Embracing uncertainty in human activity recognition: A fuzzy logic framework for interpretable and context-aware reasoning

David Díaz Jiménez
University of Jaén
ddjimene@ujaen.es

Carmen Martínez-Cruz
University of Granada
cmcruz@ugr.es

Juan F. Gaitán-Guerrero
University of Jaén
jgaitan@ujaen.es

Jose L. López-Ruiz
University of Jaén
llopez@ujaen.es

Antonio.P. Albín-Rodriguez
University of Jaén
aalbin@ujaen.es

Macarena Espinilla
University of Jaén
mestevez@ujaen.es

Abstract

Human Activity Recognition (HAR) in real-world environments is inherently uncertain — shaped by ambiguous sensor signals, behavioral variability, and contextual dynamics that challenge traditional machine learning approaches. Despite growing interest in robustness and explainability, most current systems still treat uncertainty as a nuisance to be minimized rather than a structural feature to be modeled. This paper proposes a conceptual shift: positioning fuzzy logic as the core paradigm for designing HAR systems that are interpretable, adaptive, and uncertainty-aware. We present a theoretical framework in which fuzzy reasoning is integrated throughout the HAR pipeline — from sensor abstraction and context modeling to soft, interpretable activity inference and natural language explanations. By framing uncertainty as a representational and inferential asset, rather than a limitation, our approach enables systems that align more closely with the complexity of human behavior and the demands of human-centered AI. The framework is modular, extensible, and designed for transparency — making it suitable for long-term deployment in smart environments, particularly in domains like elderly care, remote monitoring, and assistive technologies. This work contributes a structured foundation for building next-generation HAR systems that move beyond black-box classification, supporting ethical, explainable, and context-sensitive activity recognition.

Keywords: Human Activity Recognition (HAR), Uncertainty Modeling, Fuzzy Logic, Explainable AI (XAI), Context-Aware Systems

1. Introduction

HAR has become a fundamental capability within intelligent systems deployed in smart home environments (Amirjavid, 2013). These systems aim to detect and interpret daily behaviors by processing data from a variety of sensors, enabling applications such as ambient assisted living, remote healthcare, and personalized automation. Over the past decade, advances in sensing technologies and machine learning have driven rapid progress in this field. However, from our experience working with sensorized environments and behavior monitoring platforms, it is clear that significant challenges persist—particularly when systems are deployed beyond controlled settings and must respond to the unpredictability of real life (Gayathri et al., 2020).

One of the most persistent and under-addressed of these challenges is *uncertainty* (Rodríguez, 2016). It arises in many forms: noisy or incomplete sensor readings, variations in how different individuals perform the same activity, blurred transitions between actions, or simply the coexistence of behaviors that defy crisp categorization. In practical terms, uncertainty is not an occasional disturbance—it is a structural condition of real-world HAR.

Nonetheless, many conventional systems are not designed with this in mind. Data-driven models, especially those based on deep learning, have demonstrated impressive results in benchmark datasets. Yet these models depend on large volumes of labeled data, tend to generalize poorly to new contexts, and often operate as black boxes—difficult to interpret or adjust when behavior shifts or exceptions occur (Lu, 2023). On the opposite end, knowledge-based systems (e.g., rule-based or semantic approaches) offer transparency and control, but often lack the flexibility

URI: https://hdl.handle.net/10125/111631
978-0-9981331-9-5

needed to handle behavioral diversity or noisy input streams (Hoelzemann et al., 2021).

This long-standing tension between performance and interpretability suggests that alternative paradigms are needed—ones that can formally accommodate uncertainty without sacrificing adaptability or clarity. Fuzzy logic, rooted in the theory of fuzzy sets, provides a well-established but underutilized method for representing concepts that are inherently vague or partial. Rather than assigning binary classifications, fuzzy logic enables reasoning with linguistic descriptors (such as "moderate movement" or "likely cooking") and degrees of membership, allowing systems to reflect the fluidity of human behavior more faithfully.

While the potential of fuzzy logic has been acknowledged in HAR literature, its use has typically been limited to auxiliary roles—such as threshold adjustment or uncertainty smoothing (Arrotta et al., 2022; Kia et al., 2025). It is rarely adopted as the foundational reasoning mechanism guiding the system's design. In our view, this represents a missed opportunity.

