

ORIGINAL RESEARCH ARTICLE

An intelligent patient bed architecture based on fuzzy cognitive maps, multimodal Internet of Things sensing, and machine learning

Long Mei¹, Chee Siong Teh^{1*}, Xing Wang², Zhidong Fang³, Chun Zheng², and Huadong Chen⁴

¹Department of Cognitive Science, Faculty of Cognitive Sciences & Human Development, Universiti Malaysia Sarawak, Kota Samarahan, Sarawak, Malaysia

²Department of Nursing, Faculty of Modern Health Care, Anhui Sanlian University, Hefei, Anhui, China

³Shanghai Sanlianren Technology Co., Ltd., Shanghai, China

⁴Shanghai Sanlian Institute for Wellness & Eldercare Research, Shanghai, China

Abstract

Ageing is a prime contributor to the rising demand for safe, uninterrupted care at the bedside. Many existing smart-bed systems are reactive, using individual thresholds instead of reasoning about the patient's state. Pressure injuries, falls, and poor sleep quality are issues for older adults, and mobility issues are also a concern. This study introduces and tests a proof-of-concept intelligent patient bed architecture based on fuzzy cognitive maps (FCMs), multi-modal IoT sensing, machine-learning prediction, and closed-loop actuation towards proactive elderly care. A design science research framework guided four linked phases: FCM construction through literature synthesis and expert elicitation ($n = 12$), multimodal sensing and machine-learning development, architecture-level evaluation in a digital twin, and a pilot usability study. A controlled laboratory dataset from 50 older participants comprising 210,000 pressure maps and 14,500 annotated movement events was used. A convolutional neural network (CNN)–long short-term memory (LSTM) model classified posture and transitions, a radial basis function–support vector machine (SVM) stratified fall risk, and an 11-node FCM translated predictive outputs into context-sensitive actions. Digital twin testing covered 100 virtual patient-days; usability was explored with 20 stakeholders. The FCM matched expert-defined responses in 87.3% of predefined scenarios. The CNN–LSTM achieved 92.4% test accuracy, and the SVM achieved 87.6% sensitivity for the high fall risk class. Mean sensor-to-action latency was 1.3 seconds, the false-alarm rate was 0.7 per virtual patient-day, and the mean System Usability Scale score was 76.8. With simulated sensor dropout at or below 25%, FCM agreement declined to 82.1%. The findings support the technical plausibility of combining causal FCM reasoning with multimodal sensing and predictive models in an intelligent patient bed. However, evidence remains preliminary due to the small sample size, the controlled laboratory setting in which the data were collected, and the simulation-based system-level testing. Physical prototyping, external model comparison, component ablation, and long-term clinical deployment are required before clinical effectiveness can be established.

*Corresponding author:

Chee Siong Teh
(csteh@unimas.my)

Citation: Mei L, Teh CS, Wang X, Fang Z, Zheng C, Chen H. An intelligent patient bed architecture based on fuzzy cognitive maps, multimodal Internet of Things sensing, and machine learning. *Artif Intell Health*. doi: 10.36922/AIH026240060

Received: June 12, 2026

Revised: July 4, 2026

Accepted: July 7, 2026

Published online: August 4, 2026

Copyright: © 2026 Author(s). This is an Open-Access article distributed under the terms of the Creative Commons Attribution License, permitting distribution, and reproduction in any medium, provided the original work is properly cited.

Publisher's Note: AccScience Publishing remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Keywords: Fuzzy cognitive maps; Intelligent patient bed; Multimodal Internet of Things sensing; Machine learning; Elderly care; Digital twin

1. Introduction

Population aging is driving a growing demand for safe and responsive bed-based care. Pressure injuries and falls are still common within the nursing-home population, and sleep disturbances, pain, and limited mobility all contribute to further loss of independence and quality of life and are prevalent within the nursing-home setting.^{1–5}

Despite this, most commercially available systems are event-oriented and react only when a threshold is exceeded, rather than integrating weak, evolving indications of discomfort, intention to move, disorientation, and fall risk. Another common problem is processing sensor streams in isolation, without a shared patient-state model that can provide context-aware justifications for actions.^{6–9}

The technical ground for adaptive health care systems has been extended recently. Previous studies did not focus on smart-bed evaluations but still are relevant to designing alternatives for multi-scale feature extraction, modeling long-range dependencies, and making adaptive decision policies, including Wavelet-based channel-wise Mamba attention-Net, which has combined wavelet decomposition with channel-spatial Mamba attention; and C2DEEP-OT, which has combined multi-agent deep reinforcement-learning with an optimized attentive Transformer. In this regard, the present work distinguishes architectural novelty from demonstrated predictive superiority and does not claim that the convolutional neural network (CNN)–long short-term memory (LSTM) model is superior to alternative approaches without direct head-to-head evaluation on a shared dataset.

The work is driven by four unmet needs: (i) a real-time cognitive model that describes interacting states of patients as opposed to individual alarms; (ii) a common architecture that connects multimodal sensing with temporal prediction and causal reasoning; (iii) a closed-loop actuation design with safety and human-overriding controls; and (iv) transparent pre-deployment testing, which documents the sensors that fail, the latency or delays they experience, and the assumptions made during simulation. FCM-based medical decision support has been examined in healthcare.^{10,11} Related work has addressed posture and sleep monitoring¹², ambient cognitive assessment¹³, adaptive elderly-care reasoning^{14,15}, smart-bed comfort and monitoring^{16–18}, in-home sensing and multimodal interaction^{19,20}, cognitive assisted-living systems^{21,22}, caregiver acceptance and clinical use²³, explainable FCMs and geriatric decision support^{24,25}, unobtrusive bed monitoring and sensor-supported care coordination^{26,27}, FCM engineering methods²⁸, usability assessment²⁹, pressure-injury burden³⁰, and intention inference for assistive robotics.³¹ These streams have

rarely been integrated into a single, coherent bed-control architecture.

For this purpose, a three-layer intelligent patient bed architecture is proposed in this article ([Figure 1](#)). The perceptual layer consists of pressure signatures, inertial signatures, rail force, and environmental signatures. The analytical layer utilizes a CNN–LSTM to recognize posture and transitions and a radial basis function (RBF)–support vector machine (SVM) to classify fall risk. The cognitive-reasoning layer integrates prediction results and causal relations among discomfort, movement intention, fall risk, alertness, pressure injury risk, and repositioning need, using an 11-node fuzzy cognitive map (FCM). Actions can be subject to safety thresholds, audit logging, and caregiver override.

The key contributions may be summarized as follows. First, the study formulates an FCM as an interpretable real-time reasoning layer between predictive models and bed actuation. Second, the study describes a custom-built database comprising 50 elderly subjects, 210,000 pressure maps, and 14,500 annotated movement events. Third, the study combines posture classification and fall risk stratification into a single patient state model. Fourth, the paper introduces a digital twin testing approach to evaluate latency, sensor dropout, and closed-loop safety before physical implementation. Fifth, the study provides preliminary usability information among elderly people and caregivers. The research aims to understand whether the FCM can mimic expert responses, whether the predictive models meet the predefined technical specifications, whether the combined system is stable under perturbations in simulation, and whether stakeholders find the suggested interaction acceptable.

2. Data and methods

2.1. Study design and system architecture

This study followed a design science research paradigm, in which a technological artifact is specified, implemented, and evaluated against explicit functional requirements.³² The mixed-methods design comprises four phases: cognitive modeling; multimodal sensing and predictive model development; system integration with digital twin evaluation; and pilot human-factor assessment. Evidence from each phase informs the next, while the final phase identifies constraints that must be resolved before physical or clinical deployment ([Figure 2](#)).

The architecture proposed for hardware implementation included four sensor groups: a 32×32 pressure mapping array with a 1-Hz sampling rate; triaxial inertial measurement units with 100-ms sampling; force-

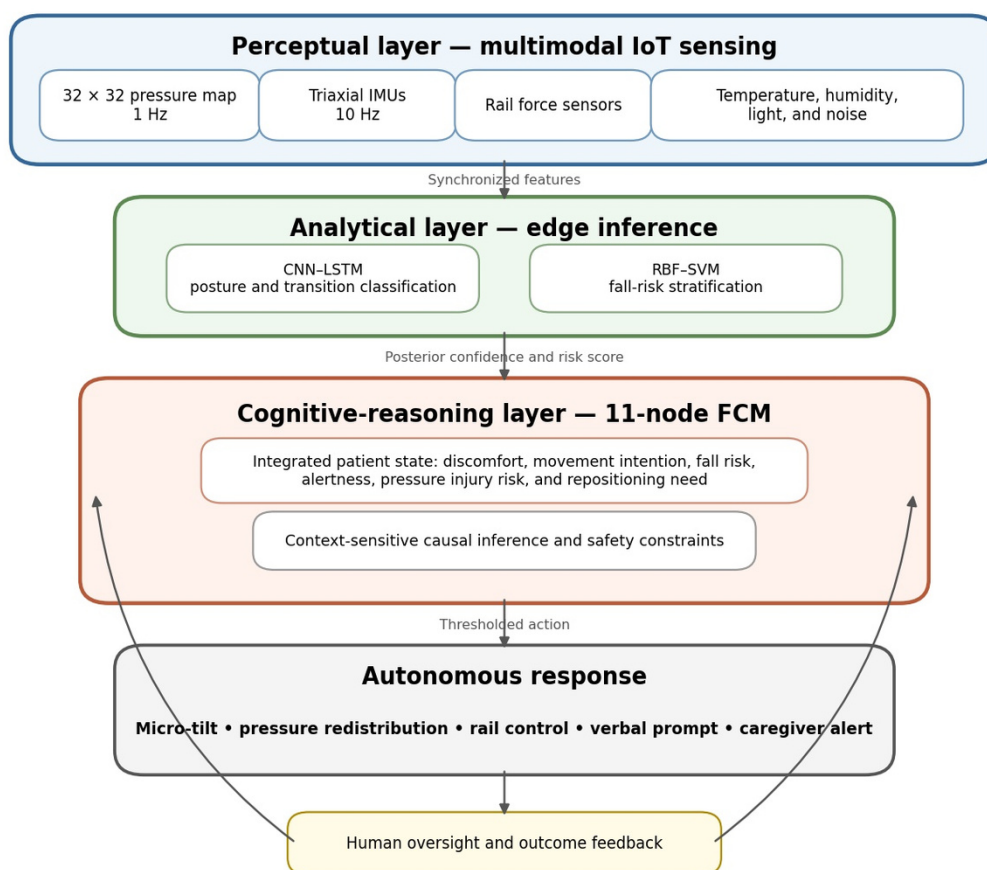


Figure 1. A three-layer intelligent patient bed architecture. Multimodal sensing feeds machine learning inference; normalized predictions activate an 11-node fuzzy cognitive map (FCM) that generates explainable, safety-constrained actions with human oversight.

