

A Systematic Review and Conceptual Framework for Smart Chair Technologies in Sitting Posture Monitoring

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Abstract

Introduction: One of the reasons for musculoskeletal problems and deteriorating health is prolonged sitting in non-ergonomically structured positions. **Objective:** The current research aims to carefully examine the state-of-the-art of smart chair technologies for sitting posture monitoring and correction and to propose an integrated conceptual framework to guide future investigations.

Method: A systematic literature review guided by the PRISMA framework was conducted on studies addressing sensor modalities, posture detection algorithms and ergonomic effects, and 20 studies were included in the final synthesis. **Result and Discussion:** The major findings were mostly shown that two main technologies, pressure and vision-based systems were utilized principally for the deep learning algorithms-CNNs categorization of postures. Newer ways have been offered to make users more adaptable and comfortable such as the use of non-invasive devices and transfer learning. However, there are substantial issues with the poor sensor resolution, lack of long-term validation and restricted system customisation.

Conclusion: Thus, the multimodal framework calls for feedback systems that report to users, as well as adaptable basic sensors and sophisticated algorithms. This would enhance posture monitoring and encourage proper sitting habit in the long run.

Introduction

Prolonged sitting in non-ergonomic postures is a prevalent occupational health concern. Office workers spend approximately two-thirds of their working day seated (Alaca et al., 2025), and recent systematic evidence associates sedentary behaviour, including workplace sitting, with musculoskeletal pain conditions (Dzakpasu et al., 2021). Longer sitting time, poor sitting posture, fewer breaks and more static sitting behaviour have been associated with low back pain among office workers (Alaca et al., 2025), and prolonged static sitting is regarded as one of the main workplace risk factors for musculoskeletal disorders (Markova et al., 2024). Beyond musculoskeletal outcomes, uninterrupted sitting impairs postprandial metabolic regulation, whereas regular interruptions of sitting lower blood glucose and insulin responses (Dong et al., 2024). These adverse effects also translate into reduced productivity, increased absenteeism and higher health care costs (Pereira & Plácido da Silva, 2023).

Smart chairs address this problem by embedding sensing, computation and feedback into everyday seating (Odesola et al., 2024). Their operation can be described as a three-stage pipeline. In the sensing stage, force-sensitive resistors, pressure arrays, load cells or capacitive textile sensors integrated into the seat and backrest capture the body–chair interaction unobtrusively (Luna-Perejón et al., 2021; Martínez-Estrada et al., 2023; Pereira & Plácido da Silva, 2023). In the classification stage, machine learning and deep learning models transform these signals into posture categories (Aminosharieh Najafi et al., 2022; Tsai et al., 2023). In the feedback stage, the recognised posture and sitting duration are returned to the user through vibration, light, sound or a mobile application so that the user can correct the posture or take a break. For example, a modular smart chair combining a pressure sensor, vibration motors, an LED strip and Bluetooth Low Energy communication detected correct posture with 94.78% accuracy in a pilot study involving 83 students, and 97.59% of the users adjusted their posture after an alert (Rakauskas et al., 2025).

Despite this progress, integrating existing knowledge remains difficult because studies differ widely in sensor configurations, posture definitions and validation protocols, and no standard definition of sitting postures has yet been established (Kappattanavar et al., 2021). Previous reviews have concentrated mainly on the sensing and classification stages: Kappattanavar et al. (2021) synthesised sensor networks and algorithms for posture classification, and Odesola et al. (2024) evaluated detection and classification strategies and the effectiveness of sensor technologies in smart sensing chairs. Less attention has been given to how sensing, classification, feedback and long-term personalisation should be combined into a single system suitable for office use, and to the practical constraints of privacy and on-chair computation. The novelty of this review therefore lies in consolidating the evidence across the entire sensing–classification–feedback pipeline and translating it into an integrated conceptual framework for smart office chairs.

