Artificial Intelligence Integration in a Multisensor Smart Sofa: Architecture, On-Device Models and Research Directions

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Abstract— This paper presents the integration of artificial intelligence (AI) into a multisensor smart sofa designed for long-term monitoring of user behaviour and structural health. The system combines load cells, pressure sensors, inertial and vibration sensing, as well as temperature and humidity, to transform a conventional upholstered sofa into a cyber-physical product. On top of the signal acquisition and preprocessing chain, a compact AI layer is implemented to classify usage scenarios and sitting posture, detect shocks and abnormal events, monitor sedentary behaviour, and estimate a wear score and the remaining useful life (RUL) of the sofa. Compared with existing smart chairs, cushions and posture-monitoring systems, the proposed solution focuses on explainable models that can run on a resource-constrained microcontroller while still offering meaningful feedback to users and manufacturers. The paper summarises the data pipeline, the main AI modules and their implementation constraints, and discusses open research directions for AI in smart upholstered furniture.

Keywords— smart sofa, upholstered furniture, multisensor system, artificial intelligence, posture recognition, sedentary behaviour, remaining useful life, condition-based maintenance.

Introduction

Research on smart seating started mainly from clinical applications. In these works, pressure mapping is used to prevent pressure ulcers in wheelchair users and elderly patients [1], [2]. Clinical studies show that optimised seat cushions and real-time pressure feedback can reduce the risk of ulcers, because they help to control peak pressures and exposure time [1].

Later, smart chairs and office chairs were proposed for posture classification and sitting behaviour monitoring in everyday environments. Reviews describe systems that use pressure mats, load cells and inertial sensors together with machine learning models to detect sitting positions, sitting habits and discomfort [3], [4]. These devices usually provide simple feedback, such as telling the user to sit upright or not to lean forward.

Smart cushions go one step further. They embed arrays of force-sensitive or textile sensors in a flexible pad and use AI to recognise sitting postures and to support posture training [5]–[7]. Some projects implement microcontroller-based pressure sensing systems for office environments [8]. However, most of these solutions focus only on the human user. They do not consider the structural health and lifetime of the furniture item itself, and many of them rely on cloud resources instead of running all logic locally.

The smart sofa developed in the underlying doctoral research addresses this gap. A multisensor node is integrated into an upholstered sofa and acquires, in real time, data about weight distribution, contact pressure, shocks, vibrations and environmental conditions. AI models, designed to be small and explainable, are used to classify usage scenarios and simple postures, detect abnormal events and estimate a Remaining Useful Life (RUL) indicator at sofa level. The paper focuses on the AI part of this system and explains how it is implemented on a low-cost microcontroller.

The goals of the paper are: (i) to review AI-based approaches for smart seating and condition monitoring that are relevant for a multisensor sofa system; (ii) to describe the AI architecture implemented in the smart sofa prototype, including the data pipeline, the features and the on-device models; (iii) to discuss how the AI modules support user feedback, sedentary behaviour alerts and RUL estimation; and (iv) to outline research directions for AI in smart upholstered furniture.

2. Related Work on AI for Smart Seating and Condition Monitoring

In clinical settings, pressure mapping is already an established tool. It is used to design and evaluate seat cushions that reduce peak pressures and protect sensitive areas of the body [1], [2]. Studies report that carefully designed cushions and regular repositioning, guided by pressure maps, can reduce the incidence of pressure ulcers in high-risk patients [1].

Outside the clinic, smart sensing chairs and office chairs use pressure mats and load cells to detect sitting posture and habits [3], [4]. Machine learning is often used to classify postures from labelled datasets, and the output is converted to short messages to the user. For example, the chair can suggest to sit more upright or to reduce asymmetry. Some systems also monitor the time spent in each posture to provide basic feedback on sedentary behaviour [3].

Smart cushion systems embed small arrays of FSR or textile sensors in a seat pad. They train machine learning models to recognise postures and to provide posture coaching [5]–[7]. Other works propose microcontroller-based pressure sensing systems for sitting posture detection in offices [8]. These solutions show that useful AI functions can be implemented with a limited number of sensors and modest computing resources.

At the furniture level, there are research prototypes of smart couches designed for assisted living. For example, sensorised couches have been tested with patients with cognitive diseases to monitor how the furniture is used [3], [4]. However, these systems usually employ simple rule-based logic and do not include explicit RUL or structural health indicators.