Abbreviations: CNN: Convolutional neural network; IoT: Internet of Things; LSTM: Long short-term memory; RBF: Radial basis function; SVM: Support vector machine.

sensitive rail components; and environmental sensors for temperature, humidity, illumination, and noise levels. The bedside edge gateway coordinated four timed sequences: data acquisition and verification every 100 ms; machine learning and FCM update every 1 second; safety-controlled actuation every 10 to 60 seconds; and long-term evaluation of patient-specific results. As hardware prototyping is beyond the current scope of work, manufacturer-specific part numbers cannot be considered as valid hardware selection criteria. The interface specifications and communication profile are provided in Section 2.3.2.

2.2. Fuzzy cognitive map development

2.2.1. Variable identification and expert elicitation

The selection of FCM variables was performed through two steps. In the first step, a literature search across the Scopus, PubMed, IEEE Xplore, and Google Scholar databases identified 24 relevant terms for elderly care, smart beds,

risk of pressure injury, falls, sleep, discomfort, intention to move, and cognitive alertness. The second step involved the rating of each term by 12 experts, including three geriatricians, three geriatric nurses, two physiotherapists, two biomedical engineers, and two informal caregivers, on a five-point relevance scale. Terms that had a mean score of 4.0 or higher and 80% agreement were considered. The expert panel composition is summarized in Table 1, and 11 terms fulfilled the criterion (Table 2).

2.2.2. Fuzzy cognitive map construction and causal weight elicitation

Pairwise causal influences among the 11 concepts were elicited with a connection-matrix procedure consistent with current engineering guidance for FCM construction and validation.²⁸ Experts assigned weights in the interval $[-1, +1]$, where the sign indicates the causal direction and the magnitude indicates the strength. Expert matrices were

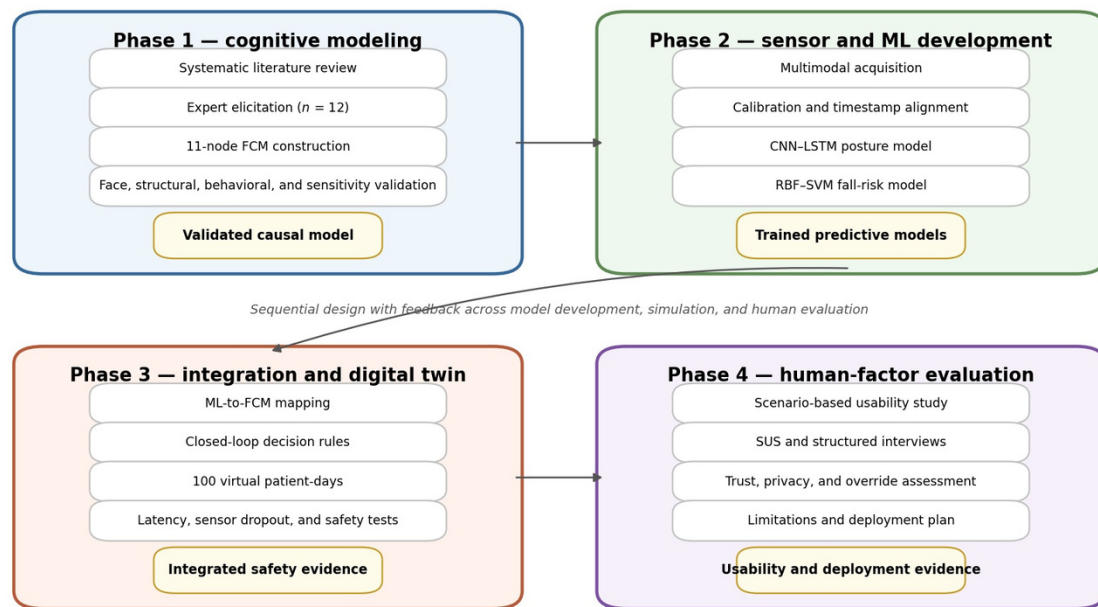


Figure 2. Four-phase methodological workflow. Larger text and explicit phase outputs show the progression from causal model construction to predictive modeling, digital twin stress testing, and human-factor evaluation.

Abbreviations: CNN: Convolutional neural network; LSTM: Long short-term memory; ML: Machine learning; RBF: Radial basis function; SUS: System Usability Scale; SVM: Support vector machine.

Table 1. Expert panel composition for fuzzy cognitive map variable validation

Expert category	N	Experience requirement	Role in validation
Geriatricians	3	≥8 years of elderly care	Clinical variable evaluation
Geriatric nurses	3	≥5 years of bedside care	Practical care assessment
Physiotherapists	2	Fall prevention expertise	Mobility/fall risk assessment
Biomedical engineers	2	Assistive device design	Technical feasibility review
Informal caregivers	2	≥3 years of caregiving	Real-world care insights

aggregated using credibility weights derived from relevant experience and inter-expert consistency; an intraclass correlation coefficient greater than 0.75 was required. The resulting matrix $W \in [-1,1]^{(11 \times 11)}$ defines the directed FCM (**Equation 1**):

$$C_i(t+1) = f[C_i(t) + \sum_{j=1}^N w_{ji} C_j(t)] \quad (1)$$

where $C_i(t)$ is the activation of concept i at iteration t , w_{ji} is the causal weight from concept j to concept i , and $f(\cdot)$ is the bounded activation function (**Equation 2**):

$$f(x) = 1/[1 + \exp(-\lambda x)] \quad (2)$$

where $\lambda = 1$ is the sigmoid steepness parameter. Network density is defined as **Equation 3**:

$$D = L/[N(N-1)] \quad (3)$$

where L is the number of non-zero directed links and $N = 11$ is the number of concepts. Normalized out-degree and in-degree centralities are shown as **Equations 4** and **5**, respectively:

$$C_{out}(i) = (1/N) \sum_{j=1}^N |w_{ij}| \quad (4)$$

$$C_{in}(i) = (1/N) \sum_{j=1}^N |w_{ji}| \quad (5)$$

2.2.3. Fuzzy cognitive map simulation and validation

Five prespecified clinical scenarios were examined: high discomfort ($D = 0.9$), elevated movement intention ($MI = 0.8$), high fall risk ($FR = 0.9$), reduced cognitive

Table 2. Final 11 fuzzy cognitive map variables, operational definitions, and measurement modalities

Symbol	Variable	Operational definition	Measurement modality
D	Perceived discomfort	Subjective pain, pressure, or positional distress	Pressure sensors, heart rate variability, micro-movements
MI	Movement intention	Cognitive/motor preparation for repositioning or bed exit	Gaze, limb tension, trunk motion
FR	Fall risk	Probability of fall during bed exit or repositioning	Fall history, mobility score, motion instability
SQ	Sleep quality	Efficiency and physiological characteristics of sleep	Actigraphy, respiratory monitoring
CA	Cognitive alertness	Consciousness, attentiveness, and responsiveness	Reaction time, behavioral variability
PR	Pressure injury risk	Likelihood of tissue damage from prolonged pressure	Interface pressure map, immobility duration
AL	Agitation level	Degree of restlessness, anxiety, or agitation	Movement intensity, vocalizations, heart rate variability
RN	Repositioning need	Clinical necessity for posture change	Immobility duration, interface pressure
CG	Caregiver availability	Proximity and responsiveness of caregiving staff	Nurse-call system, scheduling data
AP	Autonomy preference	Patient preference for independent or assisted action	Behavioral history, patient-stated preferences
EC	Environmental comfort	Ambient conditions affecting patient comfort and sleep	Temperature, humidity, light, noise

alertness (CA = 0.2), and combined discomfort with reduced alertness (D = 0.9; CA = 0.2). Mental Modeler (web platform; version information was not displayed) supported structural visualization, MATLAB Fuzzy Logic Toolbox R2023b supported numerical simulation, and Python 3.11 with NetworkX (exact NetworkX release not retained) supported integration checks. Validation comprised expert face review, structural analysis using **Equations 3–5**, convergence and perturbation tests, and sensitivity analysis across $\lambda \in \{0.5, 1.0, 2.0\}$ with $\pm 5\%$ activation noise.^{14,24,28}

2.3. Multimodal Internet of Things sensing and data fusion

The multimodal framework translates diverse data streams into aligned, quality-controlled windows. Sensor-level processing filters out invalid readings and normalizes modalities; feature-level processing transforms pressure maps, inertial sensor readings, rail forces, and environmental readings into clinical descriptors; decision-level processing transforms predictor outputs into FCMs and ultimately into safe actions. Quality flags from the individual modalities were intentionally retained so that any missing or erroneous channels are not treated as normal readings.^{21,22}

2.3.1. Sensor calibration, synchronization, and preprocessing

For implementational purposes, calibration was conducted functionally. Zeroing of the pressure sensor array was performed without loading and verified with distributed reference loads on the mattress surface; estimation of

inertial measurement unit (IMU) static offsets was conducted on stationary segments; rail force channels were zeroed before each experimental scenario; and the ambient sensors were cross-checked against laboratory reference instrumentation. Every sample was timestamped monotonically at the bedside gateway. Given that the fastest data sampling loop ran at a 100 ms rate, synchronization was provided with 100 ms alignment resolution and not reported as sub-millisecond hardware-level time stamps. Pressure frames were mapped to the nearest second-long inference window, while high-frequency inertial and rail force signals were summarized within that window by mean, standard deviation, peak magnitude, energy and displacement-related features.