This paper presents a theoretical framework in which fuzzy logic is positioned as a central structuring principle for HAR systems operating under uncertainty. The framework is not proposed as a finished solution, but rather as a conceptual model to support the systematic integration of fuzzy reasoning across all phases of activity recognition: sensor abstraction, context modeling, inference, and output explanation.

Our aim is not to introduce a new algorithm, nor to compare performance metrics across models, but to articulate a framework that can serve as a starting point for designing HAR systems that are robust, interpretable, and aligned with the complexities of human-centered environments. We argue that such a framework is not only technically sound, but increasingly necessary in light of current priorities in artificial intelligence—particularly those related to transparency, adaptability, and ethical system design.

To guide the reader through this theoretical proposal, the paper is organized as follows. In Section 2, we explore the multiple forms of uncertainty that characterize HAR in real-world environments, examining their origins and implications. Section 3 introduces the proposed architecture, detailing its four-stage structure from sensor abstraction to output explanation. Section 5 illustrates the framework through a practical use case situated in elderly care, highlighting its interpretability and contextual flexibility. Section 6 offers a critical discussion of the framework's strengths, limitations, and directions for future research, and finally, Section 7 concludes the paper by reflecting on the broader contributions and potential of adopting fuzzy reasoning as a core paradigm in HAR.

2. Characterizing uncertainty in HAR

Uncertainty is a defining characteristic of HAR systems in real-world environments. While the term frequently appears in the literature, especially in discussions of system performance or sensor limitations, it is rarely addressed as a core design element. In our experience working with sensor-based monitoring platforms in everyday settings, uncertainty is not a peripheral issue — it is central to the challenge of making sense of human behavior from imperfect data. This section explores the multiple forms of uncertainty inherent to HAR, their impact on system design, and how they motivate the fuzzy logic-based approach proposed in this work.

2.1. Defining uncertainty in HAR contexts

Uncertainty in HAR refers to the lack of full confidence or clarity in identifying, interpreting, or labeling human activities. Unlike engineered processes, human behavior is inherently variable, context-sensitive, and rarely reducible to discrete, repeatable states (Rodríguez, 2016). People perform the same activity in different ways depending on their preferences, habits, or context, and the signals produced by sensors often reflect this variability in ambiguous or contradictory forms (Dubey et al., 2022).

In contrast to structured tasks such as industrial automation — where sensors operate in well-defined and tightly controlled conditions — smart homes present a messier picture. Activities unfold across time and space with degrees of intensity, overlap, and environmental influence (Kalimuthu et al., 2021). For instance, "having lunch" may involve standing at the kitchen counter, walking between rooms, or sitting in silence — all producing different sensor patterns. Capturing such variability requires recognizing that many sensor signals may only partially reflect an activity, and that these fragments must be interpreted within a broader, uncertain context (Ronao and Cho, 2016).

2.2. Sources and layers of uncertainty

Based on our observations and existing literature, uncertainty in HAR arises from several interacting sources:

- **Sensor-level uncertainty**, due to imprecise measurements, signal loss, occlusions, or interference. Sensors may fail to detect an activity altogether or generate false positives, especially in ambient systems where noise is hard to distinguish from signal (Akbari and Jafari, 2019; Bi et al., 2012; Sekaran et al., 2024).

- **Contextual uncertainty**, which stems from the ambiguity of environmental or spatial conditions. The same set of sensor readings may indicate different activities depending on the time of day, room layout, or concurrent behaviors (Dashdorj et al., 2014; Meditskos and Kompatsiaris, 2017).

- **Behavioral uncertainty**, resulting from differences in how individuals carry out similar tasks. For example, "preparing for bed" may include a wide range of actions with varying order and duration, depending on the person (Niu et al., 2016; Ryoo and Aggarwal, 2008).

- **Temporal uncertainty**, as transitions between activities are rarely discrete. Many actions blend into one another, are performed in bursts, or occur simultaneously, complicating segmentation and classification based on fixed windows (Artikis et al., 2021; Najeh et al., 2022; Ryoo and Aggarwal, 2009).

- **Semantic uncertainty**, which reflects the vagueness or cultural variability of activity definitions. Concepts like "cleaning" or "relaxing" are broad, subjective, and context-dependent, yet we often ask systems to recognize them as if they were uniform labels (Culmone et al., 2015; Nguyen and Mellor, 2020).

