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

## Introduction

According to the (Gill et al., 2023) in 2020, musculoskeletal disorders (MSDs) was ranked 2nd as the leading non-fatal disability that has been affecting more than a billion people worldwide. In Finland alone, MSD has 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 (US Bone and Joint Initiative, 2014) has concluded that quite a few individuals across different age groups are currently suffering from it. **(Schmidt et al., 2021)** reported that musculoskeletal disorders (MSDs) can often originate during childhood due to abnormal postures, which can further lead to 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 **(Stephen Bevan, 2013**), MSDs have cost the 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.

Furthermore, with the rapid advancement in data sensor technology and Artificial Intelligence, there should be new and creative solutions for continuous posture and health monitoring, allowing for personalized medicine and improved quality of life for individuals suffering from MSDs. With this in mind various studies have implemented smart sensing equipped with sensors with the goal of accurately classifying one’s postures based on different sitting positions. Furthermore, this literature review aims to evaluate related studies and identify research gaps that can pave the way for further investigation. 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.

## Literature Review

Similar studies:

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| Reference | Methods | Sensors | Postures | Classification | Results | Research Gaps |
| (Pereira and Plácido Da Silva, 2023) | ML trained on weight (center of mass) dataset measured from sensors. | Load Cell  Conductive nappa (connected to a single-lead sensor) was used for ECG measurements. | 5 | K-NN Model for posture evaluation.  DBSCAN (clustering algorithm) for the ECG segmentation | Achieved **98.5%** for 5 posture positions and **85%** using 7 positions.  ECG segmentation performance (88.21%) and accuracy (90.50%) | Only 10 subjects participated in the testing |
| (Ahmad et al., 2021) | Obtaining pressure data, which are sampled and processed in real-time using ML | Array of 16 screen printed pressure sensor units | 4 | K-NN, SVM, Decision Tree, Random Forest and LightGBM | LightGBM achieved the highest accuracy at **99.03%** | Only 32 volunteers were utilized in the testing phase. The testing data could be improved.  Limited number of postures. |
| (Huang et al., 2017) | The use of artificial neural network classifier to detect sitting postures in real-time | 52 by 44 piezo-resistive sensor array | 8 | ANN | The overall classification accuracy of eight sitting postures reached **92.2%** | Focused on only static sitting postures.  Wider range of sitting posture classification |
| (Martínez-Estrada et al., 2023) | Removable textile sensors, utilizing a presence textile capacitive sensor and microcontroller-based real-time monitoring to detect and prevent incorrect sitting postures | 10 Presence textile capacitive sensor  (embroidered) | 8 | N/A | The data gathered shows each sensor reading under different postures. | Five individuals were involved in the testing. (Bad quality of testing data)  More testing is needed to know its usefulness in a real-life setting.  There wasn’t any proper evaluation done to determine the accuracy of the readings that were found.  No informative feedback to the user  Lack of AI/ML prediction |
| (Matuska et al., 2020) | The integration of IoT to detect Bad postures in real-time with user feedback via a mobile app. | Six flexible force sensors | 9 | Utilization of Average Standard deviation with 3 Threshold values to determine good/bad postures | The system used standard deviation to determine the postures. It was categorized in to  “GREEN”, “YELLOW”, and “RED.”  Data was sent using the MQTT protocol | (12) Limited number participants (test data)  Nowhere to determine its accuracy. |
| (Aminosharieh Najafi et al., 2022) | The use of ML and pressure t | 8 Force Sensing Resistors (FSR) | 8 | MLP, CNN, RNN, LSTM, LSTM, BDLSTM, CNN-LSTM, CNLSTMLSTM CVLSTM, and an Echo Memory Network (EMN) | The Echo memory network model (EMNM) achieved the best accuracy with 91.68% | Low number of sitting postures.  Only 40 subjects using in the testing |