Preprocessing was conducted in a fixed order: checking for out-of-range values and saturation events; median filtering to reduce impulsive pressure noise; low-pass filtering of inertial sensor data; correcting the baseline of rail force channels; normalizing each modality based on training set statistics; windowing into 1-second windows; and fusing features. Missing channels were marked. Windows lacking sufficient valid information were forwarded to the monitoring state and not imputed as normal (**Table 3**).

2.3.2. Hardware circuit and edge gateway communication specification

Figure 3 shows the prototype circuit route from each transducer to the bedside gateway. The 32×32 pressure array was read using row- and column-addressing, analog multiplexing, and analog-to-digital conversion prior to

one-hertz frame construction. Each triaxial IMU was interfaced digitally using either inter-integrated circuit or serial peripheral interface and sampled at 10 Hz. The rail force measurement was constructed via a full Wheatstone bridge, instrumentation amplification, anti-aliasing filtering, and analog-to-digital conversion. Environmental sensors, such as temperature, humidity, light, and noise, used digital sensor interfaces and were synchronized to the nearest second inference window. The gateway applied

monotonic timestamps, sequence numbering, a calibration ID, and a channel quality mask before buffering/fusion. Local inference, FCM reasoning, and the safety interlock were kept on the bedside gateway so that a failure of the external dashboard would not deprive essential monitoring capability. Actuation was separated from the isolated controller by a mechanical travel limit, position feedback, watchdog, command timeout, fault acknowledgment, and emergency manual stop. Table 4 provides a reference

Table 3. Calibration, synchronization, and preprocessing specification for each sensing modality

Modality	Calibration/quality check	Timing and preprocessing	Output to fusion
Pressure matrix	Unloaded zeroing; distributed reference-load check; saturated-cell flag	1-Hz frame; median noise filter; baseline correction; training-set normalization	Pressure map, contact area, center of pressure, and regional load
Triaxial inertial measurement unit	Static bias estimate from stationary segment; range check	100-ms samples grouped into 1-s windows; low-pass filter	Mean, variance, peak acceleration, energy, motion instability
Rail force channel	Pre-scenario zero; span and saturation check	100-ms samples grouped into 1-s windows; baseline correction	Grip onset, peak force, and force duration
Ambient sensors	Comparison with laboratory reference instrument	Nearest-timestamp alignment; range check and normalization	Temperature, humidity, light, and noise indices
Gateway clock	Monotonic timestamp applied at acquisition	100-ms alignment resolution; one-second inference windows	Synchronized multimodal record with quality mask

Table 4. Reference hardware-interface and edge gateway communication profile for physical implementation

Block	Circuit/interface path	Rate and transport	Required message fields	Quality and safety control
Pressure array	32 × 32 cells → row/column scanner → analog multiplexer → ADC → frame builder	1-Hz frames; local wired interface	Timestamp, frame_id, calibration_id, matrix or derived features, cell-validity mask	Unloaded zero, distributed-load check, open/saturated-cell flag, frame sequence check
Corner IMUs	Triaxial digital IMU → I ² C or SPI → gateway buffer	10-Hz samples; 1-s feature window	Timestamp, sensor_id, ax, ay, az, range/status flag	Startup static-bias estimate, range check, missing-sample counter
Rail-force channels	Strain gauges → Wheatstone bridge → instrumentation amplifier → anti-alias filter → ADC	10-Hz samples; 1-s feature window	Timestamp, rail_side, force, zero_offset, saturation/status flag	Pre-scenario zero, span check, overload and cable-fault flag
Ambient channels	Temperature, humidity, light, and noise sensors → I ² C or UART	Nearest-timestamp alignment to 1-s window	Timestamp, temperature, humidity, illuminance, sound index, status	Reference-instrument check, range validation, stale-data flag
Gateway inference	Monotonic clock → ring buffer → preprocessing → CNN-LSTM/SVM → FCM → safety gate	1-Hz inference; authenticated MQTT over TLS for external exchange	device_id, sequence, model_version, quality mask, class probabilities, risk score, FCM states, reason_code	Device authentication, access control, local fallback, audit log, out-of-order rejection
Actuation and acknowledgement	Isolated actuator controller → driver → motor/linear actuator → position and limit feedback	Command/acknowledgement transaction with expiry	command_id, action, target, expiry, reason_code; acknowledgement, position, watchdog, fault_code	Hard limits, watchdog, emergency stop, safe-state return, duplicate-command rejection

Abbreviations: ADC: Analog-to-digital converter; CNN: Convolutional neural network; FCM: Fuzzy cognitive map; I²C: Inter-integrated circuit; IMU: Inertial measurement unit; LSTM: Long short-term memory; MQTT: Message queuing telemetry transport; SPI: Serial peripheral interface; SVM: Support vector machine; TLS: Transport layer security; UART: Universal asynchronous receiver/transmitter.

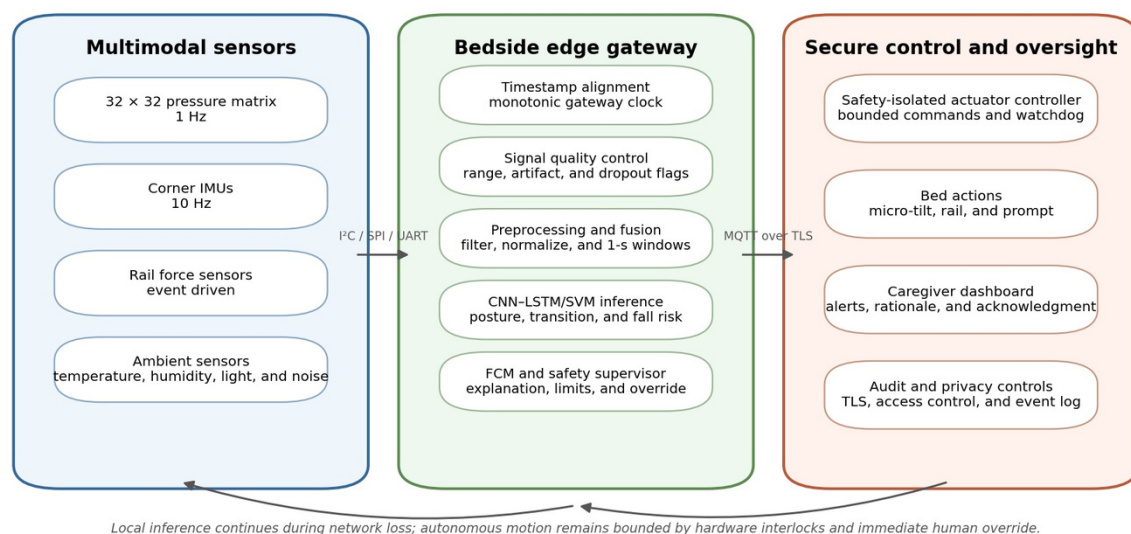


Figure 3. Reference sensor interface, bedside gateway, and safety-isolated actuation schematic. The diagram shows the pressure-matrix scanner and conversion stage, digital sensor buses, rail force bridge conditioning, gateway inference, authenticated messaging, watchdog control, position feedback, audit logging, and immediate human override.

Abbreviations: CNN: Convolutional neural network; FCM: Fuzzy cognitive map; I2C: Inter-integrated circuit; IMUs: Inertial measurement units; LSTM: Long short-term memory; MQTT: Message queuing telemetry transport; SPI: Serial peripheral interface; SVM: Support vector machine; TLS: Transport layer security; UART: Universal asynchronous receiver/transmitter.

interface and message format for implementation purposes. Physical prototyping was governed by regulations, and exact component part numbers, printed circuit board design, and pin assignments had to be specified (Table 5).

Table 5. Temporal operation layers of the integrated sensing and reasoning system

System layer	Time interval	Function
High-frequency loop	100 ms	Sensor data acquisition and preprocessing
Mid-frequency loop	1 s	ML inference and FCM cognitive state updates
Low-frequency loop	10 s–1 min	Smart-bed actuation commands and caregiver alerts
Long-term adaptation	Daily/weekly	FCM weight adjustment based on patient outcomes

Abbreviations: FCM: Fuzzy cognitive map; ML: Machine learning.

2.4. Machine learning model development

2.4.1. Dataset construction

A dedicated movement database was collected from 50 elderly subjects who were 65 years or older (mean 72.4 ± 5.8 years; 54% women; Mini-Mental State Examination:

18–30). In a laboratory setting, the subjects performed resting, repositioning, sitting up, and exiting from bed movements. Requirements for inclusion were written informed consent, daily bed use of at least 8 hours, and the absence of acute infections and active injuries at sensor contact points. From the pressure sensor array, 210,000 frames were collected along with inertial and environmental sensor data. Two trained coders annotated 14,500 movement transition events with Cohen's kappa = 0.87 (Figure 4). The small sample size and controlled environment are considered limitations for external validity but not for population-level performance results.