Accordingly, this study aims to (1) systematically review recent research on smart chair technologies for sitting posture monitoring, (2) critically compare the sensor modalities and posture recognition algorithms used in these systems, together with their ergonomic and health implications, (3) identify methodological limitations and research gaps, and (4) propose an integrated conceptual framework to guide future research and implementation.

Methods

Review design

This study was designed as a systematic literature review followed by conceptual framework development. The review process was reported following the PRISMA guideline (Page et al., 2021), and the synthesised evidence served as the basis for the conceptual framework presented in the Results and Discussion section.

Databases

Literature was retrieved from five electronic databases, namely Scopus (n = 48), Google Scholar (n = 36), IEEE Xplore (n = 24), ScienceDirect (n = 12) and SpringerLink (n = 8), yielding 128 records. An additional 12 records were identified from the reference lists of relevant articles (n = 9) and from manual searching (n = 3), giving a total of 140 records (Figure 1).

Search strategy

Keywords related to the technology, the application and the analytical approach were combined using Boolean operators as follows: ("smart chair" OR "sensing chair" OR "smart cushion") AND ("sitting posture" OR "seated posture") AND ("monitoring" OR "recognition" OR "classification") AND ("pressure sensor" OR "machine learning" OR "deep learning" OR "ergonomic*"). The terms were adapted to the syntax of each database and applied to titles, abstracts and keywords. The search covered publications from (2021) to (2025).

Eligibility criteria

Studies were included if they (a) were original research articles that developed or evaluated a chair- or seat-based system for monitoring, classifying or correcting sitting posture; (b) employed sensing technologies (pressure/force, load, capacitive, vision-based or hybrid) and/or computational algorithms for posture recognition; (c) reported the sensing configuration, algorithm and performance or ergonomic outcomes; and (d) were written in English or Indonesian. Studies were excluded if they were not related to smart chairs or posture monitoring, were not original research (review papers, editorials or proceedings abstracts), or focused on smart wheelchairs solely for mobility, navigation or health monitoring without a primary emphasis on sitting posture.

Screening process

After duplicates were removed, 98 records remained. Title and abstract screening excluded 60 records because they were not relevant to smart chairs or posture monitoring (n = 33), were not original research articles (n = 15), were review papers, editorials or proceedings abstracts (n = 8), or were not written in English or Indonesian (n = 4). The full texts of the remaining 38 articles were then assessed for eligibility, and 18 were excluded owing to unclear or incomplete methodology (n = 7), lack of focus on posture monitoring or ergonomic aspects (n = 6), insufficient data for analysis (n = 3) or no relation to smart chair technology (n = 2). Finally, 20 studies were included in the synthesis (Figure 1).

