Artificial intelligence model for continuous, in-home, posture and health monitoring including user feedback and predictions of clinical assessment.

David Faith Odesola

Table of Contents

[List of Figures 2](#_Toc152710007)

[Introduction 2](#_Toc152710008)

[Search Strategy 3](#_Toc152710009)

[Sitting Posture Monitoring Systems 4](#_Toc152710010)

[History of Smart Sensing chairs 4](#_Toc152710011)

[Sensor systems 5](#_Toc152710012)

[Sensing Chair using Pressure Sensors 5](#_Toc152710013)

[Sensing Chair using Flex Sensors 7](#_Toc152710014)

[Sensing Chair using Mixed Sensors 8](#_Toc152710015)

[Sitting Posture Classification 8](#_Toc152710016)

[(Internet of Things) IoT Integration and Connectivity 8](#_Toc152710017)

[Challenges and Limitations 8](#_Toc152710018)

[Different Sitting postures 8](#_Toc152710019)

[Smart Wheelchair Systems 8](#_Toc152710020)

[User Feedback System 8](#_Toc152710021)

[Quality of Testing Data 8](#_Toc152710022)

[Research Gaps 8](#_Toc152710023)

[Future Directives and Trends 8](#_Toc152710024)

[The use and impact of Mobile apps in the healthcare sector 8](#_Toc152710025)

[Commercialization 9](#_Toc152710026)

[Conclusion 9](#_Toc152710027)

[References 9](#_Toc152710028)

[Appendixes 12](#_Toc152710029)

# List of Figures

[Figure 1 - A Map of Similar Studies on Smart Sensing Chairs 4](#_Toc152122250)

[Figure 2 - Force Sensing Resistor 5](#_Toc152122251)

## Introduction

According to (Gill et al., 2023) in 2020 alone, musculoskeletal disorders (MSDs) had been ranked 2nd as the leading non-fatal disability which has been affecting more than a billion people worldwide. In Finland, MSD had taken the spotlight as being the leading cause of temporal disability within the nation, through which a lot of resources allocated towards the health services (Martimo, 2010). It might be misconceived that only the elderly are the only ones that suffer from this condition. However, a report by (European Agency for Safety and Health at Work., 2021) has concluded that quite a number of individuals across different age groups are currently suffering from it. It was reported that MSDs can often originate during the childhood stage mainly due to adoption of abnormal postures and low physical activities, which subsequently lead to long-term chronic pain, discomfort, and physical limitations. Traditional examination and treatment procedures most often consist of regular clinical visits and are currently viewed as being inconvenient and costly. According to (Bevan, 2015), MSDs have said to have cost the European Union (EU) over 2% of its gross domestic product (GDP), which is estimated to be over €240bn each year. There is no doubt that this is a steadily growing concern that needs to be properly addressed.

Nowadays, most of the in-office work requires workers to be in a seated position for an extended period, which is said to have adverse effects to one’s health. According to (Arora and Khatri, 2022) and (Putsa et al., 2022), prolong sitting is one of the leading causes of MSDs among office workers. It is therefore recommended that the users should go for small walk breaks after every few hours. The integration of smart sensing chairs that would be actively monitored and provide feedback on one’s health and activity levels would be deemed quite useful.

Furthermore, with the rapid advancement in data sensor technology and Artificial Intelligence in this present age, there should be new and commercialized solutions out there in the market for continuous posture and health monitoring. There is no doubt that these types of systems have the potential of contributing towards the idea of personalized healthcare and improving the quality of life, especially for individuals that are suffering from MSDs.

With that in mind, various research studies have investigated the development of posture monitoring systems which are aimed at detecting bad sitting postures to help the end user in maintaining the right sitting posture at every given time. These types of systems are named as “smart sensing chairs” which goes all the way back to a research study done by (Tan et al., 2001), which fitted a chair with a pressure distribution sensor in order to classify a user’s sitting postures which was just first of many. Furthermore, with a lot of research papers being published in this field, this literature review aims to evaluate related studies and identify research gaps that can pave the way for further investigation into this study. By exploring existing studies, it is possible to gain a better understanding of the current state on the implementation of a smart sensing chair for posture classification and health monitoring.

