporal Ontological Query Processing in IoE Environments**. *International Journal of Computers and Their Applications (IJCA)*, 32(3), September 2025.
- Maza Abdelouahab , Sabri Lyazid, and Agti Nadia (2025). **Adaptive Human Activity Recognition with Deep Q-Networks: A Reinforcement Learning Approach**. In *Proceedings of the 13th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS)*, Poland.

Bibliography

---

[1] H. Rachlin, "Skinner (1938) and Skinner (1945)," *Behavior and Philosophy*, vol. 46, pp. 100-113, 2018.

[2] J. Piaget, *The Origins of Intelligence in Children*, M. Cook, Trans. New York, NY, USA: W. W. Norton & Company, 1952. doi: 10.1037/11494-000.

[3] L. S. Vygotsky, *Mind in Society: The Development of Higher Psychological Processes*, M. Cole, V. John-Steiner, S. Scribner, and E. Souberman, Eds. Cambridge, MA, USA: Harvard University Press, 1978. [En ligne]. Disponible sur : `https://home.fau.edu/musgrove/web/vygotsky1978.pdf`

[4] Frijda, N.H "Emotion, Cognitive Structure, and Action Tendency", Cognition and Emotion 1:115-43, 1987.

[5] Gibson, J. J. (1977). The theory of affordances. In R. Shaw & J. Bransford (Eds.), *Perceiving, Acting, and Knowing: Toward an Ecological Psychology* (pp. 67–82). Hillsdale, NJ: Lawrence Erlbaum Associates.

[6] Gibson, J. J. (1979). *The Ecological Approach to Visual Perception.* Boston: Houghton Mifflin.

[7] Noël Carroll, *Beyond Aesthetics: Philosophical Essays*, Cambridge University Press, New York, 2001.

[8] L. Sabri, S. Bouznad, S. Rama Fiorini, A. Chibani, E. Prestes, Y. Amirat, "An integrated semantic framework for designing context-aware internet of robotic things systems," *Integrated Computer-Aided Engineering*, vol. 25, no. 2, pp. 137–156, 2018.

[9] D. D. Onthoni, P. K. Sahoo, "Artificial-intelligence-assisted activities of daily living recognition for elderly in smart home," *Electronics*, vol. 11, no. 24, p. 4129, 2022.

[10] Y. Nan, N. H. Lovell, S. J. Redmond, K. Wang, K. Delbaere, K. S. van Schooten, "Deep learning for activity recognition in older people using a pocket-worn smartphone," *Sensors*, vol. 20, no. 24, p. 7195, 2020.

[11] A. Hayat, F. Morgado-Dias, B. P. Bhuyan, R. Tomar, "Human activity recognition for elderly people using machine and deep learning approaches," *Information*, vol. 13, no. 6, p. 275, 2022.

[12] P. Lissa, C. Deane, M. Schukat, F. Seri, M. Keane, E. Barrett, "Deep reinforcement learning for home energy management system control," *Energy and AI*, vol. 3, p. 100043, 2021.

[13] A. Rajuroy, B. Mary Johnson, "The Home Automation Energy-Efficient using Multi-Agent Deep Reinforcement Learning," 2024, Dec.

[14] Y. Wang, M. Valipour, O. Zatarain, M. Gavrilova, A. Hussan, N. Howard, S. Patel, "Formal Ontology Generation by Deep Machine Learning," in *Proceedings of ICCI-CC 2017*, 2017, doi:10.1109/ICCI-CC.2017.8109723.

[15] L. Dissing, T. Bolander, "Implementing Theory of Mind on a Robot Using Dynamic Epistemic Logic," in *Proceedings of the International Joint Conference on Artificial Intelligence (IJCAI)*, pp. 1615–1621, 2020.

[16] D. Liu, D. Li, K. Gao, Y. Song, Z. Zhou, "Context-aware inverse reinforcement learning for modeling individuals' daily activity schedules," *Engineering Applications of Artificial Intelligence*, vol. 146, p. 110279, 2025.

[17] J. M. Alcayaga, O. A. Menéndez, M. A. Torres-Torriti, J. P. Vásconez, T. Arévalo-Ramirez, A. J. P. Romo, "LSTM-Enhanced Deep Reinforcement Learning for Robust Trajectory Tracking Control of Skid-Steer Mobile Robots Under Terra-Mechanical Constraints," *Robotics*, vol. 14, p. 74, 2025, doi:10.3390/robotics14060074.

[18] H. Zhou, Y. Zhao, Y. Liu, S. Lu, X. An, Q. Liu, "Multi-sensor data fusion and CNN-LSTM model for human activity recognition system," *Sensors*, vol. 23, no. 10, 2023.

[19] E. Genc, M. Yildirim, Y. Salman, "Human activity recognition with fine-tuned CNN-LSTM," *Journal of Electrical Engineering*, vol. 75, pp. 8–13, 2024, doi:10.2478/jee-2024-0002.

[20] H. Ullah, A. Munir, "Human activity recognition using cascaded dual attention CNN and bi-directional GRU framework," *Journal of Imaging*, vol. 9, no. 7, 2023.

