Review

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

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**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 that needs to be properly addressed. The mortality rates caused by MSDs are said to be among the lowest seen. This phenomenon has most likely led to shift of attention and resources towards other health priorities with higher mortality rates [4].

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 [5] and neurological disorders [6]. Overall, individuals across different age groups and not just the elderly are currently suffering from MSD [7]. 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 [7]. According to Kulon et al. [8], 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 [9]. According to [10] and [11], 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 [12,13]. 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 [14].

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.

Various research studies which will be later discussed have investigated the development of posture monitoring systems, with an aim to assist the end user in maintaining the right sitting posture at every given time. These types of systems are named “smart sensing chairs”. This concept goes all the way back to the first research study that was done by Tan et al back in 2001 [15], who fitted a chair with a pressure distribution sensor to classify a user’s sitting postures which was just first of many.

1. 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, the objective is to have a comprehensive understanding within the field of 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. The research method that would be used is the study would be based on the Cochrane review methodology. Overall, there are 9 steps involved with this systematic review process which is the following:

1. Formulation of Research Questions

2. Protocol

3. Search Strategy

4. Study Screening and Selection

5. Data Extraction

6. Bias Risk Assessment

7. Data Synthesis

8. Discussion

9. Conclusion and Recommendations

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? |
|  |  |

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. 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 20 years.

* Smart Sensing Chair
* Sitting Posture Recognition
* Posture Classification
* Sitting Posture Classification using AI/Machine Learning
* Sitting Posture Monitoring
* Sitting Posture Detection

Data Extraction

The Data Extraction phase primarily focused on extracting the relevant information relating to the research questions. 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

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. The entire literature review screening process can be seen in Figure 1 below. Overall, a total of 33 papers across various research databases were identified for further consideration.

A diagram of a paper

Description automatically generated

Figure 3 - Literature Review Process

Discussion

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. A total of 33 relevant research literatures were carefully selected and examined as seen in Table 1. This literature has 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

Tan et al. [15] 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 years, various research studies have implemented different variations of these smart sensing chair concepts ranging from different sensors to various classification methods for posture detection. Figure 5 gives a rough visualization of the research landscape on smart sensing chair technology.

A bunch of white circles with green circles with white text

Description automatically generated

Figure 4 - Timeline Map of Similar Literatures

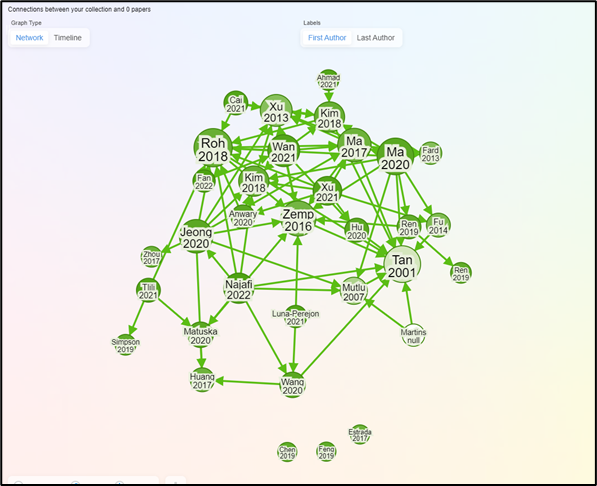


Figure 5 - A Map of Similar Studies on Smart Sensing Chairs

Sensor systems

The published studies are based on the use of diverse types of sensor devices to detect 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 Image Processing

Sensing Chair using Pressure Sensors

[Overview of Sensor technology]

Pressure sensing technology are utilized in various applications ranging from medical devices to robotics equipment. These sensors can detect pressure points and can be used in various scenarios. Furthermore, this section would be evaluating the pressure sensors being used within the context of smart chair seating. The criterion of evaluation involves components such as its cost effectiveness and measurement accuracy.

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 direct pressure is applied to the sensor [16]. It is normally composed of a conductive polymer-based material. To be able to get the reading from this sensor, it is usually connected directly to a microcontroller such as an Arduino or the like get its raw data reading. Figure 5 shows an example of how an FSR sensor commonly looks like.