## Search Strategy

This literature review paper is aimed at conducting a systematic review of similar studies done on smart sensing chair technology. Articles that were examined came from various online publication sources such as Semantic Scholar, Google Scholar, IEEE Explore to name some of them. To aid in the search for the relevant articles though different database systems, a list of important keywords was clearly defined to ensure that the most relevant papers came in the search results. Additionally, some of these keywords were combined to achieve better search results. Below are some of the search terms that was used.

1. Smart Sensing Chair
2. Sitting Posture Recognition
3. Posture Classification
4. Sitting Posture Classification using AI/Machine Learning
5. Sitting Posture Monitoring

## Sitting Posture Monitoring Systems

As previously stated, the development of a sitting posture monitoring system is not an entirely new concept, rather it is an area that has been explored by multiple researchers in the past until this present day. This section would be going over different research projects that developed their variation of smart sensing chairs. To efficiently conduct this literature review, at least 30+ relevant research literatures were carefully selected and examined as seen in Table 1. have been published focusing on the of the use of unobtrusive means for the classification of different sitting positions. Systematically examining these papers would surely some shed light on the most common machine learning algorithms and sensors being used to be able to classify various sitting postures.

### History of Smart Sensing chairs

As previously stated, (Tan et al., 2001) was the first research seen to pioneer the idea of a smart sensing chair that is capable of detecting one’s posture by using pressure distribution sensors integrated into the chair. Over the past few years, various research studies have implemented different variations of these smart sensing chair concepts ranging from different sensors to various classification methods to posture detection as shown in Figure 1. Furthermore, a literature connection map (on similar studies) done on smart sensing chairs was constructed as shown in Figure 2 below. This figure gives a rough visualization of the amount of research being done in landscape of smart sensing chair technology.