These sources often interact. A small deviation in a user's routine — for example, moving more slowly due to fatigue — might generate atypical motion patterns that deviate from training data. If this occurs during a lighting change or in a transitional space (like a hallway), even a well-trained system may misclassify the behavior. Without explicit strategies to reason under uncertainty, HAR systems become fragile and overly dependent on narrowly defined data patterns.

2.3. Current limitations in addressing uncertainty

Despite the centrality of uncertainty, most HAR systems are not designed to handle it natively. Data-driven models are commonly trained on clean, annotated datasets and optimize for accuracy under the assumption of deterministic relationships between input and output. Probabilistic approaches — such as Hidden Markov Models or Conditional Random Fields — can represent uncertainty through statistical likelihoods, but often require strong assumptions about temporal structure and noise distribution (Meng et al., 2022).

Knowledge-driven models, on the other hand, tend to manage uncertainty through fixed rules and thresholds. Some attempt to incorporate symbolic approximations or confidence intervals, but without a coherent mechanism to combine partial evidence or reason across vague concepts, their capacity to handle ambiguity remains limited. Hybrid models may merge data-driven and rule-based techniques, but these integrations often increase system complexity without fully resolving uncertainty (Gayathri et al., 2015; Wang et al., 2022).

In our view, this gap reflects a deeper theoretical issue: many systems treat uncertainty as a nuisance to be minimized, rather than a structural aspect of behavior recognition that must be formally represented and reasoned about.

2.4. Embracing uncertainty through fuzzy logic

From a cognitive and design perspective, modeling uncertainty as a first-class property can lead to more resilient and human-aligned systems. Just as humans reason through approximations, expectations, and degrees of belief — especially in ambiguous or incomplete situations — intelligent systems should be able to make inferences based on partial truths and flexible boundaries (Cassenti and Kaplan, 2021).

Fuzzy logic offers a natural formalism for this. It allows the representation of graded confidence, linguistic categories, and rule-based reasoning that can integrate heterogeneous and imprecise data sources. Because it operates on the notion of degrees of membership rather than binary classifications, it accommodates ambiguity without resorting to rigid thresholds or opaque statistical models (Yager, 2020).

Equally important, fuzzy systems support interpretability. Rules can be inspected, refined, and expanded by human experts. This is particularly valuable in HAR domains such as healthcare or assisted living, where understanding why a system made a certain inference is often as important as the inference itself (Demongivert et al., 2021; Dubey et al., 2022).

Rather than discarding uncertainty as noise, the framework we propose views it as structure — an essential dimension of the recognition process. By formalizing this view through fuzzy logic, we believe

HAR systems can move closer to the complexity and subtlety of real-life human behavior (Collins et al., 2023).

In the next section, we describe the theoretical basis of fuzzy logic and how its principles can be systematically applied to the design of context-aware, interpretable HAR systems.

3. Theoretical framework architecture

In the preceding sections, we have argued that fuzzy logic provides a solid theoretical and practical foundation for managing the uncertainty that characterizes real-world HAR. Rather than treating it as an add-on or corrective mechanism, we propose that fuzzy reasoning should guide the architecture of HAR systems from the outset. Based on this principle, we introduce a modular framework structured around four core stages: (1) sensor abstraction and pre-processing, (2) context representation, (3) fuzzy activity inference, and (4) decision explanation and output management. Each stage contributes to the system's overall ability to reason under imprecision, adapt to variation, and offer interpretable results. A detailed overview of this framework can be seen in Figure 1.

3.1. Sensor abstraction and pre-processing

HAR systems rely on a wide variety of sensors, each with its own limitations and noise profiles. In our experience working with smart home deployments, we have seen how motion detectors, door sensors, ambient monitors, and wearable devices produce streams of data that are not always reliable or easy to interpret in isolation.

To address this, the first stage of the framework focuses on *fuzzy abstraction*: translating raw sensor data into fuzzy linguistic variables. Instead of setting hard thresholds to classify a motion value as "active" or "inactive", we define overlapping membership functions — e.g., "low," "moderate," or "high" motion — that better reflect the ambiguity often present in sensor readings. Similarly, temperature values might be interpreted as "cool," "comfortable," or "warm," and proximity signals from RSSI as "near" or "far."

This process allows the system to retain the richness and imprecision of the original signals, avoiding the brittleness that comes from overly rigid categorizations. It also provides a shared vocabulary for subsequent reasoning stages.