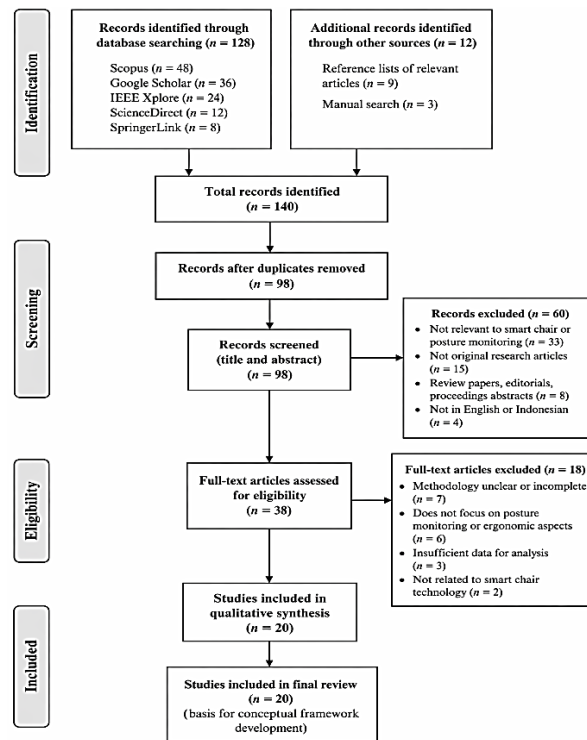


Figure 1. PRISMA Diagram of the Literature Selection Process

Data synthesis

For each included study, the sensor modality and placement, the posture recognition algorithm, the number of postures and participants, the reported performance, the feedback mechanism and the evaluation setting were extracted. Because sensor configurations, posture definitions and validation protocols were heterogeneous, a meta-analysis was not feasible; the findings were therefore synthesised narratively and thematically along the sensing, classification and feedback stages of the smart chair pipeline, and recurring limitations were mapped onto the components of the proposed framework. Clinical, ergonomic and review articles cited in this paper provide background and context only and were not counted among the 20 included studies.

Results and Discussion

This section synthesises the 20 included studies along the sensing, classification and feedback stages of the smart chair pipeline, followed by their ergonomic implications, methodological limitations and the proposed conceptual framework. The findings from this systematic review have revealed that the trend in the development of smart chair technology has changed considerably, where the usage of single-sensor technology has moved towards multi-sensor technology with integration of AI algorithms. Pressure sensors (FSR) are still the most dominant technology because of being non-invasive, cost-effective, and easy to integrate, but they have limited spatial resolution (Kappattanavar et al., 2021; Odesola et al., 2024). To address this problem, recent studies have started using the combination of pressure sensors with visual sensors (RGB-D), IMU and bio-signal sensors (Morales-Nolasco et al., 2024; Pereira & Plácido da Silva, 2023).

Sensor Technologies for Sitting Posture Monitoring

The sensor modalities include pressure sensor arrays, force sensitive resistors (FSRs), load cells, capacitive textile sensors and vision-based systems (Aminosharieh Najafi et al., 2022; Luna-Perejón et al., 2021; Martínez-Estrada et al., 2023). Pressure sensors provide relatively weak signals, but they are non-invasive, affordable and easy to embed in seat cushions; therefore, they remain the most widely used modality. Their layout and spatial resolution differ between systems and affect feature extraction and classification results (Morales-Nolasco et al., 2024; Wan et al., 2021). Vision-based systems using RGB-D cameras such as Kinect can capture three-dimensional body motion, but they require considerable computational power and a controlled environment (Kulikajevs et al., 2021). However, data privacy problems and opposition from users generally prevent the implementation of vision-based systems in actual workplaces, making such systems inappropriate for the office context. This has led researchers to develop invisible sensing solutions, such as load cells fixed under the seat or sensors embedded directly in seat cushions and armrests that maintain detecting capabilities while safeguarding worker privacy (Pereira & Plácido da Silva, 2023). Hybrid sensor systems further exploit the complementary nature of different data sources to enhance the reliability of posture evaluation (Morales-Nolasco et al., 2024; Pereira & Plácido da Silva, 2023). Table 1 compares the main sensor modalities used in current research.

Table 1
Comparison of the main sensor modalities used in smart chair research

Sensor Modalities	Advantages	Disadvantages / Challenges
Pressure Sensor / FSR	Non-intrusive, low cost, and easy to integrate into seat cushions.	Spatial resolution is often limited and requires high density for greater precision.
Visual-based systems (e.g., Kinect)	Highly detailed 3D motion capture.	Requires high computational resources and a controlled environment.
Hybrid Systems	Uses complementary data to improve reliability.	Complexity of integrating data from various sources.

Smart furniture has also been investigated for other applications, including wheelchairs that increase the safety and mobility of individuals with paralysis. One study developed an IoT-based wheelchair equipped with multiple sensors, autonomous navigation and user-friendly voice and touch interfaces, supported by real-time data processing and cloud connectivity (Gracewin et al., 2025). Recent smart wheelchair systems have integrated AI-assisted control with multimodal sensing for both mobility and health monitoring. These systems can monitor physiological parameters such as electrocardiogram (ECG), blood oxygen saturation (SpO₂), and heart rate, while incorporating intelligent navigation and autonomous mobility functions (Kumar et al., 2024; Hou et al., 2024). Pressure-based posture detection has likewise been applied to wheelchair seats to reduce the risk of pressure ulcers (Jaffery et al., 2022).