2.4.2. Convolutional neural network–long short-term memory posture classifier

The CNN–LSTM was developed to integrate spatial pressure patterns with temporal transition information. The three convolutional blocks had 3×3 convolutional filters and max-pooling with 32, 64, and 128 filters. These frame-level representations were then fed into two LSTM layers with 128 hidden units each. The dataset was stratified and split into training, validation, and testing sets in a 70:15:15 ratio. The training settings were: the Adam optimizer with a learning rate of 0.001, a batch size of 32, a dropout rate of 0.30, a maximum of 50 epochs, and an early stopping patience of 10 epochs.

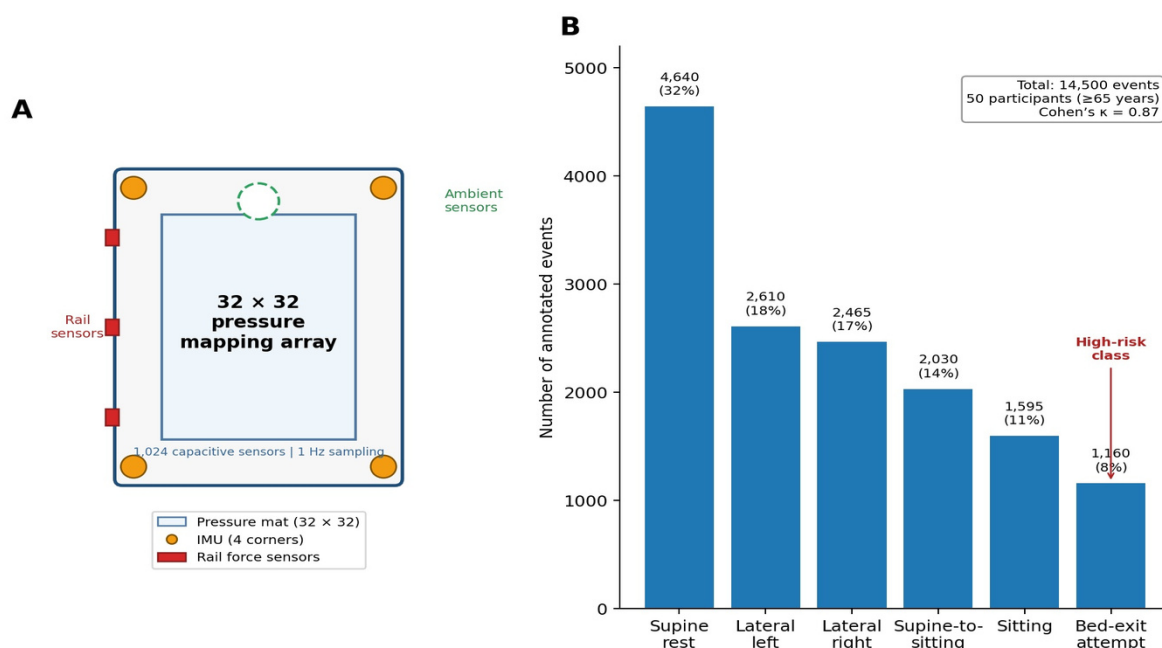


Figure 4. Dataset construction overview. (A) Functional sensor placement and (B) distribution of 14,500 annotated movement-transition events across six posture and transition classes.

2.4.3. Hyperparameter selection and component-evaluation protocol

The analysis archive retained highlights of the final CNN-LSTM architecture, participant-level partition (70:15:15), normalization during training only, optimizer, learning rate, batch size, dropout, stopping rule, and criteria selection for safety, and did not include the trial history needed to reconstruct all candidate scores. Table 6 serves as an audit trail, with confirmed values being confirmed and non-retained items clearly labeled and not estimated. A full replication run should include the same preprocessing parameters and the same number of participants (i.e., the same partitions), store the best checkpoint/epoch, export validation macro-F1, bed exit sensitivity, loss, latency, and model hash per participant (candidate), and record the random seed and software environment. CNN-only, LSTM-only, gated recurrent unit (GRU), attention-based, Transformer, and reinforcement-learning alternatives remained the same as the record structure. There were no numerically calculated results for non-executed configurations that were inferred from the preserved hybrid model.

2.4.4. Support vector machine fall risk classifier

An SVM with an RBF kernel stratified fall risk into low, moderate, or high categories. Predictors included movement velocity, acceleration variability, center-of-

mass displacement, fall history, and clinical mobility scores. Fivefold stratified cross-validation was considered with $C \in \{0.1, 1, 10, 100\}$ and $\gamma \in \{0.001, 0.01, 0.1, 1\}$. The synthetic minority oversampling technique was applied during training to reduce class imbalance; the validation and test partitions were not oversampled.

2.4.5. Machine learning-to-fuzzy cognitive map integration

The CNN-LSTM class probabilities and SVM risk scores were normalized to $[0,1]$ and mapped to the corresponding concepts of FCM (Table 7). The concept activation was refreshed at every 1-s inference cycle. The FCM then used the current prediction, prior state, causal weights and safety thresholds to decide if an intervention was required (Table 8). The commands were no longer sent directly from the predictive models, but to the isolated actuation controller.

2.5. Digital twin simulation and pilot usability evaluation

2.5.1. Digital twin framework

A digital twin was created for architecture-level testing before prototype development.^{33–36} The combination of MATLAB R2023b and Simulink connected a patient-state model and a bed system model. The patient twin model consisted of 11 FCM concepts, patient posture or transition state, and patient-specific risk input data. The bed twin

Table 6. Documented convolutional neural network–long short-term memory configuration, candidate space, selection rule, and retained audit status

Parameter	Prespecified candidate values	Retained setting	Selection/record status
Convolution filters	16–32–64; 32–64–128; 64–128–256	32–64–128	Final setting confirmed; run-level score history not retained
Kernel size	3 × 3; 5 × 5	3 × 3	Chosen with validation macro-F1
Long short-term memory depth/units	1 or 2 layers; 64, 128, or 256 units	2 layers; 128 units	Final setting verified
Dropout	0.20; 0.30; 0.50	0.30	Final setting verified
Learning rate	0.0001; 0.0005; 0.001	0.001	Final setting verified
Batch size	16; 32; 64	32	Final setting verified
Optimizer	Adam; RMSprop	Adam	Final setting verified
Training control	Maximum 50 epochs; patience 5 or 10	50 epochs; patience 10	Final setting verified
Primary criterion	Validation macro-F1	Validation macro-F1	Bed exit sensitivity as secondary safety criterion
Data partition	Participant-level 70:15:15; class stratification	70:15:15 stratified split	Confirmed in methods; split manifest not present in retained archive
Normalization	Training-partition parameters only	Training-only normalization	Confirmed; prevents validation/test leakage
Random seed	One recorded seed per run	Not retained	Must be exported in any replication package
Executed trial count	One row for every tested configuration	Not retained	Cannot be reconstructed from the final configuration
Best epoch/checkpoint	Best validation macro-F1 with early stopping	Best weights restored; exact epoch not retained	Checkpoint and hash required for independent verification
Software audit	Python, library, device, and model hash	Python 3.11/scikit-learn 1.3 reported; full training environment not retained	Environment file and checkpoint hash required for complete rerun

Note: Run-level audit requirement: run_id, architecture, participant-split identifier, seed, preprocessing version, hyperparameters, best epoch, validation macro-F1, bed exit sensitivity, area under the curve, inference latency, checkpoint path, and cryptographic model hash should be exported together. These fields define the complete tuning record expected for subsequent independent comparison.

model included sensor availability, inference time, decision threshold, actuator delay, and safety limit. Several custom MATLAB functions were used to update the FCM model and import machine learning results. Testing involved 100 days for five prespecified scenarios.

2.5.2. Patient behavior, actuation, and sensor dropout modeling

Every virtual day was created through a series of scenario windows, each containing prescribed values for FCM activation, dwell time, and bounded perturbation. The behavior was modeled using transitions between the resting, repositioning, sitting up, and bed exit states; no disease progression, changes in biomechanical properties of tissues, or impact of medication was included in the simulation. Actuation was defined as a delayed and bounded transition to the new state: micro-tilt decreased regional pressure, while rail elevation and caregiver alert decreased the likelihood of an independent bed exit. The

safety logic prohibited actuations beyond the prescribed travel distance and timing constraints. The 25% dropout condition was implemented by randomly masking a quarter of the modality-specific windows during fusion. The masked channels received a clear indication of a missing value; other channels could continue to influence the FCM, with no substitute value provided for any missing data point.

2.5.3. Pilot usability study

The usability pilot study involved 20 participants: 10 older individuals with varying levels of mobility, 5 professional caregivers, and 5 informal caregivers. Following an orientation session, the participants engaged in role-playing exercises that included high risk of falls, extended immobility, nighttime discomfort, and agitation. The system's usability was evaluated using the System Usability Scale (SUS), which ranges from 0 to 100.²⁹ Interviews

assessed the usefulness, trustworthiness, privacy issues, safety concerns, alerts, and willingness to adopt automated movements. This was performed through qualitative thematic coding.

Table 7. Mapping of machine learning outputs to fuzzy cognitive map concept activations

Machine learning model output	Corresponding fuzzy cognitive map concept(s)
Posture classification confidence	Movement intention (MI), repositioning need (RN)
Fall risk prediction score	Fall risk (FR)
Sleep-stage detection	Sleep quality (SQ), cognitive alertness (CA)
Pressure distribution analysis	Perceived discomfort (D), pressure injury risk (PR)

Table 8. Fuzzy cognitive map inference thresholds and corresponding smart-bed responses

FCM inference condition	Actuation response
D > 0.7 and RN > 0.7	Micro-tilt activation and pressure redistribution
MI > 0.6 and FR > 0.7	Rail elevation, verbal safety prompt, caregiver notification
CA < 0.3 and AL > 0.6	Increased monitoring frequency, reduced intervention intensity
SQ < 0.4 and PR < 0.5	Gentle micro-adjustments to improve sleep comfort

Abbreviations: AL: Agitation level; CA: Cognitive alertness; D: Perceived discomfort; FCM: Fuzzy cognitive map; FR: Fall risk; MI: Movement intention; PR: Pressure injury risk; RN: Repositioning need; SQ: Sleep quality.