3.2. Context representation

Human activities are inherently context-dependent. The same pattern of motion might mean different things depending on the time of day, location, or prior behavior. A key strength of fuzzy logic is its capacity to incorporate this kind of context without resorting to fixed or binary labels.

In this second stage, environmental and temporal variables — such as location within the home, time windows, or ambient conditions — are also represented as fuzzy sets. For instance, a user may be "mostly in the kitchen," or "approaching evening," and such contextual states are incorporated directly into the inference rules.

We also account for individual variability through fuzzy user profiles. A "typical morning routine" for one user may involve more prolonged inactivity than for another. Modeling these patterns as fuzzy temporal or behavioral modifiers allows the system to adapt without needing extensive retraining.

3.3. Fuzzy activity inference

At the heart of the framework lies the fuzzy inference engine. This is where the system combines fuzzy descriptors of sensor data and context to infer likely activities. Rules are constructed in the following form:

> **IF** motion is moderate **AND** room is kitchen **AND** time is close to noon **THEN** activity is cooking (with high confidence)

Each rule can draw from any of the fuzzy variables previously defined, and multiple rules may fire simultaneously. The result is a set of weighted activity hypotheses, reflecting degrees of belief rather than binary decisions.

Unlike black-box models, the inference process here is transparent. Rules can be reviewed, adjusted, or refined over time. They can also be expanded as new activities, sensors, or behaviors are introduced. This supports both explainability and long-term maintainability — two requirements that are often in tension in HAR system design.

We find it especially valuable that the system can support *coexisting hypotheses*. For instance, if the system infers a 0.7 degree of confidence in "cooking" and a 0.4 in "cleaning," it may delay action, request confirmation, or prepare both response paths. This flexibility is essential when data is ambiguous or overlapping.

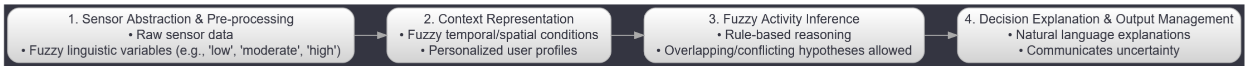

Figure 1. Architecture of the proposed theoretical framework

3.4. Decision explanation and output management

The final stage of the framework addresses how the system communicates its conclusions. In many real-world applications — particularly in health or care contexts — the ability to explain why a particular activity was inferred is not optional. It affects user trust, safety, and compliance.

Fuzzy logic supports this directly. Because the inference process is rule-based, the system can generate explanations grounded in its own internal logic. For example:

> Activity classified as cooking (confidence: 0.76), based on moderate motion in the kitchen during late morning hours.

This kind of output not only aids debugging and validation but also provides users and caregivers with insight into system behavior. When the system's confidence is low or multiple activities are similarly probable, it can defer automation, raise a flag, or seek clarification from the user.

This stage ensures that uncertainty is not only managed internally but also communicated outwardly in meaningful ways. It closes the loop between sensing, reasoning, and interaction — which we believe is essential for trustworthy HAR systems.

Taken together, these four stages provide a comprehensive and interpretable structure for HAR systems designed to operate under uncertainty. Each stage builds upon the others to support flexible, context-aware recognition that aligns more closely with the reality of human behavior in sensor-rich environments. In the next section, we reflect on the broader implications of this framework and suggest directions for extending it further.

4. Illustrative use case: supporting behavioral monitoring in elderly care

To better convey how the proposed framework might operate in practice, we describe a hypothetical but representative use case drawn from common patterns observed in ambient assisted living scenarios. The purpose here is to illustrate how fuzzy logic can be employed as a coherent reasoning strategy for interpreting real-world activity under uncertainty.

4.1. Scenario overview

Consider an elderly resident, Ms. Elena, who lives alone in a medium-sized apartment equipped with ambient sensors (motion detectors, door contacts, light and temperature sensors) and a wearable device providing basic activity and location data. The goal of the HAR system is to unobtrusively monitor her daily routines to detect potential deviations that could indicate risks such as isolation, disorientation, or health deterioration.

Ms. Elena typically wakes up around 7:30–8:00 AM, prepares breakfast, and spends the morning alternating between light movement in the kitchen and periods of stillness in the living room. Her activity level tends to drop significantly in the afternoons, and she often rests or naps. In the evening, she prepares a light meal and watches TV before going to bed between 10:30 and 11:00 PM.