Figure - A Force Sensing Resistor

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 6 - Textile Pressure Sensor composition [17]

A few research studies were found to have used textile sensors to classify sitting postures. One of which was Kim et al [17], 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 [18]. Additionally, Martínez-Estrada et al [19] also developed something similar by using 10 presence textile capacitive sensor (embroidered) sensors.

Pressure Sensors Placement Strategy

Furthermore, it was said that among studies there are two main approaches being employed in the placement of pressure/FSR sensors among smart sensing chairs systems: using a dense sensor array and a sparse sensor array [13]. A dense sensor array can be 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 idea of having several individual pressure sensors placed at strategic point around the chair.

Dense Sensor Array

According to Ma et al in 2020 a dense Sensor Array is said to be more costly compared to its counterpart [20]. As shown in Table 2 summarizes the list of studies that used a dense sensor array. Xu et al, [18] 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 [21] 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 [22] 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. [23] achieved a 95.30% accuracy using 8x8 pressure array and a CNN classifier to classify 5 sitting postures among children. Similarly, Cai et al. [24] utilized a flexible pressure sensor array (400mm x 400mm) placed on the bottom seat cushion to recognize 6 different sitting postures. Ran et al. [25] 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. [26] 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. [27] 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. [28] also implemented a similar system that analyses the hip pressure, which subsequently achieved an accuracy of 99.82 using CNN. Table 2 summarizes the studies that applied the approach of using dense sensor array.

**Table 2.** List of Studies using Dense Sensor Array

|  |  |  |
| --- | --- | --- |
| **Reference** | **Author** | **Sensor** |
| [18] | Xu et al., 2013 | Textile Pressure Sensor Array |
| [21] | Huang et al., 2017 | 52x44 Piezo-Resistive Sensor Array |
| [22] | Kim et al., 2018 | Textile Pressure Sensors (Woven Fabric) |
| [23] | Kim et al., 2018 | 8x8 Pressure Mat Sensor |
| [24] | Cai et al., 2021 | 400mm x 400mm Flexible Array Pressure Sensor |
| [25] | Ran et al., 2021 | 11 × 13 Pressure Array (IMM00014, I-MOTION) |
| [26] | Ahmad et al., 2021 | Screen Printed Pressure sensor units (16 Array) |
| [27] | Wang et al., 2021 | 2 Pressure Sensors Array (FSR) |
| [28] | Fan et al., 2022 | 44 × 52 Pressure Sensor Array |

Sparse Sensor Array

**Table 3.** List of Studies using sparse Sensor Array

|  |  |  |
| --- | --- | --- |
| **Reference** | **Author** | **Sensor** |
| [29] | Mutlu et al., 2007 | 19 4x4 Pressure sensors (Force Sensing Resistors) |
| [30] | Matuska et al., 2020 | 6 Flexible Force Sensors (FSR402) |
| [31] | Amniochorion Najafi et al., 2022 | 8 Force Sensing Resistors |
| [32] | Hu et al., 2020 | 6 Flex Sensors |
| [33] | Jeong and Park, 2021 | 6 Pressure Sensors & 6 Infrared Reflective Distance Sensors |
| [34] | Martins et al. 2013 | 8 Low resolution matrices of Pressure Sensors |
| [35] | Ma et al., 2017 | 12 Pressure Sensor (Force Sensitive Resistor) |
| [36] | Zemp et al., 2016 | 16 Force Sensor |
| [37] | Tsai et al., 2023 | 13 pressure sensors (FSR-406) |
| [38] | Luna-Perejón et al., 2021 | 6 Force Sensitive Resistors (FSR) |
| [20] | Ma et al., 2020 | 6 FSR Sensors |
| [39] | Ren et al, 2013 | 6 Square-Type force Sensing Resistors |
| [40] | Fu and MacLeod, 2014 | 8 Force Sensing Resistors FSR 406 |
| [41] | AbuTerkia et al, 2022 | 5 Flex sensors |
| [42] | La Mura et al, 2023 | 4 FSR Pressure Sensors |
| [43] | Haeyoon Cho et al., 2019 | 16 Pressure sensors & 2 Ultrasonic sensors |
| [44] | Bourahmoune et al., 2022 | 9 E-Textile Pressure Sensor |

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. [38] added 6 sensors which was placed on the seating cushion and resulted in an 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. in 2018 [45] 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 [46] 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 7 - Load Cells

Sensing Chair using Flex Sensors

Flex sensors are another variation of sensors that are being used by myriad 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 [47].