From the maintenance and reliability point of view, the concept of Remaining Useful Life has been widely studied for industrial equipment. RUL prediction methods use sensor data and models to estimate the time until a component reaches its end of life [9]. Condition-based maintenance (CBM) guidelines explain how sensor data and diagnostic algorithms can be used to trigger maintenance actions based on actual condition instead of fixed schedules [10]. Extensive reviews on fault diagnosis and fault-tolerant control underline the importance of robust sensor fusion and anomaly detection in intelligent systems [11], [12].

The smart sofa described in this paper combines these directions. It uses AI for posture and behaviour recognition, similar to smart cushions and chairs [3]–[8], and it also computes CBM-inspired indicators, such as RUL and usage scores, based on multisensor data and diagnostic rules [9]–[12]. At the same time, the sofa can be seen as part of a smart environment, where furniture is not passive but contributes data and indicators to the overall ambient intelligence [13].

IoT devices and cyber-physical systems bring additional constraints. Multisensor aerial platforms, such as air-scanning sniffer quadcopters for environmental monitoring, must balance sensing, communication and on-board processing against strict limits on energy and payload [14]. Noje et al. show how approximation-based operators can reduce the complexity of signal processing on resource-constrained embedded nodes [15]-[17]. These works are relevant for the smart sofa, because they support the idea that AI modules must be both computationally efficient and robust, so that they can run reliably on a low-cost microcontroller.

3. Multisensor Smart Sofa Platform

The smart sofa is based on a standard upholstered three-seat couch. A dedicated multisensor node is integrated into the structure and the upholstery. In this way, the prototype behaves as a normal piece of furniture for the user, but it also records how the sofa is loaded and how it is used over time.

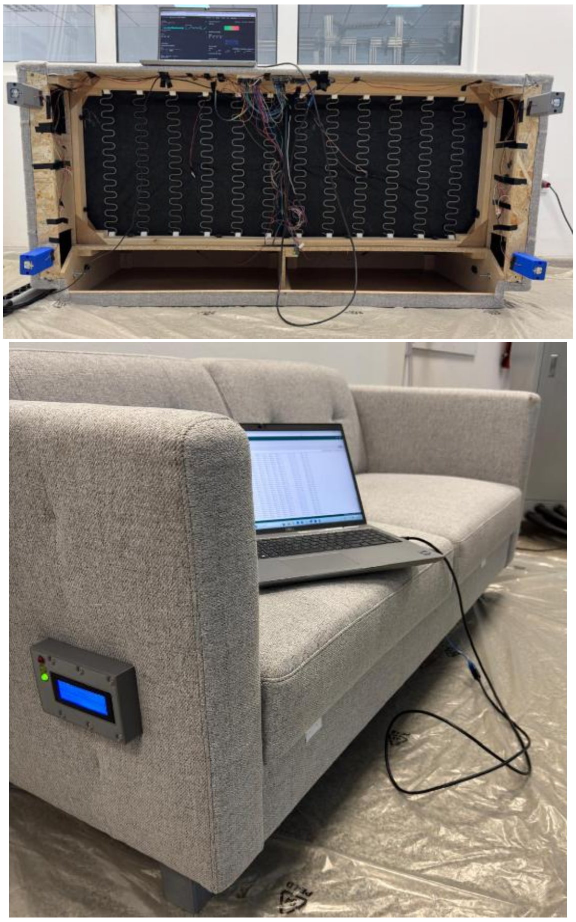

Figure 1 Smart sofa prototype

Four half-bridge load cells with HX711 conditioning modules are mounted in the sofa legs to measure total weight and left/right distribution. Force-sensitive resistors (FSR) and low-cost piezoresistive patches are embedded in the seat and backrest to reconstruct simple pressure maps and to detect zones of interest. An inertial measurement unit (IMU) and a vibration sensor detect shocks, micro-movements and structural vibrations, while a temperature–humidity sensor monitors the micro-climate in the upholstery.

The sensors are read by an Arduino-class microcontroller. Basic preprocessing includes offset compensation, moving-average filtering and feature extraction, such as total weight, weight difference between left and right, maximum and average pressure in defined zones, number of shocks, time of occupancy and daily mean values of temperature and humidity. This classical signal processing stage provides the input features for the AI layer.