[21] Y. Abdulazeem, H. M. Balaha, W. M. Bahgat, M. Badawy, "Human action recognition based on transfer learning approach," *IEEE Access*, vol. 9, pp. 82058–82069, 2021.

[22] M. Shrestha, S. P. Pandey, "Human action recognition using deep learning methods," in *Proceedings of the 14th IoE Graduate Conference*, vol. 14, pp. 305–312, 2023.

[23] C. Xu, J. Shen, F. Fan, T. Qiu, Z. Mao, "An enhanced human activity recognition algorithm with positional attention," in *Proceedings of the 14th Asian Conference on Machine Learning*, PMLR, pp. 1181–1196, 2023.

[24] M. Akter, S. Ansary, M. A. Khan, D. Kim, "Human activity recognition using attention-mechanism-based deep learning feature combination," *Sensors*, vol. 23, no. 12, p. 5715, 2023.

[25] W. Xiong, Z. Wang, "TCN-attention-HAR: human activity recognition based on attention mechanism time convolutional network," *Scientific Reports*, vol. 14, 2024.

[26] S. Cao, Z. Wang, "Human behavior recognition based on sparse transformer with channel attention mechanism," *Sensors*, vol. 23, 2023.

[27] U. Oleh, R. Obermaisser, A. S. Ahammed, "A review of recent techniques for human activity recognition: Multimodality, reinforcement learning, and language models," *Algorithms*, vol. 17, 2024.

[28] K. Wang, A. Saragadam, J. Kaur, A. Dogra, S. Cao, M. Ghafurian, ..., P. P. Morita, "A Contactless Method for Recognition of Daily Living Activities for Older Adults Based on Ambient Assisted Living Technology," *Internet of Things*, p. 101502, 2025.

[29] I. H. Sarker, A. S. M. Kayes, "ABC-RuleMiner: User behavioral rule-based machine learning method for context-aware intelligent services," *Journal of Network and Computer Applications*, vol. 168, p. 102762, 2020.

[30] B. Pan, Z. Cao, E. Adeli, J. C. Niebles, "Adversarial cross-domain action recognition with co-attention," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 34, no. 07, pp. 11815–11822, Apr. 2020.

[31] W. Kim, J. Lee, L. Peternel, N. Tsagarakis, A. Ajoudani, "Anticipatory robot assistance for the prevention of human static joint overloading in human–robot collaboration," *IEEE Robotics and Automation Letters*, vol. 3, no. 1, pp. 68–75, 2017.

[32] S. D. Achirei, M. C. Heghea, R. G. Lupu, V. I. Manta, "Human activity recognition for assisted living based on scene understanding," *Applied Sciences*, vol. 12, no. 21, p. 10743, 2022.

[33] Y. Liu, N. Zhou, “Jumping Action Recognition for Figure Skating Video in IoT Using Improved Deep Reinforcement Learning,” *Information Technology and Control*, vol. 52, no. 2, pp. 309–321, 2023.

[34] M. R. Shahabian Alashti, M. H. Bamorovat Abadi, P. Holthaus, C. Menon, F. Amirabdollahian, “Lightweight human activity recognition for ambient assisted living,” in *ACHI 2023: The Sixteenth International Conference on Advances in Computer-Human Interactions*, IARIA, 2023.

[35] B. P. L. Lau, Z. Koh, Y. Zhou, B. K. K. Ng, C. Yuen, M. L. Low, “Location-based activity behavior deviation detection for nursing home using IoT devices,” *Internet of Things*, vol. 22, p. 100702, 2023.

[36] C. Aggar, G. Sorwar, C. Seton, O. Penman, A. Ward, “Smart home technology to support older people’s quality of life: a longitudinal pilot study,” *International Journal of Older People Nursing*, vol. 18, no. 1, p. e12489, 2023.

[37] J. K. Tsai, C. C. Hsu, W. Y. Wang, and S. K. Huang, *Deep learning-based real-time multiple-person action recognition system*, *Sensors*, vol. 20, no. 17, p. 4758, 2020.

[38] A. Strzelecki, B. Kolny, and M. Kucia, *Smart Homes as Catalysts for Sustainable Consumption: A Digital Economy Perspective*, MDPI Journal, Basel, Switzerland, 2024.

[39] M. H. Zafar, S. M. S. Bukhari, M. Abou Houran, S. Kumayl, R. Moosavi, M. Mansoor, N. Al-Tawalbeh, and F. Sanfilippo, “Step towards secure and reliable smart grids in Industry 5.0: A federated learning assisted hybrid deep learning model for electricity theft detection using smart meters,” *Energy Reports*, vol. 10, 2023.

[40] A. Thomar and A. Pattnaik, “Smart Energy Management in Renewable Energy Systems,” in *AIPP Books Smart Energy Management Systems and Renewable Energy Resources*, 2021.

[41] R. Selvaraj, V. M. Kuthadi, and S. Baskar, “Smart building energy management and monitoring system based on artificial intelligence in smart city,” *Sustainable Energy Technologies and Assessments*, vol. 56, Mar. 2023.

[42] M. Łatuszy and K. Nermend, “Energy Decision Making: Problems, Methods, and Tools—An Overview,” *MDPI Journals, Energies*, 2022.

