Review

Smart-Sensing Chairs for Sitting Posture Detection, Classification and Monitoring: A Systematic Literature Review

David Odesola 1 Janusz Kulon 1 , Shiny Verghese 1, Adam Partlow 2, and Colin Gibson 2

|  |
| --- |
| **Citation:** To be added by editorial staff during production.  Academic Editor: First name Lastname  Received: date  Revised: date  Accepted: date  Published: date    **Copyright:** © 2024 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/). |

1 Faculty of Computing, Engineering and Science, University of South Wales, Pontypridd, Wales, UK; 30025293@southwales.ac.uk; j.kulon@southwales.ac.uk; shiny.verghese@southwales.ac.uk

2 Rehabilitation Engineering Unit, Cardiff and Vale University Health Board, Cardiff, Wales, UK; j.kulon@southwales.ac.uk

**Abstract:** Improper sitting posture is the act of sitting in an asymmetric or an uneven way. If maintained for an extended period, it can negatively affect one’s wellbeing and can lead to long-term health conditions such as spinal deformity and musculoskeletal disorders. With the current advancement in sensor technology, there are different methods that are being employed within the research sphere with hopes of tackling improper sitting postures. This study aims to systematically review some of the existing literature to shed some insight into the common approaches being adopted in the detection and classification of improper sitting postures. Over the past 2 decades, various research studies have explored the concept of a smart sensing chair in the monitoring of sitting postures. Furthermore, an in-depth search was conducted across 3 main research databases which were MDPI, IEEE, and Google Scholar. The selection criteria primarily focused on studies that used non-invasive means in the monitoring of sitting postures. After filtering out all the irrelevant and duplicated articles, there were a total of 33 research articles and journals identified. Overall, it was observed that the Force Sensing Resistor (FSR) is the commonly used sensor for sitting posture detections. Additionally, the CNN (Convolutional Neural Networks) and the ANN (Artificial Neural Networks) were 2 of the most used machine learning models for sitting posture classification. The reviewed studies also highlighted a gap within the research field, revealing that a significant emphasis is drawn on the validating the proposed sitting posture algorithm, while the critical evaluation on the user feedback system for posture correction is often dismissed upon.

**Keywords:** smart sensing chair; musculoskeletal disorders; sitting posture classification

1. Introduction

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 [1]. It was also reported that over 7.1 million UK adults have been suffering with MSD and have cost the economy over £4.1 billion each year [2]. According to Bevan in 2015 [3], 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. This suggests that there is a steadily growing concern over this illness that needs to be properly addressed.

MSD originates from various factors and can emerge from a combination of events during a period. MSD can be a result ranging from various factor such as congenital defects [4] and neurological disorders [5]. Overall, individuals across different age groups and not just the elderly are currently suffering from MSD [6]. MSDs can develop from early stages in life by the frequent adoption of abnormal postures and low physical activities, which can subsequently lead to long-term chronic pain, discomfort, and physical limitations [6]. According to Kulon et al. [7], traditional methods of assessment are currently viewed as time consuming and most often rely on the use of large health care equipment such as Magnetic resonance imaging (MRI), X-rays and CT Scans.

Within an in-office work environment, staff members are often expected to be in a seated position for an extended period, which can be detrimental to one’s health and could lead to exacerbation of long-term musculoskeletal conditions such as back pains and spinal deformities [8]. According to [9] and [10], prolonged sitting has been one of the leading causes of MSDs that has been affecting office workers. These individuals often suffer pain in their lower back area. Studies conducted among daily office workers, conclude that there is a strong correlation between prolong sitting and severe back pains affecting the lumbar area [11,12]. To combat this issue, a recommendation is that the users take stroll breaks every few hours. The incorporation of exercise breaks as a daily routine, potentially increases cognitive functions in the long-term thus improving muscle strength [13].

The integration of smart sensing chairs into a home or office work environments, actively monitoring and providing feedback on user’s health and activity levels would be deemed quite useful. Furthermore, with the rapid advancement in data sensor technology and Artificial Intelligence, there should be new and commercialized solutions for continuous posture and health monitoring. Such systems have the potential of contributing towards the idea of personalized healthcare and improving the quality of life, especially for individuals suffering from MSDs.

1.2 History of Smart Sensing chairs

According to various studies found, Tan et al. back in 2007 [14] was seen as one of the first research study that pioneered the idea of a smart sensing chair capable of classifying an individual’s sitting posture based on pressure sensors integrated into the chair. Over the years, there has been an increase in the number of research studies being published on the concept of sitting posture classification on smart sensing chairs as shown in Figure 1 below. On average, around 500 studies have been published on this research topic annually in the last 5 years alone. Furthermore, this data suggests that there is a trend and a lot of interest in this research topic which explains the constant rise in publication year after year.

Figure 1 – Accumulative number of Research Papers published on smart sensing chair systems over the past decade. The research database that queried that was searched against was MDPI, IEEE, and Google Scholar.

1.3 Improper Sitting Posture

What is typically considered a good sitting posture? There is no doubt that individuals from various walks of life adopt different sitting postures knowingly and unknowingly. Hence, what is considered “good” sitting posture for some might be highly uncomfortable and not ideal for another. For instance, individuals that are suffering from permanent mobility impairment or those that are wheelchair bound, might have a different meaning of what is considered as a good sitting posture for them and might not be applicable for others. According to Slater et al. [15], there isn’t that one “correct” sitting posture that fits all due to the fact the people different spinal properties. However, it has been usually been advised by doctors and healthcare professionals to sit in an upright lordotic position which involves having your spine in an upright position [16]. According to various studies found [17,18], there are 8 different sitting postures which are: 1. Upright Sitting, 2. Slouching, 3. Leaning Forward, 4. Leaning Backward, 5. Leaning Right, 6. Leaning Left, 7. Right Leg Crossed, 8. Left Leg Crossed. Need to add more content here.

1.4 Aim and Objectives

The primary aim of this literature review study is to evaluate published papers on smart sensing chair systems, aiming to understand the methods being employed in posture classification. By exploring existing studies, it is possible to analyze current trends such as commonly used sensors and machine learning algorithms being adopted as well as potential research gaps. Ultimately, this review paper aims to provide valuable insight for researchers in the development of non-invasive smart sensing chair systems.