2.6. Statistical analysis

Predictive performance metrics included accuracy, sensitivity, specificity, precision, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). Sensitivity was the primary SVM metric because of the higher cost of missing high-risk patients. The FCM agreement was the ratio of 20 scenarios in which the system reaction corresponded to the reaction predefined by experts. Metrics of the digital twin included sensor-to-action delay, the fraction of events processed within 2 seconds, the number of false alarms per virtual patient-day, and FCM agreement with dropout. Dropout sensitivity analysis was the only available numerical perturbation of the system: masking 25% of modality-specific observation windows decreased FCM agreement by 5.2 percentage

points, from 87.3% to 82.1%. SUS was reported as mean score, standard deviation, and 95% confidence interval (CI). Event annotation agreement was measured by Cohen's κ . Analysis was performed using Python 3.11 (scikit-learn 1.3, SciPy 1.11, pandas 2.1) and MATLAB R2023b. Head-to-head ablation studies were performed on all variants on the same participants' partitions and not reported together with the results.

3. Results

3.1. Intelligent patient bed architecture

The integrated architecture linked multimodal acquisition, predictive inference, causal FCM reasoning, and safety-constrained action (Figure 5). In the digital twin evaluation, mean sensor-to-action latency was 1.3 ± 0.4 s and remained below the prespecified two-second threshold. This result demonstrates timing feasibility within the simulated implementation; it does not establish equivalent latency in a physical hospital network.

Table 9 provides a visual technical comparison of representative smart-bed systems and the proposed architecture. It also identifies GRU, attention/Transformer, and reinforcement-learning families as relevant same-dataset benchmarks. The table compares sensing, temporal modelling, reasoning and action, evidence context, latency, and principal limitations. Because the cited systems use different populations, labels, sensors, and validation protocols, literature values were not treated as a head-to-head ranking. Same-dataset superiority remains untested and is stated as an experimental requirement.

3.2. Fuzzy cognitive map causal reasoning and scenario simulation

The aggregated FCM had a network density of 0.68, indicating extensive interconnection among the clinical concepts. Fall risk was the strongest receiver ($C_{in} = 0.82$), whereas perceived discomfort was the strongest driver ($C_{out} = 0.74$). Inter-expert consistency was good (intraclass correlation coefficient = 0.81; 95% CI: 0.74–0.88). Across tested initial conditions, activation values converged within 8–12 iterations.

Table 10 summarizes the five scenario simulations. High discomfort propagated to repositioning need (0.83) and pressure injury risk (0.78), initiating micro-tilt and pressure redistribution. Reduced cognitive alertness increased fall risk (0.76) and agitation level (0.71), leading to more intensive monitoring. The combined-risk scenario activated both repositioning and safety pathways. Across 20 predefined scenarios, 87.3% of system responses matched expert expectations, exceeding the prespecified 85% technical target.

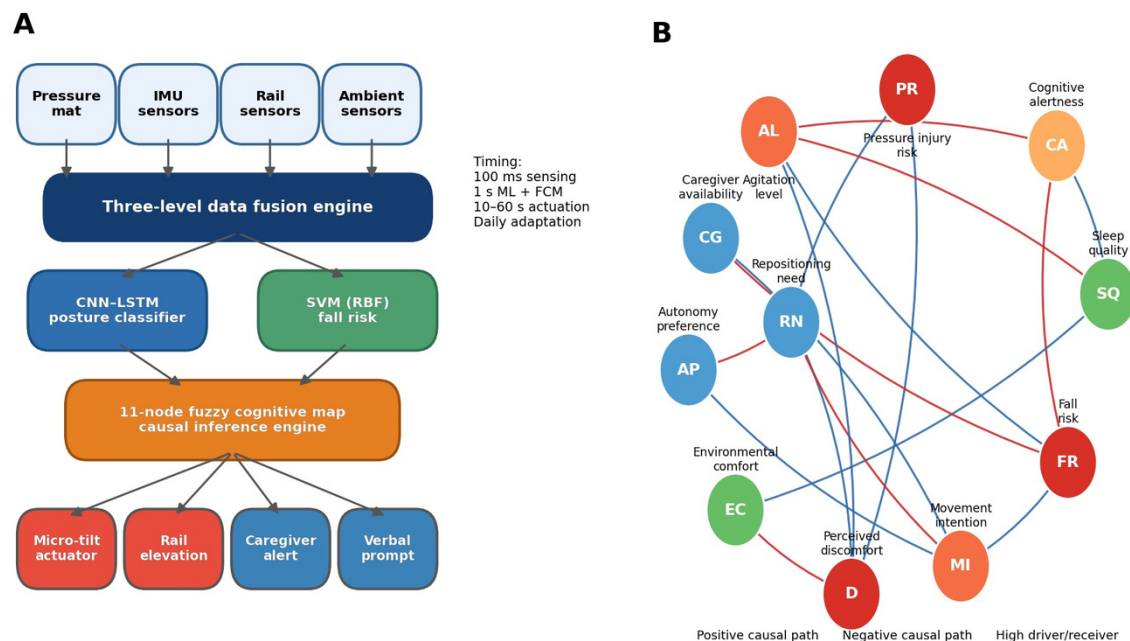


Figure 5. Detailed system architecture. (A) Data-flow blocks and (B) the 11-node FCM causal graph. The figure shows predictive inputs, causal integration, and the actuation path.

Abbreviations: CNN: Convolutional neural network; FCM: Fuzzy cognitive map; LSTM: Long short-term memory; RBF: Radial basis function; SVM: Support vector machine.

3.3. Machine learning model performance

The CNN–LSTM achieved 92.4% overall test accuracy (95% CI: 91.1%–93.7%) across six posture and transition classes. Performance was highest for stable supine posture ($F1 = 0.96$) and remained lower, but clinically relevant, for bed exit attempts (sensitivity = 89.2%; $F1 = 0.87$). The bed exit AUC was 0.97. The RBF–SVM achieved 87.6% sensitivity (95% CI: 84.9%–90.3%) for the high fall risk class, 91.4% specificity, and an AUC of 0.93 (Table 11; Figure 6). These figures describe the retained models only; they do not establish superiority over GRU, Transformer, attention-based, or reinforcement-learning alternatives.

The findings available can enable partial component analysis but not full retraining ablation. Full CNN–LSTM, RBF–SVM, FCM scenario test, sensor dropout perturbation, and closed-loop digital twin timing were performed in different settings and thus cannot be cancelled out as variations. The only numerical perturbation in the dataset is the 25% sensor window mask perturbation, which resulted in a 5.2 percentage-point drop in FCM agreement. Table 12 presents the differences between the measurements obtained and the precise comparisons required to analyze CNN spatial coding, LSTM temporal coding, multimodal fusion, FCM reasoning, and autonomous actuation. Each requested variation needs to be retrained/rerun on the same subject split, using the same preprocessing, criteria,

seeds, and measures. No numerical baseline was set for any variation that was not run.

3.4. Digital twin and usability evaluation

In 100 “virtual patient days,” 96.4% of all high-priority events were detected and connected to an appropriate simulated response within two seconds. The false alarm rate was 7 per virtual patient-day. When 25% of modality-specific observation windows were masked, FCM agreement declined from 87.3% to 82.1%, indicating graceful but incomplete degradation (Figure 7). The results are based on documented assumptions for the simulation, and correlated sensor failures, network congestion and physical actuator failures were not tested.

The pilot usability study produced a mean SUS score of 76.8 (standard deviation: 8.4; 95% CI: 72.1–81.5), within the conventional “good” range.²⁹ Older participants rated brief verbal explanations as trustworthy in 72% of trials, while formal caregivers gave the highest mean SUS score (81.2). Four themes were identified: perceived safety benefits, initial concerns about automated bed movement, concerns about continuous sensing and privacy, and a preference for customizable alerts. These findings are preliminary because the sample was small and did not represent multiple institutions, cultures, cognitive-impairment levels, or accessibility needs (Table 13).

Table 9. Visual technical comparison of representative smart-bed systems, alternative model families, and the proposed architecture

System/framework	Sensors/input	Temporal or predictive model	Reasoning and action	Evidence and latency	Main limitation
Botia <i>et al.</i> ⁷	Motion and ambient sensors	Rule-based context	No causal layer; alerts only	In-home AAL; latency NR	Reactive monitoring; no intent model
Hong ¹⁸	Pressure and motion	Threshold logic	No causal layer; limited bed adjustment	Prototype; latency NR	Static rules; limited personalization
Lee <i>et al.</i> ³⁴	Spatial-behavior sensors	Pattern rules	Environmental service actions	Smart-bedroom prototype; latency NR	Not a bed-centered cognitive loop
Bai <i>et al.</i> ¹⁶	Pressure distribution	Quantitative comfort analysis	No causal layer or actuation	Controlled resting study; latency NR	Comfort assessment only
Laurino <i>et al.</i> ¹⁷	Bed pressure and motion	Sleep analysis	Monitoring without autonomous response	Real-world sleep monitoring; latency NR	No intervention pathway
Liu <i>et al.</i> ¹²	Distributed triaxial accelerometers	Parallel spatiotemporal network	Prediction only; no decision layer	Posture study; latency NR	No causal integration or actuation
Zhao <i>et al.</i> ²⁰	Multimodal human-robot interaction	Adaptive interaction model	Implicit reasoning; partial actuation	Multifunctional bed prototype; latency NR	No explicit causal patient-state model
GRU benchmark family	Aligned sensor sequences	Gated recurrent units	External safety controller required	Common-dataset test required; latency not measured	No explicit spatial pressure encoder
Attention/Transformer family	Multimodal sequences or embeddings	Long-range attention	External safety controller required	Common-dataset test required; latency not measured	Higher data and compute demand
Reinforcement-learning controller	State, action, and reward signals	Adaptive policy learning	Closed-loop policy; causal transparency not inherent	Safe simulator and reward validation required	Reward sensitivity and safety verification
Proposed architecture	32 × 32 pressure at 1 Hz; IMU at 10 Hz; rail and ambient sensors	CNN-LSTM + RBF-SVM	11-node FCM; bounded micro-tilt, rail, prompt, and caregiver alert	$n = 50$ laboratory data; 100 virtual patient-days; 1.3 ± 0.4 s simulated latency	No physical deployment or same-dataset external benchmark

Abbreviations: AAL: Ambient assisted living; CNN: Convolutional neural network; FCM: Fuzzy cognitive map; GRU: Gated recurrent unit; IMU: Inertial measurement unit; LSTM: Long short-term memory; NR: Not reported; RBF: Radial basis function; SVM: Support vector machine.

