Digital Twin Framework for Context-Aware Safety Adherence Monitoring Using IMU-Based Digital Biomarkers

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***Abstract*—This paper presents a digital twin framework for monitoring people with dementia safety adherence using multimodal data from wearable smart glasses in home settings. Monitoring adherence to safety measures during activities of daily living (ADL) can serve as a useful proxy for evaluating cognitive and functional decline. The proposed framework integrates inertial measurement unit (IMU) data with environmental perception to infer user safety adherence behaviour relative to environmental hazards and home safety interventions using fuzzy logic (FL). The inferred behaviours are temporally aggregated to generate digital biomarkers that enable longitudinal tracking of cognitive decline. Experimental results demonstrate the feasibility of the framework in capturing and analysing safety adherence dynamics, showing its potential for long-term cognitive health monitoring.**

***Keywords*—Dementia, Digital Twin, Digital Biomarker, Safety Adherence, Fuzzy Logic**

I. INTRODUCTION

The safety of people with dementia (PwD) who live alone is a significant concern to family members [1]. In the United Kingdom, this population is substantial, with approximately 120,000 individuals living independently [2]. While home safety interventions, including environmental modifications such as improved lighting, installation of grab bar and handrail, and hazard removal have demonstrated effectiveness in reducing fall risk, their sustained benefit depends on continued user engagement [3]. Some studies have argued that these fall prevention strategies that are effective for cognitively healthy older adults have generally shown limited success among PwD [4]. Adherence remains a significant challenge, as PwD may struggle to consistently follow or comply with prescribed measures [5-6].

Research shows that caregiver support directly influences adherence behaviours amongst PwD [7]. Hence, living alone limits adherence to safety interventions [8] and reduce insight into cognitive decline which may compromise safety over time [9]. While some studies have examined adherence to medication [7] and exercise interventions [10] among PwD, there remains a notable gap in the literature on adherence to home safety interventions, particularly regarding how PwD follow such measures in their own homes. Monitoring adherence to safety measures during activities of daily living (ADL) can serve as a useful proxy for evaluating cognitive and functional decline.

To address this gap, this paper proposes a digital twin (DT) framework to monitor cognitive decline in PwD based on their safety adherence behaviour towards potential home hazards and safety interventions. The framework integrates inertial measurement unit (IMU) based motion data with object detection to infer user safety adherence relative to environmental safety cues using fuzzy logic (FL). The inferred adherences are aggregated over time to generate digital biomarkers that enable longitudinal monitoring. This approach enables the detection of subtle behavioural deviations, which may reflect emerging changes in attention and executive functioning as a result of cognitive decline. The main contributions of this paper are as follows: (1) DT framework integrating IMU sensing and environmental perception for behaviour monitoring. (2) FL–based method for context-aware safety adherence inference. (3) Temporal biomarker extraction and modelling based on IMU data.

II. RELATED WORKS

Digital twin (DT) technology has emerged as a transformative paradigm in healthcare [11]. It is a data-driven virtual representation of a physical entity that uses real-time, bidirectional data integration to support prediction and decision-making [12-13]. Sensor-based devices capable of generating IMU data play a critical role in data acquisition for DT systems, as they enable continuous capture of motion dynamics necessary for real-time synchronisation and accurate representation of physical behaviour [14]. DT technology in dementia research is still at an early and emerging stage, with only a limited number of studies demonstrating its feasibility across specific applications [12]. These applications include early detection, personalised care, multimodal digital biomarker integration, reduce sample sizes for randomised controlled trial (RCT) and continuous monitoring of disease progression [12, 15-16].

III. MATERIALS AND METHODS

A. Conceptual Framework

The proposed DT framework comprises two tightly integrated layers: (1) the Physical Entity and (2) the Digital

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Replica, as illustrated in Fig 1. These interconnected components facilitate continuous, real-time monitoring of the user's environment and movement pattern in a closed-loop. The proposed DT framework provides real-time safety feedback to users through an AR smart glass, while simultaneously delivering visual analytics to a stakeholder dashboard for monitoring and decision support. To derive a digital biomarker of cognitive decline, time-series features were computed through temporal aggregation of user safety adherence inference signal. Consequently, longitudinal analysis of these features enables monitoring and early detection of cognitive decline in real-world settings.

B. Physical Entity

The physical entity layer captures environmental and movement data using AR smart glasses with a forward-facing camera and integrated IMU sensors (accelerometer, gyroscope, and magnetometer), serving as the primary multimodal data acquisition device. The multimodal data acquired is transmitted to the DT's virtual replica for further processing and analysis. Table 1 shows a sample of the IMU dataset. Fig 2 presents corresponding image frames captured over a 5-second interval during routine home activities.