Figure – Timeline Map of Similar Literatures

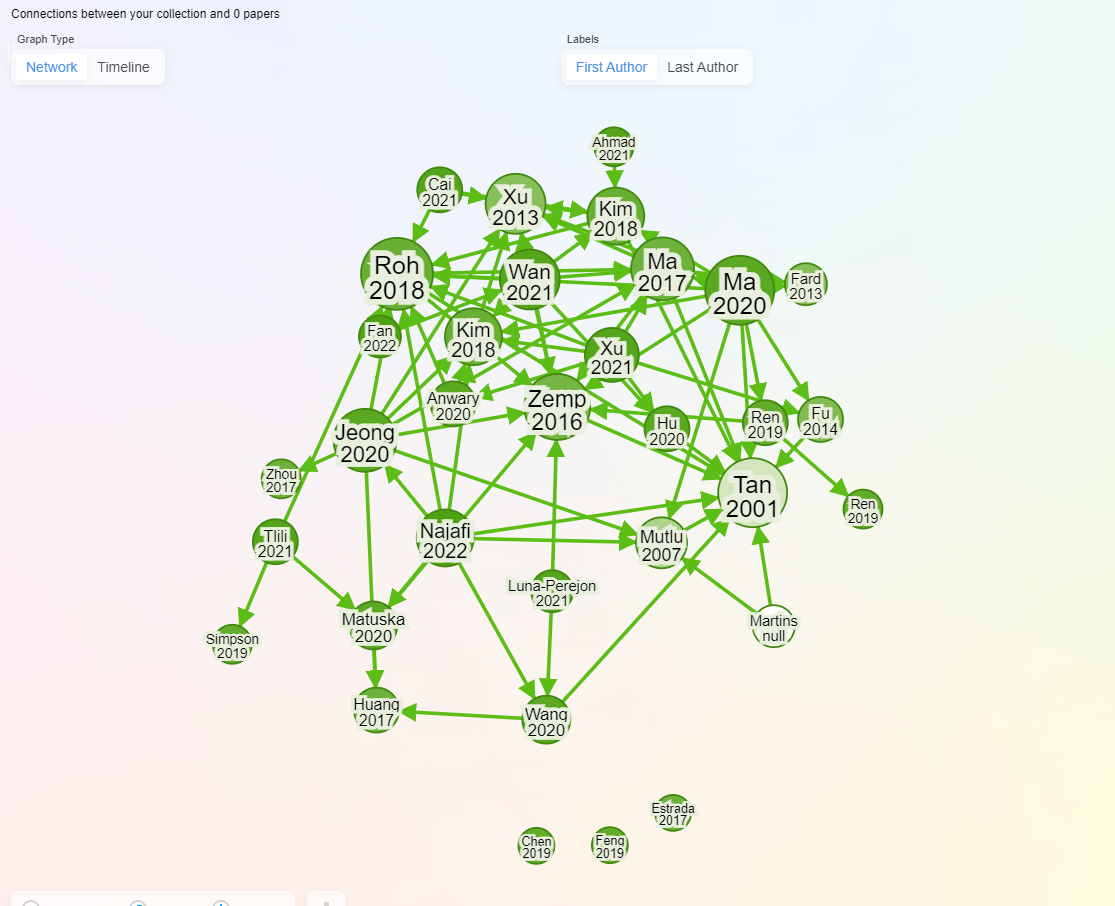


Figure - A Map of Similar Studies on Smart Sensing Chairs

## Sensor systems

As anticipated, various scholarly papers use different types of sensor devices to detect different sitting postures. In summary, they can be divided into 4 overarching categories:

* Smart Sensing Chairs using Pressure Sensors
* Smart Sensing Chairs using Flex Sensors
* Smart Sensor Chairs using Mixed Sensor Systems
* Smart Sensing Chairs using Computer Vision Systems

### Sensing Chair using Pressure Sensors

##### Force Sensing/Sensitive Sensor (FSR)

Force Sensing Resistors are also known as force sensors which are commonly used to measure the forces applied to its surface area. These sensors work by varying their output resistance based on the pressure being applied to it. Typically, the overall resistance decreases as more pressure is applied (Sadun et al., 2016). To be able to get the reading from this sensor, it normally connected directly to a microcontroller such as an Arduino or like get its reading. Figure 1 shows an example of how a FSR sensor commonly looks like.



Figure - A Force Sensing Resistor

Focusing on studies that integrated FSRs in to their studies, (Mutlu et al., 2007) integrated 19 different FSRs into the seating cushion and used the SimpleLogistic ML algorithm to achieve 78% accuracy in classifying 10 different postures. (Tsai et al., 2023) used 13 pressure sensors classify 10 sitting postures and was able to achieve an accuracy of 99.10% using the SVM ML algorithm. (Aminosharieh Najafi et al., 2022) applied 8 sensors (4 on the seating cushion and 4 on the back rest) and used EMN algorithm to classify 8 sitting posture and achieved an accuracy of 91.68%. In addition to this, there was a Desktop Graphical User Interface (GUI) application which displayed the senor reading in real-time. (Luna-Perejón et al., 2021) add 6 sensors placed on the seating cushion and resulted in a 81.5% classification accuracy using SOM (ISOM-SPR) ML algorithm.

##### Load Cells

Load cells are another variation of force sensor which is commonly used to measure monitor sitting postures. Under the hood, it works by converting the mechanical force being applied to it into digital signals which can be read by microcontrollers. (Roh et al., 2018) developed a smart chair by integrating 4 load cell sensors within the chair sitting cushion to classify 6 sitting postures. An accuracy of 97.94% was achieved using a SVM (RBF kernel) ML model. Similarly, (Pereira and Plácido Da Silva, 2023) distributed 3 load cells across the seat’s cushion in order to classify 8 sitting postures; overall they were able to a classification accuracy of 98.50%.

##### Textile Pressure Sensor

A textile-based pressure sensor is normally composed of a soft fabric material. This sensor consists of a conductive thread pattern placed over a dielectric material that serves as a substrate between the threads. Figure 4 shows an example of how each layer within the textile pressure sensor is structured.



Figure - Textile Pressure Sensor composition (Pizarro et al., 2018)

A few research studies were found to have used textile sensors to classify sitting postures. One of which was (Kim et al., 2018b) who developed a washable textile pressure sensor and incorporated it into their chair system to classify 7 sitting posture using a decision algorithm. (Xu et al., 2013) proposed a “eCushion” device which is made up of a textile pressure array sensor that is capable of detect 7 different sitting postures at 85.9% accuracy. (Martínez-Estrada et al., 2023) also developed something similar by using 10 presence textile capacitive sensor (embroidered) sensors.