1. Research Methodology

This paper is aimed at conducting a systematic review of similar research studies done on smart sensing chair technology. Overall, there are 7 steps involved with this systematic review process which is the following:

1. Formulation of Research Questions

2. Search Strategy

3. Study Screening and Selection

4. Data Extraction

5. Data Synthesis

6. Discussion

7. Conclusion and Recommendations

2.1 Formulation of Research Questions

The following questions as seen in Table 1 are the research questions that are relevant to this systematic review.

**Table 1.** Research Questions

|  |  |
| --- | --- |
| **ID** | **Research Question** |
| RQ1 | What are the sensors that are mostly being used among similar studies? |
| RQ2 | What methods are being used to classify different sitting postures? |
| RQ3 | What are the limitations and research gaps seen with existing studies? |
| RQ4 | What are the user feedback mechanism being implemented? |
|  |  |

2.2 Search Strategy

Articles that were examined came from various online publication databases which are Google Scholar, IEEE Explore, and MDPI. 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 as shown in Table 2. Additionally, some of these “keywords” were combined to achieve better search results. Below are some of the search terms that was used. Additionally, filters were applied to find relevant studies that were published in the past 2 decades.

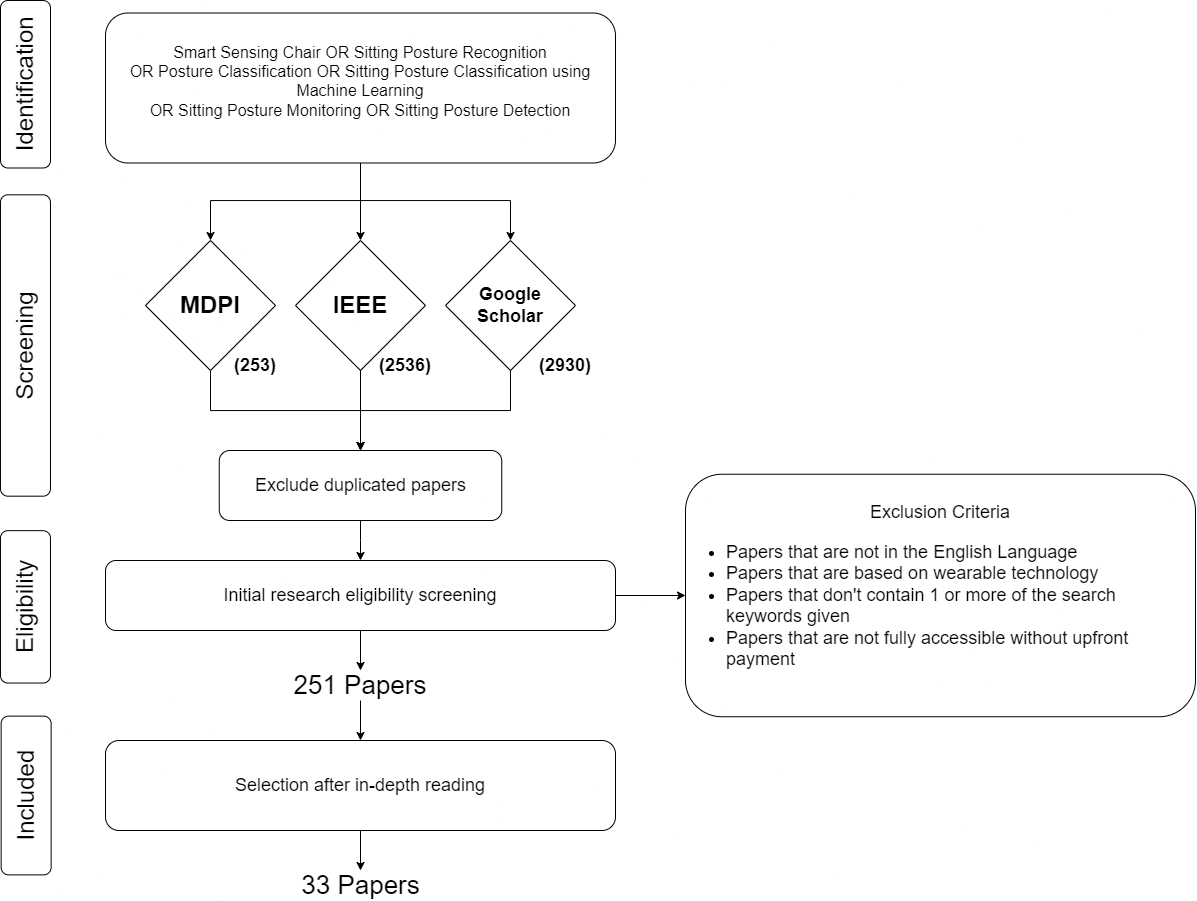
**Table 2.** List of Search Keywords

|  |  |
| --- | --- |
| **ID** | **Keywords** |
| SQ1 | Smart Sensing Chair |
| SQ2 | Sitting Posture Recognition |
| SQ3 | Posture Classification |
| SQ4 | Sitting Posture Classification using Machine Learning |
| SQ5 | Sitting Posture Monitoring |
| SQ6 | Sitting Posture Detection |
|  |  |

2.3 Study Screening and Selection

The initial screening of research papers involves reviewing both their title and abstract content to identify its relevancy to the research topic. As previously stated, a search filter was applied to narrow down the research studies that were published in the past 20 years. Additionally, to further narrow down the relevant papers, a list of exclusion criteria was highlighted. Research papers that didn’t employ non-invasive methods in the classification of sitting postures were excluded in the review.

The entire literature review screening process can be seen in Figure 3 below. Overall, a total of 33 papers across various research databases were identified.