Table 10. Fuzzy cognitive map scenario simulation results: input conditions, key concept activations, and triggered actions

Scenario	Input condition	Key FCM outputs (activation value)	Actuation triggered
High discomfort	D = 0.9	RN = 0.83, PR = 0.78, MI = 0.64	Micro-tilt, pressure redistribution
Elevated move Intention	MI = 0.8	FR = 0.72, CG = 0.68, RN = 0.61	Rail elevation, caregiver alert
High fall risk	FR = 0.9	CG = 0.87, AP = 0.44, MI = 0.66	Rail elevation, verbal prompt
Cognitive decline	CA = 0.2	AL = 0.71, FR = 0.76, MI = 0.59	Increased monitoring, soft intervention
Combined risk	D = 0.9, CA = 0.2	RN = 0.86, FR = 0.81, AL = 0.73	Micro-tilt, rail elevation, alert

Abbreviations: AL: Agitation level; CA: Cognitive alertness; CG: Caregiver availability; D: Perceived discomfort; FCM: Fuzzy cognitive map; FR: Fall risk; MI: Movement intention; PR: Pressure injury risk; RN: Repositioning need.

Table 11. Summary of retained model performance on the test set

Model	Task	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC-ROC	Target met?
CNN-LSTM	Posture classification	92.4	89.2 ^a	94.1	0.97	Yes (≥90%)
SVM (RBF)	Fall risk stratification	89.8	87.6	91.4	0.93	Yes (≥85%)
FCM inference	Cognitive reasoning	87.3 [†]	—	—	—	Yes (≥85%)

Note: ^aSensitivity for the bed exit-attempt class. [†] FCM agreement with expert-defined responses across 20 predefined scenarios. These component metrics are not a formal model ablation.

Abbreviations: AUC-ROC: Area under the receiver operating characteristic curve; CNN: Convolutional neural network; LSTM: Long short-term memory; RBF: Radial basis function; SVM: Support vector machine.

Table 12. Measured component evidence and exact same split ablation matrix required for independent verification

Component/ variant	Evidence or execution rule	Result currently supported	Metrics for same-split test	Interpretation
Full CNN-LSTM	Held-out posture and transition test set	Accuracy 92.4%; bed exit sensitivity 89.2%	Accuracy, macro-F1, bed exit sensitivity, AUC, latency	Retained hybrid performance; does not isolate CNN or LSTM
RBF-SVM fall risk model	Held-out risk-classification test set	High-risk sensitivity 87.6%; specificity 91.4%	Sensitivity, specificity, macro-F1, AUC	Supports the separate fall risk pathway
FCM reasoning layer	20 expert-defined scenarios	Agreement 87.3%	Scenario agreement, action errors, convergence, latency	Causal-response consistency, not predictive accuracy
25% sensor-window mask	Randomly mask one quarter of modality-specific windows before fusion	Agreement 82.1%; decrease 5.2 percentage points	Agreement, false alarms, event handling, latency	Only retained numerical perturbation; not modality-specific
Closed-loop digital twin	100 virtual patient-days	96.4% handled within 2 s; 0.7 false alarms/day	Event handling, false alarms, action appropriateness, latency	Supports simulated timing and action logic
CNN-only	Replace recurrent block with frame-level classifier; identical split and tuning budget	Requires rerun	Accuracy, macro-F1, sensitivity, AUC, latency	Isolates temporal contribution
LSTM-only	Use sequence descriptors without CNN spatial encoder; identical split and tuning budget	Requires rerun	Accuracy, macro-F1, sensitivity, AUC, latency	Isolates spatial contribution
Single-modality/leave-one-modality-out	Pressure-only, IMU-only, rail-only, and one-modality-removed runs	Requires rerun	Macro-F1, sensitivity, false alarms, robustness	Quantifies multimodal-fusion contribution
FCM removed/fixed thresholds	Replace FCM with matched threshold rules in the same digital twin	Requires simulation rerun	False alarms, missed actions, inappropriate actions, latency	Quantifies causal reasoning contribution
Alert-only/actuation disabled	Retain detection but suppress autonomous actuation	Requires simulation rerun	Event handling, caregiver alerts, response time, safety violations	Separates monitoring from action policy
GRU/attention/Transformer	Identical participant split, preprocessing, tuning budget, and metrics	Requires model retraining	Macro-F1, sensitivity, AUC, latency, parameter count	Provides direct state-of-the-art comparison
Reinforcement-learning policy	Common safe simulator, explicit reward, constrained action space, and held-out scenarios	Requires policy training and safety validation	Reward components, unsafe actions, false alarms, latency	Compares adaptive action selection and transparency

Abbreviations: AUC: Area under the curve; CNN: Convolutional neural network; FCM: Fuzzy cognitive map; GRU: Gated recurrent unit; IMU: Inertial measurement unit; LSTM: Long short-term memory; RBF: Radial basis function; SVM: Support vector machine.

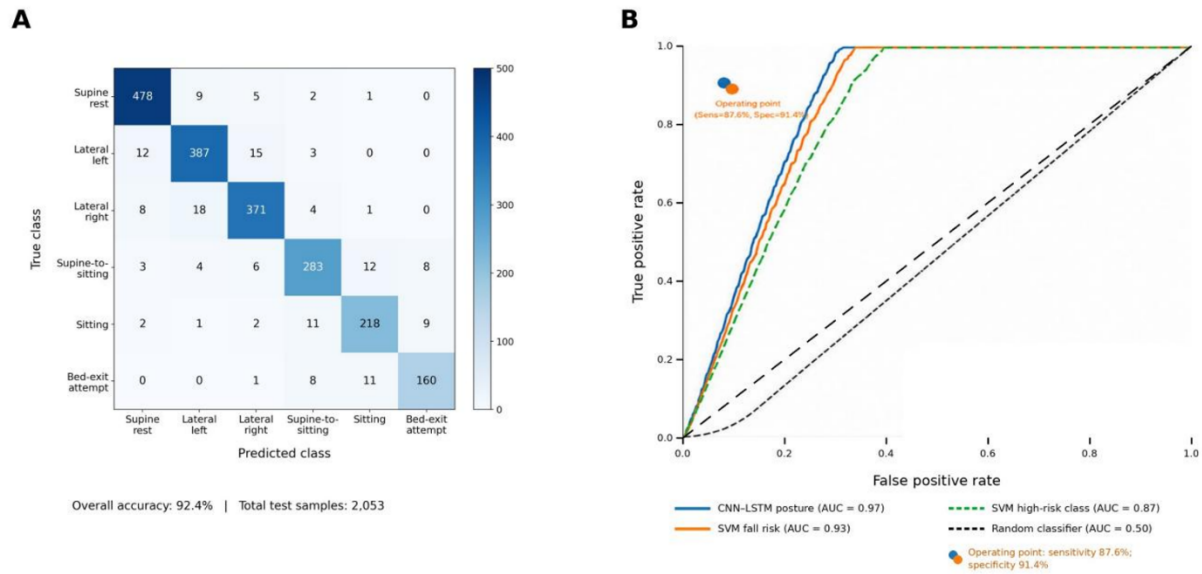


Figure 6. Retained model evaluation. (A) CNN-LSTM confusion matrix and (B) ROC curves for the retained CNN-LSTM and SVM models. Abbreviations: AUC: Area under the curve; CNN: Convolutional neural network; LSTM: Long short-term memory; ROC: Receiver operating characteristic; SVM: Support vector machine.