[43] S. M. Patil, M. Vijayalashmi, and R. Tapaskar, “IoT based solar energy monitoring system,” in *International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS)*, Chennai, India, pp. 1574–1579, 2017.

[44] Z. Jebroni, J. Afonso, and B. Tidhaf, “Home Energy Monitoring System Towards Smart Control of Energy Consumption,” in *Green Energy and Networking*, 2019.

[45] S. Benhamaid, A. Bouabdallah, and H. Lakhlef, “Recent advances in energy management for Green-IoT: An up-to-date and comprehensive survey,” *Journal of Network and Computer Applications*, vol. 198, 2022.

[46] Maza, A., & Sabri, L. (2025). Green Energy for Enhancing the Internet of Everything Applications in Rural Areas. *Proceedings of the First International Conference on Green Engineering*, Algeria.

[47] D. Riboni and F. Murru, "Unsupervised recognition of multi-resident activities in smart-homes," *IEEE Access*, vol. 8, pp. 201985–201994, 2020.

[48] C. Khnaisser, V. Looten, L. Lavoie, A. Burgun, and J.-F. Ethier, "Building ontology-based temporal databases for data reuse: An applied example on hospital organizational structures," *Health Informatics Journal*, vol. 30, no. 2, 2024.

[49] J. Madiha, A. M. Naif, A. Abdulwahab, A. S. Saud, A. A. Nouf, and J. Ahmad, "Deep ontology-based human locomotor activity recognition system via multisensory devices," *IEEE Access*, vol. 11, pp. 105466–105478, 2023.

[50] F. G. Seyede, D. T. William, and A. Douglas L., "Sequential information-theoretic and reification-based approach for querying multi-information sources," *Aerospace Information Systems*, vol. 16, no. 12, pp. 575–587, 2019.

[51] M. J. O’Connor and K. D. Amar, "A method for representing and querying temporal information in OWL," in *Biomedical Engineering Systems and Technologies*, Springer, Berlin, Heidelberg, vol. 127, pp. 97–110, 2011.

[52] Z. Xixi, L. Bin, Y. Li, D. Zhaoyun, and Z. Cheng, "TGR: Neural-symbolic ontological reasoner for domain-specific knowledge graphs," *Applied Intelligence*, vol. 53, no. 20, pp. 23946–23965, 2023.

[53] M. Larhrib, M. Escribano, C. Cerrada, and J. J. Escribano, "An ontological behavioral modeling approach with SHACL, SPARQL, and RDF applied to smart grids," *IEEE Access*, vol. 12, pp. 82041–82056, 2024.

[54] I. Theofilos, G. George, K. Kostis, K. Konstantina, and M. Manolis, "Evaluating geospatial RDF stores using the benchmark Geographica 2," *IEEE Access*, vol. 10, pp. 189–228, 2021.

[55] B. Zouhaier, G. Fabio, and R. Bouaziz, "SQWRL: A TSQL2-like query language for temporal ontologies generated from JSON big data," *Big Data Mining and Analytics*, vol. 6, no. 3, pp. 288–300, 2023.

[56] S. Batsakis, I. Tachmazidis, and G. Antoniou, "Representing time and space for the semantic web," *International Journal of Artificial Intelligence Tools*, vol. 26, no. 3, p. 1750015, 2017.

[57] O. Fabrizio, G. Damien, and D. O'Sullivan, "RDF Reification Benchmark using the Biomedical Knowledge Repository," in *Proceedings of the 15th International Conference on Semantic Computing (ICSC)*, 2020.

[58] T. M. Ta, N.-T. H. Nguyen, and H. T. Nguyen, "Key-value based data hiding method for NoSQL database," in *Proceedings of the 10th International Conference on Knowledge and Systems Engineering (KSE)*, 2018.

[59] F. G. Francesco, M. C. Stefano, and S. Stefano, "Exploit hierarchical label knowledge for deep learning," in *Proceedings of the IEEE 32nd International Symposium on Computer-Based Medical Systems (CBMS)*, 2019.

[60] N. Yamada, K. Sakamoto, G. Kunito, Y. Isoda, K. Yamazaki, and S. Tanaka, "Applying ontology and probabilistic model to human activity recognition from surrounding things," *IPSJ Digital Courier*, vol. 3, pp. 506–517, 2007.

[61] S. Jiang, W. Wu, N. Tomita, C. Ganoe, and S. Hassanpour, *Multi-Ontology Refined Embeddings (MORE): A hybrid multi-ontology and corpus-based semantic representation model for biomedical concepts*, Journal of Biomedical Informatics, vol. 111, 103581, 2020, doi: 10.1016/j.jbi.2020.103581.

[62] M. Naeem, G. Paragliola, and A. Coronato, "A reinforcement learning and deep learning based intelligent system for the support of impaired patients in home treatment," *Expert Systems with Applications*, vol. 168, p. 114285, 2021, doi: 10.1016/j.eswa.2020.114285.

[63] Gill, M. S., Westermann, T., Steindl, G., Gehlhoff, F., & Fay, A. (2024). Integrating Ontology Design with the CRISP-DM in the Context of Cyber-Physical Systems Maintenance. *Proceedings of the 2024 IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, 1–8.