### Sensing Chair using Flex Sensors

Flex sensors are another variation of sensors that is being used by various studies to classify different sitting postures. A flex sensor, also known as a bend sensor works by measuring the degree of displacement resulting from the bending action being applied to the sensor (Sreejan and Narayan, 2017).

It was seen that the primary use of flex sensors in the classification of sitting postures is not a widely popular approach among various studies. Overall, there were only 2 studies identified that utilized this method for sitting posture detection. The first was by (Hu et al., 2020, p.202) who developed a smart sensing chair using 6 flex sensors and a 2-layer Artificial neural network (ANN) for detecting 7 sitting postures and achieved an accuracy of 97.43%. The second was by (AbuTerkia et al., 2022) which also developed a similar system without the use of an ML model which aimed at detecting 7 different sitting postures.



Figure - Flex Sensor

### Sensing Chair using Mixed Sensors

While most studies utilize a singular type of sensor for posture detection, there are a selected few study that involved more than one type of sensor into their proposed smart chair system. With this method, the different sensors would theoretically work hand in hand to achieve the best classification outcome.

(Jeong and Park, 2021) utilized 6 pressure sensors (placed on the seating cushion) along with 6 Infrared Reflective Distance Sensors (placed on the back rest). Using the K-Nearest Network (KNN), they were able to classify 11 different sitting postures while achieving an accuracy of 92%. This study also highlighted one of the main limitations seen with other smart sensing systems that simply relied on pressure sensors is that the angle of trunk rotation can’t be detected. (Ma et al., 2020) developed a smart seating cushion which employed the use 6 FSR sensors for detecting different sitting postures and an Inertial measurement unit (IMU) sensor to monitor user activity.

### Sitting Posture Classification

Taking an in-depth look at Table 1 it was seen that across all the gathered research papers, there are varying postures being classified. The minimum was by (Feng et al., 2019) who used RFID tag to classify 3 sitting postures (a. Sitting straight, b. Leaning Forward, c. Leaning Backward). On the other hand, (Wang et al., 2021) looked at detecting up to 15 different postures which was the highest among other studies. Upon further analysis, it was quick evident to see that the more most sitting postures that is being classified; the less accuracy it’s performance it would be. Hence, that is one of the main reasons why most studies limit the number of postures to 5-7.

### (Internet of Things) IoT Integration and Connectivity

(Ma et al., 2020) emphasized on the use of IoT-Based technology in it being capable of seamless monitoring seating activities.

### Challenges and Limitations

### Different Sitting postures

### Smart Wheelchair Systems

### User Feedback System

### Quality of Testing Data

### Research Gaps

* Most research stops at the posture classification phase.
* Not much effort is focused on the user feedback aspects.

### Future Directives and Trends

### The use and impact of Mobile apps in the healthcare sector

The use of mobile phones in the healthcare sector has rapidly been gaining in popularity in recent times. Mobile Health (MHealth) apps are mobile applications that are mostly tailored towards assisting both medical professionals and patients in the aspects of health management. According to (Lohnar, 2016), the number of mHealth apps are expected to be on an upward trend.

According to various studies, there are a series of hurdles and issues that must be put into consideration during the implementation of mHealth app.

### Commercialization

## Conclusion

## References

AbuTerkia, I., Hannoun, M., Suwal, B., Ahmed, M.S. and Sundaravdivel, P. (2022) ‘FPGA-based smart chair recognition system using flex sensors’. in *2022 IEEE 15th Dallas Circuit And System Conference (DCAS)*. Dallas, TX, USA: IEEE, pp. 1–2. Available at: https://ieeexplore.ieee.org/document/9845620/ (Accessed: 4 December 2023).

Ahmad, J., Sidén, J. and Andersson, H. (2021) ‘A Proposal of Implementation of Sitting Posture Monitoring System for Wheelchair Utilizing Machine Learning Methods’. *Sensors* 21(19), p. 6349. doi: 10.3390/s21196349.