These routines, while stable in broad terms, exhibit day-to-day variability — in timing, intensity, and sequence — depending on her mood, weather, and occasional visits. Conventional HAR systems might struggle with this irregularity, especially when sensor data is ambiguous or incomplete.

4.2. Fuzzy abstraction and context encoding

Sensor values are abstracted into fuzzy linguistic variables. Motion intensity in the kitchen is categorized as *low*, *moderate*, or *high*; temperature readings are mapped to *cool*, *comfortable*, or *warm*; time is segmented into fuzzy intervals such as *early morning*, *midday*, or *late evening*.

Contextual information is encoded similarly. For instance, if motion is detected in the kitchen and ambient light is increasing, the system infers that it is *probably morning*. Elena's typical sleep interval is represented as a fuzzy temporal window, allowing for gradual waking patterns or delayed bedtimes.

4.3. Fuzzy inference in action

At 7:45 AM, low motion is detected in the bedroom, followed by moderate motion in the hallway and a door opening into the kitchen. A rule of the form:

> **IF** motion is moderate AND location is kitchen AND time is early morning

> **THEN** activity is breakfast preparation (confidence: 0.65)

is partially activated. The system also considers a secondary rule:

> **IF** motion is low AND location is bedroom AND time is early morning
> **THEN** activity is waking up (confidence: 0.45)

The system infers both hypotheses with associated confidences, reflecting the fluid nature of transitions. These are passed to a higher-level decision module, which may wait for additional evidence before triggering any alert or notification.

4.4. Interpretable output and adaptive responses

Rather than committing to a discrete label, the system generates an explanation:

> "Elena is likely preparing breakfast (0.65 confidence), based on moderate motion in the kitchen during early morning hours."

If, by contrast, no kitchen activity is detected by 10:00 AM and bedroom motion remains low, the system may generate a different output:

> "Elena has not shown her usual morning routine. Low activity in bedroom since 7:00 AM. Consider checking in if pattern continues."

To illustrate how the framework operates in practice, we present a representative use case in elderly care. This scenario involves typical sensor events and their interpretation using fuzzy inference. The full data flow, from raw signals to interpretable explanations, is depicted in Figure 2.

This form of soft alerting respects personal variability while still enabling early intervention. Fuzzy confidence levels can be used to guide decisions such as escalating to caregivers, logging anomalies, or triggering unobtrusive prompts.

4.5. Reflection

This scenario illustrates how fuzzy logic can support HAR in messy, real-world conditions without forcing artificial crispness onto ambiguous data. Rather than reducing activity recognition to a matter of pattern matching, it becomes a process of contextual interpretation — one that aligns more closely with how humans themselves perceive and reason about behavior.

While this example is simplified, it reflects dynamics we have encountered in pilot studies and system design consultations. It also highlights the value of interpretability, especially in sensitive contexts where system transparency and adaptability matter as much as accuracy.

4.6. Practical considerations for implementation

While the framework has been presented primarily as a theoretical model, its practical implementation requires explicit strategies for constructing, maintaining, and validating the fuzzy rule base. This aspect is critical to ensure that the system remains interpretable and adaptable in real-world environments.

- Creation of the rule base: Rules can be initially elicited through participatory design involving domain experts, caregivers, and end users. This ensures that the linguistic variables and membership functions reflect practical knowledge and contextual nuances. Semi-automated techniques, such as rule extraction from annotated datasets or clustering-based fuzzy modeling, can complement expert input.

- Maintenance and evolution: As user routines evolve or new sensors are integrated, the rule base must be iteratively refined. Tools for rule visualization and interactive editing would allow experts and even non-technical stakeholders to adapt the system without retraining from scratch. Incremental updates help preserve transparency while accommodating behavioral variability.

- Validation and evaluation: Beyond accuracy metrics, validation should assess robustness under uncertainty, interpretability of explanations, and user trust. This can be achieved through longitudinal pilot studies in smart homes, comparing system outputs with ground truth annotations and user feedback. Additionally, sensitivity analyses of membership functions and rule interactions can help identify redundancies or inconsistencies.

By addressing these practical dimensions, the framework moves from a purely conceptual model toward an actionable methodology. These considerations not only strengthen the feasibility of implementation but also highlight the role of fuzzy logic in enabling iterative, participatory, and ethically grounded system design.