[64] Hallou, A., Fissaa, T., Hafiddi, H., & Nassar, M. (2022). A DSPL and Reinforcement Learning Approach for Context-Aware IoT Systems Development. *International Journal of Security and Privacy in Pervasive Computing (IJSPPC)*, 14(1), 1–22.

[65] A. Vassiliades, N. Bassiliades, F. Gouidis, and T. Patkos, "A knowledge retrieval framework for household objects and actions with external knowledge," in *Semantic Systems. In the Era of Knowledge Graphs: 16th International Conference on Semantic Systems (SEMANTiCS 2020)*, Amsterdam, The Netherlands, Sept. 7–10, 2020, pp. 36–52. Springer International Publishing.

[66] I. A. Klampanos, A. Davvetas, A. Koukourikos, and V. Karkaletsis, "ANNETT-O: An ontology for describing artificial neural network evaluation, topology and training," *International Journal of Metadata, Semantics and Ontologies*, vol. 13, no. 3, pp. 179–190, 2019.

[67] M. Chang, G. D'Aniello, M. Gaeta, F. Orciuoli, D. Sampson, and C. Simonelli, "Building ontology-driven tutoring models for intelligent tutoring systems using data mining," *IEEE Access*, vol. 8, pp. 48151–48162, 2020.

[68] D. D. Onthoni and P. K. Sahoo, "Artificial-intelligence-assisted activities of daily living recognition for elderly in smart home," *Electronics*, vol. 11, no. 24, p. 4129, 2022.

[69] S. Shiroshita, S. Maruyama, D. Nishiyama, M. Y. Castro, K. Hamzaoui, G. Rosman, and A. Gaidon, "Behaviorally diverse traffic simulation via reinforcement learning," in *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS)*, pp. 2103–2110, Oct. 2020.

[70] A. Nadafian, M. Mozafari, T. Masquelier, and M. Ganjtabesh, *Brain-inspired Computational Modeling of Action Recognition with Recurrent Spiking Neural Networks Equipped with Reinforcement Delay Learning*, arXiv preprint arXiv:2406.11778, 2024.

[71] I. Dasgupta, Z. Kurth-Nelson, S. Chiappa, J. Mitrovic, P. Ortega, E. Hughes, and J. Wang, *Meta-reinforcement learning of causal strategies*, in *The Meta-Learning Workshop at the Neural Information Processing Systems (NeurIPS)*, 2019.

[72] R. Chandra, S. Dongre, and S. Agarwal, *MLtoGAI: Semantic Web based with Machine Learning for Enhanced Disease Prediction and Personalized Recommendations using Generative AI*, *SSRN Electronic Journal*, 2024, doi: 10.2139/ssrn.4891490.

[73] S. Bl and R. Bhaskar, *A Modelling of Context-Aware Elderly Healthcare Eco-System (CA-EHS) Using Signal Analysis and Machine Learning Approach*, *Wireless Personal Communications*, vol. 119, 2021, doi: 10.1007/s11277-021-08341-2.

[74] S. Deng, J. Z. Pan, J. Chen, and H. Chen, *Deep learning for knowledge-driven ontology stream prediction*, in *China Conference on Knowledge Graph and Semantic Computing*, Singapore: Springer Singapore, 2018, pp. 52–64.

[75] Y. Wang *et al.*, *Formal ontology generation by deep machine learning*, in *Proc. 2017 IEEE 16th Int. Conf. on Cognitive Informatics & Cognitive Computing (ICCI*CC)*, IEEE, 2017, pp. 43–52.

[76] Y. He, J. Chen, H. Dong, I. Horrocks, C. Allocca, T. Kim, and B. Sapkota, *Deeponto: A Python package for ontology engineering with deep learning*, *Semantic Web*, vol. 15, no. 5, pp. 1991–2004, 2024.

[77] Wörgötter, F., Ziaeetabar, F., Pfeiffer, S., Kaya, O., Kulvicius, T., & Tamosiunaite, M. (2020). *Humans predict action using grammar-like structures.* Scientific Reports, 10, Article 4535. https://doi.org/10.1038/s41598-020-60923-5

[78] C. Qin, M. Zhang, Z. Li, and L. Chen, "Shaping the future: How robot programming education changes the attitudes of robotics among rural primary school students in a developing country," *Education and Information Technologies*, vol. 30, no. 6, pp. 7045–7076, Apr. 2025.

[79] M. Krötzsch, F. Maier, A. Maier, and P. Hitzler, "A Better Uncle for OWL: Nominal schemas for integrating rules and ontologies," in *Proc. 20th Int. Conf. World Wide Web*, pp. 645–654, ACM, 2011.

[80] A. Fath, N. Hanna, Y. Liu, S. Tanch, T. Xia, and D. Huston, "Indoor infrastructure maintenance framework using networked sensors, robots, and augmented reality human interface," *Future Internet*, vol. 16, no. 5, p. 170, May 2024.

[81] Z. Du, L. He, Y. Chen, Y. Xiao, P. Gao, and T. Wang, "Robot Cloud: Bridging the power of robotics and cloud computing," *Future Generation Computer Systems*, vol. 74, pp. 337–348, Sep. 2017.