Table 1 Sensors and AI-relevant features

Sensor	Type	Unit	AI role
Load cells	Load-cell + HX711	Total weight, left/right weight	Presence detection, number of users, overload, imbalance, entry into the wear score/RUL
Force sensor	FSR406	Local pressure on seating and support areas (rest and backrest)	User location, posture, pressure distribution, micro-motion index for sedentary lifestyle

Inertial measurement unit	GY-521	3-axis acceleration, peaks |a|	Shock detection, activity level, confirmation of large movements versus static stays
Vibrations sensor	PVDF / piezoelectric	Mechanical impulses, vibration signal	Shock confirmation, differentiating between accidental knocks and normal use
Temperature/ humidity	AHT25	Temperature (°C), relative humidity (%)	Mold risk estimation, environmental factor in wear score
Real time clock / EEPROM	DS3231 + EEPROM	Calendar time, hours/minutes of use	Daily aggregation of indicators and calculation of RUL over long periods (days, months)

On the output side, the sofa provides local feedback through a 20×4 LCD and a tri-colour LED "semaphore" mounted on the front. The LED encodes global status (OK, warning, alert), while the LCD displays key indicators such as total weight, number of users, sedentary status, mould risk, and a numerical score of usage and RUL. Events and time series are logged through the serial interface and can be visualised in a dashboard for offline analysis. The AI models must therefore operate under two constraints: limited memory and computing power on the microcontroller, and the need for explainable, traceable decisions that can be communicated to non-expert users via simple messages.

4. AI Architecture and Data Pipeline\

To place AI in context, the data flow of the smart sofa can be seen as a four-stage pipeline: sensing; preprocessing and feature extraction; AI layer; and user interface with logging. In the sensing stage, load cells provide total weight and left/right distribution. Pressure sensors in the seat and backrest produce coarse pressure maps. The IMU and vibration sensor measure shocks and micro-movements, and the temperature–humidity sensor captures the environmental conditions.

In the preprocessing and feature extraction stage, each raw signal is filtered and normalised. Features such as total weight, weight difference, occupancy time, average and maximum pressure in regions, shock counts and micro-movement indexes are computed over fixed windows. These features form compact descriptions of the current state of the sofa and its user.

The AI layer receives feature vectors and outputs discrete labels, such as "one user centred", "two users" or "edge sitting". It also produces anomaly flags, for example "possible sensor fault", and continuous scores, such as a wear score and a RUL estimate. Finally, the user interface and logging stage maps labels and scores to simple messages and LED states, while events are stored in EEPROM and exported via serial logs for further analysis.

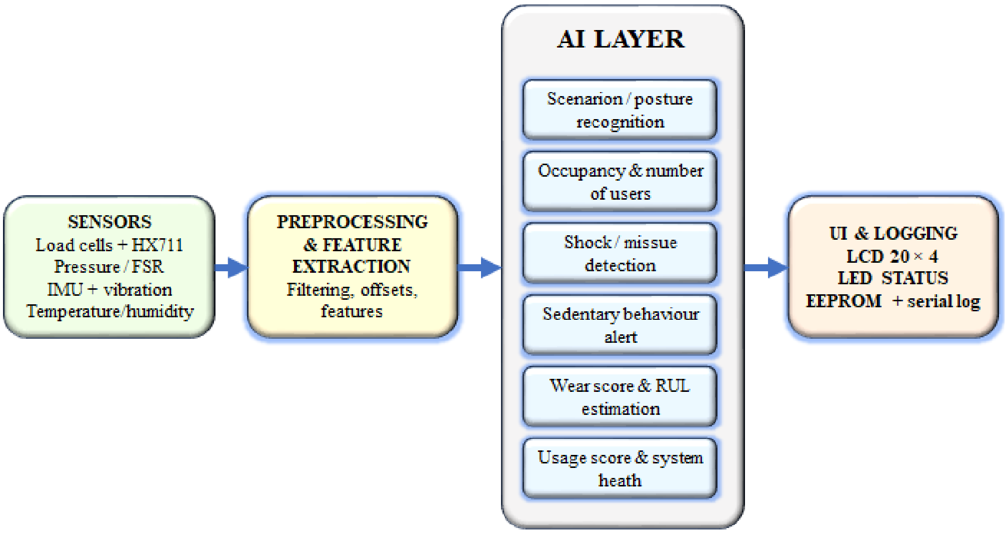

Figure 2 Block diagram of data pipeline and AI architecture

The AI architecture adopted in the prototype is hybrid. Training and model selection are performed on a PC using Python. Several candidate models are evaluated, such as small decision trees, shallow random forests, simple k-nearest neighbour models and lightweight regression models. Once a model is chosen, it is translated into C code and deployed on the Arduino. The structure and parameters are kept in a form that is compatible with the microcontroller and with the dashboard implementation. This workflow follows recommendations for efficient signal processing in IoT devices, where algorithmic complexity must be controlled in order to fit the limits of edge hardware [15].