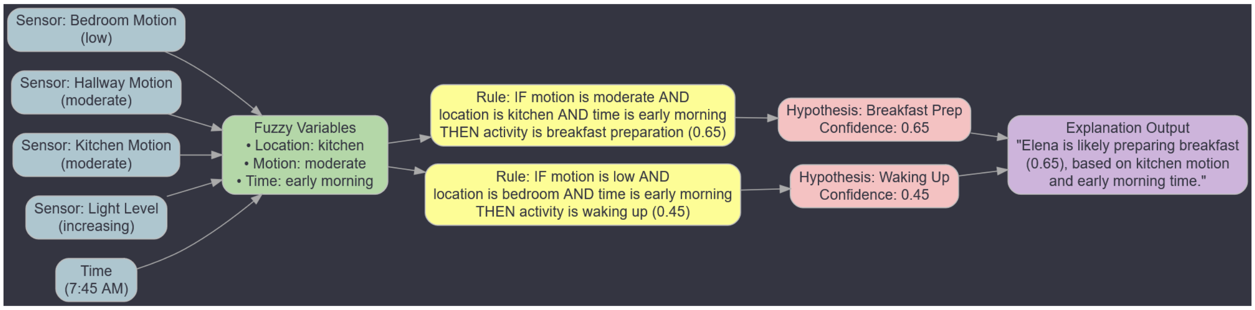

Figure 2. Illustrative use case: supporting behavioral monitoring in elderly care

5. Discussion and future perspectives

The framework developed in this paper presents a paradigm shift in the design of HAR systems by positioning uncertainty not as an incidental weakness, but as a core structural feature. By grounding our approach in fuzzy logic, we propose a pathway toward systems that can reason more effectively under ambiguity, handle behavioral variability, and remain interpretable in the face of complexity.

A central contribution of this work lies in its emphasis on representing uncertainty formally throughout the entire recognition process. Traditional machine learning methods, while effective in well-labeled datasets, often falter in noisy or dynamic environments. In contrast, fuzzy logic offers a methodology that does not merely tolerate uncertainty but incorporates it as a meaningful part of the reasoning process. This results in HAR systems that can produce more nuanced interpretations, support human oversight, and adapt to contextual subtleties — capabilities essential in domains such as ambient assisted living.

Another key advantage of the framework is its modularity. Unlike monolithic models that require full retraining when environments or behaviors shift, the fuzzy rule base can be extended incrementally. We have found that this flexibility is particularly beneficial in real-life deployments, where routines evolve over time and new sensor types may be introduced. This architecture encourages iterative refinement and supports collaborative development, where domain experts and users alike can shape system behavior.

However, this approach is not without its limitations. One of the most pressing challenges is the construction and maintenance of the fuzzy rule base and membership functions. While the interpretability of these components is an asset, creating them requires domain knowledge and time. As systems scale, rule interactions may become opaque or redundant, and ensuring consistency across hundreds of fuzzy rules can become burdensome. In our own experience designing prototype systems, we have seen how the lack of visual or assisted tooling for fuzzy design impedes broader adoption.

To move from concept to application, several research avenues warrant further exploration:

- **Empirical validation:** Future work should evaluate the performance of this framework in real-world deployments across a range of smart home scenarios. Metrics should include not only recognition accuracy, but also robustness under uncertainty, user interpretability, and system adaptability over time.

- **Interactive tooling and user engagement:** Developing graphical tools that allow non-technical stakeholders — such as caregivers or behavioral experts — to visualize, refine, and co-create fuzzy rules would lower the barrier to entry and promote participatory design.

- **Integration with learning-based models:** Hybrid approaches, such as neuro-fuzzy systems or fuzzy rule extraction from neural networks, offer promise. However, maintaining interpretability in these models must remain a guiding design constraint.

- **Longitudinal studies and personalization:** Beyond technical performance, long-term studies should explore how users experience and respond to uncertainty-aware systems, especially as behaviors evolve or deviate from historical norms.

We believe that embracing uncertainty through fuzzy reasoning can support HAR systems that are not only smarter, but also more ethical, transparent, and human-aligned. The framework presented here is a step toward that vision, but realizing its full potential will depend on interdisciplinary collaboration, investment in tool development, and sustained empirical work.

6. Conclusions and future work

This paper has presented a theoretical framework for Human Activity Recognition (HAR) grounded in fuzzy logic, aiming to treat uncertainty not as a limitation to be reduced but as a structural property of human activity that must be explicitly modeled. The proposed architecture, structured into four stages—sensor abstraction, context modeling, fuzzy inference, and decision explanation—offers a modular and transparent design that enhances interpretability, adaptability, and contextual sensitivity.