[82] L. Fiorini, R. Esposito, M. Bonaccorsi, C. Petrazzuolo, F. Saponara, R. Giannantonio, G. D. Petris, P. Dario, and F. Cavallo, "Enabling personalised medical support for chronic disease management through a hybrid robot-cloud approach," *Autonomous Robots*, vol. 41, no. 5, pp. 1263–1276, Jun. 2017.

[83] L. Hu, Y. Jiang, F. Wang, K. Hwang, M. S. Hossain, and G. Muhammad, "Follow me Robot-Mind: Cloud brain based personalized robot service with migration," *Future Generation Computer Systems*, vol. 107, pp. 324–332, Jun. 2020.

[84] J. Lin, K. Zhong, T. Gong, X. Zhang, and N. Wang, “A simulation-assisted point cloud segmentation neural network for human–robot interaction applications,” *Journal of Field Robotics*, vol. 41, no. 8, pp. 2689–2704, Dec. 2024.

[85] H. Nasereddin and G. M. Knapp, *Hybrid robotic reinforcement learning for inspection/correction tasks*, *Procedia Manufacturing*, vol. 39, pp. 406–413, 2019.

[86] A. Qureshi, Y. Nakamura, Y. Yoshikawa, and H. Ishiguro, *Intrinsically motivated reinforcement learning for human-robot interaction in the real-world*, *Neural Networks*, vol. 107, 2018, doi:10.1016/j.neunet.2018.03.014.

[87] L. D. Hansen and T. Bolander, *Implementing theory of mind on a robot using dynamic epistemic logic*, in *Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence (IJCAI)*, 2020, International Joint Conference on Artificial Intelligence Organization.

[88] Yuan, F., Hasnaeen, N., Zhang, R., Bible, B., Taylor, J., Qi, H., Yao, F., & Zhao, X. (2025). *Integrating Reinforcement Learning and AI Agents for Adaptive Robotic Interaction and Assistance in Dementia Care*. arXiv preprint arXiv:2501.17206. https://doi.org/10.48550/arXiv.2501.17206

[89] Zhang, M., Tian, G., Zhang, Y., & Duan, P. (2021). *Service skill improvement for home robots: Autonomous generation of action sequence based on reinforcement learning. Knowledge-Based Systems*, 212, 106605. https://doi.org/10.1016/j.knosys.2020.106605

[90] S. Suman, A. Etemad, and F. Rivest, *Potential impacts of smart homes on human behavior: A reinforcement learning approach*, IEEE Transactions on Artificial Intelligence, vol. 3,

[91] H. Oliff, Y. Liu, M. Kumar, M. Williams, and M. Ryan, *Reinforcement learning for facilitating human-robot-interaction in manufacturing*, Journal of Manufacturing Systems, vol. 56, pp. 326–340, Jul. 2020. doi: 10.1016/j.jmsy.2020.06.018.

[92] M. Qiu, E. Najm, R. Sharrock, and B. Traverson, "Reinforcement Learning Based Architectures for Dynamic Generation of Smart Home Services," in *2022 21st IEEE International Conference on Machine Learning and Applications (ICMLA)*, Nassau, Bahamas, 2022, pp. 7–14. doi: 10.1109/ICMLA55696.2022.00010.

[93] S. Batsakis and E. G. M. Petrakis, "Representing temporal knowledge in the semantic web: The extended 4d fluents approach," in *Combinations of Intelligent Methods and Applications*, vol. 8, pp. 55–69, 2011.

[94] T. Cui, W.-Q. Wei, H. R. S., S. Guergana, and G. C. Christopher, "Cntro: A semantic web ontology for temporal relation inferencing in clinical narratives," in *AMIA Annual Symposium Proceedings*, vol. 13, pp. 787–791, 2010.

[95] S. Benelhaj-Sghaier, A. Gillet, and Leclercq, "Knowledge Graph Multilevel Abstraction: A Property Graph Reification Based Approach," in J. Araújo, J. L. de la Vara, M. Y. Santos, and S. Assar (eds), *Research Challenges in Information Science*, 2024.

[96] M. O'Connor and A. Das, "Sqwrl: a query language for OWL," in *Proceedings of the 6th International Conference on OWL: Experiences and Directions (OWLED'09), Volume 529*, pp. 208–215, CEUR-WS.org, Aachen, Germany, 2009.

[97] A. Sheth and K. Thirunarayan, *Semantics Empowered Web 3.0: Managing Enterprise, Social, Sensor, and Cloud-based Data and Services for Advanced Applications*, Morgan & Claypool Publishers, ACM Digital Library, 2012.

[98] A. Kostovska, S. Džeroski, and P. Panov, "Semantic description of data mining datasets: An ontology-based annotation schema," in *Proceedings of the International Conference on Discovery Science*, Cham: Springer International Publishing, 2020.