**Figure 2**. Literature Review Process

Data Extraction and Analysis

The data extraction phase primarily focused on extracting the relevant information from the research papers gathered. This was achieved by individually reading through each paper in hopes of gathering useful data, especially on the methods and techniques being employed in the development of a smart sensing chair system. Listed below are the following information that was captured while going through each research paper:

* Authors
* Published Year
* Sensors Used
* Sensor Placement
* Number of Postures Classified
* Recognized Postures
* Classification Method
* Classification Accuracy
* Limitations
* User Feedback System
* Is Realtime
* Method Used

1. Technologies Used in Smart Sensing Chairs
   1. Overview of Sensor Technologies
      1. Force Sensing/Sensitive Sensor (FSR)

Force Sensing Resistors, also known as force sensors, are commonly used to measure the forces and physical pressure applied to its surface area. These sensors work by varying their output resistance based on the pressure being applied to it. A FSR sensor is typically composed of a conductive polymer-based material that is integrated between 2 metal electrodes [19]. Typically, the conductive material changes in resistivity as more direct pressure are applied on the sensor’s z-axis. Additionally, FSR sensors are also known to be very cost-effective and have been utilized in various fields ranging from robotics to medical applications [20]. However, the main limitation seen with these sensors is that it can be susceptible to drift errors which can negatively affect the accuracy of its readings. There are different methods such as sensor calibration and other advanced force computing techniques to mitigate this issue [21]. Listed in Table 3 are some of the commercially available FSR sensors as well as some of its technical specifications.

|  |  |
| --- | --- |
| A ruler next to a square piece of electronic device  Description automatically generated | A measuring device next to a ruler |
| (**a**) | (**b**) |

**Figure 2.** Examples of FSR sensors (**a**) Square shaped FSR sensor (FSR01CE) [22]; (**b**) Circle shaped FSR sensor (FSR03CE) [22].

**Table 3.** Technical specifications on FSR Sensors commercially available

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Manufacturer** | **Dimensions**  **(Length x Width, Thickness) (mm)** | **Force Sensitivity Range (Newtons)** |  |
| FSR 402 [23] | Interlink Electronics | 14.68 x 14.68 x 0.46 | 0.1 - 100N |  |
| FSR 406 [24] | Interlink Electronics | 39.6 x 39.6 x 0.46 | 0.1 – 100N |  |
| FSR01CE [22] | Ohmite | 39.70 x 39.70 x 0.375 | Up till 49 N |  |

* + 1. Textile Pressure Sensor

A textile-based pressure sensor is normally composed of a soft fabric-based material. This sensor consists of a conductive thread pattern placed over a dielectric material that serves as a substrate between the threads [21]. Figure 3 shows an example of how each layer within the textile pressure sensor is structured. One of the main advantages seen with textile force sensors is the fact that it is quite flexible, and it seamlessly integrates with garments making it unobstructive to the end user. Hence, this type of sensor tends to be quite popular among wearable technologies.

|  |  |
| --- | --- |
| Sensors 18 01190 g001 | A black square with white lines on it  Description automatically generated |
| (**a**) | (**b**) |

Figure 3. Textile Pressure Sensor (a) Textile Pressure Sensor composition [21]; (b) PreCaTex sensor [22].

A few research studies were found to have used textile sensors to classify sitting postures. One of which was Kim et al [23], who developed a washable textile pressure sensor and incorporated it into their chair system to classify 7 sitting postures using a decision algorithm. Another study proposed a “eCushion” device which is made up of a textile pressure array sensor that can detect 7 different sitting postures at 85.9% accuracy [24]. Additionally, Martínez-Estrada et al [22] also developed something similar by using 10 presence textile capacitive sensor (embroidered) sensors.

* + 1. Load Cells

Load cells also known as Strain Guage Loads cells are another variation of force sensor which is commonly used to measure monitor sitting postures. The sensor works by converting the mechanical force being applied to it into digital signals which can be read by microcontrollers.

**Table 4.** Technical specifications on Load cells Sensors commercially available

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Manufacturer** | **Dimensions**  **(Length x Width) (mm)** | **Capacity (kg)** |  |
| SEN-10245 [23] | SparkFun Electronics | 34 x 34 | 40-50 |  |
| P0236-142 [25] | Hanjin Data Corps | 34 x 34 | - |  |

Roh et al. in 2018 [25] 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 in 2023 [17] 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%.

Several wires connected to a device

Description automatically generated with medium confidence

**Figure 4**. 50 KG Load Cells (SEN-10245)

* + 1. Flex Sensors

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 [26]. It was seen that the primary use of flex sensors in the classification of sitting postures is not a widely popular approach among numerous studies.

Overall, there were only 2 studies identified that utilized this method for sitting posture detection. The first was by Hu et al [27] 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 [28] which also developed a similar system without the use of an ML model which aimed at detecting 7 different sitting postures.

A long yellow and black device

Description automatically generated with medium confidence

**Figure 5**. Flex Sensor

* + 1. Image Sensors

These image-based sensors such as a camera and 3d image sensors typically integrate with a computer vision algorithm which works by capturing visual elements from an image. In the classification of sitting postures, there is normally a digital camera actively positioned directly at the subjects. Furthermore, with the use of image processing libraries such as OpenPose or OpenCV, researchers were able analyze each video frame to determine the sitting posture.

This method is not a very popular option among the research studies found. However, there were a few studies found that used imaging systems. Mallare et al. in 2017 [60] developed a system utilizing 2 digital cameras, strategically positioned at (front and side) angles in the detection of bad sitting postures. Overall, they were only able to achieve an accuracy of 61.3% using the SVM algorithm. Additionally, Chen et al. in 2019 [52] further improved on this by using an Astra3D Sensor which is a 3D depth camera. With the utilization of the OpenPose library along with CNN for the posture classification, they were able to achieve an overall accuracy of 90%.

* 1. Pressure Sensors Placement Strategy

Since the use of pressure sensors is quite a popular option among research studies, Ma et al [29] stated that there are two main approaches being employed in the placement of this sensors among smart sensing chairs systems which are dense sensor array configuration and a sparse sensor array configuration. A dense sensor array typically involves the use of a flexible mat or an e-textile material that contains multiple pressure sensors that are interconnected together, functioning as a single unit. On the other hand, a sparse sensor array goes the concept of having several individual pressure sensors placed at strategic point around the chair.