Aminosharieh Najafi, T., Abramo, A., Kyamakya, K. and Affanni, A. (2022) ‘Development of a Smart Chair Sensors System and Classification of Sitting Postures with Deep Learning Algorithms’. *Sensors* 22(15), p. 5585. doi: 10.3390/s22155585.

Arora, S.N. and Khatri, S. (2022) ‘Prevalence of work-related musculoskeletal disorder in sitting professionals’. *International Journal Of Community Medicine And Public Health* 9(2), p. 892. doi: 10.18203/2394-6040.ijcmph20220259.

Bevan, S. (2015) ‘Economic impact of musculoskeletal disorders (MSDs) on work in Europe’. *Best Practice & Research Clinical Rheumatology* 29(3), pp. 356–373. doi: 10.1016/j.berh.2015.08.002.

Cai, W., Zhao, D., Zhang, M., Xu, Y. and Li, Z. (2021) ‘Improved Self-Organizing Map-Based Unsupervised Learning Algorithm for Sitting Posture Recognition System’. *Sensors* 21(18), p. 6246. doi: 10.3390/s21186246.

Chen, K. (2019) ‘Sitting Posture Recognition Based on OpenPose’. *IOP Conference Series: Materials Science and Engineering* 677(3), p. 032057. doi: 10.1088/1757-899X/677/3/032057.

European Agency for Safety and Health at Work. (2021) *Musculoskeletal disorders among children and young people: prevalence, risk factors and preventive measures : a scoping review.* LU: Publications Office. Available at: https://data.europa.eu/doi/10.2802/511243 (Accessed: 21 November 2023).

Fan, Z., Hu, X., Chen, W.-M., Zhang, D.-W. and Ma, X. (2022) ‘A deep learning based 2-dimensional hip pressure signals analysis method for sitting posture recognition’. *Biomedical Signal Processing and Control* 73, p. 103432. doi: 10.1016/j.bspc.2021.103432.

Fard, F.D., Moghimi, S. and Lotfi, R. (2013) ‘Evaluating Pressure Ulcer Development in Wheelchair-Bound Population Using Sitting Posture Identification’. *Engineering* 05(10), pp. 132–136. doi: 10.4236/eng.2013.510B027.

Feng, L., Li, Z. and Liu, C. (2019) ‘Are you sitting right?-Sitting Posture Recognition Using RF Signals’. in *2019 IEEE Pacific Rim Conference on Communications, Computers and Signal Processing (PACRIM)*. Victoria, BC, Canada: IEEE, pp. 1–6. Available at: https://ieeexplore.ieee.org/document/8985070/ (Accessed: 25 October 2023).

Fu, T. and Macleod, A. (2014) ‘IntelliChair: An Approach for Activity Detection and Prediction via Posture Analysis’. in *2014 International Conference on Intelligent Environments*. China: IEEE, pp. 211–213. Available at: http://ieeexplore.ieee.org/document/6910450/ (Accessed: 20 November 2023).

Gill, T.K. et al. (2023) ‘Global, regional, and national burden of other musculoskeletal disorders, 1990–2020, and projections to 2050: a systematic analysis of the Global Burden of Disease Study 2021’. *The Lancet Rheumatology* 5(11), pp. e670–e682. doi: 10.1016/S2665-9913(23)00232-1.

Hu, Q., Tang, X. and Tang, W. (2020) ‘A Smart Chair Sitting Posture Recognition System Using Flex Sensors and FPGA Implemented Artificial Neural Network’. *IEEE Sensors Journal* 20(14), pp. 8007–8016. doi: 10.1109/JSEN.2020.2980207.

Huang, M., Gibson, I. and Yang, R. (2017) ‘Smart Chair for Monitoring of Sitting Behavior’. *KnE Engineering* 2(2), p. 274. doi: 10.18502/keg.v2i2.626.

Jeong, H. and Park, W. (2021) ‘Developing and Evaluating a Mixed Sensor Smart Chair System for Real-Time Posture Classification: Combining Pressure and Distance Sensors’. *IEEE Journal of Biomedical and Health Informatics* 25(5), pp. 1805–1813. doi: 10.1109/JBHI.2020.3030096.

Kim, J.S. et al. (2018a) ‘Predicting Surgical Complications in Patients Undergoing Elective Adult Spinal Deformity Procedures Using Machine Learning’., pp. 762–770. doi: 10.1016/j.jspd.2018.03.003.