[99] F. Paischer, T. Adler, M. Hofmarcher, and S. Hochreiter, "Semantic HELM: A Human-Readable Memory for Reinforcement Learning," in *Proceedings of the Thirty-Seventh Conference on Neural Information Processing Systems (NeurIPS)*, 2023. [Online]. Available: https://openreview.net/forum?id=ebMPmx5mr7

[100] D. Triboan, L. Chen, F. Chen, and Z. Wang, "Semantic segmentation of real-time sensor data stream for complex activity recognition," *Personal and Ubiquitous Computing*, vol. 21, Jun. 2017, doi: 10.1007/s00779-017-1005-5.

[101] H. Belhadi, K. Aklii Astouati, Y. Djenouri, and J. Lin, *Exploring Pattern Mining for Solving the Ontology Matching Problem*, In: 2019, pp. 85–93, doi: 10.1007/978-3-030-30278-8_11.

[102] F. Altuhaifa and D. Al Tuhaifa, *Developing an Ontology Representing Fall Risk Management Domain Knowledge*, Journal of Medical Systems, vol. 48, no. 1, p. 47, 2024.

[103] U. K. Sridevi, Sophia Sudhir, and Shanthi Palaniappan, *Elderly behavior prediction using a deep learning model in smart homes*, in *Applications of Deep Learning and Big IoT on Personalized Healthcare Services*, IGI Global, 2020, pp. 115–131.

[104] M. Periša, P. Teskera, I. Cvitić, and I. Grgurević, *Empowering people with disabilities in smart homes using predictive informing*, Sensors, vol. 25, no. 1, p. 284, 2025.

[105] P. Hohenecker and T. Lukasiewicz, *Ontology reasoning with deep neural networks*, Journal of Artificial Intelligence Research, vol. 68, pp. 503–540, 2020.

[106] Arguello Casteleiro, M., Maseda Fernandez, D., Demetriou, G., Read, W., Fernandez Prieto, M. J., Des Diz, J., …, & Stevens, R. (2017). A case study on Sepsis using PubMed and Deep Learning for Ontology Learning. In *Informatics for Health: Connected Citizen-Led Wellness and Population Health* (pp. 516–520). IOS Press.

[107] Vassiliades, A., Bassiliades, N., Gouidis, F., & Patkos, T. (2020). A knowledge retrieval framework for household objects and actions with external knowledge. In *Semantic Systems in the Era of Knowledge Graphs: 16th International Conference on Semantic Systems, SEMANTiCS 2020, Amsterdam, The Netherlands, September 7–10, 2020, Proceedings 16* (pp. 36–52). Springer International Publishing.

[108] L. Sabri, A. Chibani, Y. Amirat, and G. P. Zarri, “Semantic and architectural approach for spatio-temporal reasoning in ambient assisted living,” in *Proc. International Joint Conference on Artificial Intelligence (IJCAI)*, Barcelona, Spain, 2011, pp. 77–84.

[109] G. P. Zarri, *Representation and Management of Narrative Information: Theoretical Principles and Implementation*, Advanced Information and Knowledge Processing. Springer Verlag, 2009.

[110] J. McCarthy et P. J. Hayes, "Some Philosophical Problems from the Standpoint of Artificial Intelligence", dans Machine Intelligence, vol. 4, B. Meltzer et D. Michie, Ed., Edinburgh, UK: Edinburgh University Press, 1969, pp. 463–502

[111] S. Barry et C. Chair-Welty, "FOIS introduction: Ontology: towards a new synthesis", dans *Proceedings of the International Conference on Formal Ontology in Information Systems - Volume 2001 (FOIS ’01)*, Ogunquit, Maine, USA, 2001, pp. 3–9. New York, NY, USA: ACM. [En ligne]. Disponible sur : `http://doi.acm.org/10.1145/505168.505201`

[112] T. R. Gruber, "Toward principles for the design of ontologies used for knowledge sharing," *International Journal of Human-Computer Studies*, Kluwer Academic Publishers, 1993, pp. 907–928.

[113] R. Studer, V. R. Benjamins et D. Fensel, "Knowledge engineering: principles and methods," Data & Knowledge Engineering, vol. 25, no. 1-2, pp. 161–197, 1998. Amsterdam, The Netherlands: Elsevier Science Publishers B. V. `http://dx.doi.org/10.1016/S0169-023X(97)00056-6`

[114] M. Uschold et M. Gruninger, "Ontologies: Principles, methods and applications," Knowledge Engineering Review*, vol. 11, pp. 93–136, 1996.

[115] P. A. Gómez, F.-L. Mariano et O. Corcho, "Ontological Engineering, with examples from the areas of Knowledge," dans *Management, e-Commerce and the Semantic Web*, Springer, 2004, pp. 3–15.

[116] M. Minsky, *A Framework for Representing Knowledge*, Cambridge, MA, USA: Massachusetts Institute of Technology, 1974.

[117] M. R. Quillian, "Word concepts: A theory and simulation of some basic semantic capabilities," *Behavioral Science*, vol. 12, pp. 410–430, 1967.

[118] F. W. Lehmann et E. Y. Rodin, *Semantic networks in artificial intelligence*, vol. 12, International Series in Modern Applied Mathematics and Computer Science. Oxford, UK: Pergamon Press, 1992. `http://books.google.fr/books?id=wItQAAAAMAAJ`

[119] R. J. Brachman, "What's in a concept: Structural foundations for semantic networks," *Int. Journal of Man-Machine Studies*, vol. 9, pp. 127–152, 1977.