However, the most intricate designs of smart wheelchairs are multi-functional. Such sophistication is not required for office chairs, which focus mainly on sitting duration and body position. Consequently, the technological system of a smart office chair can be simpler, which reduces production costs without losing essential functions. The main difference lies in the kinematic needs of the user. Most of the research in the smart wheelchair domain deals with navigation, mobility control and health monitoring of people with serious physical limitations. Smart office chairs, on the other hand, are

intended to minimise static and dynamic ergonomic stresses. This approach is relevant for preventing chronic spinal problems and musculoskeletal disorders (MSDs) caused by prolonged sitting (Dzakpasu et al., 2021).

Posture Recognition Algorithms

Smart chairs use algorithms that can identify various positions. They use sensors and machine learning to identify and categorize sitting postures in real-time to aid in the prevention of musculoskeletal problems. Commonly utilized machine learning approaches in sitting posture identification systems include Convolutional Neural Network (CNN) and Artificial Neural Network (ANN). These methods improve the categorization performance of pressure sensor data (Kappattanavar et al., 2021; Odesola et al., 2024).

Currently, deep learning models are prevailing, especially CNNs, since these approaches automatically extract features and achieve high accuracy (Fan et al., 2022; Morales-Nolasco et al., 2024). Transfer learning is increasingly used to adjust a pre-trained model to new sensor combinations; for example, Morales-Nolasco et al. (2024) applied it to interpret pressure maps obtained from a different pressure mapping system. This strategy is beneficial to tackle the problems of small datasets and sensor differences. Classical classifiers, such as decision trees, k-nearest neighbours and support vector machines, are also widely used, and with informative features their performance can approach that of deep learning (Bourahmoune et al., 2022; Tsai et al., 2023; Wan et al., 2021). Moreover, different users, and even the same user across repetitions, may produce different pressure patterns for the same posture, which motivates user-specific model adaptation over long-term use (Aminosharieh Najafi et al., 2022).

Deep models provide precision, but at a heavy computational cost. For example, in a comparison of seven deep learning models on an eight-sensor chair, the best-performing echo memory network required 162,248 trainable parameters, whereas a multilayer perceptron with only 480 parameters achieved almost the same accuracy (90.83% vs. 91.68%) and was selected as the better trade-off (Aminosharieh Najafi et al., 2022). Large CNN architectures are therefore difficult to deploy on the memory- and power-constrained microcontrollers embedded in a chair. Lightweight alternatives, such as classical machine learning, compact neural networks designed for low-cost IoT devices and TinyML optimisation techniques, keep latency and energy consumption low without relying on cloud computation (Luna-Perejón et al., 2021; Tsai et al., 2023).

Following this approach, Rakauskas et al. (2025) developed a smart chair that tracks sitting duration and the quality of the user's posture in real time using pressure sensors and microcontroller logic. It can distinguish whether the user is sitting and whether the backrest is appropriately adjusted. These sensors function by sensing a change in resistance. The sensor is an open circuit with no pressure applied. When pressure is applied to particular spots the circuit is completed and resistance of the order of several hundred ohms is obtained. Tsai et al. (2023) identified key areas on the chair surface and applied several machine learning techniques to recognise ten common sitting postures, achieving an accuracy of up to 99.1%. Pereira and Plácido da Silva (2023) classified sitting positions from load cells fixed under the seat with accuracies above 97.4% for five classes, which may help improve working conditions and user health.