* + 1. Dense Sensor Array

Xu et al, [30] used a textile pressure sensor array along with a dynamic time wrapping based algorithm to classify 7 sitting postures with 85.90 accuracy. Huang et al., 2017 [31] used a 52x44 Piezo-Resistive Sensor Array which was placed on the bottom seating. Using the ANN classifier, they were able to achieve a classification accuracy of 92.2%. Kim et al., 2018 [32] developed a washable fabric-based sensor array. Even after one thousand independent washes, the capacitance reading from textile sensors array had not deteriorated. Kim et al. [33] achieved a 95.30% accuracy using 8x8 pressure array and a CNN classifier to classify 5 sitting postures among children. Similarly, Cai et al. [34] utilized a flexible pressure sensor array (400mm x 400mm) placed on the bottom seat cushion to recognize 6 different sitting postures. Ran et al. [35] installed a 11 × 13 Pressure Sensor Array (IMM00014, I-MOTION) which communicated with a Raspberry PI computer which achieve a 96.22% classification accuracy using a 5-layer ANN classifier. Ahmad et al. [36] embedded a 16 screen pressure sensor array, also using a raspberry pi for sitting classification which obtained an high accuracy of 99.03% using LightGBM machine learning algorithm. Wang et al. [37] developed 2 sets of interconnected sensor sheets which cover both backrest and the seating cushion of the smart sensing chair. Using the SNN classifier, their proposed system could distinguish 15 different sitting postures with an accuracy of 88.52%, which is among the highest number of postures being classified. Finally, Fan et al. [38] also implemented a similar system that analyses the hip pressure, which subsequently achieved an accuracy of 99.82 using CNN.

**Table 4.** Studies using Dense Sensor Array Configuration

|  |  |  |
| --- | --- | --- |
| **Sensor** | **Accuracy** | **# of Postures** |
| Textile Pressure Sensor Array [30] | 85.90% | 14 |
| 52x44 Piezo-Resistive Sensor Array [31] | 92.20% | 8 |
| Textile Pressure Sensors (Woven Fabric) [32] | - | 7 |
| 8x8 Pressure Mat Sensor [33] | 95.30% | 5 |
| 400mm x 400mm Flexible Array Pressure Sensor [34] | 95.67% | 6 |
| 11 × 13 Pressure Array (IMM00014, I-MOTION) [35] | 97.07% | 7 |
| Screen Printed Pressure sensor units (16 Array) [36] | 99.03% | 4 |
| 2 Pressure Sensors Array (FSR) [37] | 88.52% | 15 |
| 44 × 52 Pressure Sensor Array [38] | 99.82% | 5 |

* + 1. Sparse Sensor Array

Mutlu et al. in 2007 [10] integrated 19 different FSRs into the seating cushion and used the Simple Logistic Regression ML algorithm to achieve 78% accuracy in classifying 10 different postures. Tsai et al. [11] used 13 pressure sensors to classify 10 sitting postures and was able to achieve an accuracy of 99.10% using the SVM ML algorithm. Aminosharieh Najafi et al. [12] 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. [39] added 6 sensors which was placed on the seating cushion and resulted in an 81.5% classification accuracy using SOM (ISOM-SPR) ML algorithm.

**Table 5.** Studies using sparse Sensor Array Configuration

|  |  |  |
| --- | --- | --- |
| **Sensor** | **Accuracy** | **# of Postures** |
| 19 4x4 Pressure sensors (Force Sensing Resistors) [40] | 78% | 10 |
| 6 Flexible Force Sensors (FSR402) [41] | - | 9 |
| 8 Force Sensing Resistors [18] | 91.68% | 8 |
| 6 Flex Sensors [27] | 97.43% | 7 |
| 6 Pressure Sensors & 6 Infrared Reflective Distance Sensors [42] | 92% | 11 |
| 8 Low resolution matrices of Pressure Sensors [43] | 70% | 8 |
| 12 Pressure Sensor (Force Sensitive Resistor) [44] | 99.47% | 5 |
| 16 Force Sensor [45] | 90.90% | 7 |
| 13 pressure sensors (FSR-406) [46] | 99.10% | 10 |
| 6 Force Sensitive Resistors (FSR) [39] | 81% | 7 |
| 6 FSR Sensors [29] | 89% | 5 |
| 6 Square-Type force Sensing Resistors [47] | - | - |
| 8 Force Sensing Resistors FSR 406 [48] | - | 7 |
| 5 Flex sensors [28] | - | 7 |
| 4 FSR Pressure Sensors [49] | - | 6 |
| 16 Pressure sensors & 2 Ultrasonic sensors [50] | 96% | 15 |
| 9 E-Textile Pressure Sensor [51] | 98.82% | 15 |

* 1. Machine Learning Models

Multiple machine learning algorithms across various studies are being adopted to classify different sitting postures. Two of the most used ML models among research studies were the CNN (Convolutional Neural Networks) [33,38,50,52,53] and ANN (Artificial Neural Networks) [31,35,39,43,47]. Other algorithms being used were KNN (K-Nearest Neighbors) [17,43], Decision Tree [29,48], SVM (Support Vector Machine) [25,46], RF (Random Forest) [45,54], SNN (Spiking Neural Network) [37], SLR (Simple Logistic Regression) [40], Self-Organizing Map [34], and Dynamic time Wrapping [30]. On the other hand, there were 7 studies that didn’t employ the use ML models in the classification of sitting postures [32,41,47,55–57]. Instead, most of these studies resulted in the implementation of straightforward threshold-based system. In the implementation of this approach, if the sensor data surpassed a specified threshold, a given posture is identified.

To perform a concrete validation on an ML model’s performance and accuracy, most studies result in various methods such as the use of a confusion matrix and performance comparison between different ML models. A confusion matrix is a powerful analytical tool that is used to measure the performance of machine learning algorithms. For binary classification models, there are only 4 possible options within a 2x2 matrix table which is True Positive (TP), True Negative (TN), False Positive (FP), and a False Negative (FN). On the other hand, for multi-class models, the confusion matrix goes beyond a 2x2 matrix, for it becomes a NxN matrix. The N value signifies the number of classes being present [58].