The selected models follow the trend of tiny machine learning. The number of parameters is kept low and the inference time is kept below a few milliseconds, while the accuracy remains acceptable for the target application. At the same time, the models are kept interpretable: decision trees are written as nested if–else rules, and linear regressions are expressed as weighted sums with clear physical meaning.

5. AI Modules in the Smart Sofa

The AI layer is organised into several modules. Each module addresses a specific task and uses dedicated features derived from the multisensor data. The main modules cover scenario and posture recognition, occupancy and number of users, shock and misuse detection, sedentary behaviour alerts, wear score and RUL estimation, and usage score and system health.

Table 2 – Summary of AI modules in the smart sofa

AI module / task	Main input features	Model / logic	Outputs
Scenario / posture recognition	Total weight; left/right weight distribution; seat pressure zones	Small decision tree trained on labelled scenarios; implemented as threshold-based rules on microcontroller	Usage scenario label (free, 1 user centred, 1 user off-centre, 2 users, edge sitting, etc.)
Occupancy & number of users	Total weight; leg load distribution; hysteresis thresholds	Binary decision for occupancy; 2-class classifier (1 vs. 2 users) using simple tree or softmax layer	Occupancy flag (0/1); estimated number of users (0, 1, 2)
Shock and misuse detection	IMU acceleration magnitude; vibration	Binary classifier with temporal window; rule-based confirmation	Shock event flag; shock counter; contribution to

	sensor envelope; time coincidence of peaks	when both sensors indicate a shock	wear score and RUL
Sedentary behaviour alert	Occupancy state; total weight; micro-movement index from FSR and IMU; sedentary timer	Timer-based logic combined with thresholds on micro-movement index and minimum weight	Sedentary alert flag; LED blinking pattern; log of sedentary episodes
Wear score & RUL estimation	Aggregated usage indicators (hours of use, time over weight limits, number of shocks, L/R imbalance, adverse T/RH)	Low-order linear regression with quantised coefficients; mapping to dimensionless wear score	RUL estimate (years); wear score from 0 to 10
Usage score & system health	Shock counter; time near limits; sedentary episodes; L/R imbalance; sensor coherence metrics	Rule-based aggregation of indicators; simple anomaly detection vs. reference profiles	Usage score; system status flags; potential sensor/structural anomaly flags

5.1 Scenario and Posture Recognition

The first module distinguishes between basic usage scenarios and simple postures. The main classes include: sofa free, one user sitting in a balanced position, one user sitting off-centre, two users, and atypical loading such as sitting on the edge. The features are mainly total weight, left/right distribution and pressure patterns in the seat region. A small decision tree classifier is trained on labelled data obtained from laboratory sessions with controlled scenarios. The tree is then implemented directly as a sequence of threshold-based conditions in the microcontroller code. This is similar to smart cushion systems and smart posture chairs, where a limited number of pressure sensors and machine learning methods are used to recognise sitting postures and behaviours [5]–[8].

5.2 Occupancy and Number of Users

Occupancy is treated as a binary decision (occupied versus free) based on total weight above a minimum threshold. This avoids false positives generated by objects left on the sofa. The number of users is estimated using a two-class classifier (one versus two users) that can be implemented as a small decision tree or a softmax model with one or two dense layers. The key features are again total weight and its distribution between left and right legs. The classification result is used not only for displaying the number of users on the LCD, but also as input for higher-level modules. For example, sedentary behaviour is only evaluated if there is at least one user, and structural stress is interpreted differently for one heavy user compared with two lighter users.