Ergonomics, Feedback and Health Outcomes

Non-ergonomic sitting postures create unequal loading of the body, which over time may contribute to musculoskeletal disorders (Dzakpasu et al., 2021; Markova et al., 2024). Prolonged uninterrupted sitting also impairs postprandial glucose and insulin responses, which are markers of cardiometabolic risk (Dong et al., 2024). In addition, sustained sitting keeps the back, neck and spine under continuous load, which may lead to muscle tension, joint discomfort and low back pain (Alaca et al., 2025).

Smart chair technology offers a way to recognise and monitor sitting posture continuously in order to reduce these risks. As an ergonomic device, a smart chair has two primary tasks: informing users when they adopt a poor posture and reminding them to change their posture or take a break. This helps to reduce health concerns connected to long stationary postures. Feedback modalities combining visual dashboards, vibration and real-time posture prompts aim to promote adherence; in a pilot study, 97.59% of users responded to alerts by adjusting their posture within an average of 3.27 s (Rakauskas et al., 2025). Usability surveys have also rated such systems as user-friendly and responsive (Tsai et al., 2023), suggesting that simple and non-intrusive feedback supports continued use. However, evidence on long-term efficacy and sustained behaviour change remains limited, as only a few studies have been conducted in free-living environments (Kappattanavar et al., 2021).

Workplace ergonomics applies these principles to achieve an optimal seating position and to limit the effect of sitting postures on users' health, particularly musculoskeletal disorders. Owing to the constant technological improvements, smart chairs have emerged as a new way to monitor and provide real-time feedback on sitting position. Therefore, intelligent chairs act both as ergonomic devices and as technological facilitators that strengthen the connection between sitting position and user health.

Trends and Methodological Limitations

Recent systems increasingly adopt modular designs. For instance, one smart chair combines a pressure sensor, vibration motors, an LED strip and Bluetooth Low Energy (BLE) communication to display sitting duration and posture maintenance in real time and to deliver feedback based on its embedded detection algorithm (Rakauskas et al., 2025). Other studies favour pressure sensor arrays combined with CNN algorithms, and transfer learning helps mitigate the problems caused by limited datasets (Morales-Nolasco et al., 2024). However, many present systems rely on low-resolution pressure sensors, which cannot adequately characterise the pressure distribution of the human body. Higher-density pressure mapping, which represents seat pressure as an image, can therefore improve the accuracy of posture detection (Fan et al., 2022; Wan et al., 2021).

A primary challenge for posture detection systems is the variation in the anthropometric features of users. Therefore, systems need further calibration or personalisation based on user data; for example, Bourahmoune et al. (2022) incorporated users' body mass index into posture labelling and achieved an accuracy of 98.82% across 15 sitting postures. Continuous monitoring of long-term sitting behaviour, rather than isolated posture snapshots, could also support behaviour change and better health, as sitting behaviour shows the strongest association with low back pain (Alaca et al., 2025).

However, practical implementation of machine learning is limited by sensor resolution, lack of standardized validation techniques, and absence of longitudinal investigations. Much of the research has also been undertaken in laboratory settings or

over very short time frames, limiting the ability to examine long-term impacts and the permanence of behaviour modification (Kappattanavar et al., 2021).

Feedback techniques that help induce behavioral change without disrupting the user's work are essential but under-researched (Odesola et al., 2024). The reviewed studies present strong software architectures but show weakness in sensor resolution, adaptability to the environment, and long-term evaluations.

Integrated Conceptual Framework

Thus, the key value of the current article is the development of an Integrated Conceptual Framework which shifts from simple monitoring to adaptive intervention (Figure 2). The novelty and value of this framework is its ability to be more comprehensive as it includes not just data acquisition but also personalization through continuous learning and feedback from users to achieve lasting behavioral changes. With the help of multimodal sensors and intelligent algorithms, the limitations identified above can be addressed.