Beyond algorithmic performance, the approach highlights the importance of integrating linguistic reasoning, non-binary decisions, and comprehensible explanations, which are essential in sensitive domains such as home-based care and elderly monitoring. This perspective opens a new space for systems that, in addition to recognizing activities, can foster trust, support human oversight, and enable adoption in real-world environments.

Looking ahead, several research directions emerge as priorities:

- Scalability and machine learning: exploring rule induction, fuzzy clustering, and neuro-fuzzy models to automatically build and adapt rule bases from real-world data while preserving interpretability.

- Participatory design and tools: developing interfaces that empower caregivers and users to define, visualize, and refine fuzzy variables, thus promoting inclusive system design.

- Trust, ethics, and long-term engagement: conducting longitudinal studies to evaluate how users perceive and rely on systems that communicate confidence levels instead of categorical outputs.

- Hybrid integration and transparency: investigating architectures that combine fuzzy reasoning with deep learning, ensuring that adaptability does not compromise explainability.

- Multi-user scenarios: extending the framework to shared environments where social interactions and identity disambiguation introduce new challenges for uncertainty-aware reasoning.

Taken together, this paper offers a conceptual foundation for advancing toward a new generation of HAR systems capable of reasoning under uncertainty in ways that reflect the complexity of everyday life. Realizing this potential will require interdisciplinary research across computer science, behavioral science, interaction design, and ethics. When embraced as a foundational principle, fuzzy logic can support the development of systems that are not only smarter but also fairer, more adaptive, and genuinely aligned with the lived experiences of their users.

Acknowledgements

Grant PID2021-127275OB-I00 funded by MICIU/AEI/10.13039/501100011033 and by "ERDF A way of making Europe"

References

Akbari, A., & Jafari, R. (2019). A deep learning assisted method for measuring uncertainty in activity recognition with wearable sensors. *2019 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*, 1–5.

Amirjavid, F. (2013). *A fuzzy temporal data-mining model for activity recognition in smart homes*. Université du Québec à Chicoutimi.

Arrotta, L., Civitarese, G., & Bettini, C. (2022). Knowledge infusion for context-aware sensor-based human activity recognition. *2022 IEEE International Conference on Smart Computing (SMARTCOMP)*, 1–8.

Artikis, A., Makris, E., & Paliouras, G. (2021). A probabilistic interval-based event calculus for activity recognition. *Annals of Mathematics and Artificial Intelligence*, *89*(1), 29–52.

Bi, Y., Nugent, C., & Liao, J. (2012). An evidential framework for associating sensors to activities for activity recognition in smart homes. *Advances in Computational Intelligence: 14th International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems, IPMU 2012, Catania, Italy, July 9-13, 2012, Proceedings, Part III 14*, 564–574.

Cassenti, D. N., & Kaplan, L. M. (2021). Robust uncertainty representation in human-ai collaboration. *Artificial Intelligence and Machine Learning for Multi-Domain Operations Applications III*, *11746*, 249–262.

Collins, K. M., Barker, M., Espinosa Zarlenga, M., Raman, N., Bhatt, U., Jamnik, M., Sucholutsky, I., Weller, A., & Dvijotham, K. (2023). Human uncertainty in concept-based ai systems. *Proceedings of the 2023 AAAI/ACM*

Conference on AI, Ethics, and Society, 869–889.

Culmone, R., Giuliodori, P., Quadrini, M., et al. (2015). Human activity recognition using a semantic ontology-based framework. *International Journal on Advances in Intelligent Systems*, *8*(1&2), 159–168.

Dashdorj, Z., Sobolevsky, S., Serafini, L., & Ratti, C. (2014). Human activity recognition from spatial data sources. *Proceedings of the third ACM SIGSPATIAL international workshop on mobile geographic information systems*, 18–25.

Demongivert, C., Bouchard, K., Gaboury, S., Lussier, M., Kenfack-Ngankam, H., Couture, M., Bier, N., & Giroux, S. (2021). Handling of labeling uncertainty in smart homes using generalizable fuzzy features. *Proceedings of the Conference on Information Technology for Social Good*, 248–253.