5.3 Shock and Misuse Detection

Shocks and potentially harmful events are detected by combining the acceleration magnitude from the IMU with the vibration sensor signal. A peak acceleration above a configurable threshold, within a narrow time window around a vibration burst, is interpreted as a confirmed shock. This logic can be seen as a simple binary classifier with two sensor inputs and a temporal coincidence condition. The idea is similar to condition-based maintenance approaches, where several parameters must indicate an abnormal state before an alarm is generated [10]. For each confirmed shock, an event is stored, the LED turns red and the LCD displays an alert together with a short recommendation. These events also contribute to the wear score and the RUL estimation.

5.4 Sedentary Behaviour Alert

Sedentary behaviour is one of the clearest examples of how AI turns raw sensor data into direct user feedback. Sedentary episodes are defined as continuous sitting on the sofa with sufficient weight, combined with a low level of micro-movement. The module uses an occupancy timer, the total weight and a micro-movement index that is computed from FSR variations and IMU signals. If the sofa is occupied and the total weight is relatively stable while the micro-movement index remains below a minimum threshold, a sedentary timer is increased. When the timer exceeds a configurable limit, for example 45–60 minutes, the system raises a sedentary alert: the LED switches to flashing yellow, the LCD suggests a short break, and the event is logged. If the user stands up or moves more actively, the timer is reset or slowed down. This approach is consistent with AI-assisted posture coaching systems, which combine posture recognition with time thresholds to encourage healthier sitting patterns [5]–[7].

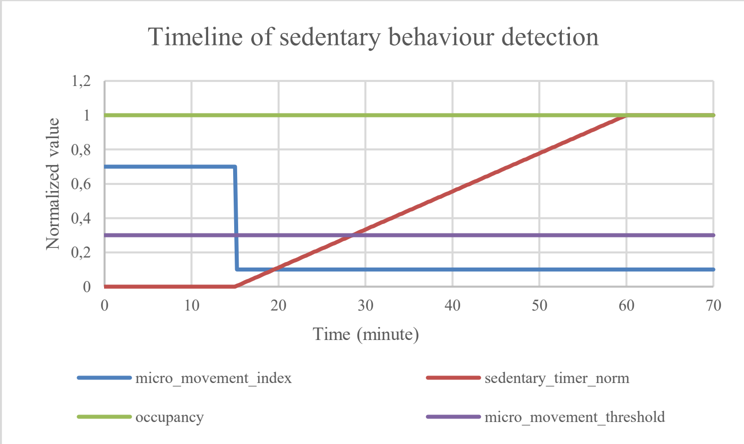

Figure 3 Example timeline of sedentary behaviour detection

5.5 Wear Score and Remaining Useful Life Estimation

The RUL module estimates how much useful lifetime remains for the sofa, based on usage history and mechanical stress indicators. The model starts from a reference lifetime, for example ten years, and adjusts it according to the cumulative "dose" of mechanical loading. Relevant factors include hours of use, time under high weight, number of shocks, left/right imbalance, and periods with adverse environmental conditions such as high humidity. In the thesis, a linear regression model with quantised coefficients was selected for implementation on the microcontroller. The model maps aggregated usage indicators to a RUL value expressed in years. The regression is trained on synthetic or experimentally derived scenarios and then translated into low-precision arithmetic suitable for the microcontroller. To provide an intuitive interpretation, a wear score between 0 and 10 is derived from the RUL estimate. A score close to 10 indicates usage compatible with the nominal lifetime, while lower scores indicate accelerated wear. The concept is aligned with RUL prediction methods in industrial equipment, where sensor data and operational profiles are used to estimate remaining lifetime [9].

Table 3 Factors used in the RUL model and their qualitative influence

Factor	Indicator	Trend	Observation
Time of use	Busy hours/ day; very long sessions	↑ wear	High sedentary lifestyle accelerates the wear of soft components (cover, foam, padding)
Loading and distribution L/R	Average weight; variation in L/R ratio	↑ wear when it is large/ unbalanced	It wears the structure locally
Shocks/ impact	Number/ amplitude of events	↑ wear	Correlated with breakage/ noise complaints