The framework consists of six interconnected components. First, the input layer combines pressure-based sensors (2D/3D pressure matrices, FSRs and capacitive textile sensors) with optional vision-based and additional sensors, such as inertial measurement units and bio-signal sensors. Second, the processing layer performs data acquisition and preprocessing, feature extraction and posture classification using machine learning, deep learning, transfer learning or hybrid models. Third, the output layer translates the classified posture into ergonomic parameters, such as pressure distribution, load asymmetry, sitting duration and posture change frequency, and into risk indicators. Fourth, the intervention layer delivers audio, visual and haptic feedback, smart chair adjustments and personalised ergonomic guidance. Fifth, the outcome layer targets improved sitting posture, reduced musculoskeletal risk, comfort, productivity and long-term behavioural change. Sixth, the data and continuous learning layer stores data, supports analytics and updates the models for adaptive personalisation. To preserve privacy and reduce latency, non-vision sensing and on-chair (edge) processing are prioritised, vision-based sensors are treated as optional reference modalities, and cloud services are used mainly for aggregated data and model updates.

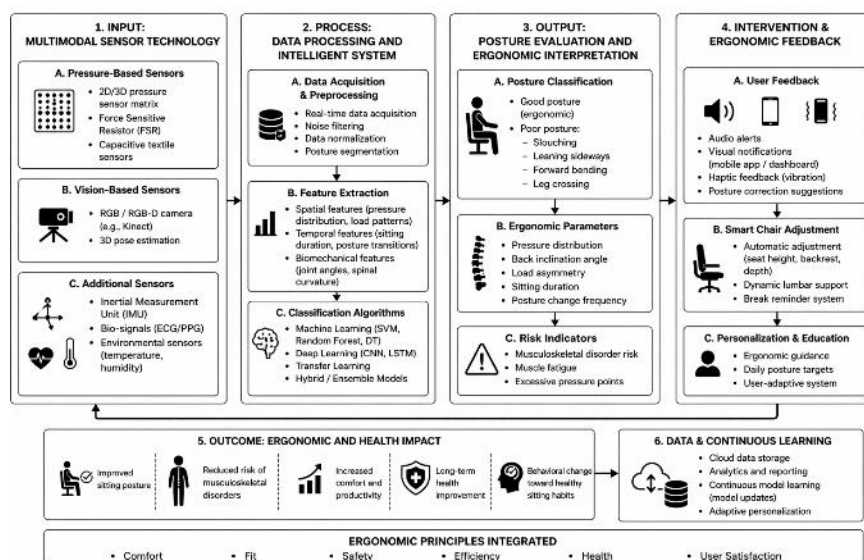


Figure 2. Conceptual Framework of the Smart Chair

Research Gaps and Future Directions

From the above synthesis, the development of smart chairs calls for a multi-pronged effort: (1) designing measurable, high-resolution but non-invasive sensors that can be configured for varied seating positions; (2) combining sensing techniques to collect holistic ergonomic information; (3) personalising the adaptive model through continuous learning that takes into account the unique biometrics and usage behaviour of each user; (4) conducting longitudinal studies in real working environments to determine the behavioural, ergonomic and health implications of smart chairs; (5) developing standardised posture definitions and validation protocols that allow comparison across studies (Kappattanavar et al., 2021); and (6) investigating multimodal feedback systems that combine audio, tactile and visual cues according to users' preferences and context. These directions correspond to the components of the conceptual framework shown in Figure 2.

Conclusion

This systematic review outlines the current state of smart chair research, in which pressure-based sensing combined with machine learning, particularly CNN-based deep learning, constitutes the most prominent approach, while vision-based systems serve mainly as complementary or reference modalities. At the same time, the review identified three crucial issues that remain insufficiently addressed in the literature: (1) privacy concerns that limit the acceptance of vision-based technology in office spaces, (2) the computational trade-offs of conventional CNNs that complicate edge computing on chair microcontrollers, and (3) the lack of distinction between the kinematics of mobility ergonomics (e.g., in wheelchairs) and dynamic load distribution in office chairs for MSD prevention.