[120] R. J. Brachman, "Structured inheritance networks," *Int. Journal of Man-Machine Studies*, vol. 9, pp. 127–152, 1978.

[121] R. J. Brachman et J. G. Schmolze, "An overview of the KL-ONE knowledge representation system," *Cognitive Science*, vol. 9, pp. 171–216, 1985.

[122] R. M. MacGregor, "Inside the LOOM description classifier," *SIGART Bull. ACM*, vol. 2, no. 3, pp. 88–92, 1991. New York, NY, USA: ACM. `http://doi.acm.org/10.1145/122296.122309`

[123] F. Baader et B. Hollunder, "KRIS: Knowledge Representation and Inference System," *SIGART Bull.*, vol. 2, no. 3, pp. 8–14, juin 1991. New York, NY, USA: ACM. `http://doi.acm.org/10.1145/122296.122298`

[124] W.A. Woods et J.G. Schmolze, "The KLONE family," *Computers & Mathematics With Applications*, vol. 23, no. 2-5, pp. 133–177, 1992.

[125] I. Horrocks et P. F. Patel-Schneider, "KR and Reasoning on the Semantic Web: OWL," dans *Handbook of Semantic Web Technologies*, J. Domingue, D. Fensel et J.A. Hendler, Éds., Springer, 2011, chap. 9, pp. 365–398. DOI: 10.1007/978-3-540-92913-0. `download/2010/HoPa10a.pdf`

[126] Horrocks, I. (2005). “OWL Rules, OK?” In *Rule Languages for Interoperability.*

[127] Horrocks, I., Patel-Schneider, P. F., Boley, H., Tabet, S., Grosof, B., & Dean, M. (2004). *SWRL: A Semantic Web Rule Language Combining OWL and RuleML*. W3C Member Submission. Available at: `http://www.w3.org/Submission/SWRL/`.

[128] Meditskos, G., & Bassiliades, N. (2011). *CLIPS-OWL: A framework for providing object-oriented extensional ontology queries in a production rule engine. Data & Knowledge Engineering*, 70, 661–681.

[129] C. Patel, J. Cimino, J. Dolby, A. Fokoue, A. Kalyanpur, A. Kershenbaum, L. Ma, E. Schonberg et K. Srinivas, "Matching patient records to clinical trials using ontologies," dans *Proceedings of the 6th International The Semantic Web and 2nd Asian Conference on Asian Semantic Web Conference (ISWC'07/ASWC'07)*, Busan, Korea, 2007, pp. 816–829. Berlin, Heidelberg: Springer-Verlag. [En ligne]. Disponible sur : `http://dl.acm.org/citation.cfm?id=1785162.1785223`

[130] D. V. McDermott, "A temporal logic for reasoning about processes and plans," *Cognitive Science*, vol. 6, pp. 101–155, 1982.

[131] J. F. Allen, "An interval-based representation of temporal knowledge," dans *Proceedings of the 7th International Joint Conference on Artificial Intelligence - Volume 1 (IJCAI'81)*, Vancouver, BC, Canada, 1981, pp. 221–226. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc

[132] J.F. Allen, "Maintaining knowledge about temporal intervals," *Commun. ACM*, vol. 26, no. 11, pp. 832–843, 1983. New York, NY, USA: ACM. DOI: 10.1145/182.358434. [En ligne]. Disponible sur: `http://doi.acm.org/10.1145/182.358434`

[133] J.F. Allen, "Towards a general theory of action and time," *Artif. Intell.*, vol. 23, no. 2, pp. 123–154, Jul. 1984. Essex, UK: Elsevier Science Publishers Ltd. DOI: 10.1016/0004-3702(84)90008-0. [En ligne]. Disponible sur: `http://dx.doi.org/10.1016/0004-3702(84)90008-0`

[134] P. Hallot, *Relations spatio-temporelles dans un espace-temps primitif. Un essai de simplification de l'analyse spatio-temporelle*, Mémoire de maîtrise, Université de Liège, Faculté des sciences, Sciences géographiques, 2006. "

[135] H.J. Levesque, F. Pirri et R. Reiter, "Foundations for the Situation Calculus," *Electron. Trans. Artif. Intell.*, vol. 2, pp. 159–178, 1998. [En ligne]. Disponible sur : `http://www.ep.liu.se/ej/etai/1998/005/`

[136] R. Reiter, *Knowledge in Action: Logical Foundations for Specifying and Implementing Dynamical Systems*, Cambridge, MA, USA: MIT Press, 2001.

[137] J. McCarthy, "Circumscription—A Form of Non-Monotonic Reasoning," in *Artificial Intelligence*, 1980.

[138] Manfred, J. (2005). *Narratology: A Guide to the Theory of Narrative.* English Department, University of Cologne. Available at `http://www.uni-koeln.de/~ame02/pppn.htm`.

[139] Bal, M. (1997). *Narratology: Introduction to the Theory of Narrative* (2nd ed.). Toronto: University of Toronto Press.