* 1. Integration with (Internet of Things) IoT

Over recent years, IoT has gained in popularity and has become a game changer within certain industries. It was projected that by the year 2030, there would be over 50 billion devices interconnected through IoT [45]. Within the context of smart sensing chair system, Ma et al. [23] highlighted the effectiveness of integrating IoT-based systems into healthcare sensors systems due to its major advantage of being able to seamlessly monitor user’s health data in real-time. The use of IoT systems for remote health monitoring is believed to not only reduce medical costs but could also aid in the early detection of chronic illnesses. Subsequently, this could potentially accelerate the treatment and improve overall life expectancy of an individual.

Now focusing on papers on smart sensing chairs that utilized IoT-based technology, Matuska et al. [39] used an Arduino-based microcontroller which communicated using the MQTT telemetry protocol in order detect 9 different sitting postures. The sensor data was sent in real-time data to a mobile application that alerted a user if an incorrect posture is being detected by signify ‘green”, “orange”, and “red” for standard sitting, bad sitting, and heavy load on backbone respectively. Similarly [40] developed a smart sensing chair which used the Blynk 2.0 platform to stream the sensor data to the web. Other studies such as [13] and [43] similarly used IoT for bad postures detection as well as providing valuable feedback to the end-user.

* 1. User Feedback System

The integration of a feedback system into a smart sensing chair is an integral component of enhancing the user experience. From the end user’s perspective, individuals should be able to receive real-time alerts whenever an improper sitting posture is being detected. It was seen that most studies focus on the classification aspects and leave out the implementation of a feedback platform. So far only 33% (11) of all the studies incorporated a feedback platform that would encourage the user to maintain a correct posture. The implementation of mobile application was seen as the most used platform for alerting a user whenever an improper sitting posture is being detected [34,41,43,50,56]. Another common method was the use of a Desktop application which was done by some studies [37,46,49,52]. Alternatively, instead of implementing an interactive platform such as a mobile or a desktop app, Ran et al. [59], proposed the use of a haptic motor system integrated into the seating which would vibrate whenever an incorrect sitting posture is being detected. To even make the system as unintrusive as possible, [47] looked at using a RGB bulb capable of changing colors whenever an incorrect posture is being detected.

1. Discussion
   1. Technology

The vast majority of the research studies revealed that the most popular approach to develop a smart sensing chair is to employ the use of pressure sensors. Table 6 clearly shows that over the years pressure sensors have always been the preferred option in the classification of sitting posture among researchers; out of which, FSR sensors were the preferred option compared to textile pressure sensors.

Figure 6 – Number of Research Papers published on smart sensing chair technology along with the sensor being used from 2007 to 2023.

In terms of the sensor placement configuration, placing various individual pressure sensors around the chair tends to be preferred method, rather than utilizing dense pressure arrays. So far there was no correlation seen that suggested that one placement strategy that produces higher classification accuracy over the other. However, there are other variables that should be considered such as maintenance and costs. Dense sensor arrays are known to be more costly and harder to manage compared to their counterparts [29]. Due to the fact that if one or more of the individual sensing units within the array is faulty, it would be required to replace the entire sensor array unit instead of the individual sensor. Add to this.

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 [42] utilized 6 pressure sensors (placed on the seating cushion) along with 6 Infrared Reflective Distance Sensors (placed on the back rest). By using the K-Nearest Network (KNN), they were able to classify eleven different sitting postures while achieving an accuracy of 92%. This study also highlighted one of the main limitations seen with other smart sensing systems. It was stated that the main limitation of entirely relying on pressure sensors is that the angle of spinal trunk rotation cannot be detected, which is an important aspect of a sitting posture. Similarly, Cho et al. [50], used 16 pressure sensors place on the sitting cushion along with 2 ultrasonic sensors placed at the neck support region. With this configuration, they were able to achieve 96% accuracy using LBCNet to classify fifteen sitting postures. Ma et al. [29] developed a smart seating cushion which employed the use of 6 FSR sensors for detecting different sitting postures and an Inertial measurement unit (IMU) sensor to monitor user activity.

* 1. Classification Algorithm

Figure 6 as shown below provides an overview of the machine learning models being utilized and how it correlates the number of postures classified against the overall classification accuracy. Overall, the data suggested that the accuracy of the machine learning model negatively influenced the number of sitting postures being classified. It is evident to see that the more sitting postures that are being classified, the less accuracy its classification accuracy would be. Hence, that is one of the main reasons why most studies on average limit the number of postures to 5-7 positions, which are leaning left, leaning right, leaning backward, upright sitting, and leaning forwards [56]. The study that had the least number of postures classified was by Feng et al. [52] who used RFID tag along with a camera sensor to classify 3 sitting postures (a. Sitting straight, b. Leaning Forward, c. Leaning Backward). On the other hand, Wang et al. [28], Cho et el. [45], Bourahmoune et al. [51] and looked at detecting up to 15 different postures which was the highest number seen among other studies found; achieving an accuracy of 88.52% , 96%, and 98.82% respectively.

Additionally, from Figure 6 below it was quite interesting to see deep learning models such as CNN and ANN aren’t much better in achieving higher classification accuracies compared to other statistical models. This phenomenon might all come down to the quantity of the dataset being used to train the model. It is known that deep leaning models tend to perform better with large datasets compared to statistical models. Furthermore, this could be theorized that there aren’t enough test subjects being used to train the deep learning models which could further improve its classification accuracy.

**Figure 6.** Comparison of Machine Learning Models: Number of Postures vs Accuracy vs Test Subjects

4.3 Research Gaps

4.3.1 Lack of User Feedback Evaluation

Looking at the current state of this research field, a majority of the studies predominantly focus on the development of algorithms that would achieve high classification accuracy. While it is valuable to find different ways and techniques to achieve better results in the detection of different sitting postures, there is however a lack of interest surrounding the implementation of user feedback systems. Most studies tend to prioritize other aspects such as sensor placement and classification accuracy and leave out the need to perform critical evaluation on user feedback systems for posture correction. As previously discussed, only 11 studies implemented a user feedback system for posture correction; 5 of which used a mobile application. Despite the low adoption, there is an apparent gap regarding the evaluations being implemented on these user feedback systems.