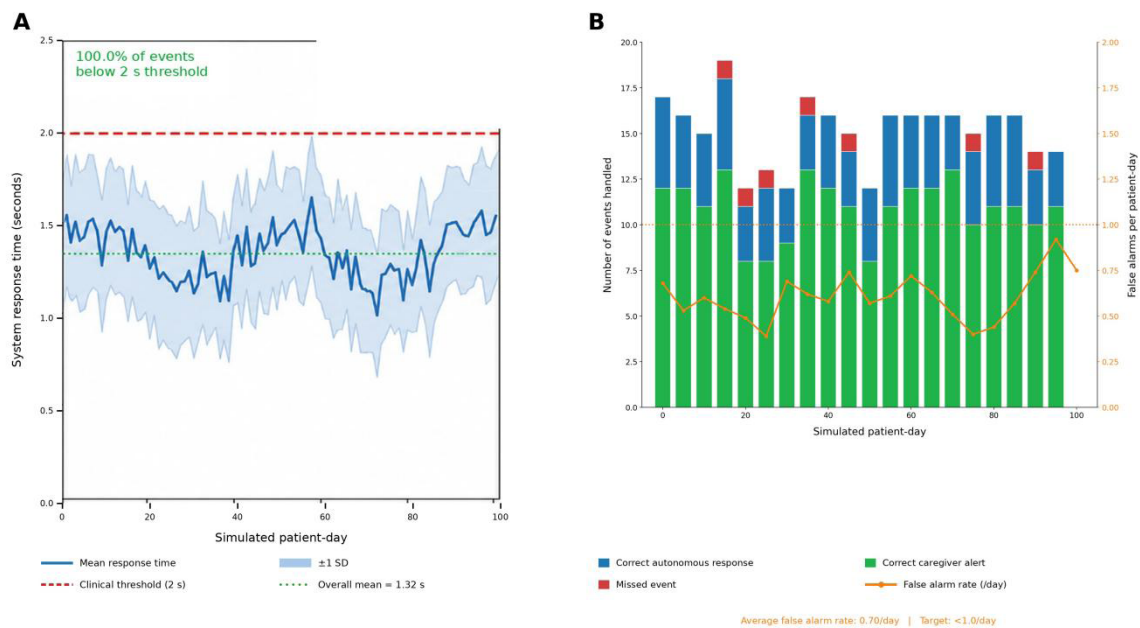


Figure 7. Digital twin outcomes over 100 virtual patient-days. (A) Simulated response time and (B) event handling with false-alarm rate.

Table 13. Pilot usability outcomes by stakeholder group ($n = 20$)

Stakeholder group	N	Mean System Usability Scale score	Trust in automation (%)	Privacy concern (%)	Perceived safety benefit (%)
Elderly volunteers	10	73.4 $\pm$ 9.1	72	64	88
Formal caregivers	5	81.2 $\pm$ 6.3	90	38	96
Informal caregivers	5	77.6 $\pm$ 7.8	80	52	88
Overall	20	76.8 $\pm$ 8.4	78	52	90

4. Discussion

4.1. Novelty and comparison with existing systems

The principal contribution is the explicit placement of an FCM between predictive analytics and bed actuation. Earlier healthcare FCMs have mainly supported diagnosis, health-factor modeling, or explainable decision support^{10,11,14,24,25}, whereas the proposed architecture uses FCM states to organize multimodal predictions and select context-sensitive actions. This design improves interpretability because each command can be linked to the concepts it activates and the causal paths it follows. It remains an architecture-level contribution rather than a clinically certified autonomous device.

The comparison in Table 9 shows that representative smart-bed studies generally emphasize monitoring, comfort analysis, posture recognition, or multimodal interaction, while explicit causal reasoning and closed-loop action are uncommon. The retained CNN-LSTM and SVM results are competitive with those of standalone systems reported in the literature, but cross-study comparisons are affected by differences in participants, sensors, labels, and evaluation protocols. Recent Mamba-attention, Transformer, and reinforcement-learning methods demonstrated powerful alternatives for medical imaging and adaptive decision systems^{37,38}, yet their relevance to smart-bed sensing must be tested on the same longitudinal dataset. Accordingly, novelty is claimed for system integration and interpretability, not universal predictive superiority.

4.2. Clinical and practical implications

In the scripted digital twin scenarios, movement intention preceded simulated bed exit events by 8–12 seconds, providing a potential window for prompts, rail control, or caregiver notification. This interval is a simulation output and should not be presented as a clinically established warning time. The low simulated false-alarm rate may help address alarm fatigue, but only prospective deployment can determine whether the benefit persists under real staffing patterns, wireless interference, atypical movement, and comorbidity.²³

For older adults, the intended benefit is proportionate assistance rather than indiscriminate automation. The FCM can incorporate discomfort, risk, alertness, caregiver availability, and autonomy preference before selecting an action. Acceptance therefore depends on understandable explanations, adjustable intervention levels, informed consent, and a reliable means to pause or override movement. The usability findings support further co-design but are insufficient to infer broad acceptance.^{8,14,24}

4.3. Ethics, privacy, security, and algorithmic transparency

However, continuous sensing from a patient bed, even without using a regular camera, still involves significant ethical risks. As such, the design must respect several data minimization principles, including only collecting the necessary data for the intended clinical function, processing identifiable data locally where possible, encrypting data both in transit and at rest, separating clinical and administrative access, and keeping the audit trail of model predictions, commands, overrides, and errors. Before deployment, role-based access control, key rotation, device authentication, secure software updates, network segmentation, and incident response processes are obligatory. Information about data sensing, storage, access, and means of stopping automated movements must be provided to patients or their legal representatives.

Beyond showing the score, algorithmic transparency requires revealing the leading FCM components, relevant confidence levels, and the rule/path that led to this decision. Inputs with low confidence and out-of-distribution should be processed through conservative monitoring or caregiver review rather than automatically escalating. The performance of the solution must be assessed by sex, age, body measurements, mobility, skin condition, cognitive state, and care setting to evaluate the inequality in false negatives and false positives. The solution is intended to assist, not to substitute for human decisions.

4.4. Limitations

There are several limitations in this study. For example, the sample size of participants was limited to only 50 persons,

and the testing environment is strictly controlled and does not account for behavioral variability, advanced dementia cases, severely disabled individuals, acutely ill patients, and disruptions to regular care. In addition, the archive included final outputs and the model's parameters but omitted the tuning process, the checkpoints of different models, the participant partition list, and individual patient files required for retraining trials. Therefore, the requested experiments using CNN only, LSTM only, GRU, Transformer, an attention mechanism, no FCM, no thresholding, no modality, and alerts only were defined in terms of controlled experiments rather than fictional numbers. The proof of system performance relied on the digital twin and not the prototype. The hardware diagram and protocol table provided the reference implementation but not the verified circuit and electrical safety report. The usability test included 20 locally recruited participants and lacked demographic diversity. FCM weights were established by a single expert panel and were not tested prospectively over the long term.

4.5. Future research directions

Future studies should involve developing a safety-engineered physical prototype and conducting benchmark testing for calibration drift, timing accuracy, actuator force, emergency-stop functionality, electrical insulation, cybersecurity, and fault recovery. A larger multi-center dataset should include participant-level partitioning with nursing homes, rehabilitation units, hospitals, and home settings. On this common dataset, CNN-only, LSTM-only, GRU, attention-based, Transformer, and reinforcement-learning models should be optimized according to the same protocol, followed by ablation studies on sensor modalities, FCM removal, and actuator policy using CIs and paired statistics. Human factors research in a prospective mode should involve a range of older adults, those with cognitive impairment, their caregivers, clinicians, accessibility experts, and privacy professionals. A longitudinal clinical trial assessing falls, pressure ulcers, disrupted sleep, alarm burden, caregiver burden, autonomy, and other adverse effects can only be conducted after completion of these recommendations.

5. Conclusion

This study provides a proof-of-concept framework for multimodal sensory input, predictive modeling, causality through FCM, and actuator operation based on safety-constrained risk prediction. The framework goes beyond mere thresholds by maintaining an interpretable patient-state model and explicitly connecting the suggested actions to risk and comfort.

Based on the available laboratory and simulated

evidence, the FCM correctly matched 87.3% of the expert-defined responses, the CNN-LSTM achieved 92.4% posture classification accuracy, and the SVM achieved 87.6% sensitivity for high fall risk. The average simulated latency was 1.3 seconds, the average false alarm rate was 0.7 alerts per virtual patient-day, and the average SUS score was 76.8. This shows technical feasibility under the stated constraints; however, no clinical utility, safety, or performance relative to alternative temporal and adaptive models can be demonstrated based on the available evidence.

Therefore, the correct interpretation of this work is a structured base for physical implementation and external validation. Any claims of fall prevention, pressure injury reduction, caregiver burden reduction, or regular clinical deployment would require significantly more realistic data, full-scale component ablation studies, and comparisons with GRU, attention, Transformer, and reinforcement-learning models. Until these criteria are fulfilled, any autonomous actions must be limited and explainable.

Acknowledgments

None.

Funding

This work was supported by the Shanghai 2025 Science and Technology Industry High Quality Development Plan Elderly Care Technology Support Project (Grant No. 25YL1901300).

Conflict of interest

The authors declare no conflicts of interest.

Author contributions

Conceptualization: Long Mei, Chee Siong Teh

Formal analysis: Long Mei, Zhidong Fang

Methodology: Long Mei, Chee Siong Teh, Xing Wang, Zhidong Fang

Supervision: Chee Siong Teh, Huadong Chen

Writing—original draft: Long Mei, Chun Zheng

Writing—review & editing: Chee Siong Teh, Xing Wang,

Zhidong Fang, Chun Zheng, Huadong Chen

All authors have read and agreed to the submitted version of the manuscript.

Ethics approval and consent to participate

Ethical approval was granted by the Ethics Committee of Anhui Sanlian University (Ref: SLHR(NM)/202603/07). This study was conducted in accordance with the Declaration of Helsinki. Sensor records were coded,

stored on a limited-use institutional server and had direct identifiers removed. This architecture is not a certified medical device, and no autonomous clinical treatment was provided during the study. Consent was obtained from the participants or their legally authorized representatives, in writing, prior to enrollment. The participants were told that they could withdraw from the study at any time without penalty.

Consent for publication

Written informed consent for publication of anonymized participant data was obtained from all participants or their legally authorized representatives.

Availability of data

The participant-level movement and pressure dataset is not publicly deposited due to ethical approval constraints on the health-related sensor data it contains. Requests for anonymized aggregate results can be directed to the corresponding author under the data use agreement. The manuscript offers the feature definitions, the preprocessing pipeline, the final model architecture, the FCM equations, the digital twin assumptions, the reference hardware interface profile, and the specific comparison/ablation protocol used in the research. The kept archive does not include participant-level data, manifest splits, the entire run history, alternative model checkpoints, chosen epochs, and checkpoint hashes; hence, their unavailability is explicitly declared.