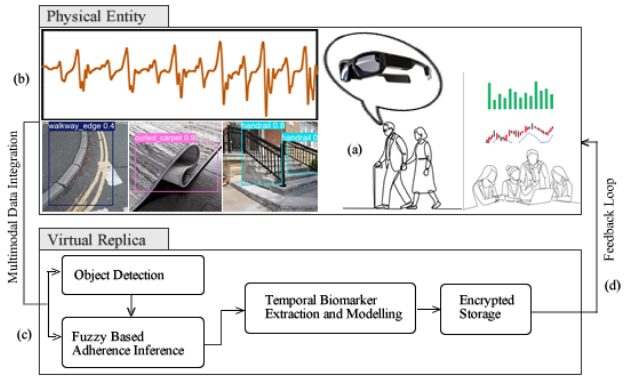

Fig 1. Digital twin framework for personalised safety cue notification and cognitive monitoring. (a) smart glasses capture environment image and movement data (b) multimodal data transmission to visual replica (c) data analysis, storage, and visualisation (d) feedback response to smart glasses and stakeholder monitoring dashboard

TABLE 1. Sample IMU Time-Series Data from Smart Glasses

Time (s)	**Acc X (m/s²)**	**Acc Y (m/s²)**	**Acc Z (m/s²)**	**Gyro X (rad/s)**	**Gyro Y (rad/s)**	**Gyro Z (rad/s)**	**Mag X**	**Mag Y**	**Mag Z**
0.5	0.20	0.02	9.70	0.03	0.00	0.02	0.30	0.10	0.40
1.0	0.10	0.05	9.68	0.04	0.01	0.02	0.32	0.11	0.38
1.5	0.05	-0.02	9.80	0.01	-0.01	0.00	0.31	0.09	0.39
2.0	-0.02	-0.05	9.82	-0.01	-0.02	-0.01	0.28	0.08	0.41
2.5	-0.08	-0.03	9.85	-0.02	-0.01	-0.02	0.27	0.07	0.42
3.0	-0.12	0.00	9.78	-0.03	0.00	-0.01	0.26	0.06	0.43
3.5	-0.05	0.04	9.74	-0.01	0.02	0.00	0.29	0.09	0.41
4.0	0.02	0.06	9.69	0.02	0.03	0.01	0.33	0.12	0.37
4.5	0.08	0.03	9.73	0.03	0.02	0.02	0.35	0.13	0.36
5.0	0.15	0.00	9.77	0.02	0.01	0.01	0.36	0.14	0.35

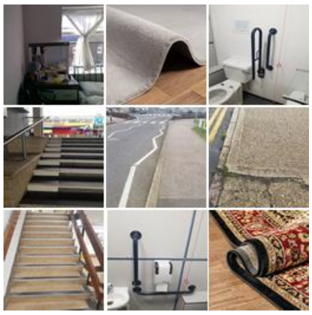

Fig 2. Sample Image Frames

C. Virtual Replica

The virtual replica layer consists of several modules designed to process multimodal data streams, extract digital biomarkers, and store the resulting outputs for further use. The functions of each module are described as follows:

- **Object Detection:** This module analyses incoming images stream from the user's smart glass during ADL using THLLOD [17]. THLLOD is an object detection pipeline designed to identify potential environmental hazards and home safety interventions in both indoor and outdoor settings. Specifically, THLLOD detects fall hazards such as stairs, curled rugs, damaged flooring, and walkway edges, as well as safety features including handrails and grab bars. These objects classes and their spatial position are transmitted to the fuzzy based adherence inference module.

- **Fuzzy Based Adherence Inference:** Based on the object of interest detected in the user environment, this module combines the object class and spatial position with IMU sensor data to estimate user safety adherence behaviour using FL. FL accounts for uncertainty and variability in movement signals derived from IMU sensor data [18]. The inference system uses a single IMU-derived lateral velocity $v_x \in \mathbb{R}$, a discrete contextual variable indicating detected object position $p \in$ *{left, centre, right}* and class $c \in$ *{hazard, safety intervention}* to estimate movement direction $d \in$ *{towards, away, uncertain}* relative to environmental clue. It uses three piecewise-linear membership functions at time t as illustrated in Fig 3 and defined in (1) - (3):

$$\mu_L(v_x) = max(0, min(1, -v_x)) \quad (1)$$
$$\mu_R(v_x) = max(0, min(1, v_x)) \quad (2)$$
$$\mu_C(v_x) = max(0, 1- |v_x|) \quad (3)$$

where μ is user motion and $\mathbb{R}$ is real numbers.