	above threshold		

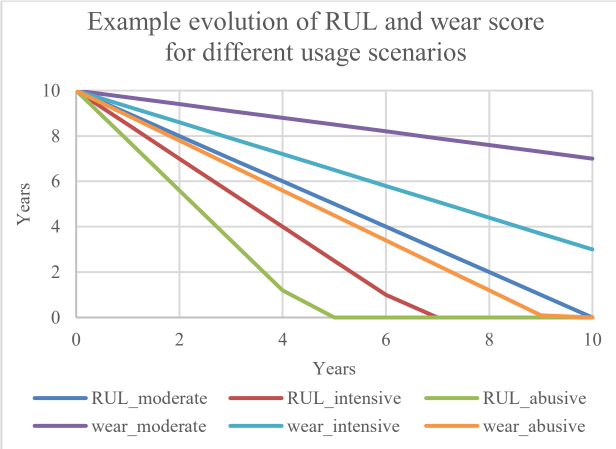

Figure 4 Example evolution of RUL and wear score for different usage scenarios

5.6 Usage Score and System Health

In addition to RUL, the AI layer computes a usage score that reflects how healthy the usage pattern is with respect to recommended limits. This score combines several elements: number of shocks, time spent near weight limits, duration of sedentary episodes and events related to unequal loading of the left and right sides. The system health perspective is complemented by diagnostic logic inspired by fault diagnosis and CBM literature [10]–[12]. Simple rules and anomaly detection mechanisms compare current sensor readings with stored reference profiles in order to identify possible sensor faults or structural changes. Examples include a leg that no longer carries its share of weight or a systematic decrease in cushioning stiffness. In future versions, more sophisticated anomaly detection models can be explored, while still keeping the implementation compatible with the microcontroller.

6. Experimental Evaluation and Discussion

The AI modules were evaluated using a combination of laboratory tests and user studies described in the thesis. In laboratory conditions, controlled loading scenarios were applied on the sofa using standardised test equipment, while the multisensor system recorded weight, pressure, acceleration and vibration signals. These datasets were used to derive features, to train and to verify the decision trees and regression models, and to tune thresholds for shocks, sedentary behaviour and mould risk.