Kim, M., Kim, H., Park, J., Jee, K.-K., Lim, J.A. and Park, M.-C. (2018b) ‘Real-time sitting posture correction system based on highly durable and washable electronic textile pressure sensors’. *Sensors and Actuators A: Physical* 269, pp. 394–400. doi: 10.1016/j.sna.2017.11.054.

Kundaliya, B., Patel, S., Patel, J., Barot, P. and Hadia, S.K. (2022) *An IoT and Cloud Enabled Smart Chair for Detection and Notification of Wrong Seating Posture*. In Review. Available at: https://www.researchsquare.com/article/rs-1999906/v1 (Accessed: 4 November 2023).

Luna-Perejón, F., Montes-Sánchez, J.M., Durán-López, L., Vazquez-Baeza, A., Beasley-Bohórquez, I. and Sevillano-Ramos, J.L. (2021) ‘IoT Device for Sitting Posture Classification Using Artificial Neural Networks’. *Electronics* 10(15), p. 1825. doi: 10.3390/electronics10151825.

Ma, C., Li, W., Gravina, R., Du, J., Li, Q. and Fortino, G. (2020) ‘Smart Cushion-Based Activity Recognition: Prompting Users to Maintain a Healthy Seated Posture’. *IEEE Systems, Man, and Cybernetics Magazine* 6(4), pp. 6–14. doi: 10.1109/MSMC.2019.2962226.

Ma, C., Li, W., Gravina, R. and Fortino, G. (2017) ‘Posture Detection Based on Smart Cushion for Wheelchair Users’. *Sensors* 17(4), p. 719. doi: 10.3390/s17040719.

Martimo, K.-P. (2010) *Musculoskeletal disorders, disability, and work*. Helsinki, Finland: Finnish Institute of Occupational Health.

Martínez-Estrada, M., Vuohijoki, T., Poberznik, A., Shaikh, A., Virkki, J., Gil, I. and Fernández-García, R. (2023) ‘A Smart Chair to Monitor Sitting Posture by Capacitive Textile Sensors’. *Materials* 16(13), p. 4838. doi: 10.3390/ma16134838.

Matuska, S., Paralic, M. and Hudec, R. (2020) ‘A Smart System for Sitting Posture Detection Based on Force Sensors and Mobile Application’. Krejcar, O. (ed.). *Mobile Information Systems* 2020, pp. 1–13. doi: 10.1155/2020/6625797.

Mutlu, B., Krause, A., Forlizzi, J., Guestrin, C. and Hodgins, J. (2007) ‘Robust, low-cost, non-intrusive sensing and recognition of seated postures’. in *Proceedings of the 20th annual ACM symposium on User interface software and technology*. Newport Rhode Island USA: ACM, pp. 149–158. Available at: https://dl.acm.org/doi/10.1145/1294211.1294237 (Accessed: 29 October 2023).

Pereira, L. and Plácido Da Silva, H. (2023) ‘A Novel Smart Chair System for Posture Classification and Invisible ECG Monitoring’. *Sensors* 23(2), p. 719. doi: 10.3390/s23020719.

Pizarro, F., Villavicencio, P., Yunge, D., Rodríguez, M., Hermosilla, G. and Leiva, A. (2018) ‘Easy-to-Build Textile Pressure Sensor’. *Sensors* 18(4), p. 1190. doi: 10.3390/s18041190.

Putsa, B., Jalayondeja, W., Mekhora, K., Bhuanantanondh, P. and Jalayondeja, C. (2022) ‘Factors associated with reduced risk of musculoskeletal disorders among office workers: a cross-sectional study 2017 to 2020’. *BMC Public Health* 22(1), p. 1503. doi: 10.1186/s12889-022-13940-0.

R, N., Sudhakar, T., Bethanney Janney, J., Krishnamoorthy, N.R., Dhanalakshmi, K. and Vigneshwaran, S. (2023) ‘Sitting posture Analysis using CNN and RCNN’. in *2023 International Conference on Bio Signals, Images, and Instrumentation (ICBSII)*. Chennai, India: IEEE, pp. 1–5. Available at: https://ieeexplore.ieee.org/document/10181038/ (Accessed: 20 November 2023).