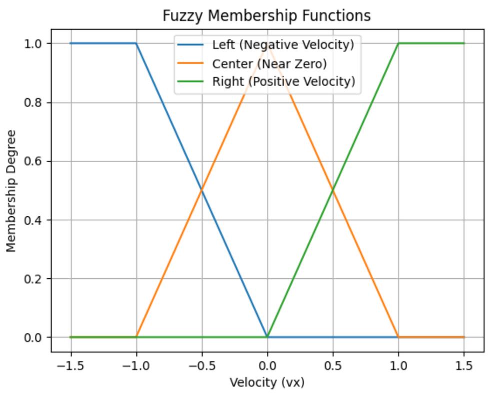

Fig 3. Motion triangular membership functions

The user's movement direction is thus determined from the output of the fuzzy membership function in relation to the detected object position p within the environmental cues, as mathematically expressed in (4):

$$(d_{towards}(t), d_{away}(t)) = \begin{cases} (\mu_L(v_x), \mu_R(v_x)), & p = left \\ (\mu_R(v_x), \mu_L(v_x)), & p = right \\ (\mu_C(v_x), max(\mu_L(v_x), \mu_R(v_x))), & p = centre \end{cases} \tag{4}$$

The corresponding user safety adherence behaviour is formalised as a context-dependent mapping between user movement direction d and object class c, as mathematically expressed in (5):

$$A(t) = \begin{cases} 1 \equiv max(\mu_{away}(p_t), \mu_{towards}(p_t)), & if \begin{cases} c_t = hazard \rightarrow \mu_{away}(p_t) \\ c_t = safety\ intervention \rightarrow \mu_{towards}(p_t) \end{cases} \\ 0 \equiv 1 - max(\mu_{away}(p_t), \mu_{towards}(p_t)), & otherwise \end{cases} \tag{5}$$

$A_t \in \{0,1\}$ denotes safety adherence inference at time t where $A_t = 1$ indicates adherence, that is the user responds appropriately to environmental cues, moving away from a detected hazard or moving towards a safety intervention. Conversely, $A_t = 0$ represents non-adherence, corresponding to incorrect, inappropriate, or uncertain responses that do not align with the expected safety-driven action.

- **Temporal Biomarker Extraction and Modelling:** In this module, discrete safety adherence inferences are converted into continuous-time representations of cognitive state to support temporal analysis. The digital biomarker is obtained by aggregating inferred safety adherence signals over a sliding window of length N using a rolling mean [19], expressed in (6):

$$Rolling\ Adherence\ (t) = \frac{1}{N}\sum_{i=t-N}^{t} A_i \tag{6}$$

where N is window size

This transformation converts noisy, event-level observations into a continuous trajectory reflecting functional capacity over time. A declining trend in A_t indicates potential cognitive deterioration. In parallel, long-term cognitive trends are modelled using an exponentially weighted moving average (EWMA) [20], given by (7):

$$Z_t = (1-\lambda)Z_{t-1} + \lambda X_t \tag{7}$$

where x_t = current adherence value, λ = smoothing factor (0-1)

- **Encrypted Storage:** To ensure data privacy and compliance with ethical and regulatory standards, the proposed framework adopts a formalised secure storage mechanism for all patient-derived digital biomarkers. Let $D = \{x_1, x_2, \ldots, x_n\}$ denote the set of digital biomarker data, where each element represents movement signals, interaction features, and behaviour inference. These data are first transformed into a structured and interoperable representation using JavaScript Object Notation (JSON), expressed in (8):

$$J = JSON(D) \tag{8}$$

This lightweight format facilitates efficient data organisation and seamless communication across system components. To protect sensitive information, the JSON object is encrypted using the Advanced Encryption Standard with a 256-bit key [21], yielding the ciphertext in (9):

$$C = AES_{256}(J,k) \tag{9}$$

where k denotes the secret encryption key. The resulting encrypted data C is then stored within the DT environment, ensuring confidentiality, integrity, and secure access.

IV. EXPERIMENTATION

A. Dataset

This study evaluates the proposed DT framework using a simulated longitudinal dataset emulating patient activity during ADL over a seven-day observation period. Time-series data were sampled at 5-second intervals, yielding a high-resolution behavioural stream. Each observation consisted of a timestamp, day index (1–7), object interaction context (categorised as hazard or intervention), motion direction (towards, away, or uncertain), and a binary adherence label. Simulation-based evaluation is widely used in healthcare analytics and computational medicine when real-world clinical data are inaccessible or when controlled experimental manipulation is required to assess model behaviour under known ground-truth conditions [22]. Synthetic datasets allow systematic control over noise, temporal structure, and behavioural variability, enabling robust validation of algorithmic performance prior to real-world deployment [23].