[140] A. I. Alexan, A. R. Alexan, and S. Oniga, "Real-Time Machine Learning for Human Activities Recognition Based on Wrist-Worn Wearable Devices," *Applied Sciences*, vol. 14, no. 1, p. 329, 2024. `https://doi.org/10.3390/app14010329`.

[141] Maza, A., & Sabri, L. (2025). Spatio-Temporal Ontological Query Processing in IoE Environments. *International Journal of Computers and Their Applications (IJCA)*, 32(3), September 2025.

[142] Maza, A., Sabri, L., & Agti, N. (2025). Adaptive Human Activity Recognition with Deep Q-Networks: A Reinforcement Learning Approach. In *Proceedings of the 13th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS)*, Poland, 2025.

[143] E. Barros, W. Souza, D. Costa, G. R. Filho, G. Figueiredo, et M. Peixoto, "Energy management in smart grids: An edge-cloud continuum approach with deep Q-learning," *Future Generation Computer Systems*, vol. 165, p. 107599, 2025.

[144] Sridevi, U. K., Sudhir, S., & Palaniappan, S. (2020). *Elderly behavior prediction using a deep learning model in smart homes.* In *Applications of Deep Learning and Big IoT on Personalized Healthcare Services* (pp. 115–131). IGI Global.

[145] Hansen, L. D., & Bolander, T. (2020). *Implementing theory of mind on a robot using dynamic epistemic logic.* In *Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence (IJCAI-20)*. International Joint Conference on Artificial Intelligence Organization. https://doi.org/10.24963/ijcai.2020/147

[146] Nguyen, H. S., Le, M. H., Lam, C. Q. L., & Duong, T. H. (2017). *Smart interactive search for Vietnamese disease by using data mining-based ontology. Journal of Information and Telecommunication*, 1(2), 176–191. https://doi.org/10.1080/24751839.2017.1323491

[147] Sharif, M., & Seker, H. (2024). *Smart EV charging with context-awareness: Enhancing resource utilization via deep reinforcement learning. IEEE Access*, 12, 7009–7027.

[148] J. Wang, B. Flanagan, and H. Ogata, "Semi-automatic construction of ontology based on data mining technique," in *Proceedings of the 6th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI)*, IEEE, 2017.

[149] Man, T., Myint, M., Guan, W., Zhukova, N. A., & Mustafin, N. (2021). A Hierarchical Data Mining Process Ontology. In *2021 28th Conference of Open Innovations Association (FRUCT)* (pp. 465–471).

[150] Li, X., & Zhang, J. (2024). Context-aware Communication for Multi-agent Reinforcement Learning. In *Proceedings of the 23rd International Conference on Autonomous Agents and Multiagent Systems (AAMAS '24)* (pp. 1156–1164). International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC.

[151] Kestel, P., et al. (2019). Ontology-based approach for the provision of simulation knowledge acquired by Data and Text Mining processes. *Advanced Engineering Informatics*, 39, 292–305.

[152] X. Zhou, W. Liang, K. I.-Kai Wang, H. Wang, L. T. Yang, Q. Jin, "Deep-Learning-Enhanced Human Activity Recognition for Internet of Healthcare Things," *IEEE Internet of Things Journal*, 2020. `https://ieeexplore.ieee.org/document/9055403`

[153] C. Fan, F. Gao, "Enhanced Human Activity Recognition Using Wearable Sensors via a Hybrid Feature Selection Method," *Sensors*, 2021. `https://www.mdpi.com/1424-8220/21/19/6434`

[154] A. M. Khalid, et al., "Human Activity Recognition Using Hybrid Coronavirus Disease Optimization Algorithm for Internet of Medical Things," *Sensors*, 2023. `https://www.mdpi.com/1424-8220/23/13/5862`

[155] W. N. Ismail, et al., "AUTO-HAR: An adaptive human activity recognition framework using an automated CNN architecture design," *Heliyon*, 2023. `https://pubmed.ncbi.nlm.nih.gov/36852018/`

[156] T. Kumrai, et al., "Human Activity Recognition with Deep Reinforcement Learning using the Camera of a Mobile Robot," *IEEE PerCom*, 2020. `https://staff.itee.uq.edu.au/jaga/proceedings/percom2020/papers/p127-kumrai.pdf`

[157] S. Mekruksavanich, A. Jitpattanakul, "Device Position-Independent Human Activity Recognition with Wearable Sensors Using Deep Neural Networks)," *Applied Sciences*, 2024. `https://www.mdpi.com/2076-3417/14/5/2107`

[158] D. Navakauskas, et al., "Wearable Sensor-Based Human Activity Recognition: Performance and Interpretability of Dynamic Neural Networks," *Sensors*, 2025. `https://www.mdpi.com/1424-8220/25/14/4420`

[159] Y. Mao, et al., "A Hybrid Human Activity Recognition Method Using an MLP Neural Network and Euler Angle Extraction Based on IMU Sensors," *Applied Sciences*, 2023. `https://www.mdpi.com/2076-3417/13/18/10529`

[160] S. Irfan, et al., "A Novel Hybrid Deep Learning Model for Human Activity Recognition Based on Transitional Activities," *Sensors*, 2021. `https://www.mdpi.com/1424-8220/21/24/8227`