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 [32] 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 [41] which also developed a similar system without the use of an ML model which aimed at detecting 7 different sitting postures.



Figure 8 - 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 [33] 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. [43], 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. [20] 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.

Smart Sensing Chairs using Image Processing

There were some research papers that have investigated the application of image processing in the detection of improper sitting postures. This approach mostly involves the utilization of a digital camera actively positioned directly on the subjects. Furthermore, by employing the use of image processing techniques and algorithms, one can analyze each video frame to determine the sitting posture.

Mallare et al. in 2017 [48] developed a system utilizing 2 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. Chen et al. in 2019 [49] further improved on this by using a Astra3D Sensor which is a 3D depth camera. By using the OpenPose library along with CNN for the posture classification, an accuracy of 90% was achieved.

Machine Learning Classification Method

As expected, different machine learning algorithms are being used to classify different sitting postures. Two of the most used ML models among research studies were the CNN (Convolutional Neural Networks) [23,28,43,49,50] and ANN (Artificial Neural Networks) [21,25,34,38,39]. Other algorithms being used were KNN (K-Nearest Neighbors) [34,46], Decision Tree [20,40], SVM (Support Vector Machine) [37,45], RF (Random Forest) [36,51], SNN (Spiking Neural Network) [27], SLR (Simple Logistic Regression) [29], Self-Organizing Map [24], and Dynamic time Wrapping [18]. On the other hand, there were 7 studies that didn’t employ the use ML models in the classification of sitting postures [19,22,30,39,52,53]. 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.

Machine Learning Performance Validation

To perform 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 [54].

Different Sitting Postures

Taking an in-depth look at Table 1 it was seen that across all the gathered research papers, there are varying number of postures being classified. Upon further analysis, it was quite 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 [55]. The study that had the least number of postures classified was by Feng et al. [51] 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. [27] and Bourahmoune et al. [44] looked at detecting up to 15 different postures which was the highest seen among other studies found.

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. As shown in Figure 8 below, so far only 33% (11) of all the studies incorporated a kind of 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 [24,30,34,43,52]. Another common method was the use of a Desktop application which was done by some studies [27,37,42,49]. Alternatively, instead of implementing an interactive platform such as a mobile or a desktop app, Ran et al. [56], 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, [39] looked at using a RGB bulb capable of changing colors whenever an incorrect posture is being detected.

Figure - Feedback System Percentage

(Internet of Things) IoT Integration with smart sensing chairs

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]. Ma et al.[20] 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.

System Limitations

Research Gaps

Across all the research studies, it is apparent that there are different classification methods being used to classify different sitting postures. However, as previously discussed it was seen that many studies focus on the classification aspects of things and leave out the implementation of a feedback system to guide the user in maintaining a correct sitting posture. As discussed in the previous section, only 33% (11) of studies found developed an interface that would enforce correct sitting posture; five of which implemented the use of mobile application. Overall, the implementation of a mobile application looks to be a useful approach in notifying the end-users about maintaining proper sitting postures. However, it is quite important to acknowledge the research gap in this field of interest – specifically the lack of comprehensive evaluations in accessing user’s experience with these applications.

These few studies looked at the implementation of mobile applications as a means of providing real-time feedback on one’s sitting postures. However, due to the lack of a comprehensive evaluation being conducted, a few questions are raised regarding the effectiveness, feasibility, and overall satisfaction from the user’s perspective when interacting with these apps. According to \_\_\_, it is beneficial to capture other users’ perspective on a mobile app to gain a deep understanding of its strengths and weaknesses.

To address this research gap, future studies should go beyond focusing on achieving high classification accuracy of different sitting postures and prioritize conduction user-centered evaluations on 5the implemented feedback system. Methods such as interviews, surveys, and usability testing could be employed to collect valuable feedback. With this done, it would be very easy to gauge and measure the effectiveness of the proposed feedback system.

5. Conclusions

This section is not mandatory but can be added to the manuscript if the discussion is unusually long or complex.

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**Appendix A**

**Full Literature Review Excel Table Here**

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