A Fuzzy Multimodal Framework for Interpretable Treatment Adherence Modeling from IoT Data

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Abstract. Treatment adherence in chronic diseases is inherently multidimensional and difficult to quantify using traditional instruments. This paper presents a framework in which adherence is modelled from heterogeneous Internet of Things (IoT) data by combining human activity recognition, fuzzy data fusion, and behavioural analysis. The approach integrates explicit treatment-related activities with contextual behavioural markers, enabling a continuous and interpretable representation under uncertainty. The resulting model provides clinically meaningful adherence indicators while remaining compatible with modern artificial intelligence (AI) pipelines.

Keywords: Treatment adherence · Fuzzy logic · Internet of Things · Human activity recognition · Chronic disease management · Explainable AI

1 Introduction

Long-term management of chronic diseases such as diabetes depends critically on sustained adherence to therapeutic recommendations. In practice, adherence extends beyond medication intake and involves a set of interrelated routines, including diet, physical activity, sleep, and hygiene. Capturing this complexity remains a challenge, particularly in real-world environments.

Internet of Things (IoT)-based monitoring systems offer an opportunity to observe patient behaviour continuously through wearable and ambient sensors. However, translating raw sensor streams into robust and clinically meaningful indicators is non-trivial due to noise, heterogeneity, and temporal variability.

The framework presented in [1] addresses this problem by modelling adherence as a graded construct derived from multimodal observations. This paper provides a concise and structured overview of that methodology, emphasising its implications for interpretable artificial intelligence (AI) in healthcare.

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2 Background and Motivation

Self-reported adherence instruments remain widely used due to their simplicity and low cost, but they only provide a partial and often static view of patient behaviour. Their limitations become particularly evident in long-term therapies, where adherence fluctuates over time. According to the World Health Organization, adherence averages around 50% in developed countries [2], reinforcing the need for more reliable monitoring strategies.

In contrast, sensor-based approaches enable continuous observation of daily routines. Early work in smart environments showed that behavioural patterns can be inferred from ambient signals [3, 4], paving the way for digital health systems in which behaviour is treated as a proxy for clinical state rather than as isolated events.

However, these approaches are not without challenges. Sensor data are inherently noisy, heterogeneous, and context-dependent. As a result, many existing solutions struggle with uncertainty and limited interpretability. Fuzzy data fusion has been proposed as a suitable mechanism to address these issues, allowing gradual reasoning over imperfect signals [5]. More recently, large language models have been explored to generate higher-level interpretations of behavioural data [6].

Taken together, these developments point towards hybrid frameworks that combine data-driven recognition with transparent reasoning. In this context, adherence is better understood as a dynamic and explainable state, rather than a binary outcome.

3 Proposed Methodology

The framework models adherence as the combination of two complementary components: explicit treatment-related activities and behavioural markers. Explicit activities include medication intake, physical activity, nutrition, sleep, and hygiene, each defined through sensor-derived indicators. Behavioural markers capture contextual aspects such as mobility, daily regularity, sleep quality, and sedentary behaviour.

Sensor observations are first transformed into fuzzy membership degrees using linguistic variables. Temporal smoothing is applied to reduce the impact of transient noise, and aggregation operators combine information from multiple sensors. A generic observation $m_i = \{B_j, v_i, t_i\}$ is mapped into a membership degree $\mu_A(v_i) \in [0, 1]$, where A denotes a linguistic concept such as *near*, *active*, or *resting*. The global adherence score is then defined as:

$$S = \frac{\sum_j w_j \cdot \mu_j}{\sum_j w_j}, \tag{1}$$

where μ_j denotes the adherence degree for activity j and w_j its clinical relevance.

In addition, the framework incorporates anomaly detection mechanisms that identify deviations from expected routines. These deviations can be temporal,

frequency-based, or behavioural. This distinction is important because delayed medication, skipped activity, and progressive reduction in mobility have different clinical meanings and should not be collapsed into the same non-adherence label.

4 Temporal Activity Matching

A relevant feature of the framework is its compatibility with activities inferred by machine-learning or deep-learning models. When a recognition model detects an event $a_k = \{label_k, t_k^s, t_k^e\}$, this event can be compared with the therapeutic window in which the activity is expected to occur. The matching is not crisp, but fuzzy:

$$\mu_{A_j}(a_k, W_r) = \frac{|I_k \cap [\sigma_r^s - \varepsilon, \sigma_r^e + \varepsilon]|}{|\sigma_r^e - \sigma_r^s|} \cdot \max\left(0, 1 - \frac{|t_k^s - \sigma_r^s|}{\Delta}\right), \tag{2}$$

where $I_k = [t_k^s, t_k^e]$, $W_r = [\sigma_r^s, \sigma_r^e]$ is the prescribed window, ε is a tolerance margin, and Δ controls the penalty for delayed execution.

This formulation is useful in everyday monitoring because routines are rarely exact. A meal or medication event slightly outside the expected interval should not be treated as equivalent to a completely missed activity. The fuzzy temporal degree provides a more realistic representation of partial adherence.

5 Experimental Insights

The methodology was evaluated through simulated scenarios derived from real sensor deployments. Three representative profiles were considered: high, moderate, and low adherence. Each profile reflects different levels of behavioural stability and routine consistency. The results show that the model produces coherent and interpretable adherence indicators across profiles. High-adherence scenarios exhibit stable patterns, whereas low-adherence cases present significant variability and deviations. Moderate profiles combine partially fulfilled activities with irregular contextual markers.

Each day can be represented as a multidimensional fuzzy adherence vector:

$$\mathbf{S}_D(d) = (\mu_{med}, \mu_{act}, \mu_{nut}, \mu_{sleep}, \mu_{hyg}, \mu_{mob}, \mu_{reg}, \mu_{sleepQ}, \mu_{sed}). \tag{3}$$

This representation makes it possible to inspect which dimensions explain the final score. For instance, a patient may show high medication adherence but low sleep quality and reduced mobility. In a binary model, this situation could be hidden; in the proposed framework, it becomes a partial adherence profile with clinically relevant warning signs.

6 Discussion

A central aspect of the framework is how uncertainty is propagated from raw sensing to high-level indicators. Rather than forcing sensor observations into rigid categories, fuzzy membership functions allow the model to preserve intermediate

evidence. This is particularly valuable in domestic environments, where signals are noisy and routines vary naturally across days.

From an AI perspective, the framework combines data-driven recognition with symbolic reasoning. Activity recognition models can provide candidate events, while the fuzzy layer transforms them into interpretable adherence indicators. This hybrid structure enhances transparency without excluding modern machine-learning pipelines.

The inclusion of behavioural markers further extends the model beyond task-level compliance. Adherence is not only a question of whether the patient performs a prescribed action, but also whether daily life remains organised enough to sustain treatment over time. Progressive changes in sleep regularity, mobility, or sedentarism may therefore act as early signs of deterioration.

The framework also has limitations. The validation scenarios are based on simulated profiles derived from real deployments, so long-term validation in diverse homes and clinical populations is still required. In addition, the weighting scheme should be personalised, since the relevance of each activity depends on the treatment plan, comorbidities, and clinical objectives.

7 Conclusions

This paper summarises a fuzzy multimodal framework for modelling treatment adherence from IoT data, integrating explicit activities, behavioural context, temporal matching, and anomaly detection within a unified and interpretable structure. By representing adherence as a continuous and multidimensional construct, the approach provides a practical alternative to traditional binary assessments and aligns well with modern AI-driven healthcare systems. Future work will address real-world validation, model personalisation, and integration with predictive and generative AI for patient-centred decision support.

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