To fill these gaps, this paper offers a multi-modal conceptual framework combining a non-invasive sensor matrix based on invisible sensing, algorithm optimisation for edge computing (e.g., TinyML) and an adaptive user feedback system. The paper contributes theoretically by shifting the posture monitoring paradigm from camera- and server-dependent systems towards a privacy-preserving, efficient and adaptive system in which cloud services are used mainly for aggregated data and model updates. Future research should validate the framework empirically over the long term, particularly in real working conditions, and automate the sensor calibration process to improve the accuracy of posture personalisation.

Declaration of AI Assistance

AI Tools including Chat GPT, Gemini, Claude AI were used during the preparation of this manuscript. The AI Tools were used for grammar checking, paraphrasing and translating. The Authors have checked the output of the tools.

References

- Alaca, N., Acar, A. Ö., & Öztürk, S. (2025). [Low back pain and sitting time, posture and behavior in office workers: A scoping review](#). *Journal of Back and Musculoskeletal Rehabilitation*, 38(5), 919–943. <https://doi.org/10.1177/10538127251320320>
- Aminosharieh Najafi, T., Abramo, A., Kyamakya, K., & Affanni, A. (2022). [Development of a smart chair sensors system and classification of sitting postures with deep learning algorithms](#). *Sensors*, 22(15), 5585. <https://doi.org/10.3390/s22155585>
- Bourahmoune, K., Ishac, K., & Amagasa, T. (2022). [Intelligent posture training: Machine-learning-powered human sitting posture recognition based on a pressure-sensing IoT cushion](#). *Sensors*, 22(14), 5337. <https://doi.org/10.3390/s22145337>
- Dong, Y., Pan, Y., Zhang, X., He, Q., Chen, S., Du, L., & Yin, S. (2024). [Impact of prolonged sitting interruption on blood glucose, insulin and triacylglycerol in adults: A systematic review and meta-analysis](#). *Applied Sciences*, 14(8), 3201. <https://doi.org/10.3390/app14083201>
- Dzakpasu, F. Q. S., Carver, A., Brakenridge, C. J., Cicuttini, F., Urquhart, D. M., Owen, N., & Dunstan, D. W. (2021). [Musculoskeletal pain and sedentary behaviour in occupational and non-occupational settings: A systematic review with meta-analysis](#). *International Journal of Behavioral Nutrition and Physical Activity*, 18, 159. <https://doi.org/10.1186/s12966-021-01191-y>
- Fan, Z., Hu, X., Chen, W.-M., Zhang, D.-W., & Ma, X. (2022). [A deep learning based 2-dimensional hip pressure signals analysis method for sitting posture recognition](#). *Biomedical Signal Processing and Control*, 73, 103432. <https://doi.org/10.1016/j.bspc.2021.103432>
- Gracewin, S. A., Chandru, A., Kirubakaran, D., & Gomathi, S. (2025). [Smart wheelchair for paralyzed patients using advanced IoT](#). In *Proceedings of the International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE)* (pp. 1–6). DOI: 10.1109/IITCEE64140.2025.10915296.
- Hou, L., Latif, J., Mehryar, P., Withers, S., Plastropoulos, A., Shen, L., & Ali, Z. (2024). [An autonomous wheelchair with health monitoring system based on Internet of Thing](#). *Scientific Reports*, 14, 5878. <https://doi.org/10.1038/s41598-024-56357-y>
- Jaffery, M. H., Ashraf, M. A., Almogren, A., Asim, H. M., Arshad, J., Khan, J., Rehman, A. U., & Hussien, S. (2022). [FSR-based smart system for detection of wheelchair sitting postures using machine learning algorithms and techniques](#). *Journal of Sensors*, 2022, 1901058. <https://doi.org/10.1155/2022/1901058>
- Kappattanavar, A. M., Steckhan, N., Sachs, J. P., Freitas da Cruz, H., Böttinger, E., & Arnrich, B. (2021). [Monitoring of sitting postures with sensor networks in controlled and free-living environments: Systematic review](#). *JMIR Biomedical Engineering*, 6(1), e21105. <https://doi.org/10.2196/21105>
- Kulikajevas, A., Maskeliunas, R., & Damaševičius, R. (2021). [Detection of sitting posture using hierarchical image composition and deep learning](#). *PeerJ Computer Science*, 7, e442. <https://doi.org/10.7717/peerj-cs.442>
- Kumar, A., Singh, M., Singh, M., Ramprabu, J., Dubey, A., & Mujoo, S. (2024). [A Novel Electronic Wheel Chair Design using Artificial Intelligence Assisted Smart Sensors and Controller](#). *2024 5th International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, 274–281. IEEE. DOI: 10.1109/ICICV62344.2024.00048.