Ran, X., Wang, C., Xiao, Y., Gao, X., Zhu, Z. and Chen, B. (2021) ‘A portable sitting posture monitoring system based on a pressure sensor array and machine learning’. *Sensors and Actuators A: Physical* 331, p. 112900. doi: 10.1016/j.sna.2021.112900.

Ren, X., Yu, B., Lu, Y., Chen, Y. and Pu, P. (2019) ‘HealthSit: Designing Posture-Based Interaction to Promote Exercise during Fitness Breaks’. *International Journal of Human–Computer Interaction* 35(10), pp. 870–885. doi: 10.1080/10447318.2018.1506641.

Roh, J., Park, H., Lee, K., Hyeong, J., Kim, S. and Lee, B. (2018) ‘Sitting Posture Monitoring System Based on a Low-Cost Load Cell Using Machine Learning’. *Sensors* 18(2), p. 208. doi: 10.3390/s18010208.

Sadun, A.S., Jalani, J. and Sukor, J.A. (2016) ‘Force Sensing Resistor (FSR): a brief overview and the low-cost sensor for active compliance control’. in Jiang, X., Chen, G., Capi, G., and Ishll, C. (eds.) Tokyo, Japan, p. 1001112. Available at: http://proceedings.spiedigitallibrary.org/proceeding.aspx?doi=10.1117/12.2242950 (Accessed: 23 November 2023).

Sreejan, A. and Narayan, Y.S. (2017) ‘A Review on Applications of Flex Sensors’. *International Journal of Emerging Technology and Advanced Engineering* 7(7), pp. 97–100.

Tan, H.Z., Slivovsky, L.A. and Pentland, A. (2001) ‘A sensing chair using pressure distribution sensors’. *IEEE/ASME Transactions on Mechatronics* 6(3), pp. 261–268. doi: 10.1109/3516.951364.

Tsai, M.-C., Chu, E.T.-H. and Lee, C.-R. (2023) ‘An Automated Sitting Posture Recognition System Utilizing Pressure Sensors’. *Sensors* 23(13), p. 5894. doi: 10.3390/s23135894.

Wang, J., Hafidh, B., Dong, H. and El Saddik, A. (2021) ‘Sitting Posture Recognition Using a Spiking Neural Network’. *IEEE Sensors Journal* 21(2), pp. 1779–1786. doi: 10.1109/JSEN.2020.3016611.

Xu, W., Huang, M.-C., Amini, N., He, L. and Sarrafzadeh, M. (2013) ‘eCushion: A Textile Pressure Sensor Array Design and Calibration for Sitting Posture Analysis’. *IEEE Sensors Journal* 13(10), pp. 3926–3934. doi: 10.1109/JSEN.2013.2259589.

Zemp, R., Tanadini, M., Plüss, S., Schnüriger, K., Singh, N.B., Taylor, W.R. and Lorenzetti, S. (2016) ‘Application of Machine Learning Approaches for Classifying Sitting Posture Based on Force and Acceleration Sensors’. *BioMed Research International* 2016, pp. 1–9. doi: 10.1155/2016/5978489.