B. Results

Adherence metrics were aggregated at the daily level to examine longitudinal trends and simulate progressive decline patterns. Rolling mean [19] and EWMA [20] trends were used to qualitatively assess the temporal dynamics of the digital biomarker that captures behavioural variability. Based on the simulated data used, the daily aggregation of adherence metrics over the 7-day observation period demonstrates a high degree of temporal stability, with mean adherence values consistently ranging between 0.847 and 0.853 as shown in Fig 4.

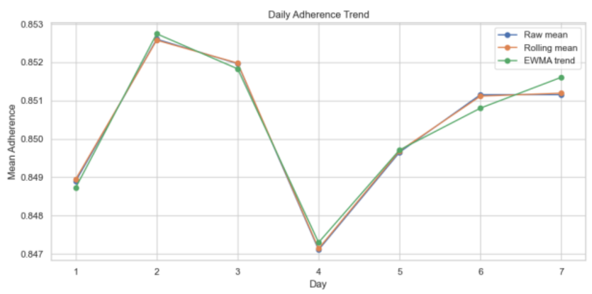

Fig 4. Daily Adherence Trend

Raw and rolling adherence values are nearly identical across all days, indicating minimal short-term variability and a naturally smooth daily signal. A slight dip is observed on Day 4 (mean ≈ 0.847), followed by quick recovery, suggesting no sustained decline or cognitive drift. The overall variation across the study period remains low (≈0.6% range), reinforcing the conclusion that safety adherence behaviour is stable and resilient to transient fluctuations.

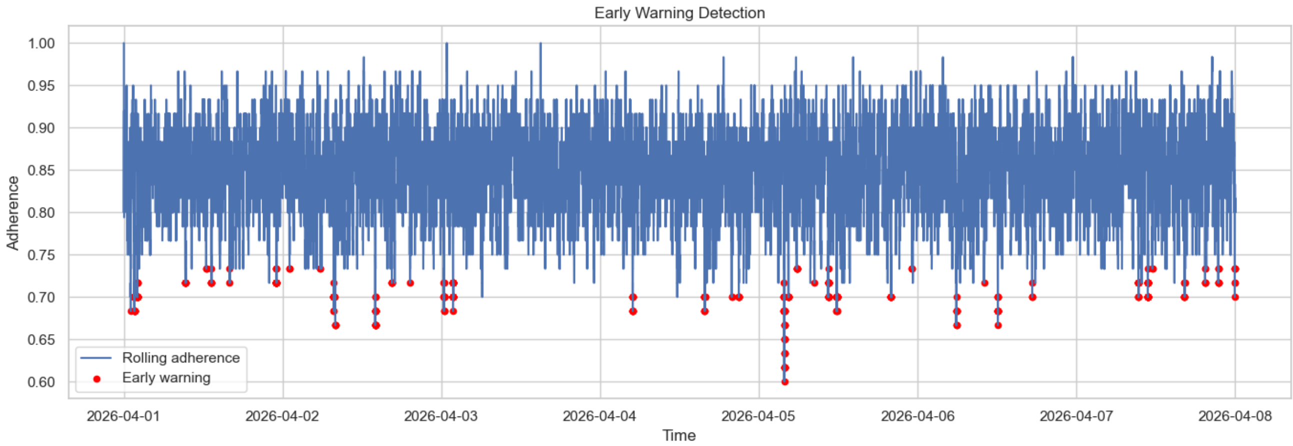

Fig 5. Early Warning Alerts

Fig 5 shows that alerts highlighting early waring cognitive decline are frequent but occupy a small fraction of the full timeline. This indicates transient behavioural disruptions rather than sustained failure. The user exhibits approximately 5–8 episodes per day, each lasting ~60–180 seconds, with a mean adherence degradation of ~10–18% relative to the long-term baseline, and occupying approximately ~3–6% of the total monitoring time.

V. CONCLUSION

This paper presents a DT-based framework for context-aware monitoring of user safety adherence to potential home hazards and safety interventions using multimodal data from smart glasses IMU sensors and environmental perception. The proposed DT framework delivers real-time safety feedback via AR smart glasses to users while providing visual analytics to stakeholder dashboard for remote monitoring of cognitive decline. Despite its promise for passive and unobtrusive behavioural monitoring, digital twin technology in healthcare is constrained by key challenges, particularly ethical and regulatory concerns to patient privacy and data security. To address these challenges, the proposed framework incorporates a privacy-by-design approach, ensuring that all stored data within the DT are securely protected.

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