Further disclosure

The authors attest that the data was not collected, statistically analyzed, trained or interpreted with the help of generative artificial-intelligence tools. No generative model for the images was used, all schematic figures were programmatically generated from the study architecture and reported output. Only editorial polishing was provided, and the authors checked all scientific statements.

References

- World Health Organization. *Ageing and Health*. World Health Organization; October 1, 2025. <https://www.who.int/news-room/fact-sheets/detail/ageing-and-health>
- Majumder S, Aghayi E, Noferesti M, *et al*. Smart Homes for Elderly Healthcare—Recent Advances and Research Challenges. *Sensors*. 2017;17(11):2496.
doi: 10.3390/s17112496
- Sugathapala RDUP, Latimer S, Balasuriya A, Chaboyer W, Thalib L, Gillespie BM. Prevalence and incidence of pressure injuries among older people living in nursing homes: A systematic review and meta-analysis. *Int J Nurs Stud*. 2023;148:104605.
doi: 10.1016/j.ijnurstu.2023.104605
- Shao L, Shi Y, Xie XY, Wang Z, Wang ZA, Zhang JE. Incidence and Risk Factors of Falls Among Older People in Nursing Homes: Systematic Review and Meta-Analysis. *J Am Med Dir Assoc*. 2023;24(11):1708-1717.
doi: 10.1016/j.jamda.2023.06.002
- Rashidi P, Mihailidis A. A Survey on Ambient-Assisted Living Tools for Older Adults. *IEEE J Biomed Health Inform*. 2013;17(3):579-590.
doi: 10.1109/jbhi.2012.2234129
- Bacchin D, Pernice GFA, Sardena M, Malvestio M, Gamberini L. Caregivers' Perceived Usefulness of an IoT-Based Smart Bed. In: *Lecture Notes in Computer Science*. Springer International Publishing; 2022:247-265.
doi: 10.1007/978-3-031-05463-1_18
- Botia JA, Villa A, Palma J. Ambient Assisted Living system for in-home monitoring of healthy independent elders. *Expert Syst Appl*. 2012;39(9):8136-8148.
doi: 10.1016/j.eswa.2012.01.153
- Chen K, Chan AHS. Gerontechnology acceptance by elderly Hong Kong Chinese: a senior technology acceptance model (STAM). *Ergonomics*. 2014;57(5):635-652.
doi: 10.1080/00140139.2014.895855
- Ni Q, García Hernando A, De la Cruz I. The Elderly's Independent Living in Smart Homes: A Characterization of Activities and Sensing Infrastructure Survey to Facilitate Services Development. *Sensors*. 2015;15(5):11312-11362.
doi: 10.3390/s150511312
- Stylios CD, Georgopoulos VC, Malandraki GA, Chouliara S. Fuzzy cognitive map architectures for medical decision support systems. *Appl Soft Comput*. 2008;8(3):1243-1251.
doi: 10.1016/j.asoc.2007.02.022
- Apostolopoulos ID, Papandrianos NI, Papathanasiou ND, Papageorgiou EI. Fuzzy Cognitive Map Applications in Medicine over the Last Two Decades: A Review Study. *Bioengineering*. 2024;11(2):139.
doi: 10.3390/bioengineering11020139
- Liu Z, Li G, Wang C, Cascioli V, McCarthy PW. Unobtrusive Sleep Posture Detection Using a Smart Bed Mattress with Optimally Distributed Triaxial Accelerometer Array and Parallel Convolutional Spatiotemporal Network. *Sensors*. 2025;25(12):3609.
doi: 10.3390/s25123609
- Akl A, Taati B, Mihailidis A. Autonomous Unobtrusive Detection of Mild Cognitive Impairment in Older Adults. *IEEE Trans Biomed Eng*. 2015;62(5):1383-1394.
doi: 10.1109/tbme.2015.2389149

14. Wu J, Chen Y, Wang Z, Hu G, Chen C. Probabilistic linguistic fuzzy cognitive maps: applications to the critical factors affecting the health of rural older adults. *BMC Med Inform Decis Mak.* 2022;22(1).
doi: 10.1186/s12911-022-02028-9
15. Kurnianingsih K, Nugroho LE, Widyawan W, Lazuardi L, Prabuwo AS, Mantoro T. Personalized adaptive system for elderly care in smart home using fuzzy inference system. *IJPCC.* 2018;14(3/4):210-232.
doi: 10.1108/ijpcc-d-18-00002
16. Bai X, Zhong M, Liu Y, Hu Y, Ma J. Comprehensive analysis of smart bed comfort across varied resting conditions using quantitative measures. *PLoS One.* 2025;20(7):e0327241.
doi: 10.1371/journal.pone.0327241
17. Laurino M, Arcarisi L, Carbonaro N, Gemignani A, Menicucci D, Tognetti A. A Smart Bed for Non-Obtrusive Sleep Analysis in Real World Context. *IEEE Access.* 2020;8:45664-45673.
doi: 10.1109/access.2020.2976194
18. Hong YS. Smart Care Beds for Elderly Patients with Impaired Mobility. *Wirel Commun Mob Comput.* 2018;2018(1).
doi: 10.1155/2018/1780904
19. Kim D, Bian H, Chang CK, Dong L, Margrett J. In-Home Monitoring Technology for Aging in Place: Scoping Review. *Interact J Med Res.* 2022;11(2):e39005.
doi: 10.2196/39005
20. Zhao D, Wu Y, Yang C, *et al.* A novel multifunctional intelligent bed integrated with multimodal human–robot interaction approach and safe nursing methods. *IET Cyber-Syst Robot.* 2023;5(3).
doi: 10.1049/csy2.12097
21. Li R, Lu B, McDonald-Maier KD. Cognitive assisted living ambient system: a survey. *Digit Commun Netw.* 2015;1(4):229-252.
doi: 10.1016/j.dcan.2015.10.003
22. Mishra N, Lin CC, Chang HT. Cognitive Inference Device for Activity Supervision in the Elderly. *Sci World J.* 2014;2014:1-12.
doi: 10.1155/2014/125618
23. Tak SH, Choi H, Lee D, Song YA, Park J. Nurses' Perceptions About Smart Beds in Hospitals. *CIN Comput Inform Nurs.* 2022;41(6):394-401.
doi: 10.1097/cin.0000000000000949
24. Apostolopoulos ID, Groumpos PP. Fuzzy Cognitive Maps: Their Role in Explainable Artificial Intelligence. *Appl Sci.* 2023;13(6):3412.
doi: 10.3390/app13063412
25. Papageorgiou EI, Billis AS, Frantzidis C, Konstantinidis EI, Bamidis PD. A preliminary fuzzy cognitive map-based decision support tool for geriatric depression assessment. In: *2013 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE).* IEEE; 2013:1-8.
doi: 10.1109/fuzz-ieee.2013.6622485
26. Tamura T, Huang M. Unobtrusive Bed Monitor State of the Art. *Sensors.* 2025;25(6):1879.
doi: 10.3390/s25061879
27. Rantz M, Lane K, Phillips LJ, *et al.* Enhanced registered nurse care coordination with sensor technology: Impact on length of stay and cost in aging in place housing. *Nurs Outlook.* 2015;63(6):650-655.
doi: 10.1016/j.outlook.2015.08.004
28. Karatzinis GD, Boutalis YS. A Review Study of Fuzzy Cognitive Maps in Engineering: Applications, Insights, and Future Directions. *Eng.* 2025;6(2):37.
doi: 10.3390/eng6020037
29. Brooke J. SUS: A "Quick and Dirty" Usability Scale. In: *Usability Evaluation In Industry.* CRC Press; 1996:207-212.
doi: 10.1201/9781498710411-35
30. Padula WV, Delarmente BA. The national cost of hospital-acquired pressure injuries in the United States. *Int Wound J.* 2019;16(3):634-640.
doi: 10.1111/iwj.13071
31. Liu R, Zhang X. Fuzzy context-specific intention inference for robotic caregiving. *Int J Adv Robot Syst.* 2016;13(5).
doi: 10.1177/1729881416662780
32. Hevner AR, March ST, Park J, Ram S. Design Science in Information Systems Research. *MIS Q.* 2004;28(1):75-106.
doi: 10.2307/25148625
33. Vallée A. Digital twin for healthcare systems. *Front Digit Health.* 2023;5.
doi: 10.3389/fdgth.2023.1253050
34. Lee H, Park SJ, Kim MJ, Jung JY, Lim HW, Kim JT. The Service Pattern-Oriented Smart Bedroom Based on Elderly Spatial Behaviour Patterns. *Indoor Built Environ.* 2012;22(1):299-308.
doi: 10.1177/1420326x12469712
35. Li J, Yang SX. Digital twins to embodied artificial intelligence: review and perspective. *Intell Robot.* 2025;5(1):202-227.
doi: 10.20517/ir.2025.11
36. Lu Q, Li M. Fault Prediction Method Towards Rolling Element Bearing Based on Digital Twin and Deep Transfer Learning. *Appl Sci.* 2025;15(23):12509.
doi: 10.3390/app152312509

37. Rehman K ur, Tian Y, Jianqiang L, *et al.* WCMA-Net: Enhancing Mammographic Cancer Diagnosis Using Wavelet-Driven Channel-Spatial Mamba Attention. *Tsinghua Sci Technol.* 2026.
doi: 10.26599/tst.2026.9010016
38. Khan S, Khan AA, Mahendran RK, *et al.* C2DEEP-OT: Utilizing Multi-Agent Deep Reinforcement Learning Algorithm and Optimized Attentive Transformer Network for Cervical Cancer Detection. *Inf Sci.* 2026;738:123047.
doi: 10.1016/j.ins.2025.123047