## Appendixes

Tables 1 – Sitting Posture Monitoring Research Papers

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Reference** | **Sensors** | **Number of Postures** | **Classification Method** | **Classification Accuracy** | **Test Subjects** | **Limitations** | **User Feedback System** | **Is Realtime** |
| (Pereira and Plácido Da Silva, 2023) | Load Cell - Posture Conductive Nappa - ECG | 5 | K-NN | 98.50% | 10 | Not used in a real-life setting | |  |
| (Ahmad et al., 2021) | Screen Printed Pressure units (16 Array) | 4 | LightGBM | 99.03% | 32 | Not used in a real life setting | |  |
| (Huang et al., 2017) | 52 by 44 Piezo-Resistive Sensor Array | 8 | ANN | 92.20% |  | No accuracy |  |  |
| (Martínez-Estrada et al., 2023) | 10 Presence textile capacitive sensor (embroidered) | 8 |  |  | 5 |  |  |  |
| (Matuska et al., 2020) | 6 Flexible Force Sensors | 9 | Average Standard deviation with 3 Threshold values to determine good/bad postures (Non AI) |  | 12 |  |  |  |
| (Aminosharieh Najafi et al., 2022) | 8 Force Sensing Resistors | 8 | EMNM | 92.68% | 40 |  |  |  |
| (Kundaliya et al., 2022) | A502 Force Sensor & Flex Sensor | 5 |  |  |  | No accuracy |  |  |
| (Ran et al., 2021) | Pressure Array (IMMM00014, I-MOTION | 7 | 5 Layer Artificial Intelligence | 97.07% | 100 |  |  |  |
| (Roh et al., 2018) | 4 Load Cells | 6 | SVM using RBF kernel | 97.94% | 24 | No accuracy |  |  |
| (Kim et al., 2018a) | Textile Pressure Sensors (Conductive Ni-Ti alloy fiber) | 7 |  |  |  | No accuracy |  |  |
| (Feng et al., 2019) | RFID tags | 3 | RF | 99.27% | 14 | Small number of postures | |  |
| (Hu et al., 2020) | 6 Flexible Force Sensors | 7 | 2 Layer ANN | 97.43% | 11 |  |  |  |
| (Jeong and Park, 2021) | 6 Pressure Sensors & 6 Infrared Reflective Distance Sensors | 11 | K-NN | 92% | 36 |  |  |  |
| Martins et al. 2013 | 8 | ANN | 93.40% | 30 |  |  |  | |
| (Mutlu et al., 2007) | 10 | SimpleLogistic | 87% | 46 |  |  |  | |
| (Ma et al., 2017) | 5 | Decision Tree (J48) | 99.47% | 12 |  |  |  | |
| (Zemp et al., 2016) | 16 Force Sensor | 7 | Random Forest | 81% - 98% | 41 |  |  |  |
| (Tsai et al., 2023) | 13 pressure sensors (FSR-406) | 10 | SVM (Linear) | 99.10% | 20 |  |  |  |
| (Kim et al., 2018a) | 8x8 Pressure Sensor | 5 | CNN | 95.30% | 10 |  |  |  |
| (Luna-Perejón et al., 2021) | 6 Force Sensitive Resistors (FSR) | 7 | ANN | 81.00% | 12 | Low accuracy |  |  |
| (Cai et al., 2021) | 3x3 Flexible Array Pressure Sensor | 6 | SOM (ISOM-SPR) | 95.67% | 40 | Few Test Samples | Mobile App |  |
| (Fan et al., 2022) | 44 × 52 Pressure Sensor Array | 5 | CNN | 99.82% | 8 | \_ Few Test Samples \_ Lack of detection of spine curvatures | N/A | YES |
| (Chen, 2019) | Astra3D Sensor |  | CNN | 90% |  | Privacy issue with Camera Can't work in bad lighting Lack of proper user feedback system for posture correction | PC Screen (Correct/Wrong) | YES |
| (Ma et al., 2020) | Pressure array | 5 | Decision Tree | 89% |  |  |  |  |
| (Fard et al., 2013) | 64 Pressure Sensors Array (40x50) cm2 | 4 |  |  | 5 | Limited number of subjects | N/A | NO |
| (Ren et al., 2019) | 6 Square-Type force Sensing Resistors |  | ANN |  |  |  | RGB LED | YES |
| (Wang et al., 2021) | 2 Pressure Sensors Array (FSR) | 15 | SNN (LSM) | 88.52% | 19 | Lack of focus on the User feedback aspects Not used in real-life setting to prove it's usefulness | Desktop App | YES |
| (Xu et al., 2013) | Electrical Textile | 7 | Naive Bayes Network | 85.90% | 14 | The mobile just visualizes the sitting pressure distribution, however the value of this is not really seen to the end user's persepective. No sort of recommendation system. | Mobile App | Yes |
| (R et al., 2023) | Web Camera | 6 | RCNN & CNN | 92.50% |  | No good user feedback/recommendation system | N/A | YES |
| (Fu and Macleod, 2014) | 8 Force Sensing Resistors (FSR) FSR 406 |  | HMM Decision Tree |  |  | Lacks Proper testing  There's a need to implement a feedback system | N/A | YES |