With the lack of a comprehensive evaluation being conducted, a few questions can be raised regarding the effectiveness, feasibility, and overall usability from the end user’s perspective when interacting with these systems. How is it certain that these systems are effective in encouraging the user to achieve better sitting postures? Performing a critical evaluation on these systems would be beneficial in various aspects. Firstly, it would provide vital information in regard to the user experience while interacting with these systems, making it quite easy to find potential gaps that could be further improved upon. Additionally, an in-depth analysis would be helpful to know if user expectations are in sync with the intended outcome of the system. Having this knowledge would give room for further improvement while ensuring that all expectations are aligned with the system’s outcomes. Methods such as interviews, surveys, and usability testing could be employed to collect valuable feedback.

4.3.2 Lack of diversity on the training dataset

The quality of the training dataset is very important during the training of machine learning model. Furthermore, test subjects are often recruited and tasked towards asserting different sitting postures for a specific duration to train the model. On average, the research studies utilize a very low number of test subjects, typically around 21 individuals. A sample size this small might not be adequate to fully represent the wide postural variances that exist within the wider population. Additionally, there also seems to be a bias towards the test subjects involved in the data collection, most of which are healthy individuals who are mocking bad sitting postures. While this no doubt simplifies the data collection phase for most studies, it fails to account for the different challenges involved in the recognition of bad sitting postures among individuals that are suffering musculoskeletal conditions. Consequently, the effectiveness of the machine learning model might be compromised when applied in real scenario settings involving a much wider demographic.

Addressing this issue requires a lot of effort which involves broadening the dataset by the inclusion of wider demographic ranging from different age groups, nationalities, occupation, and health backgrounds. Furthermore, by diversifying the training dataset, the model can be robust in classifying different sitting postures across a diverse population.

5. Conclusions & Recommendations for Future Research

This paper provides systematic literature review of the current landscape of smart sensing chair systems among research studies. Across different research studies, there are different sensors being used which are FSR sensors, textile pressure sensors, load cells, and image sensors. Out of which, it was found that FSR Sensors were the most popular option among researchers. In the placement of these sensors, there are 2 main strategies being adopted which are using a pressure sensor array or having the individual sensors dispersed around the chair. Currently, there are no significant advantages that suggest that one method is better than the other in improving the classification accuracy. However, considering other factors maintenance and costs having the sensors dispersed is considered the better option.

In the classification of sitting postures, there are a variety of machine learning models being applied. Most of which were able to achieve high classification accuracy of 90%. However, there were some gaps found in this aspect regarding the quality of the dataset being used to train the machine learning models. The test subjects are mostly healthy individuals from a small demographic population who are mocking improper sitting positions. This really brings to question the effectiveness of the model if it were to be used among a greater population, especially those suffering from musculoskeletal disorders.

**Supplementary Materials:** \_\_

**Author Contributions:** \_\_\_

**Funding:** \_\_\_

**Institutional Review Board Statement:** Not applicable

**Informed Consent Statement:** Not Applicable

**Data Availability Statement:** \_\_\_

**Acknowledgments:** \_\_\_

**Conflicts of Interest:** There are no conflicts of interest among authors.

**Appendix A**

**Full Literature Review Excel Table Here**

References

1. Gill, T.K.; Mittinty, M.M.; March, L.M.; Steinmetz, J.D.; Culbreth, G.T.; Cross, M.; Kopec, J.A.; Woolf, A.D.; Haile, L.M.; Hagins, H.; et al. 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* **2023**, *5*, e670–e682, doi:10.1016/S2665-9913(23)00232-1.

2. Ingram, M.; Symmons, D.P.M. The Burden of Musculoskeletal Conditions. *Medicine* **2018**, *46*, 152–155, doi:10.1016/j.mpmed.2017.12.005.

3. Bevan, S. Economic Impact of Musculoskeletal Disorders (MSDs) on Work in Europe. *Best Practice & Research Clinical Rheumatology* **2015**, *29*, 356–373, doi:10.1016/j.berh.2015.08.002.

4. Devi, R.R.; Singh, C.I.; Singh, K.C. Incidence and Profile of Neonatal Musculoskeletal Birth Defects at a Tertiary Hospital in North East India. *International Journal of Scientific Study* **2015**, doi:10.17354/ijss/2015/469.

5. Collange, C.; Burde, M.-A. Musculoskeletal Problems of Neurogenic Origin. *Best Practice & Research Clinical Rheumatology* **2000**, *14*, 325–343, doi:10.1053/berh.1999.0068.

6. European Agency for Safety and Health at Work. *Musculoskeletal Disorders among Children and Young People: Prevalence, Risk Factors and Preventive Measures : A Scoping Review.*; Publications Office: LU, 2021;

7. Kulon, J.; Voysey, M.; Partlow, A.; Rogers, P.; Gibson, C. Development of a System for Anatomical Landmarks Localization Using Ultrasonic Signals. In Proceedings of the 2016 IEEE International Symposium on Medical Measurements and Applications (MeMeA); IEEE: Benevento, Italy, May 2016; pp. 1–6.

8. Van Eerd, D.; Irvin, E.; Le Pouésard, M.; Butt, A.; Nasir, K. Workplace Musculoskeletal Disorder Prevention Practices and Experiences. *INQUIRY* **2022**, *59*, 004695802210921, doi:10.1177/00469580221092132.

9. Arora, S.N.; Khatri, S. Prevalence of Work-Related Musculoskeletal Disorder in Sitting Professionals. *Int J Community Med Public Health* **2022**, *9*, 892, doi:10.18203/2394-6040.ijcmph20220259.

10. Putsa, B.; Jalayondeja, W.; Mekhora, K.; Bhuanantanondh, P.; Jalayondeja, C. Factors Associated with Reduced Risk of Musculoskeletal Disorders among Office Workers: A Cross-Sectional Study 2017 to 2020. *BMC Public Health* **2022**, *22*, 1503, doi:10.1186/s12889-022-13940-0.