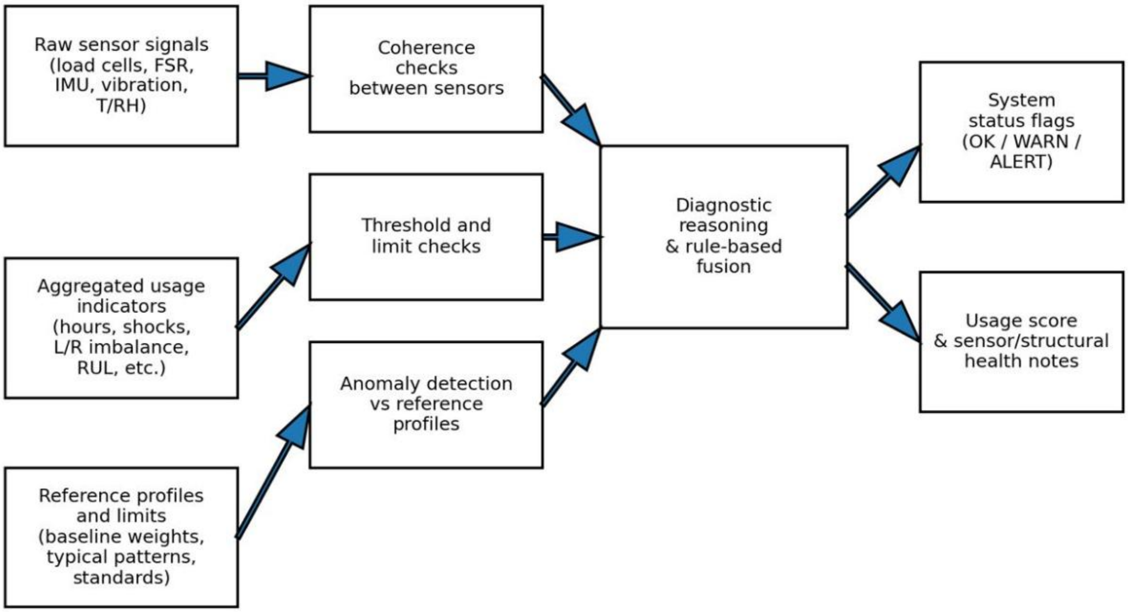

Figure 5 Schematic of diagnostic and fault-tolerance logic

Table 4 Experimental scenarios used for AI validation

Category	S1	S2	S3	S4	S5	S6
Description	Normal sitting	Edge sitting	Frequent repositioning	Rapid sitting down	Asymmetric occupancy	Two users; composite scenario from S1–S5
Objective	Baseline neutral occupancy	Edge loading / stability	Low-amplitude vibrations	Controlled shock (impact)	Effect of asymmetric habitual use	Effect of combined habits from S1–S5 with two users
Duration	15 min	5 min	10 min	5 min	10 min	15 min
Participant instructions	Slow sitting in the centre, minimal movement	Sit on the left edge for 2.5 min, then on the right edge for 2.5 min	Reposition every 30 s without dropping	Three “landings” from 10–15 cm height	5 min leaning to the left, 5 min leaning to the right	0–3 min: symmetric sitting; 3–6 min: alternating sit-to-stand; 6–9 min: lateral transfers with two users; 9–12 min: intensive load in the centre; 12–15 min: combined asymmetry
Log markers	S1_START/ END	S2_START/ END	S3_START/ END	S4_START/ END	S5_START/ END	S6_START/END
KPI (key performance indicators)	Occupancy, pressure zone, L/R balance, vibration level	L/R balance, pressure zone, WARNING/ ALERT DEZEQ (left–right imbalance)	Vibration level, pressure zone, number of WARNINGS	Shock-related indicators (peak acceleration, vibration burst count)	L/R balance, pressure zone, number of WARNINGS / ALERTS	Combined indicators from S1–S5 for two users (occupancy, imbalance, shocks, vibrations)

User-oriented experiments with different participants were then carried out on the instrumented sofa. Participants performed predefined sitting scenarios such as normal sitting, leaning on one side, sitting on the edge, two users, or repeated standing up and sitting down, followed by free usage sessions. For each session, the AI outputs were logged and compared with manual annotations and structural observations.

The results showed that the simple AI models were able to distinguish reliably between the main usage scenarios. Misclassifications occurred mainly in borderline conditions, for example when two users of very different weights were present. Sedentary alerts were triggered according to the configured time thresholds and were sensitive to micro-movements, which reduced false positives when users adjusted their posture.

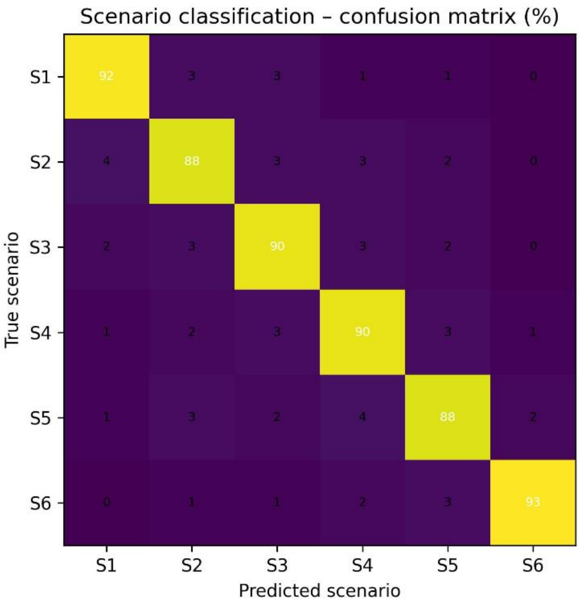

Figure 6 Accuracy or confusion matrix for scenario and posture classification

The RUL module behaved as expected in synthetic scenarios that represented moderate, intensive and abusive usage. The wear score decreased faster for sessions with repeated shocks, high loads and long sedentary periods, while remaining close to the nominal value for moderate, balanced usage. Although the absolute RUL numbers depend on model calibration and assumptions about the nominal lifetime, the relative behaviour across scenarios is consistent and can support maintenance decisions and user awareness.

7. Conclusions and Future Work

This paper has presented the integration of artificial intelligence into a multisensor smart sofa. Starting from the hardware platform and the data pipeline, the paper has focused on the AI modules for scenario recognition, sedentary behaviour, shock detection, wear scoring and RUL estimation. The results show that compact, explainable models can be embedded in a resource-constrained controller and still provide meaningful, real-time feedback to users and manufacturers, while also supporting a condition-based maintenance perspective on the furniture lifetime.

Compared with existing smart chairs and cushions, the smart sofa extends the scope from posture and comfort monitoring to structural health and lifetime indicators, and from laboratory-style pressure mapping to an integrated, product-like implementation [3]–[9]. At the same time, the link with RUL and condition-based maintenance methods suggests that similar AI techniques used for industrial assets can be adapted to domestic furniture [9]–[12].