Dubey, A., Lyons, N., Santra, A., & Pandey, A. (2022). Xai-bayeshar: A novel framework for human activity recognition with integrated uncertainty and shapely values. *2022 21st IEEE International Conference on Machine Learning and Applications (ICMLA)*, 1281–1288.

Gayathri, K., Easwarakumar, K., & Elias, S. (2020). Fuzzy ontology based activity recognition for assistive health care using smart home. *International Journal of Intelligent Information Technologies (IJIIT)*, *16*(1), 17–31.

Gayathri, K., Elias, S., & Shivashankar, S. (2015). Composite activity recognition in smart homes using markov logic network. *2015 IEEE 12th Intl Conf on Ubiquitous Intelligence and Computing and 2015 IEEE 12th Intl Conf on Autonomic and Trusted Computing and 2015 IEEE 15th Intl Conf on Scalable Computing and Communications and Its Associated Workshops (UIC-ATC-ScalCom)*, 46–53.

Hoelzemann, A., Sorathiya, N., & Van Laerhoven, K. (2021). Data augmentation strategies for human activity data using generative adversarial neural networks. *2021 IEEE International Conference on Pervasive Computing and Communications Workshops and other Affiliated Events (PerCom Workshops)*, 8–13.

Kalimuthu, S., Perumal, T., Yaakob, R., Marlisah, E., & Babangida, L. (2021). Human activity recognition based on smart home environment and their applications, challenges. *2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, 815–819.

Kia, Z., Yadollahzaeh-Tabari, M., & Motameni, H. (2025). Human activity recognition by body-worn sensor data using bi-directional generative adversarial networks and frequency analysis techniques. *The Journal of Supercomputing*, *81*(1), 1–34.

Lu, Z. (2023). Deep learning-based human activity recognition algorithms: A comparative study. *2023 IEEE International Conference on Image Processing and Computer Applications (ICIPCA)*, 1041–1046.

Meditskos, G., & Kompatsiaris, I. (2017). Iknow: Ontology-driven situational awareness for the recognition of activities of daily living. *Pervasive and Mobile Computing*, *40*, 17–41.

Meng, X.-B., Li, H.-X., & Chen, C. P. (2022). A two-stage bayesian learning-based probabilistic fuzzy interpreter for uncertainty modeling. *Applied Soft Computing*, *131*, 109786.

Najeh, H., Lohr, C., & Leduc, B. (2022). Dynamic segmentation of sensor events for real-time human activity recognition in a smart home context. *Sensors*, *22*(14), 5458.

Nguyen, V., & Mellor, L. (2020). Fuzzy mlns and qstags for activity recognition and modelling with rush. *2020 IEEE 23rd international conference on information fusion (FUSION)*, 1–8.

Niu, X., Wang, Z., Xiao, W., & Pan, Z. (2016). Uncertainty sampling based posterior probability extreme learning machine for human activity recognition. *International Journal of Smart Home*, *10*(11), 95–108.

Rodríguez, N. D. (2016). *Semantic and fuzzy modelling for human behaviour recognition in smart spaces: A case study on ambient assisted living* (Vol. 23). Ios Press.

Ronao, C. A., & Cho, S.-B. (2016). Human activity recognition with smartphone sensors using deep learning neural networks. *Expert systems with applications*, *59*, 235–244.

Ryoo, M. S., & Aggarwal, J. K. (2008). Human activities: Handling uncertainties using fuzzy time intervals. *2008 19th International Conference on Pattern Recognition*, 1–5.

Ryoo, M. S., & Aggarwal, J. K. (2009). Stochastic representation and recognition of high-level group activities: Describing structural uncertainties in human activities. *2009 IEEE computer society conference on computer vision and pattern recognition workshops*, 11–11.

Sekaran, S. R., Han, P. Y., You, L. Z., & Yin, O. S. (2024). Feature-level fusion multi-sensor aggregation temporal network for smartphone-based human activity recognition. *Journal of Telecommunications and the Digital Economy*, *12*(3), 29–50.

Wang, J., Zhou, Z.-J., Ming, Z.-C., Zhang, P., Lian, Z., & Li, Z.-G. (2022). Inference, optimization, and analysis of an evidential reasoning rule-based modeling approach. *IEEE Transactions on Aerospace and Electronic Systems*, *59*(4), 3907–3923.

Yager, R. R. (2020). Using fuzzy measures for modeling human perception of uncertainty in artificial intelligence. *Engineering Applications of Artificial Intelligence*, *87*, 103228.