11. Keskin, Y. Correlation between Sitting Duration and Position and Lumbar Pain among Office Workers. *Haydarpasa Numune Med J* **2019**, doi:10.14744/hnhj.2019.04909.

12. Bontrup, C.; Taylor, W.R.; Fliesser, M.; Visscher, R.; Green, T.; Wippert, P.-M.; Zemp, R. Low Back Pain and Its Relationship with Sitting Behaviour among Sedentary Office Workers. *Applied Ergonomics* **2019**, *81*, 102894, doi:10.1016/j.apergo.2019.102894.

13. Yoon, D.H.; Lee, J.-Y.; Song, W. Effects of Resistance Exercise Training on Cognitive Function and Physical Performance in Cognitive Frailty: A Randomized Controlled Trial. *J Nutr Health Aging* **2018**, *22*, 944–951, doi:10.1007/s12603-018-1090-9.

14. Tan, H.Z.; Slivovsky, L.A.; Pentland, A. A Sensing Chair Using Pressure Distribution Sensors. *IEEE/ASME Trans. Mechatron.* **2001**, *6*, 261–268, doi:10.1109/3516.951364.

15. Slater, D.; Korakakis, V.; O’Sullivan, P.; Nolan, D.; O’Sullivan, K. “Sit Up Straight”: Time to Re-Evaluate. *J Orthop Sports Phys Ther* **2019**, *49*, 562–564, doi:10.2519/jospt.2019.0610.

16. Korakakis, V.; O’Sullivan, K.; O’Sullivan, P.B.; Evagelinou, V.; Sotiralis, Y.; Sideris, A.; Sakellariou, K.; Karanasios, S.; Giakas, G. Physiotherapist Perceptions of Optimal Sitting and Standing Posture. *Musculoskeletal Science and Practice* **2019**, *39*, 24–31, doi:10.1016/j.msksp.2018.11.004.

17. Pereira, L.; Plácido Da Silva, H. A Novel Smart Chair System for Posture Classification and Invisible ECG Monitoring. *Sensors* **2023**, *23*, 719, doi:10.3390/s23020719.

18. Aminosharieh Najafi, T.; Abramo, A.; Kyamakya, K.; Affanni, A. Development of a Smart Chair Sensors System and Classification of Sitting Postures with Deep Learning Algorithms. *Sensors* **2022**, *22*, 5585, doi:10.3390/s22155585.

19. Paredes-Madrid, L.; Matute, A.; Bareño, J.; Parra Vargas, C.; Gutierrez Velásquez, E. Underlying Physics of Conductive Polymer Composites and Force Sensing Resistors (FSRs). A Study on Creep Response and Dynamic Loading. *Materials* **2017**, *10*, 1334, doi:10.3390/ma10111334.

20. Sadun, A.S.; Jalani, J.; Sukor, J.A. Force Sensing Resistor (FSR): A Brief Overview and the Low-Cost Sensor for Active Compliance Control.; Jiang, X., Chen, G., Capi, G., Ishll, C., Eds.; Tokyo, Japan, July 11 2016; p. 1001112.

21. Velásquez, E.I.G.; Gómez, V.; Paredes-Madrid, L.; Colorado, H.A. Error Compensation in Force Sensing Resistors. *Sensing and Bio-Sensing Research* **2019**, *26*, 100300, doi:10.1016/j.sbsr.2019.100300.

22. Ohmite Ohmite FSR Series Integration Guide: Force Sensing Resistor 2018.

23. Interlink Electronics FSR 402 Data Sheet.

24. Interlink Electronics FSR 406 Data Sheet.

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

26. Sreejan, A.; Narayan, Y.S. A Review on Applications of Flex Sensors. *International Journal of Emerging Technology and Advanced Engineering* **2017**, *7*, 97–100.

27. Hu, Q.; Tang, X.; Tang, W. A Smart Chair Sitting Posture Recognition System Using Flex Sensors and FPGA Implemented Artificial Neural Network. *IEEE Sensors J.* **2020**, *20*, 8007–8016, doi:10.1109/JSEN.2020.2980207.

28. AbuTerkia, I.; Hannoun, M.; Suwal, B.; Ahmed, M.S.; Sundaravdivel, P. FPGA-Based Smart Chair Recognition System Using Flex Sensors. In Proceedings of the 2022 IEEE 15th Dallas Circuit And System Conference (DCAS); IEEE: Dallas, TX, USA, June 17 2022; pp. 1–2.

29. Ma, C.; Li, W.; Gravina, R.; Du, J.; Li, Q.; Fortino, G. Smart Cushion-Based Activity Recognition: Prompting Users to Maintain a Healthy Seated Posture. *IEEE Syst. Man Cybern. Mag.* **2020**, *6*, 6–14, doi:10.1109/MSMC.2019.2962226.

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

31. Huang, M.; Gibson, I.; Yang, R. Smart Chair for Monitoring of Sitting Behavior. *KEG* **2017**, *2*, 274, doi:10.18502/keg.v2i2.626.

32. Kim, M.; Kim, H.; Park, J.; Jee, K.-K.; Lim, J.A.; Park, M.-C. Real-Time Sitting Posture Correction System Based on Highly Durable and Washable Electronic Textile Pressure Sensors. *Sensors and Actuators A: Physical* **2018**, *269*, 394–400, doi:10.1016/j.sna.2017.11.054.

33. Kim, Y.; Son, Y.; Kim, W.; Jin, B.; Yun, M. Classification of Children’s Sitting Postures Using Machine Learning Algorithms. *Applied Sciences* **2018**, *8*, 1280, doi:10.3390/app8081280.

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

35. Ran, X.; Wang, C.; Xiao, Y.; Gao, X.; Zhu, Z.; Chen, B. A Portable Sitting Posture Monitoring System Based on a Pressure Sensor Array and Machine Learning. *Sensors and Actuators A: Physical* **2021**, *331*, 112900, doi:10.1016/j.sna.2021.112900.

36. Ahmad, J.; Sidén, J.; Andersson, H. A Proposal of Implementation of Sitting Posture Monitoring System for Wheelchair Utilizing Machine Learning Methods. *Sensors* **2021**, *21*, 6349, doi:10.3390/s21196349.