Future work will focus on several directions. First, longer-term data collection with real users will allow better calibration and validation of the RUL and anomaly detection models. Second, incremental and personalised AI models could adapt to specific users and usage patterns while preserving privacy, for example by keeping all computations on the sofa and limiting data export. Third, more advanced fault diagnosis techniques for sensors and structure can be explored, inspired by recent work on fault-tolerant control and CBM [11], [12]. Finally, the smart sofa can be integrated into broader smart home environments, where its AI-derived indicators contribute to overall wellbeing and energy-aware operation [13].

References

[1] D. M. Brienza et al., "A randomized clinical trial on preventing pressure ulcers with wheelchair seat cushions," J. Rehabil. Res. Dev., vol. 47, no. 3, pp. 215–228, 2010.

[2] P. Ghosh et al., "Advances in technology-driven strategies for preventing pressure ulcers: Role of real-time pressure mapping," Clin. Biomech., vol. 105, pp. 106029, 2024.

[3] D. F. Odesola et al., “Smart Sensing Chairs for Sitting Posture Detection: A Review,” Sensors, 2024.

[4] Z. Vlaović et al., “Smart Office Chairs with Sensors for Detecting Sitting Positions and Sitting Habits,” Technical Gazette, 2022.

[5] M.-C. Tsai, E. T.-H. Chu, and C.-R. Lee, "An Automated Sitting Posture Recognition System Utilizing Pressure Sensors," Sensors, vol. 23, no. 13, Art. no. 5894, Jun. 2023, doi: 10.3390/s23135894.

[6] M. Ghasemi et al., “AI-powered Posture Training: Application of Machine Learning for Sitting Posture Coaching with LifeChair,” in Proc. IJCAI, 2019.

[7] N. R. Putra et al., “Detection of Sitting Posture for Employees Using Microcontroller and Pressure Sensors,” in Proc. Int. Conf. on Informatics and Creative Multimedia, 2025.

[8] H. Ertan, H. Alemdar, Ö. D. Incel, and C. Ersoy, “A smart couch design for improving the quality of life of the patients with cognitive diseases,” 2012. [Online]. Available: https://hdl.handle.net/11511/39159

[9] Z. Kang, C. Catal, B. Tekinerdogan, F. Li, and X. Xu, “Remaining Useful Life (RUL) Prediction of Equipment in Production Lines Using Artificial Neural Networks,” Sensors, vol. 21, no. 3, p. 932, 2021, doi: 10.3390/s21030932.

[10] H. N. Teixeira et al., “Condition-based maintenance implementation: a literature review,” Procedia Manufacturing, 2020.

[11] F. Zhao et al., “Deep Multimodal Data Fusion: A Survey,” ACM Comput. Surv., 2024.

[12] F. Ahmad et al., “A comprehensive review of fault diagnosis and fault-tolerant control systems,” Journal of the Franklin Institute, 2022.

[13] Relevant Software, “How to Build an IoT Dashboard: Benefits, Challenges, and Process,” Blog article, Aug. 2024; plus similar IoT dashboard and data-visualization resources, accessed Dec. 2025.

[14] E. Kuantama, R. C. Tarca, S. Dzitac, I. Dzitac, T. Vesselenyi, and I. Tarca, “The Design and Experimental Development of Air Scanning Using a Sniffer Quadcopter,” Sensors, vol. 19, no. 18, p. 3849, 2019.

[15] D. Noje, I. Dzitac, N. Pop, and R. C. Tarca, “IoT Devices Signals Processing Based on Shepard Local Approximation Operators Defined in Riesz MV-Algebras,” Informatica, vol. 31, no. 1, pp. 131–142, 2020, doi: 10.15388/20-INFOR395.

[16] D., Noje, R. Tarca, I. Dzitac and N. Pop, ”IoT Devices Signals Processing Based on Multi-Dimensional Shepard Local Approximation Operators in Riesz MV-Algebras”. International Journal of Computers Communications & Control, 14(1), pp. 56-62, 2019.

[17] D.C. Noje, O.G. Moldovan, O.C. Novac, M.C. Novac, and R.C. Ţarcă, ”Flexible system architecture used to collect and store signals acquired by IoT devices”. In 2024 16th International Conference on Electronics, Computers and Artificial Intelligence (ECAI) (pp. 1-5). IEEE, 2024.