- Luna-Perejón, F., Montes-Sánchez, J. M., Durán-López, L., Vazquez-Baeza, A., Beasley-Bohórquez, I., & Sevillano-Ramos, J. L. (2021). [IoT device for sitting posture classification using artificial neural networks](https://doi.org/10.3390/electronics10151825). *Electronics*, 10(15), 1825. <https://doi.org/10.3390/electronics10151825>
- Markova, V., Markov, M., Petrova, Z., & Filkova, S. (2024). [Assessing the impact of prolonged sitting and poor posture on lower back pain: A photogrammetric and machine learning approach](https://doi.org/10.3390/computers13090231). *Computers*, 13(9), 231. <https://doi.org/10.3390/computers13090231>
- Martínez-Estrada, M., Vuohijoki, T., Poberznik, A., Shaikh, A., Virkki, J., Gil, I., & Fernández-García, R. (2023). [A smart chair to monitor sitting posture by capacitive textile sensors](https://doi.org/10.3390/ma16134838). *Materials*, 16(13), 4838. <https://doi.org/10.3390/ma16134838>
- Morales-Nolasco, I., Arias-Guzman, S., & Garay-Jiménez, L. (2024). [A method for complex posture recognition during long-term sitting using neural networks and pressure mapping systems](https://doi.org/10.1016/j.bspc.2024.106306). *Biomedical Signal Processing and Control*, 95, 106306. <https://doi.org/10.1016/j.bspc.2024.106306>
- Odesola, D. F., Kulon, J., Verghese, S., Partlow, A., & Gibson, C. (2024). [Smart sensing chairs for sitting posture detection, classification, and monitoring: A comprehensive review](https://doi.org/10.3390/s24092940). *Sensors*, 24(9), 2940. <https://doi.org/10.3390/s24092940>
- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ... Moher, D. (2021). [The PRISMA 2020 statement: An updated guideline for reporting systematic reviews](https://doi.org/10.1136/bmj.n71). *BMJ*, 372, n71. <https://doi.org/10.1136/bmj.n71>
- Pereira, L., & Plácido da Silva, H. (2023). [A novel smart chair system for posture classification and invisible ECG monitoring](https://doi.org/10.3390/s23020719). *Sensors*, 23(2), 719. <https://doi.org/10.3390/s23020719>
- Rakauskas, Z., Macaitis, V., Vasjanov, A., & Barzdenas, V. (2025). [Ergonomic innovation: A modular smart chair for enhanced workplace health and wellness](https://doi.org/10.3390/s25134024). *Sensors*, 25(13), 4024. <https://doi.org/10.3390/s25134024>
- Tsai, M.-C., Chu, E. T.-H., & Lee, C.-R. (2023). [An automated sitting posture recognition system utilizing pressure sensors](https://doi.org/10.3390/s23135894). *Sensors*, 23(13), 5894. <https://doi.org/10.3390/s23135894>
- Wan, Q., Zhao, H., Li, J., & Xu, P. (2021). [Hip positioning and sitting posture recognition based on human sitting pressure image](https://doi.org/10.3390/s21020426). *Sensors*, 21(2), 426. <https://doi.org/10.3390/s21020426>