37. Wang, J.; Hafidh, B.; Dong, H.; El Saddik, A. Sitting Posture Recognition Using a Spiking Neural Network. *IEEE Sensors J.* **2021**, *21*, 1779–1786, doi:10.1109/JSEN.2020.3016611.

38. Fan, Z.; Hu, X.; Chen, W.-M.; Zhang, D.-W.; Ma, X. A Deep Learning Based 2-Dimensional Hip Pressure Signals Analysis Method for Sitting Posture Recognition. *Biomedical Signal Processing and Control* **2022**, *73*, 103432, doi:10.1016/j.bspc.2021.103432.

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

40. Mutlu, B.; Krause, A.; Forlizzi, J.; Guestrin, C.; Hodgins, J. Robust, Low-Cost, Non-Intrusive Sensing and Recognition of Seated Postures. In Proceedings of the Proceedings of the 20th annual ACM symposium on User interface software and technology; ACM: Newport Rhode Island USA, October 7 2007; pp. 149–158.

41. Matuska, S.; Paralic, M.; Hudec, R. A Smart System for Sitting Posture Detection Based on Force Sensors and Mobile Application. *Mobile Information Systems* **2020**, *2020*, 1–13, doi:10.1155/2020/6625797.

42. Jeong, H.; Park, W. Developing and Evaluating a Mixed Sensor Smart Chair System for Real-Time Posture Classification: Combining Pressure and Distance Sensors. *IEEE J. Biomed. Health Inform.* **2021**, *25*, 1805–1813, doi:10.1109/JBHI.2020.3030096.

43. Martins, L.; Lucena, R.; Belo, J.; Santos, M.; Quaresma, C.; Jesus, A.P.; Vieira, P. Intelligent Chair Sensor. In *Engineering Applications of Neural Networks*; Iliadis, L., Papadopoulos, H., Jayne, C., Eds.; Communications in Computer and Information Science; Springer Berlin Heidelberg: Berlin, Heidelberg, 2013; Vol. 383, pp. 182–191 ISBN 978-3-642-41012-3.

44. Ma, C.; Li, W.; Gravina, R.; Fortino, G. Posture Detection Based on Smart Cushion for Wheelchair Users. *Sensors* **2017**, *17*, 719, doi:10.3390/s17040719.

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

46. Tsai, M.-C.; Chu, E.T.-H.; Lee, C.-R. An Automated Sitting Posture Recognition System Utilizing Pressure Sensors. *Sensors* **2023**, *23*, 5894, doi:10.3390/s23135894.

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

48. Fu, T.; Macleod, A. IntelliChair: An Approach for Activity Detection and Prediction via Posture Analysis. In Proceedings of the 2014 International Conference on Intelligent Environments; IEEE: China, June 2014; pp. 211–213.

49. La Mura, M.; De Gregorio, M.; Lamberti, P.; Tucci, V. IoT System for Real-Time Posture Asymmetry Detection. *Sensors* **2023**, *23*, 4830, doi:10.3390/s23104830.

50. Cho, H.; Choi, H.-J.; Lee, C.-E.; Sir, C.-W. Sitting Posture Prediction and Correction System Using Arduino-Based Chair and Deep Learning Model. In Proceedings of the 2019 IEEE 12th Conference on Service-Oriented Computing and Applications (SOCA); IEEE: Kaohsiung, Taiwan, November 2019; pp. 98–102.

51. Bourahmoune, K.; Ishac, K.; Amagasa, T. Intelligent Posture Training: Machine-Learning-Powered Human Sitting Posture Recognition Based on a Pressure-Sensing IoT Cushion. *Sensors* **2022**, *22*, 5337, doi:10.3390/s22145337.

52. Chen, K. Sitting Posture Recognition Based on OpenPose. *IOP Conf. Ser.: Mater. Sci. Eng.* **2019**, *677*, 032057, doi:10.1088/1757-899X/677/3/032057.

53. R, N.; Sudhakar, T.; Bethanney Janney, J.; Krishnamoorthy, N.R.; Dhanalakshmi, K.; Vigneshwaran, S. Sitting Posture Analysis Using CNN and RCNN. In Proceedings of the 2023 International Conference on Bio Signals, Images, and Instrumentation (ICBSII); IEEE: Chennai, India, March 16 2023; pp. 1–5.

54. Feng, L.; Li, Z.; Liu, C. Are You Sitting Right?-Sitting Posture Recognition Using RF Signals. In Proceedings of the 2019 IEEE Pacific Rim Conference on Communications, Computers and Signal Processing (PACRIM); IEEE: Victoria, BC, Canada, August 2019; pp. 1–6.

55. Martínez-Estrada, M.; Vuohijoki, T.; Poberznik, A.; Shaikh, A.; Virkki, J.; Gil, I.; Fernández-García, R. A Smart Chair to Monitor Sitting Posture by Capacitive Textile Sensors. *Materials* **2023**, *16*, 4838, doi:10.3390/ma16134838.

56. Kundaliya, B.; Patel, S.; Patel, J.; Barot, P.; Hadia, S.K. *An IoT and Cloud Enabled Smart Chair for Detection and Notification of Wrong Seating Posture*; In Review, 2022;

57. Fard, F.D.; Moghimi, S.; Lotfi, R. Evaluating Pressure Ulcer Development in Wheelchair-Bound Population Using Sitting Posture Identification. *ENG* **2013**, *05*, 132–136, doi:10.4236/eng.2013.510B027.

58. Tharwat, A. Classification Assessment Methods. *ACI* **2021**, *17*, 168–192, doi:10.1016/j.aci.2018.08.003.

59. Ran, X.; Wang, C.; Xiao, Y.; Gao, X.; Zhu, Z.; Chen, B. A Portable Sitting Posture Monitoring System Based on a Pressure Sensor Array and Machine Learning. *Sensors and Actuators A: Physical* **2021**, *331*, 112900, doi:10.1016/j.sna.2021.112900.

**Disclaimer/Publisher’s Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.